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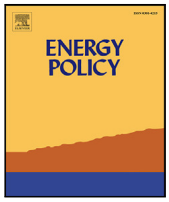

Research article

Spatial–temporal dynamics of structural unemployment in declining coal mining regions and potentialities of the 'just transition'

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ABSTRACT

A rapid decarbonisation of the United States economy is expected to disproportionately impact regions historically embedded in domestic fossil fuel production. For decades, social scientists have documented the economic and human toll of deindustrialisation, foreshadowing the transitional risks that these regions may face amidst decarbonisation. However, econometric studies evaluating the magnitude, duration, and spatial distribution of unemployment impacts in declining mining regions remain scarce, despite their pertinence to policymaking. Therefore, using econometric estimation methods that control for unobserved heterogeneity via two-way fixed effects, spatial effects, heterogeneous time trends, and grouped fixed effects for a panel of 3,072 US counties covering 2002–2019, we demonstrate that coal mine closures induce a contemporaneous rise in county unemployment rate with spatial ripple effects. Furthermore, evidence of local-level resilience to such shocks over a two-year time horizon is weak. To further account for county-level heterogeneity, we construct a typology of coal counties based on qualities theorised to be resilient to industrial decline. Our findings suggest the significant potential of investing in alternative sectors in localities with promising levels of economic diversity, retraining job seekers, providing relocation support in rural areas, and subsidising childcare in places with low female labour force participation.

1. Introduction

In 2021, President Joe Biden committed his administration to decarbonising the US economy by decreasing greenhouse gas emissions to 50%–52% below 2005 levels by 2030 with a view towards net-zero emissions by 2050 (White House Briefing Room, 2021). In August 2022, the Inflation Reduction Act (IRA) was passed constituting a significant step in the direction of these ambitious goals, aiming jointly to reduce inflation, lower prescription medicine prices, and invest heavily in domestic energy production with a focus on clean energy. Climate and energy security investments stipulated in the IRA total 369 billion US$ (Library of Congress, 2022). Although the full potential of the IRA remains to be realised, and is indeed subject to great uncertainty, recent estimates suggest that the policy puts the US on track to reduce greenhouse gas emissions by 32%–42% compared to 2005 levels in 2030, 6–11 percentage points lower than without the IRA (Bistline et al., 2023b,a). Thus, as the political momentum behind decarbonisation increases, the question of how to usher in a 'Just Transition' – ensuring minimal adverse impacts from and the equitable sharing of the benefits of decarbonisation – is front of mind for environmental and climate justice advocates concerned about impacts on workers, consumers, and frontline communities (McCauley and Heffron, 2018; Pollin and Callaci, 2019; Piggot et al., 2019; Newell and Mulvaney, 2013; Cha and Pastor, 2022).

The International Energy Agency predicts 50,000 layoffs in the US coal sector by 2030 while up to a quarter million US oil and gas jobs are also threatened (International Energy Agency, 2021). Because fossil fuel deposits are highly concentrated geographically, a decline in output will be felt most sharply in a few select regions with deep roots in the industry (Hendrickson et al., 2018; Snyder, 2018; Rickard, 2020). Although the IRA lists several generic initiatives to support American workers, only two policy objectives can be described as targeting fossil fuel workers specifically: a 10% increase in the clean energy tax credit for infrastructure projects operating in or near "energy communities" and a 5 billion US$ fund providing low-cost loans and refinancing for energy infrastructure, with the notable caveat that qualifying projects

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should "retool, repower, repurpose, or replace energy infrastructure that has ceased operations" (Library of Congress, 2022). These provisions follow evident commitment from the Biden administration to confront questions of both environmental and broader equality concerns with the creation of the Justice 40 initiative and a racial equality executive order, for example (National Archives and Records Administration, 2021). However, these measures are just a small sample of a larger set of proposed Just Transition policy responses for workers that range from completely compensatory (i.e. direct income support, relocation assistance, interim health care coverage, pension payouts) to active labour market policies (i.e., education, training, and reskilling) and investments in alternative sectors, whether green or otherwise, to provide new job opportunities (Pollin and Callaci, 2019; Piggot et al., 2019; Pollin et al., 2021, 2014). Determining the appropriate scale of Just Transition policies requires knowledge of the magnitude, duration, and spatial distribution of adverse impacts. Similarly, determining which proposed policies are most effective in reducing these adverse impacts requires localised knowledge of the salient demographic characteristics of communities facing the highest employment risks.

Thus, we present empirical evidence of the multi-dimensional impact of the already experienced, prolonged, and consistent contraction in US coal production over the past two decades on local communities and a typology of US coal counties capturing relative unemployment risks. We make two significant contributions to existing literature. We first contribute empirical econometric evidence exploring the spatio-temporal nature of employment dynamics resulting from coal decline in order to illuminate the relative usefulness of proposed Just Transition policy interventions, including those outlined in the IRA. While numerous qualitative studies have proffered various ethical principles to guide a 'Just Transition' amid structural decarbonisation (Healy and Barry, 2017; Jenkins et al., 2018), econometric evidence exploring these real-world barriers to transitional justice is scarce. In-depth regional investigation of the effects of fossil energy industry reliance on employment has generally been done qualitatively, through vulnerability assessments or sociological and ethnographic analyses (Snyder, 2018; Snell, 2018; Abraham, 2017; Sovacool et al., 2021; Bell and York, 2010; Raimi, 2021; Carley et al., 2018a,b). The available econometric research has mostly concentrated on oil and gas, specifically oil prices and the macroeconomy (Hamilton, 1983; Munasib and Rickman, 2015; Paredes et al., 2015; Miljkovic and Ripplinger, 2016; Weinstein, 2014; Marchand, 2012) with a smaller minority of studies focused on coal (Douglas and Walker, 2017; Black et al., 2005a,b; Blonz et al., 2023; Black et al., 2002; Betz et al., 2015). Furthermore, such results are rarely framed from the Just Transition perspective until a recent study by Scheer et al. (2022). Therefore, we analyse the magnitude, persistence, and geographic distribution of employment shocks following coal mine closures using a tailor-fit econometric modelling approach. More specifically, we employ dynamic panel and spatial econometric methods to account for latent common factors and spatial spill-over effects to achieve greater precision in the estimation of employment shocks caused by structural changes to the US coal sector.

Second, by employing machine learning techniques of agglomerative hierarchical clustering we establish a typology of the relative vulnerability of coal mining communities to inform future research and policymaking in a period of accelerating energy transitions. To our knowledge, three other studies have defined comparable typologies using theoretical frameworks.[1] Snyder employs three indicators to proxy education, poverty, and rurality, Raimi proposes twelve, and a more recent typology by Hincapie-Ossa et al. look at *all* energy communities rather than coal communities specifically (Snyder, 2018; Raimi, 2021; Hincapie-Ossa et al., 2023). Our work supplements this work in three ways: by presenting an intermediate number of vulnerability axes, striking a balance between multidimensionality and succinctness; by operationalising the typology through hierarchical clustering analysis in the context of coal communities only; and by reincorporating our typology into our econometric analysis via grouped fixed effects. This combined evidence aims to help policymakers determine the optimal mix and geographic targeting of transition assistance from a suite of proposed responses, including alternative (preferably green) sectoral investment, active labour market policies, compensatory transition support for laid-off workers in the most vulnerable counties, and other social policies.

Combined, these two methods of analysis allow us to make more robust estimates of the scale of assistance needed to alleviate adverse impacts of a decarbonisation transformation on communities in a manner that is in tune with diverse local needs. Furthermore, the results provide timely insight into the potentialities of the Inflation Reduction Act currently undergoing implementation across the country.

In what follows, we first outline our empirical strategy for estimating several panel data models using a suite of purpose-fit specifications and describe our motivation and method for creating a typology of US coal counties. Second, we briefly outline the data used to conduct the empirical analysis. Finally, we describe the results of our econometric and cluster-typological analyses followed by a discussion of the context-dependent policy implications and recommendations based on this combined evidence.

2. Methods

Below, we outline the methods employed using the data described in Section 3 to carry out the (1) econometric modelling and (2) implement the typology via agglomerative hierarchical clustering.

2.1. Econometric estimation

This study's panel data analysis is based on five baseline model specifications. Table 1 below provides algebraic formulas and technical details of each. All models were estimated using the county-level panel dataset described in Section 3 spanning from 2002 to 2019. Several models (specified in Table 1) were estimated on a subset of coal counties, defined as counties that had active coal mines between 2002 and 2019. The model specifications are motivated as follows:

- Model 1 evaluates if a change in the number of active coal mines affects county unemployment rate.
- Models 2–5 aim to identify through what channel the unemployment rate varies due to a change in active coal mines (i.e., a change in the number of employed workers or in the size of the labour force). This is studied by regressing the county unemployment rate determinants (number of employed persons, number of unemployed persons, labour force size, and population size) on the same indicators for changes in the number of active coal mines.

Models 1–5 (without superscripts) were estimated using the canonical two-way fixed effects (TWFE) estimator, with standard errors clustered by county and year to address within-cluster correlation and heteroskedasticity.[2] Prior to model estimation, all variables were first-difference transformed to address non-stationarity (Castle and Hendry, 2019). This yielded stationary I(0) covariates, with the additional benefit that the effects of first-difference variables are easy to interpret.

The TWFE estimator, like other estimators used in ordinary least squares regression modelling, requires the restrictive condition of cross-sectional independence. In practice, any unobserved cross-section dependencies, such as structural breaks, global stochastic trends, or spatial (spill-over) effects, in the underlying data generating process are

[1] See Raimi (2021) for a broader review of similar vulnerability assessments.

[2] All TWFE models were estimated using the *fixest* package in R.

Table 1
Model specifications.

#	Model specification	Results
1*	$\Delta UER_{it} = \boldsymbol{\beta}\begin{pmatrix}\boldsymbol{X}_{it}\\ \Delta log(RealGDPPC)_{it}\end{pmatrix} + \alpha_i + \gamma_t + \varepsilon_{it}$	Figs. 1 and 2 Appendix B.1: Tables S8–S9
2*	$\Delta log(Employed\,Persons)_{it} =$	Fig. 3 Appendix B.1: Tables S8–S9
3*	$\Delta log(Unemployed\,Persons)_{it} =$	
4*	$\Delta log(Labor\,Force)_{it} =$	
	$\boldsymbol{\beta}\begin{pmatrix}\boldsymbol{X}_{it}\\ \Delta log(RealGDP)_{it}\\ \Delta log(Population)_{it}\end{pmatrix} + \alpha_i + \gamma_t + \varepsilon_{it}$	
5*	$\Delta log(Population)_{it} = \boldsymbol{\beta}\begin{pmatrix}\boldsymbol{X}_{it}\\ \Delta log(RealGDP)_{it}\end{pmatrix} + \alpha_i + \gamma_t + \varepsilon_{it}$	
1^{SEM}	$Y_{it} = \boldsymbol{\beta}\boldsymbol{X}_{it} + \alpha_i + \gamma_t + U_{it}$ $U_{it} = \delta W_i U_t + \varepsilon_{it}$	Fig. 2 Appendix B.2 Tables S13, S14, S15, S16, S18
1^{SLX}	$Y_{it} = \boldsymbol{\beta}\boldsymbol{X}_{it} + \boldsymbol{\theta}\boldsymbol{W}_i\boldsymbol{X}_t + \alpha_i + \gamma_t + U_{it}$ $U_{it} = \delta W_i U_t + \varepsilon_{it}$	
1^{SLM}	$Y_{it} = \boldsymbol{\beta}\boldsymbol{X}_{it} + \rho W_i Y_t + \alpha_i + \gamma_t + \varepsilon_{it}$	
$1\text{-}5^{SARAR}$	$Y_{it} = \boldsymbol{\beta}\boldsymbol{X}_{it} + \rho W_i Y_t + \alpha_i + \gamma_t + U_{it}$ $U_{it} = \delta W_i U_t + \varepsilon_{it}$	
$1\text{-}5^{HTT(d)}$	$Y_{it} = \boldsymbol{\beta}\boldsymbol{X}_{it} + \sum_{l=1}^{d}\lambda_{il} f(t) + \alpha_i + \gamma_t + \varepsilon_{it}$	Fig. 2 Appendix B.3: Tables S19, S20

Variable definitions:
i: denotes each county for i=1, 2,...3,072 counties
t: denotes each year for t=2002, 2003,...2019
$\boldsymbol{\alpha_i}$: unit-fixed effects
$\boldsymbol{\gamma_t}$: time-fixed effects
$\boldsymbol{X_{it}}$: Vector of independent variables (Δ Active $Mines_{it}$, Δ Active $Mines_{it\text{-}1}$, Δ Active $Mines_{it\text{-}2}$). For Models $1\text{-}5^{[SEM,\ SLM,\ SARAR]}$ and $1\text{-}5^{[HTT(1),HTT(2)]}$ this represents all independent variables denoted in Models 1-5, respectively.
***log (Real GDPPC)*$_{it}$**: natural logarithm of county-level real GDP per capita.
***log (Real GDP)*$_{it}$**: natural logarithm of county-level real GDP.
***log(Population)*$_{it}$**: natural logarithm of county-level population.
$\boldsymbol{Y_{it}}$: Relevant dependent variable denoted by model number.
$\boldsymbol{\beta}$: Vector of regression coefficients to be estimated.
$\boldsymbol{\rho}$: Spatial autoregression parameter.
$\boldsymbol{\delta}$: Spatial autocorrelation parameter.
$\boldsymbol{\theta}$: Regression coefficient on spatially lagged treatment variables.
$\boldsymbol{W_i}$: N X N spatial weight matrix for neighbours of unit i where N = 3,072.
λ_{il}: Individual loadings parameter per unit i and factor l in heterogeneous trend models.
f(t): Unobserved time-varying common factors used in heterogeneous trend models.
$\boldsymbol{\Delta UER_{it}}$: Change in unemployment rate in county i in year t.

* Indicates model was also applied to a subset of coal counties only.

assumed to be captured sufficiently using linear additive two-way (unit and time) fixed effects. In many real-world circumstances, this assumption is too restrictive (Imai and Kim, 2019). Although it can accommodate time-invariant confounders, the TWFE estimator comes at the expense of potential dynamic misspecification (Plumper and Troeger, 2019). Insufficient accounting for cross-sectional dependence can lead to inaccurate and inconsistent regression coefficient estimates (Pesaran, 2014; Anselin and Bera, 1998). Indeed, this concern appears justified in the present study as several diagnostic tests could not reject the presence of significant cross-sectional dependence in Models 1-5 (Anselin, 1996, 1988; Millo, 2017). Therefore, in order to account for cross-sectional dependence detected in the data, we employed various spatial econometric and heterogeneous time trend models outlined below.

2.1.1. Spatial econometric models

First, four spatial econometric models were estimated: a spatial autoregressive model (SLM), a spatial error model (SEM), a spatial autoregressive model with autoregressive error structure (SARAR), and a spatial Durbin error model (SLX) incorporating spatially lagged treatment variables and a spatial error term (Lee and Yu, 2010; Anselin and Bera, 1998).[3] In addition to the SLX, given the extent of spatial dependence in our data (Anselin and Bera, 1998; Anselin, 1996), the SARAR model was selected as the most suitable spatial feature specification based on AIC and BIC information criteria.[4] Beyond serving as a robustness check on our initial TWFE estimates, the SLM and SARAR models provide additional valuable information: namely, they tell us whether the impact of mine closures exhibit regional spill-over effects.

2.1.2. Heterogeneous trends models

Second, we employ latent factor modelling which assumes the panel data model exhibits a factor-analytic error structure. In this approach, one or more latent (unobserved) common factors can be estimated via iterative principal component analysis (the "interactive fixed effects" estimator proposed in (Bai, 2009)), or instead, approximated via cross-sectional averages of the dependent and independent variables (the "common correlated effects" estimator proposed in (Pesaran, 2006)). Another method is to estimate the unobserved factors semi-parametrically via functions that capture unit-specific time trends (the "heterogeneous time trends" estimator proposed in (Kneip et al., 2012)). We apply the heterogeneous time trends estimator because it permits unobserved components to be non-stationary and exhibit smooth time trends. It is therefore well-suited for capturing unobserved

[3] All spatial models were estimated using the *splm* package in R.

[4] Information about testing for residual spatial dependence on spatial models can be found in Appendix C.1.

trends related to long run energy prices, automation, and technical efficiency advances.[5] The AIC or BIC criteria for one- and two-factor models showed no significant benefit of including more than one factor when computing these heterogeneous time trends.[6]

2.2. Typology and grouped fixed effects

To define and operationalise our typology we perform agglomerative hierarchical clustering analysis on a cross-sectional dataset containing information on salient demographic characteristics of the 252 counties identified as coal counties as well as the total set of 3,072 contiguous US counties (Ketchen and Shook, 1996; Murtagh and Contreras, 2012; Rodriguez et al., 2019). Prior to running the clustering analysis, the indicators used were scaled to have a mean of zero and standard deviation of one. Applying three of the most common methods (elbow, silhouette, and gap statistic) for determining the optimal number of clusters to identify yielded inconclusive results for the coal counties, proposing between two and four clusters (Tibshirani et al., 2001; Rousseeuw, 1987). In the case of the complete contiguous US dataset, the three tests to identify the optimal number of clusters revealed consistent results, suggesting three as the optimal number of clusters. Thus, to aid in an eventual comparison of coal counties to US counties overall, each dataset was clustered into three "types". Variables considered in the clustering analysis include an urban/rural index, population size, educational attainment, economic security, female labour force participation, economic diversity, and political attitudes.

This hierarchical clustering serves a dual purpose. First, we present a constructed typology that sheds light on the diversity and geographical distribution of various challenges faced by coal communities across the US. Second, the resulting 'cluster membership' information obtained from the tripartite typology of coal counties was used to re-estimate Model 1 using grouped fixed effects, allowing for partially heterogeneous slope coefficients for each independent variable of interest.[7]

The results of all aforementioned regressions (Appendices B and D), tests (Appendix C), model selection methods (Appendix B.2), and clustering (Appendices C.3 and D) can be found in the Supplementary Materials.

3. Data

Below, we outline the data collected and used to approach the (1) outlined econometric models and (2) construct the typology via agglomerative hierarchical clustering.

3.1. Econometric estimation

A panel dataset was created using economic variables from the US Department of Commerce's Bureau of Economic Analysis (BEA), the US Bureau of Labor Statistics (BLS), and the US Census Bureau for 3,072 contiguous US counties from 2002 to 2019. Annual data on active coal mines in each county came from the Energy Information Administration (EIA) and the Mine Safety and Health Administration (MSHA). The change in the number of active coal mines[8] in a county in a given year is the main independent variable of interest. The BLS reports the county unemployment rate change from the prior year, our main dependent variable (Table 1: Model 1). As dependent variables, we additionally investigate the change in the natural logarithm of employed persons, unemployed persons, total labour force, and population size (Table 1: Models 2 to 5). Appropriate combinations of real GDP per capita, real GDP, and population (all in natural logarithms) were included as control variables in each model.

Additionally, the US Census Bureau maintains a county adjacency matrix for all US counties indicating which counties share a border. This adjacency file was adapted to incorporate information on contiguous US counties when estimating Models 1-5$^{[SEM,\ SLM,\ SARAR,\ SLX]}$.

3.2. Typology

A dataset of selected social, economic, and political characteristics of the contiguous counties observed in the panel dataset was sourced from the US Census Bureau, US Department of Agriculture, the MIT Election Data and Science Lab, and Chmura, a private producer of economic data that imputes a county-level economic diversity index. Selected variables include educational attainment, population size, median incomes, female labour force participation, economic diversity, rural–urban classification, and political party affiliation.

Appendix A.2 of the Supplementary Materials provides additional details on the indicators chosen including theoretical motivation and the data sources used.

4. Results

4.1. Historical impact of coal decline: Magnitude, temporal persistence, and spatial spill-over

Using the econometric estimation methods that control for unobserved heterogeneity and cross-sectional dependence, as outlined in Table 1, we demonstrate that coal mine closures induce a significant and consistent contemporaneous rise in the unemployment rate across US counties. In each case, we incorporate two time lags of the independent variable to evaluate the temporal persistence of impacts of production shocks.

We expect that the closure of a coal mine would induce an increase in the county-level unemployment rate. Such an effect is unlikely to occur solely because of employment losses in the coal industry specifically but likely in combination with spill-over effects from such employment losses onto the jobs and livelihoods of those whose work is conducted in support of coal county functioning (i.e., education, services, retail). This hypothesis is consistent with macroeconomic theory positing that there are direct, indirect, and induced jobs associated with a given economic activity (Bacon and Kojima, 2011).

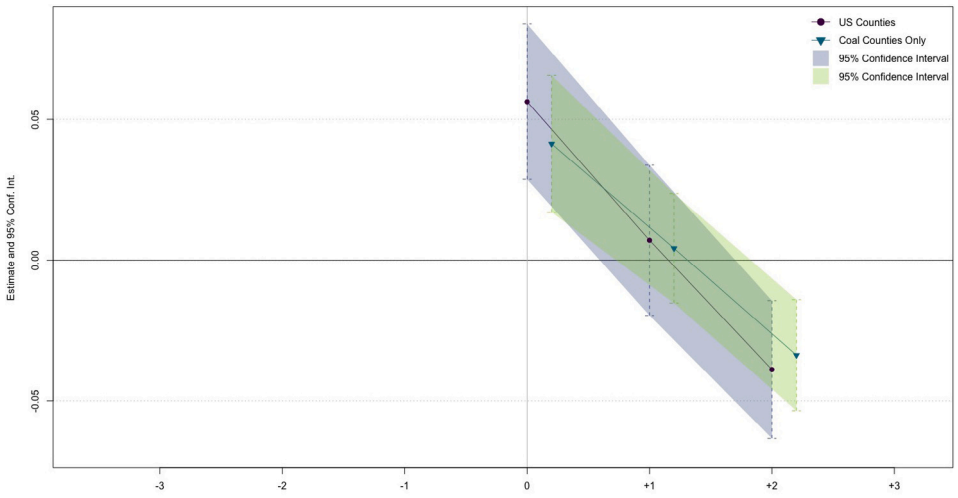
Model 1 finds that a single coal mine closure (one-unit decrease in the number of active mines) is associated with a 0.056 (0.041; restricted coal county sample in parentheses) percentage point increase in county unemployment rate. For the model using all US counties (coal counties only), we reject the null hypothesis of no effect at the 0.1% (1%) level. When evaluating dynamics, the unemployment rate neither seems to continue to increase nor recover a year after coal mine closures are reported with a further change in unemployment rate imperceptibly different from zero. However, two years later, the unemployment rate appears to recover slightly, decreasing by 0.039 (0.034) percentage points at a 1% (1%) level of statistical significance

[5] In contrast, the method of (Bai, 2009) assumes the latent factors are stationary (stochastically bounded), and although the method of (Pesaran, 2006) can be validly extended to settings with non-stationary factors (Kapetanios et al., 2011), its small sample properties are not ideal for the present study's dataset and for the dynamic model specifications we wish to estimate.

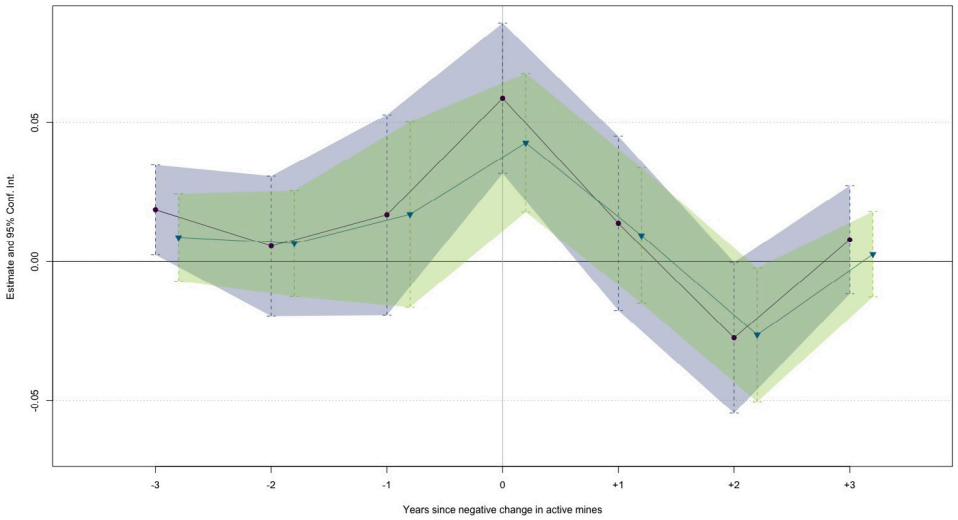
[6] These heterogeneous trend models were implemented using the *phtt* package in R.

[7] The modified Model 1 with grouped fixed effects was estimated using the *fixest* package in R.

[8] From the MSHA database, mines were considered active if they had not been classified as "closed" or "abandoned". This included mines that were labelled as "active" or, in a few cases, "inactive" but not yet closed or abandoned.



(a)



(b)

Fig. 1. Fig. 1 illustrates the sequence of responses in county unemployment rate to a one-unit change in active mines at time $t = 0$ and associated 95% confidence intervals. Fig. 1(a) represents the regression coefficients from Model 1 and Fig. 1(b) demonstrates the regression coefficients of the same model with three leads and three lags to demonstrate the lack of anticipatory or further lagged impacts beyond two years. For simplified interpretation, the sign of the impact has been flipped to illustrate the change in unemployment rate resulting from a decrease in active mines. The *y*-axis indicates the time since the change in active mines was reported. Exact coefficients for Fig. 1(a) are reported in S9 and for Figure Fig. 1(b) are reported in S29. Additional variations of lags and leads are displayed for illustrative purposes in Tables S29 of Appendix E of the Supplementary Materials.

on the dataset of all US counties (coal counties). A linear combination of the coefficient estimates suggests a non-persistent nature of the unemployment rate change. Coefficient estimates are reported in Fig. 1 of the main text and Tables S8 and S9 of Appendix B.1 of the Supplementary Materials.

In the Supplementary Materials, we provide evidence that these results are robust to (1) distinguishing between the closure of surface versus underground mines; (2) controlling for the share of county-level employment in coal mining; and (3) controlling for heterogeneity in mine size proxied by local production volumes and reported capacity. Notably, these robustness checks all confirm the overall pattern of the unemployment rate response as reported above. Furthermore, (1) demonstrates that the contemporaneous effect of a change in active *underground* mines is nearly twice the magnitude of the effect associated with a *surface* mine closure and (2) finds that the magnitude of the contemporaneous response increases and the evidence of a "recovery" two years following a mine closure becomes weaker as a county's share of employment in mining increases.

Fig. 2 displays the coefficient estimates reported by Models 1, $1^{[SEM,\ SLM,\ SARAR,\ SLX]}$, and Models $1^{[HTT(1),\ HTT(2)]}$ along with their respective 95% confidence intervals. In short, the spatial and heterogeneous trends models confirm the results found in Model 1. Furthermore, Model $1^{[SLX]}$ indicates the presence of strong spatial diffusion of impacts not identifiable in Model 1. Model $1^{[SLX]}$ finds a nearly identical magnitude contemporaneous increase in unemployment rate from a one-unit decrease in active mines in a neighbouring county and Models $1^{[SLM,\ SARAR]}$ find a strong spatial dependence in unemployment rate fluctuations. Coefficient estimates of Models $1^{[SEM,\ SLM,\ SARAR,\ SLX]}$ and

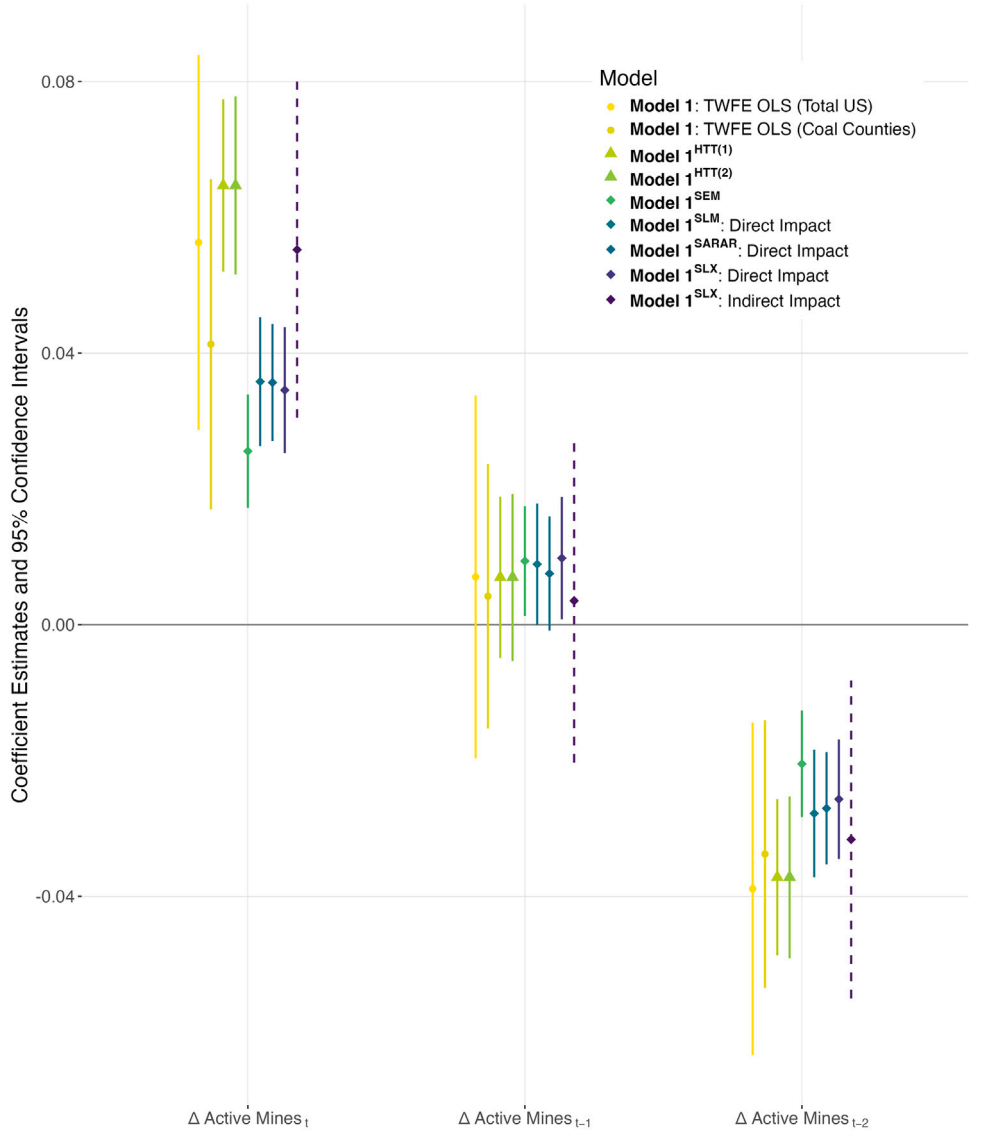


Fig. 2. Coefficient estimates and corresponding 95% confidence intervals represent the response of unemployment rate to a one-unit change in active mines in times t, $t-1$, and $t-2$ as estimated by each model estimation. The coefficients displayed for Model 1^{SLM} and Model 1^{SARAR} are the direct impacts of a change in active mines in a particular county. Confidence intervals for "indirect" impacts (i.e., impact on local unemployment rate from a change in actives mines in a neighbouring county) calculated from the SLX model are represented by dashed lines. For simplified interpretation, the sign of the impact has been flipped to illustrate the change in unemployment rate resulting from a decrease in active mines.

Models $1^{[HTT(1),\ HTT(2)]}$ are represented in Fig. 2 and can be found in Appendices B.2 and B.3, respectively, of the Supplementary Materials.[9]

Additionally, asymmetric estimation of Model 1 reveals that the magnitude and statistical significance of a response in the unemployment rate to a change in active mines is mainly attributable to a negative change. First, when incorporating a factor for whether the change was negative, the magnitude of change in time $t = 0$ increases to 0.075 percentage points (compared to 0.056 percentage points in Model 1) at the 1% significance level. Second, when incorporating a factor for whether the change in mines was positive, the magnitude of change decreases to just 0.019 percentage points and is no longer statistically significant. Altogether, this asymmetric treatment model indicates minimal, if any, employment benefits from counteracting a coal phase-out. The regression results of each of these estimations is provided in Tables S10 and S11 of Appendix B.1 the Supplementary Materials.

Given the irreducible element of unpredictability in county unemployment rates, especially with respect to the closure of an often proportionally small sector like coal, it is highly significant that our results show consistent estimates of regression coefficients across all models and reinforces our confidence in using these estimates to guide further reflections on policy responses. Overall, these figures indicate that, across the time period studied, national employment numbers decreased by as many as 4,000–5,300 workers in one year. Over the entire time period studied, our model suggests a *net* (*gross*) drop in national employment levels by between 11,000–42,500 (39,100–52,200) persons. These estimates are in line with (albeit somewhat lower, indicating likely secondary effects) than documented declines in coal sector employment levels reported by the Bureau of Labor Statistics for the same time period, further corroborating the accuracy of our estimates (U.S. Bureau of Labor Statistics, 2024). More details about how these estimates were calculated as well as more detailed

[9] Coefficient interpretation for the SLM and SARAR models requires calculating the direct intra-county and indirect inter-county impacts of the independent variables on the outcome variables (Piras, 2013). These impacts were calculated using the *spatialreg* package in R.

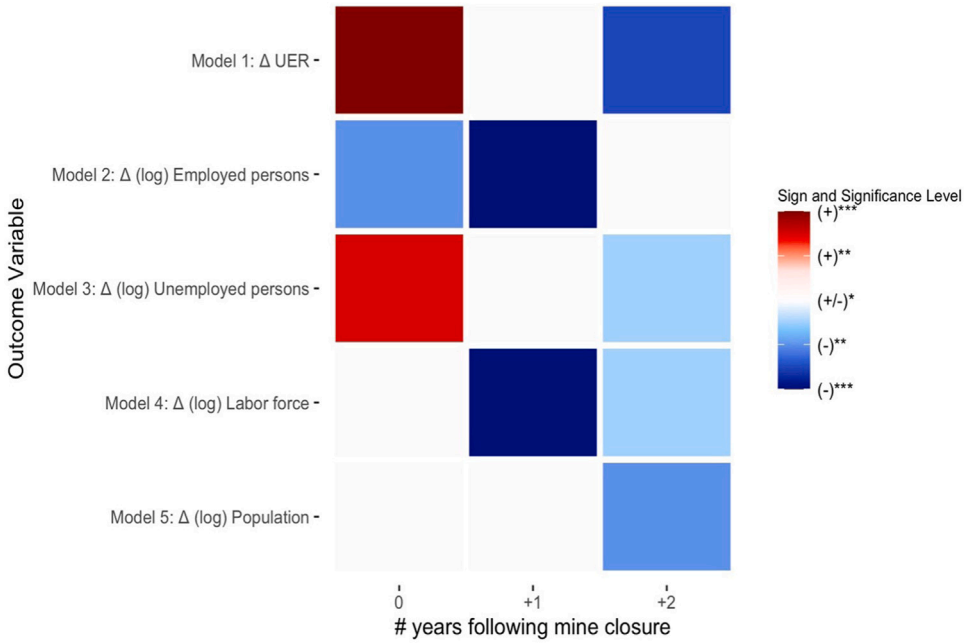


Fig. 3. This figure indicates the direction of changes (red = increase; blue = decrease) in the unemployment rate, natural log of employed persons, natural log of unemployed persons, natural log of labour force, and natural log of population at the county level from a change in active mines at time t, t-1, and t-2. The sign of the response variable has been flipped to allow for interpretation of the sign as the response to a decrease in the number of active mines. The sign and magnitude of the response is reported from the model run on all US counties. Significance codes are reported as follows: *** 0.1%, **1%; *5%. A grey box indicates an insignificant variable response. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

ranges of detected treatment effects can be found in Appendix E.9 of the Supplementary Materials.

4.2. "Recovery": Decomposing the unemployment rate response

However, given that the unemployment rate is a metric defined by other moving indicators, drawing the conclusion that adverse employment impacts of coal mine closures dissipate after two years from this evidence alone would be incomplete. More specifically, our initial results reveal responses in the unemployment rate to coal mine closures, but not which determinants of the unemployment rate might be causing these responses. To answer this question, we consider the main variables used to calculate the rate in Models 2–5: unemployed persons, employed persons, and total labour force (the sum of employed and unemployed persons). Their relationship is defined by the following equation:

$$Unemployment\ Rate = \frac{Unemployed\ Persons}{Unemployed + Employed\ Persons} = \frac{Unemployed\ Persons}{Labor\ Force} \quad (1)$$

Again, we employ the standard TWFE OLS, SARAR, and HTT(1) methods regressing each employment indicator on our independent variable for a change in active mines (including two time lags) and relevant control variables. Table 1 provides algebraic formulas and technical details of each model (Models 2–5, 2-5^{SARAR}, 2-5$^{HTT(1)}$). The sign and statistical significance of the change in each variable 0, 1, and 2 years as reported by the TWFE OLS model following a mine closure are reported in Fig. 3.

First, in the year when the change in active mines is reported, we observe the number of employed (unemployed) persons decreasing (increasing), however, we do not identify any change in the size of the labour force or population overall.

In the following year, the unemployment rate neither continues to increase nor recover. However, we observe further decreases in the number of employed persons and overall labour force size, suggesting a continued labour market response.

Finally, two years following a change in active mines, we observe a small decrease (or partial recovery) in county unemployment rate in Model 1. However, interestingly, Fig. 3 shows that this recovery is not occurring by an increase in employed persons, rather we observe the labour force and the number of unemployed persons decreasing, alongside a small decrease in overall population size. While our analysis does not allow for a detailed examination of whether this dynamic is influenced by strategies such as meeting other job opportunities, dropping out of the labour force, or retirements, future studies could investigate the interactions between those dynamics explicitly. More generally, although any causal or definitive interpretation of these results as well as their further underlying determinants (i.e., whether workers are migrating, retiring, etc.) is beyond the scope of this study, this analysis provides a useful set of hypotheses for the unemployment rate response documented in this work. Furthermore, this result echoes findings that local demand shocks induce a stock equilibrium shift through migration such that the relative unemployment rate returns to its equilibrium state (Treyz et al., 1993; Molho, 1995). Most significantly, these results indicate that the observed "recovery" in the unemployment rate outlined in the previous section should not be interpreted too literally. Rather, this latter analysis of the components of the unemployment rate provides preliminary evidence that expecting local community resilience or 'bouncing back' in response to future potential decarbonisation-related employment shocks is unrealistic.

The direction of the coefficients are confirmed by an application of the spatial lag-error model (Models 2-5^{SARAR}) models and a one-factor heterogeneous trends model (Models 2-5$^{HTT(1)}$) reported in Appendices B.2 and B.3 in the Supplementary Materials.

4.3. A new coal county typology: heterogeneity of risks, vulnerability, and needs

Next, using an agglomerative hierarchical clustering algorithm we define a novel typology or classification of the 252 US coal counties, defined as those counties that had active mines during the time period

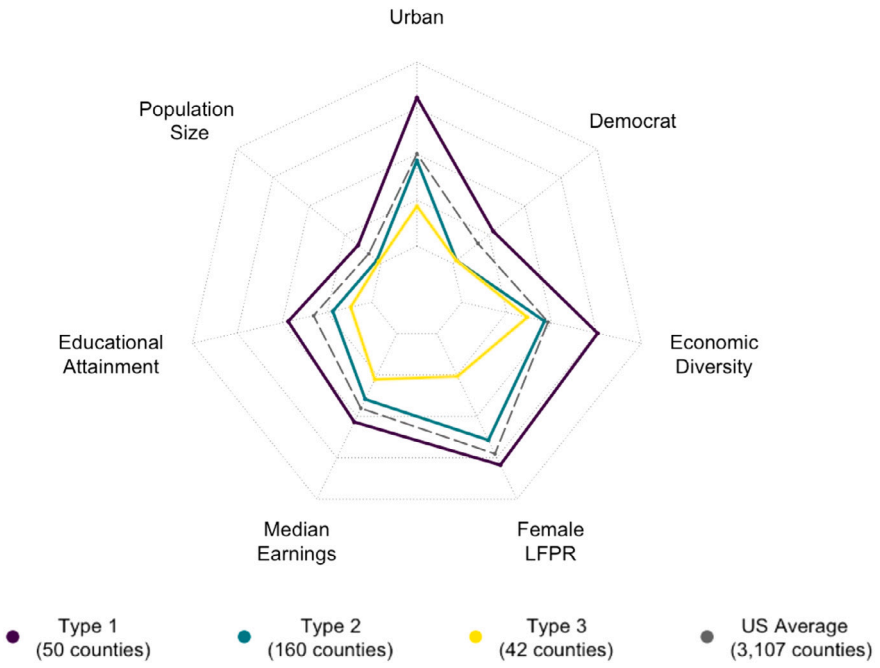


Fig. 4. The corner points of the radar plot represent the mean values of each typology characteristic per county type. The outer (inner) limit of the radar plot represents the maximum (minimum) value of each characteristic present in the dataset of coal counties. The variable for political affiliation (2016 and 2020 national election returns) is included in this radar plot for illustrative purposes. It is not included in the clustering method as nearly all counties with active coal mines between 2002 and 2019 voted for the Republican Party in the 2016 and 2020 elections. Average values for each indicator per group and the US overall used to generate this plot are reported in detail in Appendix D of the Supplementary Materials..

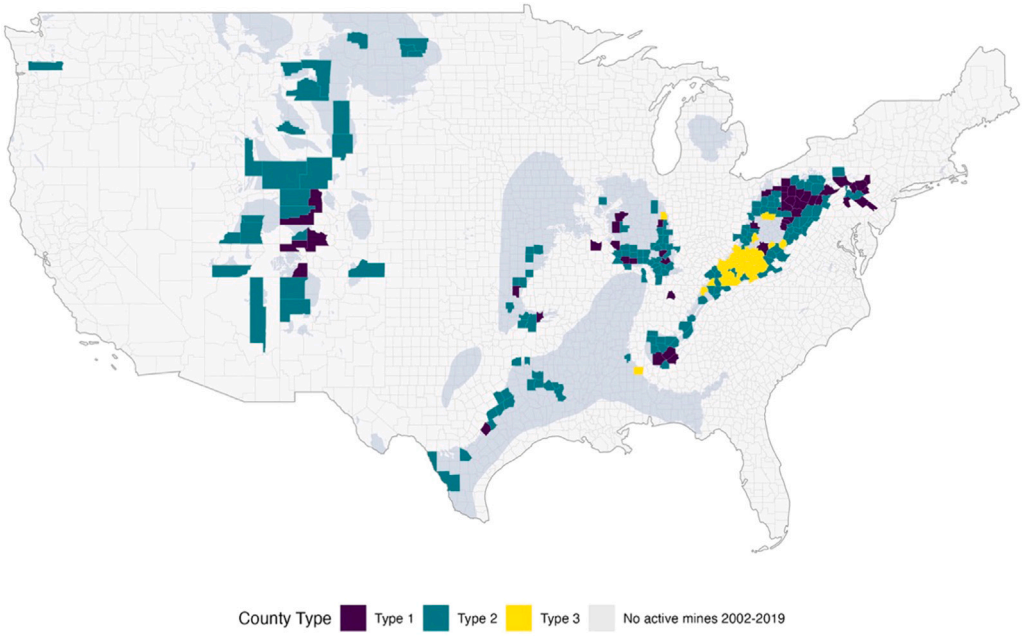


Fig. 5. Counties with active coal mines in the period 2002–2019 are colour coded according to their "type" as defined by the agglomerative hierarchical clustering performed. Type 1 counties are considered "least vulnerable" due to their relatively stronger performance across the indicators (i.e., urban with higher levels of income, educational attainment, economic diversity, female labour force participation, and population), selected in the construction of the typology whereas Type 3 counties are "most vulnerable". The shaded blue areas represent, from left to right, the Western, Interior, and Appalachian coal basins generated using data available from the US Geological Survey.

of the panel dataset analysed in the previous sections. The typology outlines relative county performance across a set of indicators (population size, rurality, economic diversity, female labour force participation rate, educational attainment, median earnings) theorised to affect a county's potential to transition successfully following an employment shock.

As presented in Fig. 4, the three identified county "types" fall into a spectrum ranging from large and urban with high levels of educational attainment, income, female labour force participation, and economic diversity (Type 1) to small and rural with lower levels of the subsequent indicators (Type 3). This pattern is perhaps unsurprising to most readers as the economic and social indicators outlined tend

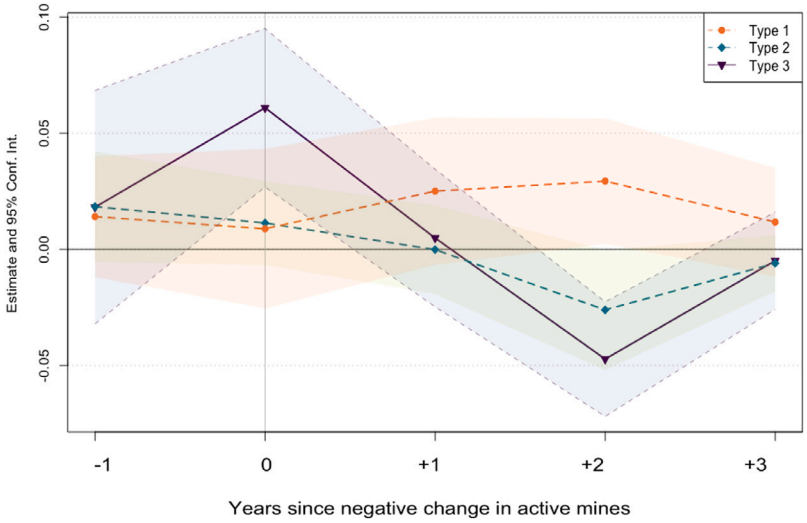


Fig. 6. As in Fig. 1, Fig. 6 presents the change in unemployment rate and associated 95% confidence interval resulting from a change in active mines. The sign of the coefficient estimate has been flipped to demonstrate the impact of a negative change in active mines. Each plotted line and confidence interval represents the response to a change in active mines by county type, as defined in Appendix D.2 in Supplementary Materials. Although Model 1 only includes the independent variables listed in $\boldsymbol{X}_{it}$ in Table 1, the additional lags and leads displayed in Fig. 6 do not greatly impact the estimates at times t = t, t+1, and t+2 and are therefore included in the figure for additional information.

to decrease between urban and rural counties. However, one of the more significant results is that Type 3, and to a lesser extent Type 2, coal counties fall well below the national average for all observed indicators that are likely to aid in an eventual transition. Furthermore, Fig. 5 demonstrates that Type 3 counties (yellow) are concentrated in the Appalachian coal region, indicating a high risk of regional decline which is already being observed in the area. The fact that Type 3 counties are clustered in one region and share most of their borders with each other or Type 2 counties (apart from one Type 1 county) also indicates a geographical limitation to accessible recovery or transition options.

4.4. Employing the typology econometrically

To put this typology to work, Model 1 was re-estimated using grouped fixed effects allowing for heterogeneous treatment effects for each county type identified. This enables us to determine whether the scale and duration of unemployment rate responses to changes in active coal mines differ across county types. Fig. 6 demonstrates the coefficient estimates over time from a year prior to three years following a change in active mines. Most notably, Fig. 6 illustrates that the greatest unemployment rate increases are observed in Type 3 counties, at a magnitude of 0.060 percentage points (1% significance level) in response to a contemporaneous one-unit decrease in active mines. The coefficient estimates associated with Type 1 and 2 counties are all much smaller in magnitude and not statistically significant.

5. Conclusion and policy implications

In this study, we investigate employment shocks in US coal-mining counties undergoing decarbonisation-related transitions using various panel econometric methods designed to address unobserved heterogeneity and cross-sectional dependence. We find that a one-unit decline in active mines increases county-level unemployment by between 0.056 to 0.064 percentage points, with little change a year later and a small 'recovery' two years later. We further determine that this 'recovery' is likely not attributable to a recovery in employment. Rather, we provide further evidence that local-level resilience to shocks to coal sector employment is weak. This latter result is particularly relevant to discussions about net-zero transition-related adjustment costs in local energy-producing communities. Spatial and heterogeneous trend models show how the TWFE OLS approach underestimates unemployment effects. Incorporating spatial diffusion shows the risk of regional spillover. Incorporating an asymmetric treatment estimation shows that opening new mines has no obvious influence on unemployment, but mine closures do. This result challenges the claim that maintaining or boosting the coal sector will contribute to employment and reveals that mine closures have a stronger impact on unemployment than was initially detected in Model 1.

Lastly, the typology outlined in this paper provides information crucial for making context-specific policy prescriptions. First, low educational attainment and female labour force participation in Type 2 and 3 counties underscore the need for reskilling, retraining, and subsidised community college or vocational training. Subsidised day-care and after-school programs will likely be necessary so parents may attend these trainings after work. Second, investments in alternative sectors will first need to consider the relative levels of economic diversity in Type 2 and 3 counties. For those counties with low economic diversity, investments ought to be considered alongside active labour market policies. Furthermore, public subsidies may be needed to stimulate investment in low-diversity areas. The IRA's proposed reinvestment in energy infrastructure looks wise in this respect. Future research can investigate which policy instruments would most effectively mitigate against avoidable socio-economic and psychological hardship in places "left behind" due to bad investment conditions and low economic diversity.

The geographical concentration of the counties we identify to be most vulnerable in the face of a net-zero transition as represented in Fig. 5 as well as the high and statistically significant coefficients on all measures of spatial correlation incorporated in our various spatial econometric models strongly suggest that spatial ripple effects of coal decline pose a significant challenge to a Just Transition. Additionally, the rural–urban split between Type 2 and 3 counties and Type 1 counties would likely require substantial inter-regional mobility or transportation upgrades to help laid-off workers find new jobs. In severe cases, relocation support should be explored for unemployed workers in rural areas with minimal economic diversity and wherever inter-regional transit is prohibitively expensive or impossible.

A main risk of a poorly managed transition is the potential to erode support for future environmental action. Recent research on popular

acceptance of environmental measures in the US indicates that environmental policy bundled with social safeguards might boost public support, offering further grounds for the social and political practicality of a Just Transition agenda (Piggot et al., 2019; Bergquist et al., 2020). Incorporating Just Transition provisions into decarbonisation policies may boost support for environmental programmes generally.

Finally, to the disservice of US communities still struggling with the effects of coal's decline, the 'situation' of US coal employees is increasingly being used as an example of failed Just Transition aspirations, with academic researchers and public commentators asking how the transition from oil and gas might avoid similar issues. This study reiterates that coal communities deserve sustained attention while also outlining a framework of inquiry that could inform future research focusing on unemployment shocks following oil and gas sector decarbonisation.

Data availability statement

The datasets used to conduct the analyses are available via a Zenodo repository. All data comprising these datasets is drawn from publicly available sources outlined and hyperlinked in Tables S1 and S6 in the Supplementary Materials.

Code availability statement

The code required to replicate this study is available via the same Zenodo repository.

CRediT authorship contribution statement

Ebba Mark: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ryan Rafaty:** Writing – review & editing, Validation, Supervision, Methodology, Formal analysis, Conceptualization. **Moritz Schwarz:** Writing – review & editing, Validation, Methodology, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary materials

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.enpol.2024.114338.

References

Abraham, J., 2017. Just Transitions for the Miners: Labor environmentalism in the Ruhr and Appalachian coalfields. New Pol. Sci. 218–240. http://dx.doi.org/10.1080/07393148.2017.1301313.

Anselin, L., 1988. Lagrange multiplier test diagnostics for spatial dependence and spatial heterogeneity. Geogr. Anal. 20 (1), 1–17. http://dx.doi.org/10.1111/J.1538-4632.1988.TB00159.X.

Anselin, L., 1996. Simple diagnostic tests for spatial dependence. Reg. Sci. Urban Econ. 26 (1), 77–104. http://dx.doi.org/10.1016/0166-0462(95)02111-6.

Anselin, L., Bera, A.K., 1998. Spatial dependence in linear regression models with an introduction to spatial econometrics. Handbook of Applied Economic Statistics. CRC Press, pp. 237–289.

Bacon, R., Kojima, M., 2011. Issues in estimating the employment generated by energy sector activities. World Bank. URL http://hdl.handle.net/10986/16969.

Bai, J., 2009. Panel data models with interactive fixed effects. Econometrica 77 (4), 1229–1279. http://dx.doi.org/10.3982/ECTA6135.

Bell, S.E., York, R., 2010. Community economic identity: The coal industry and ideology construction in West Virginia. Rural Sociol. 75 (1), 111–143. http://dx.doi.org/10.1111/J.1549-0831.2009.00004.X.

Bergquist, P., Mildenberger, M., Stokes, L.C., 2020. Combining climate, economic, and social policy builds public support for climate action in the US. Environ. Res. Lett. 15 (5), http://dx.doi.org/10.1088/1748-9326/AB81C1.

Betz, M.R., Partridge, M.D, Farren, M., Lobao, L., 2015. Coal mining, economic development, and the natural resources curse. Energy Econ. (ISSN: 0140-9883) 50, 105–116. http://dx.doi.org/10.1016/J.ENECO.2015.04.005.

Bistline, J., Blanford, G., Brown, M., Burtraw, D., Domeshek, M., Farbes, J., Fawcett, A., Hamilton, A., Jenkins, J., Jones, R., King, B., Kolus, H., Larsen, J., Levin, A., Mahajan, M., Marcy, C., Mayfield, E., McFarland, J., McJeon, H., Orvis, R., Patankar, N., Rennert, K., Roney, C., Roy, N., Schivley, G., Steinberg, D., Victor, N., Wenzel, S., Weyant, J., Wiser, R., Yuan, M., Zhao, A., 2023a. Emissions and energy impacts of the inflation reduction act. Science (ISSN: 10959203) 380, 1324–1327. http://dx.doi.org/10.1126/science.adg3781.

Bistline, J., Mehrotra, N., Wolfram, C., 2023b. Economic implications of the climate provisions of the inflation reduction act. http://dx.doi.org/10.3386/w31267, Working Paper Series, National Bureau of Economic Research, URL https://www.nber.org/papers/w31267.

Black, D., Daniel, K., Sanders, S., 2002. The impact of economic conditions on participation in disability programs: Evidence from the coal boom and bust. Amer. Econ. Rev. 92, 27–50. http://dx.doi.org/10.1257/000282802760015595.

Black, D., McKinnish, T., Sanders, S., 2005a. The economic impact of the coal boom and bust. Econ. J. 115 (503), 449–476. http://dx.doi.org/10.1111/J.1468-0297.2005.00996.X.

Black, D., McKinnish, T., Sanders, S., 2005b. Tight labor markets and the demand for education: Evidence from the coal boom and bust. ILR Review, URL https://www.jstor.org/stable/25063012.

Blonz, J., Roth-Tran, B., Troland, E, 2023. The canary in the coal decline: Appalachian household finance and the transition from fossil fuels. http://dx.doi.org/10.24148/WP2023-09, Federal Reserve Bank of San Francisco, Working Paper Series.

Carley, S., Evans, T.P., Graff, M., Konisky, D.M., 2018a. A framework for evaluating geographic disparities in energy transition vulnerability. Nat. Energy 3 (8), 621–627. http://dx.doi.org/10.1038/s41560-018-0142-z.

Carley, S., Evans, T.P., Konisky, D.M., 2018b. Adaptation, culture, and the energy transition in American coal country. Energy Res. Soc. Sci. 37, 133–139. http://dx.doi.org/10.1016/J.ERSS.2017.10.007.

Castle, J.L., Hendry, D.F., 2019. Modelling our Changing World. http://dx.doi.org/10.1007/978-3-030-21432-6.

Cha, J.M., Pastor, M., 2022. Just transition: Framing, organizing, and power-building for decarbonization. Energy Res. Soc. Sci. 90, 102588. http://dx.doi.org/10.1016/J.ERSS.2022.102588.

Douglas, S., Walker, A., 2017. Coal mining and the resource curse in the Eastern United States. J. Reg. Sci. (ISSN: 1467-9787) 57, 568–590. http://dx.doi.org/10.1111/JORS.12310.

Hamilton, J.D., 1983. Oil and the macroeconomy since World War II. J. Pol. Ec. URL https://www.jstor.org/stable/1832055.

Healy, N., Barry, J., 2017. Politicizing energy justice and energy system transitions: Fossil fuel divestment and a "just transition". Energy Policy 108, 451–459. http://dx.doi.org/10.1016/J.ENPOL.2017.06.014.

Hendrickson, C., Muro, M., Galston, W., 2018. Countering the geography of discontent: Strategies for left-behind places, The Brookings Institution. URL https://www.brookings.edu/research/countering-the-geography-of-discontent-strategies-for-left-behind-places/.

Hincapie-Ossa, D., Frey, N., Gingerich, D.B., 2023. Assessing county-level vulnerability to the energy transition in the United States using machine learning. Energy Res. Soc. Sci. (ISSN: 2214-6296) 100, 103099. http://dx.doi.org/10.1016/J.ERSS.2023.103099.

Imai, K., Kim, I.S., 2019. When should we use unit fixed effects regression models for causal inference with longitudinal data? Am. J. Political Sci. 63 (2), 467–490. http://dx.doi.org/10.1111/AJPS.12417.

International Energy Agency, 2021. World energy outlook. Paris, France, URL https://www.iea.org/reports/world-energy-outlook-2021.

Jenkins, K., Sovacool, B.K., McCauley, D., 2018. Humanizing sociotechnical transitions through energy justice: An ethical framework for global transformative change. Energy Policy 117, 66–74. http://dx.doi.org/10.1016/J.ENPOL.2018.02.036.

Kapetanios, G., Pesaran, M.H., Yamagata, T., 2011. Panels with non-stationary multifactor error structures. J. Econometrics 160 (2), 326–348. http://dx.doi.org/10.1016/j.jeconom.2010.10.001.

Ketchen, D.J., Shook, C.L., 1996. The application of cluster analysis in strategic management research: An analysis and critique. Strategic Manag. J. 17, http://dx.doi.org/10.1002/(SICI)1097-0266(199606)17:6<441::AID-SMJ819>3.0.CO;2-G.

Kneip, A., Sickles, R.C., Song, W., 2012. A new panel data treatment for heterogeneity in time trends. Econometric Theory 28 (3), 590–628. http://dx.doi.org/10.1017/S026646661100034X.

Lee, L., Yu, J., 2010. Estimation of spatial autoregressive panel data models with fixed effects. J. Econometrics 154 (2), 165–185. http://dx.doi.org/10.1016/J.JECONOM.2009.08.001.

Library of Congress, 2022. Text - H.R.5376 - 117th congress (2021–2022): Inflation Reduction Act of 2022. URL http://www.congress.gov/, Available at:Congress.gov.

Marchand, J., 2012. Local labor market impacts of energy boom-bust-boom in Western Canada. J. Urban Econ. 71 (1), 165–174. http://dx.doi.org/10.1016/J.JUE.2011.06.001.

McCauley, D., Heffron, R., 2018. Just transition: Integrating climate, energy and environmental justice. Energy Policy 119, 1–7. http://dx.doi.org/10.1016/J.ENPOL.2018.04.014.

Miljkovic, D., Ripplinger, D., 2016. Labor market impacts of U.S. tight oil development: The case of the Bakken. Energy Econ. 60, 306–312. http://dx.doi.org/10.1016/J.ENECO.2016.10.007.

Millo, G., 2017. A simple randomization test for spatial correlation in the presence of common factors and serial correlation. Reg. Sci. Urban Econ. 66, 28–38. http://dx.doi.org/10.1016/J.REGSCIURBECO.2017.05.004.

Molho, I., 1995. Spatial autocorrelation in British unemployment. J. Reg. Sci. 35 (4), 641–658. http://dx.doi.org/10.1111/J.1467-9787.1995.TB01297.X.

Munasib, A., Rickman, D.S., 2015. Regional economic impacts of the shale gas and tight oil boom: A synthetic control analysis. Reg. Sci. Urban Econ. 50, 1–17. http://dx.doi.org/10.1016/J.REGSCIURBECO.2014.10.006.

Murtagh, F., Contreras, P., 2012. Algorithms for hierarchical clustering: An overview. Wiley Interdiscip. Rev.: Data Min. Knowl. Discov. 2 (1), 86–97. http://dx.doi.org/10.1002/WIDM.53.

National Archives and Records Administration, 2021. Executive Order 14008: Tackling the Climate Crisis at Home and Abroad. Technical Report, National Archives and Records Administration, URL https://www.federalregister.gov/documents/2021/02/01/2021-02177/tackling-the-climate-crisis-at-home-and-abroad.

Newell, P., Mulvaney, D., 2013. The political economy of the "just transition". Geogr. J. 179 (2), 132–140. http://dx.doi.org/10.1111/geoj.12008.

Paredes, D., Komarek, T., Loveridge, S., 2015. Income and employment effects of shale gas extraction windfalls: Evidence from the Marcellus region. Energy Econ. 47, 112–120. http://dx.doi.org/10.1016/J.ENECO.2014.09.025.

Pesaran, M.H., 2006. Estimation and inference in large heterogeneous panels with a multifactor error structure. Econometrica 74 (4), 967–1012. http://dx.doi.org/10.1111/J.1468-0262.2006.00692.X.

Pesaran, M.H., 2014. Testing Weak Cross-Sectional Dependence in Large Panels, 34, pp. 1089–1117. http://dx.doi.org/10.1080/07474938.2014.956623.

Piggot, G., Boyland, M., Down, A., Torre, A.R., 2019. Realizing a just and equitable transition away from fossil fuels. Stockholm Environment Institute URL https://www.sei.org/publications/just-and-equitable-transition-fossil-fuels/.

Piras, G., 2013. Impact estimates for static spatial panel data models in R. URL https://researchrepository.wvu.edu/rri_pubs/13.

Plumper, T., Troeger, V.E., 2019. Not so harmless after all: The fixed-effects model. Political Anal. 27 (1), 21–45. http://dx.doi.org/10.1017/PAN.2018.17.

Pollin, R., Callaci, B., 2019. The economics of just transition: A framework for supporting fossil fuel–dependent workers and communities in the United States. Labor Stud. J. 44 (2), 93–138. http://dx.doi.org/10.1177/0160449X18787051.

Pollin, R., Chakraborty, S., Wicks-Lim, J., 2021. Employment Impacts of Proposed U.S. Economic Stimulus Programs: Job Creation, Job Quality, and Demographic Distribution Measures. Technical Report, University of Massachusetts Amherst, Political Economy Research Institute URL https://peri.umass.edu/images/Thrive-3-2-21.pdf.

Pollin, R., H., Garrett-Peltier, J., Heintz, B., Hendricks, 2014. Green Growth: A U.S. Program for Controlling Climate Change and Expanding Job Opportunities. Center for American Progress URL https://www.americanprogress.org/article/green-growth/.

Raimi, D., 2021. Mapping county-level exposure and vulnerability to the US energy transition. Resources for the Future Working Papers. URL https://www.rff.org/publications/working-papers/mapping-county-level-exposure-and-vulnerability-to-the-us-energy-transition/.

Rickard, S.J., 2020. Economic geography, politics, and policy. Ann. Rev. Pol. Sci. http://dx.doi.org/10.1146/annurev-polisci-050718-033649.

Rodriguez, M.Z., Comin, C.H., Casanova, D., Bruno, O.M., Amancio, D.R., Costa, L.F., Rodrigues, F.A., 2019. Clustering algorithms: A comparative approach. PLoS One 14, http://dx.doi.org/10.1371/JOURNAL.PONE.0210236.

Rousseeuw, P.J., 1987. Silhouettes: A graphical aid to the interpretation and validation of cluster analysis. J. Comput. Appl. Math. 20 (C), 53–65. http://dx.doi.org/10.1016/0377-0427(87)90125-7.

Scheer, A., Schwarz, M., Hopkins, D., Caldecott, B., 2022. Whose jobs face transition risk in alberta? Understanding sectoral employment precarity in an oil-rich Canadian province. Clim. Pol. 1–17. http://dx.doi.org/10.1080/14693062.2022.2086843.

Snell, D., 2018. "Just transition"? Conceptual challenges meet stark reality in a "transitioning" coal region in Australia, 15. Globalizations 550–564. http://dx.doi.org/10.1080/14747731.2018.1454679.

Snyder, B.F., 2018. Vulnerability to decarbonization in hydrocarbon-intensive counties in the United States: A just transition to avoid post-industrial decay. Energy Res. Soc. Sci. http://dx.doi.org/10.1016/j.erss.2018.03.004.

Sovacool, B.K., Turnheim, B., Hook, A., Brock, A., Martiskainen, M., 2021. Dispossessed by decarbonisation: Reducing vulnerability, injustice, and inequality in the lived experience of low-carbon pathways. World Dev. 137, 105116. http://dx.doi.org/10.1016/J.WORLDDEV.2020.105116.

Tibshirani, R., Walther, G., Hastie, T., 2001. Estimating the number of clusters in a data set via the gap statistic. J. R. Stat. Soc.: Ser. B: Stat. Methodol. 63 (2), 411–423. http://dx.doi.org/10.1111/1467-9868.00293.

Treyz, G.I., Rickman, D.S., Hunt, G.L., Greenwood, M.J., 1993. The dynamics of US internal migration. Rev. Econ. Stat. 75 (2), 209–214. http://dx.doi.org/10.2307/2109425.

U.S. Bureau of Labor Statistics, 2024. All Employees, Coal Mining [CES1021210001]. Technical Report, U.S. Bureau of Labor Statistics, URL https://fred.stlouisfed.org/series/CES1021210001.

Weinstein, A.L., 2014. Local labor market restructuring in the shale boom. J. Reg. Anal. Policy 44 (1), 71–92. http://dx.doi.org/10.22004/ag.econ.243965.

White House Briefing Room, 2021. FACT SHEET: President Biden Sets 2030 greenhouse gas pollution reduction target aimed at creating good-paying union jobs and securing U.S. leadership on clean energy technologies. White House Briefing Room, URL https://www.whitehouse.gov/briefing-room/statements-releases/2021/04/22/fact-sheet-president-biden-sets-2030-greenhouse-gas-pollution-reduction-target-aimed-at-creating-good-paying-union-jobs-and-securing-u-s-leadership-on-clean-energy-technologies/.