Charged Up: Impacts of Green Energy Transition on Local Labor Markets*

H. Ron Chan† Yichen Christy Zhou‡
The University of Manchester Clemson University

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Abstract

This paper studies the effects of utility-scale renewable energy expansion on local labor markets in the United States from 2005 to 2019. Utilizing exogenous solar and wind potentials from satellite data, we find a positive employment effect from solar and wind energy, and the effects are not short-lived. Also, solar energy contributes to wage growth. We find notable increases in jobs and business establishments in many sectors, particularly manufacturing in support of a local agglomeration effect. These gains are very localized, reflected in strong in-migration and weak local spillover. The gains are mostly concentrated among younger and lower-educated workers.

Keywords: energy transition, renewable energy, local labor markets, agglomeration, local economic shocks, distributional impacts

JEL Codes: J3, J6, L9, Q4, R1

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†Department of Economics, The University of Manchester. Contact: ron.chan@manchester.ac.uk.

‡John E. Walker Department of Economics, Clemson University. Contact: yichen2@clemson.edu.

1 Introduction

Structural changes in the economy often necessitate labor market shifts, leading to changes in overall labor demand and composition. While some sectors and skills become obsolete and certain regions decline, others gain prominence. For instance, the rise of information technology and automation reduced labor demand and increased inequality, favoring high-skilled workers (Acemoglu & Restrepo, 2018; Adão et al., 2023). Currently, many countries are undergoing a structural change driven by the energy transition, shifting from a fossil fuel-dependent economy to one led by renewable energy. This industrial transition can result in major sectoral shifts and geographical redistribution of economic opportunities for workers.

While the phase-out of coal has led to an entrenched decline in some sectors and localities, renewable energy has the potential to create new jobs and stimulate regional economies.[1] For example, young workers equipped with skills for solar panel maintenance and operation may now find more opportunities and potentially higher wage growth. Will local economies experience job creation and wage growth? If so, which sectors and what type of workers benefit from these increases? Answering these questions and identifying the winners and losers of the green-energy transition is vital for designing efficient and equitable energy policies. However, recent evidence regarding the overall workforce and its sub-population's response to renewable energy mostly comes from calibrated evidence (Wei et al., 2010; Lehr et al., 2013) and ex-ante projections (ILO, 2011; IRENA, 2021).

In this paper, we examine the causal impact of renewable energy expansion from solar and wind power on local labor market outcomes in the United States, exploring the overall effect, distributional consequences, and impacts on the local economy. We focus on the period from 2005 to 2019, during which the US witnessed substantial growth in renewable energy.

We conduct our analysis at the commuting zone (CZ) level, following the prior literature studying the effect of economy-wide industrial shocks on workers, such as the China shock and automation (e.g., Autor & Dorn, 2013; Autor et al., 2013). We examine various labor

[1] Recent studies find that the phase-out of coal has led to a decline in energy-intensive sectors, particularly impacting lower-educated workers in affected locations (Hanson, 2023; Haywood et al., forthcoming).

market outcomes, including changes in employment, labor participation, wages, and hours worked, all constructed from the Public Use Microdata Sample (PUMS) dataset from the American Community Survey (ACS). To understand the distributional effects on who gains and who loses as well as the key drivers of the overall effect, we also examine these outcomes across sub-populations, stratifying them by sectors, demographics (e.g., age, educational attainment, race, and gender), and occupation greenness.

Similar to past studies that investigated the impact of industrial shocks on local economies, we face the challenge of a potential correlation between the growth of renewable energy and changes in local labor market profiles. To address this potential endogeneity, we develop an empirical strategy that leverages exogenous variation in solar and wind potentials across commuting zones, obtained from remote sensing data. We also collect data on aggregate shocks that could drive temporal changes in renewable capacity, such as the renewable portfolio standards (RPS) at the state level and changes in the federal production tax credit (PTC) for wind energy. We interact the cross-sectional renewable potentials with policy shifters to construct our instrumental variables. This strategy allows us to predict which CZs are more likely to experience growth in solar and wind energy as the renewable industry expands. We implement our IV strategy by estimating a stacked one-year first-difference (FD) estimator.

Our findings reveal a significant increase in employment and other extensive margins resulting from renewable capacity growth, particularly solar. Specifically, a 10% expansion in solar capacity would lead to an average increase of 0.3% in both employment and labor force participation, indicating that a 12 MW increase in solar capacity would result in approximately 1,100 additional employment in its CZ in 2019. We also observe a 0.1% increase in the working-age population and a 0.3% increase in the working-age new residents, suggesting a potential in-migration effect. The expansion of wind energy has a similar effect on these margins, albeit roughly half the magnitude of the solar energy expansion. These employment effects from solar and wind energies are of the same order of magnitude as a 10% reduction in China import exposure or routine-occupation share (as in Autor & Dorn, 2013; Autor et al., 2013); similar to a 2 percentage-point decline in recent coal shock in Appalachian locations (as in Krause, 2023); and comparable to a 10% increase in national oil and gas employment (Allcott & Keniston, 2018).

We also observe wages in the local labor markets increase as a result of solar energy growth, while the effect of wind energy growth is negligible and statistically insignificant. A 10% increase in solar energy capacity would raise the average annual, weekly, and hourly wage by 0.15%-0.3% (approximately $51 in annual salary and $2 in weekly salary in 2019). Our results on employment and wages remain robust when including residential solar installations and accounting for potential spatial spillovers from neighboring CZs.

Renewable energy often faces criticisms that the new jobs created are concentrated among construction workers in the early stage of renewable projects, and consequently, the concern that the local labor market gains are likely short-lived once the construction phase concludes. Contrary to this concern, we find that the labor market gains are more than transitory, and the employment gains persist after the initial installation of renewable energy. While we find a strong increase in construction jobs, we witness a greater increase in manufacturing employment and modest employment growth across many other sectors following the increase in solar energy. Consistent with the sectoral increase in employment, we also observe an increase in business establishments across various sectors, especially in manufacturing. Similarly, we observe wage increases in many sectors as well.

The above results suggest that renewable energy has contributed to growth in their local economy, particularly from the expansion of solar energy. Several mechanisms may contribute to the overall growth. First, the sectoral increases in employment suggest a potential *local multiplier effect*, similarly observed from the recent oil and shale gas boom (Feyrer et al., 2017; Allcott & Keniston, 2018). Second, the findings regarding the new-resident population indicate an *in-migration effect*. As we also observe very weak local spillover, the gains from the renewable energy growth appear highly localized. Lastly, the *change in population composition* may contribute to the growth of the local economy. In particular, we find a CZs witnessing renewable growth also experience an increase in younger and lower-educated working-age population, which is crucial for the booming renewable sectors and many other sectors.

Consistent with our main results of a growing local economy, we observe a reduction across most government transfer payments, such as supplementary security income, food stamps, Medicaid, and social security. This finding is notable considering the simultaneous increase in population in these locations. The reductions can be attributed to both the thriving regional economies in these localities as well as the influx of young workers. Our results suggest that the demographic shift helps alleviate the financial burden on federal and local governments in providing social safety nets.

While transitioning to new energy sources offers opportunities for the broader workforce, our findings reveal substantial heterogeneity in the impacts on different groups of workers. Notably, young and less-educated workers (those with less than a high school degree) experience substantial positive gains in both employment and wages. In contrast, older workers see limited benefits, and employment among black workers even declines. Workers with the highest level of educational attainment (those with a post-graduate degree) also see moderate gains. These disparities highlight the uneven distribution of economic benefits resulting from the growth of green energy, as well as the nature of the jobs created by the growth of renewable energy.

Related to the green job literature, we also find that workers in green occupations experience a relatively greater increase in employment, particularly in the manufacturing sector. However, we find no evidence of wage increases for these workers. This suggests that while the rise of green energy has created job opportunities for workers in green occupations, it has not improved their wage profiles. This pattern stands in contrast to the previous fracking boom, which resulted in both increased employment and higher wages for workers in affected industries (e.g., Feyrer et al., 2017; Kearney & Wilson, 2018).

This work contributes to three main strands of literature. First, our study contributes to the broad literature that investigates how technological changes and macroeconomic shocks affect the local labor markets, such as China shock, automation, coal phase-out, (e.g., Autor & Dorn, 2013; Autor et al., 2013; Chetty et al., 2014; Autor et al., 2019; Acemoglu & Restrepo, 2020; Allcott & Keniston, 2018; Feyrer et al., 2017; Hanson, 2023; Krause, 2023). Some of these work explored previous boom and bust in the energy transition and their effects on labor markets, such as the oil and gas boom (e.g., Allcott & Keniston, 2018; Feyrer et al., 2017), and the decline in the coal industry (e.g., Hanson, 2023; Haywood et al., 2023; Krause, 2023). Despite the importance of the recent development of green energy, past studies have focused on calibrating the effect of green energy growth on workers (e.g., Wei et al., 2010; Lehr et al., 2013). Our study adds new insights into the green energy transition, provides empirical estimates of its local labor market effect, and explores potential mechanisms. Our employment effects are comparable to results from earlier studies on China import exposure (Autor et al., 2013) and recent coal shock (Krause, 2023), and our wage effects are comparable to past oil and gas boom (Allcott & Keniston, 2018), substantiating the labor market impact of the green energy transition.

Also, in terms of empirical methodology, many of these studies adopt a shift-share approach, constructing a measure based on cross-sectional variation from labor factor endowment such as industry-specific routine-task intensity in Autor & Dorn (2013) and coal-worker share in Hanson (2023), with time-series labor market shifters such as changes in Chinese import generation by industry in Autor et al. (2019). We construct our instrumental variable designs based on these methodologies and recent econometric discussions (e.g., Goldsmith-Pinkham et al., 2020), exploiting the unique exogenous distribution of renewable resources endowment and the industrial shocks for renewable energy.

Second, our study adds to the growing body of literature investigating the effect of green energy on local economies. This strand of work particularly focuses on understanding political support (or sometimes the lack of political support) for green energy by examining the local spillover effect (e.g., Costa & Veiga, 2021; Fabra et al., 2023; Gilbert et al., 2023b), the social equity and justice aspect for green energy (Gilbert et al., 2023a), or directly analyzing the voting pattern (Germeshausen et al., 2023). Our study adds to the literature by first examining the local labor market effects from solar and wind and exploring potential mechanisms.

Lastly, our work contributes to the literature that studies the growing demand for green occupations by analyzing task or job-listing data. Using job-listing data, Curtis & Marinescu (2023) lay out the distribution of green jobs and find solar and wind jobs listed across many industries such as manufacturing, utility, sales, etc, and Curtis et al. (2023) document the proportion of dirty jobs transitioned into clean jobs. Also, a group of studies analyzed the occupation-level green tasks data, and documented that occupations with a greater share of green tasks are in higher demand in locations experiencing shocks such as environmental regulation, infrastructure subsidies, and technological innovation (Vona et al., 2018; Popp et al., 2021, 2022). Our study contributes by examining the role of green energy (solar and wind) in creating green jobs, identifying the sectors where these jobs are added, and assessing the attractiveness of these jobs in terms of wage levels.

The rest of the paper is organized as follows. Section 2 describes the data sources and presents the motivating evidence for using renewable potentials as a source of identification. Section 3 outlines the empirical model. In Section 4, we present and discuss our estimation results and their implications. We report robustness checks in Section 5. In Section 6, we conclude.

2 Data and Background

Local labor market data. We derive labor market characteristics from the Public Use Microdata Sample of annual American Community Surveys (ACS-PUMS) conducted by the US Census Bureau between 2005 and 2019. This period coincides with a significant surge in renewable energy use in the US. These surveys, representing 1% of the US population each year, offer detailed cross-sectional microdata. They encompass comprehensive individual and household-level information, including labor market data (such as employment status, wage income, hours and weeks worked, industries, and occupations), as well as demographic data (including age, gender, race, educational attainment, and other socioeconomic factors). Our sample includes all individuals of prime working ages, defined as 16 to 64 years.

We aggregate the microdata to the CZ-level to examine local labor market outcomes (e.g., employment and wage), following the approach of studies that investigate economic shocks on local labor markets (e.g., Autor et al., 2013, 2019; Acemoglu & Restrepo, 2020; Hanson, 2023). Compared to other geographical classifications such as the metropolitan statistical areas or counties, CZ preserves strong intra-zone commuting ties and weaker inter-zone ties (see discussions in Tolbert & Sizer, 1996; Autor et al., 2013). Our final dataset encompasses 721 commuting zones across the continental US. Leveraging the richness of the microdata, we further compute local labor market outcomes for specific sub-populations, such as employment and wages for workers of different ages and educational attainment, outcomes for workers in specific sectors, and those for green occupations. These sub-population measures form the foundation of our distributional analysis.

Renewable generation capacity data. Our main explanatory variables are the operational capacity of solar and onshore wind generation in a CZ, which we use to measure the level of renewable energy penetration within each CZ.[2] We gather plant-level solar and wind power generation capacities (in megawatts) from Form-860 provided by the US Energy Information Administration (EIA) and aggregate the data to the CZ level based on the geographical location of the plants. For robustness, we also consider solar and wind power generation as additional measures. We collect plant-level net generation (in megawatt-hours) from solar and wind energy from EIA Form-923 and similarly aggregate the data to the CZ level.

Figures 1 and 2 illustrate the changes in solar and onshore wind generating capacities from 2001 to 2019. Among all the CZs in our sample, 41% of the CZs eventually adopted utility-scale solar energy, while 59% never had solar during our sample period. As for wind, 35% of the CZs ended up adopting onshore wind projects, while 65% never experienced investment in onshore wind energy during our sample period. In addition to the considerable solar and wind energy growth over time, Figures 1 and 2 reveal significant heterogeneity across CZs. Utility-scale solar energy has been widely adopted across the US, particularly in the Southwest, the East, and the Midwest. In contrast, wind energy adoption has been primarily concentrated in Texas, the Midwest, and some locations near the Great Lakes.

Renewable energy potential data. To account for the cross-sectional variation in renewable energy adoption, we utilize the renewable energy potential in each CZ, using remote-sensing

[2]For wind, we exclude offshore wind as its geographical location falls outside the CZs' political boundaries. We exclude other renewable sources, such as hydroelectric and geothermal power, as their capacities have remained stable over time in our sample period. Moreover, renewable sources like hydroelectric and geothermal power require specific geographical features that are not universally present across CZs.

data from the National Renewable Energy Laboratory (NREL). For solar energy potential, we employ the annual Solar Global Horizontal Irradiance (GHI) on a 4-km by 4-km grid, obtained from NREL's National Solar Radiation Database. The solar GHI, which measures the total solar radiation incident on a horizontal surface, is an excellent indicator of solar energy potential. It is widely used to predict potential solar power generation and is exogenous to socioeconomic outcomes. We compute the average GHI for each CZ and illustrate the distribution of solar GHI across CZs in Figure 3. As expected, solar GHI level is higher in the Southwest and Florida, and this geographic pattern aligns with the observed growth in solar capacity, as shown in Figure 1.

We collect average wind speed at the 120-meter altitude for each 2-km by 2-km onshore grid cell using NREL's Wind Prospector database to compute the wind potential. This database, produced from satellite and modeling data from 2007 to 2013, has proven instrumental in demonstrating that potential wind power generation is a cubic function of wind speed which we incorporate into our analysis. Figure 4 displays the distribution of the average 120-meter wind speed for all CZs. Regions with the highest wind potential are typically found in the mountain states, the Midwest, and parts of Texas, while areas like the Great Lake regions and sections of New England also exhibit moderate wind potential. This geographic distribution is also consistent with the observed wind adoption pattern, as depicted in Figure 2.

Data on aggregate shifters. We have gathered data on several industrial and policy shocks that could influence the adoption and expansion of solar and wind capacities. One of the most prevalent renewable policies is the renewable portfolio standards (RPS), which has been adopted at the state level across the US. RPS requires a specified percentage of the electricity sold in the state to come from renewable energy. We obtained data on the year of enactment and obligations (in MWh) from the RPS Compliance Dataset provided by the Lawrence Berkeley National Laboratory (LBNL). We also cross-referenced the Database of State Incentives for Renewables & Efficiency, following past studies on RPS (e.g., Wolverton et al., 2022). Figure 5 indicates a correlation between the early adopters and the regions where we observe solar and wind energy expansion as depicted in Figures 1 and 2.

We also sourced the production tax credit (PTC) data from the US Department of Energy. Introduced in 1992, the PTC is a national-level subsidy for wind energy production. This production subsidy has been found to drive increased investment in wind energy capacity (Aldy et al., 2022).

These shocks broadly serve as supply shifters, and help us predict when and in which major region firms are likely to adopt or expand solar and wind capacities. Our instrumental variable (IV) strategy, which we will elaborate on later, combines the variation generated by these shocks with the geographic variation derived from satellite data on renewable potentials.

For robustness, we collected data on capacities and vintage for coal-fired generating units from the EIA Form-860 as an additional shifter. We aggregated the data to the subregions defined by the North American Electricity Reliability Corporation (NERC) to take into account substitution across the state border. Appendix Figure A.1 shows that the geographic decline of coal correlates with the expansion of solar and wind in areas such as the Great Lake regions near the Rust Belt, the South, the Midwest, Texas, and Arizona, as shown in Figures 1 and 2. Also, we collect residential solar photovoltaic installation and capacity from the Tracking the Sun database from LBNL.

Other data. To investigate differences in occupations and classify their greenness, we utilized task data from the Occupational Information Network (O*NET) database, provided by the US Department of Labor. We identified green tasks and constructed green occupations using the task-level greenness, following the methodology in Vona et al. (2018). These measures enable us to calculate outcome variables (such as employment and wages) for sub-populations based on the “greenness" of their occupation.

To explore the impacts on regional economies, we collected annual business establishment data from the County Business Patterns dataset provided by the US Census Bureau and aggregated the information to the CZ level. Additionally, we compiled county-level government transfer receipts using the Regional Economic Accounts from the US Bureau of Economic Analysis, and similarly aggregated the data to each CZ. The transfer payment data include total government transfers to individuals and detailed categorical transfers such as

Supplementary Security Income, food stamps, medical transfers, Unemployment Insurance, Social Security, and more.

3 Empirical strategy

For a commuting zone (CZ) i in year t, we relate its annual changes in local labor market outcomes ΔY_{it} to its annual changes in renewable energy (RE), ΔRE_{it}, of solar and wind. We estimate the following first-difference (FD) equation:

$$\Delta Y_{it} = \beta_s \Delta RE_{it}^{solar} + \beta_w \Delta RE_{it}^{wind} + \mathbf{X}_{it}' \delta + \phi_t + \phi_s + \phi_s \cdot t + \varepsilon_{it} \tag{1}$$

Equation (1) is estimated on stacked 1-year first-differences from 2005 to 2019, with each CZ weighted using its starting population in 2005. The outcome variable Y includes extensive labor market margins (e.g., log employment and labor force participation), intensive margins and other equilibrium outcomes (e.g., log hours worked per week, log weekly wages), and other measures (e.g., log population). As discussed in Section 2, we measure renewable energy penetration using log of operating generation capacities in our baseline specification.[3] Alternatively, we use log of net generation to measure RE in one of the robustness checks.

Our primary parameters of interest are β_s for solar and β_w for wind. By construction, our first-differenced outcomes and main variables of interest eliminate time-invariant unobservables within a CZ. Our control vector $\mathbf{X}$ contains the log of the lagged population and the log of retired coal capacity: the former captures a potential scale effect, and the latter controls for the potential employment and wage effect directly from coal phasing-out. Also, we include year fixed effects ϕ_t, state fixed effects ϕ_s, and a linear year trend for each state $\phi_s \cdot t$ to control for potential unobservables such as macroeconomic trends.[4] This specification is equivalent to controlling for commuting zone fixed effects, year fixed effects and state-specific quadratic

[3] We take the log of the solar and wind capacities which are measured in 100 MW. If $capacity = 0$, we assign the log capacity, $RE \equiv log(capacity)$, as 0, and include a separate dummy variable in $\mathbf{X}$ that indicates if $capacity_{i,t-1}$ is zero. We introduce two such dummies in $\mathbf{X}$ for both solar and wind. Treating zeros using this methodology, our baseline is identical if we scale capacities in MW, 10MW, 100MW, GW, etc. Our results are similar if we include in $\mathbf{X}$ both dummies that indicate $capacity_{i,t-1} = 0$ and dummies that indicate $capacity_{it} = 0$ for both solar and wind (i.e., four dummies in total).

[4] For CZs that cross the state border, we assign state s to a CZ i if it is primarily in state s.

time trends before first differencing. Standard errors are clustered at the state level to allow for potential correlation across CZs within a state.

The empirical challenge in identifying β_s and β_w is that shocks in the local labor market may correlate with the propensity of renewable investment in a location. For instance, solar energy utilities may find it attractive to expand their business in regions with certain types of workers, such as construction workers, which may exaggerate our results. Or, they may look for routine-task intensive workers, which is likely to decline due to automation, which may underestimate our results. Our results may also be subject to a downward bias if the local government encourages new businesses, such as renewable energy, when the local economic conditions worsen.

To correct for such potential endogeneity, we employ an instrumental variable (IV) design that exploits the exogenous geographical variation in the endowed renewable potentials (RP) in solar and wind using the remote sensing data discussed above, as well as the temporal variation in industrial shocks (i.e., RPS and PTC). For each CZ i, we construct its solar potential, RP_i^{solar}, by multiplying its average solar GHI by its area to account for the size of the CZ. Similarly, for CZ i's wind potential, RP_i^{wind}, we construct it by multiplying its cubic 120-meter wind speed by its area.

We construct our instrumental variables by interacting (i) the solar and wind renewable potentials constructed above with (ii) the two temporal shifters, which include (a) a state's renewable obligation under RPS in a year and (b) the federal production tax credit that applies to a renewable source's initial year of production (in 2005 dollars per MWh). Using both sources of variation, our IVs enable us to predict which area, to what extent, and when an area is more likely to grow in renewable energy given its renewable potentials at a time when the renewables are expanding in the broader economy.

Our identification strategy resembles the shift-share approach commonly used in studies examining the effect of aggregate shocks on local labor markets. These studies typically rely on (i) the exogeneity of the 'initial share' for a sub-population of workers with various exposure to shocks within a region (e.g., industry-specific shares of routine workers, male workers, or import-exposed workers in a CZ) and (ii) the subsequent temporal 'shifts' for those industries or sub-populations in those industries in the aggregate economy (see examples in Autor & Dorn, 2013; Autor et al., 2013, 2019; Hanson, 2023 and econometric discussions in Goldsmith-Pinkham et al., 2020). Similar to shift-share IVs, we rely on the exogeneity of the 'shares', i.e., renewable potentials, as well as the exclusion restriction that the variation in renewable potentials only affects the variation in *changes* in outcomes via affecting *changes* in solar and wind capacity. Unlike typical shift-share IVs, our 'shares' only vary across CZs rather than across sub-populations or industries within a CZ.[5] While the 'shares' in past studies measure the exposure to macroeconomic conditions and policies using labor endowments in sub-populations, our 'shares' measure the exposure to renewable policy shocks using a proxy for capital productivity endowment, which we use to generate variations in the renewable energy installations across CZs.

It is worth noting that past studies have used RPS as an instrument for renewable capacity when studying other outcomes (see e.g., Johnson & Oliver, 2019, for studying electricity price volatility). While the functional form of our instruments includes both renewable potentials and policy shifters such as RPS, we only require exogeneity in the renewable potentials in identification. Related to our identification, Costa & Veiga (2021) and Fabra et al. (2023) directly use municipality fixed effects under the assumption that renewable potentials are exogenous across locations; Germeshausen et al. (2023) use the "reference yield model" which implicitly incorporates the wind speed from a benchmark simulating model produced by German's Renewable Source Acts (EEG) to study the effect of wind projects in Germany; and

[5]Canonical Bartik or Bartik-like IVs take an inner product structure and are constructed by summing or averaging over (i) sub-unit shocks, i.e., 'shifts', weighted by (ii) proxies of shock exposure, i.e., 'shares'. Goldsmith-Pinkham et al. (2020) demonstrate the identification can *solely* come from the exogeneity of 'shares' in those IVs, and the Bartik IV estimator is equivalent to a weighted GMM estimator using only 'shares' as (multiple) IVs. Alternatively, Borusyak et al. (2022) suggests consistency can be achieved if 'shares' are not exogenous but 'shifts' are quasi-random and mutually uncorrelated. Recent econometric development highlights that the estimator can be inconsistent even when 'shares' are strictly exogenous, and therefore recommends various correction techniques such as re-centering and controlling (e.g., Borusyak & Hull, forthcoming; Borusyak et al., 2024). Our IV does not take an inner product structure: (i) the 'shares' in our setting vary at the CZ level rather than the sub-population level within a CZ, and (ii) our 'shifts' are common shocks (national or in aggregate economies). Therefore, we do not sum or average the weighted shifts as in the Bartik setting, where the IVs can be vulnerable to endogeneity when 'shifts' can be anticipated (e.g., industry-specific shifts in the context of import shock). See more discussions in Borusyak et al. (2024).

Gilbert et al. (2023b) incorporate wind speed when formulating their instruments across different hexagons.

Also, we study the distributional effects of renewable energy deployment by re-estimating Equation (1) for various sub-populations of workers in a CZ. Specifically, we construct Y's such as employment and wage based on a worker's demographics (e.g., age group, race, gender, and educational attainment), sectors, occupation greenness, and industry characteristics using the detailed individual-level microdata from the ACS-PUMS dataset. We also construct Y's for some intersected groups for detailed analysis (e.g., female workers with less than a high school education, and green occupation workers in manufacturing). To gain a comprehensive understanding of the impact of renewable energy deployment on various aspects of the regional economies, we also analyze other outcomes, such as the number of business establishments and transfer payments using a similar specification.

4 Results

4.1 Effects for the overall workforce

Employment and other extensive margins. We begin by analyzing the labor market outcomes for the overall workforce in the prime working ages from 16 to 64. We estimate Equation (1) on total employment and report the results in Table 1 Panel A Column 1.[6] The increases in solar and wind capacity have led to a modest increase in total employment. To interpret the effect, we consider a 10% increase in solar or wind capacity, which approximates the annual change in these energy sources for a typical CZ (see Appendix Table A.1 Panel A.2). A 10% increase in solar generation capacity would result in a 0.29% increase in employment for a typical CZ. The effect for wind is smaller at 0.14% but remains statistically significant.

The implied percentage changes are quite sizable compared to the average annual changes in these outcomes. These results indicate notable job opportunities generated by the growth in

[6] We report the first-stage results in Appendix Table A.2. Variation in RPS obligation effectively predicts solar energy expansion, and variation in PTC helps predict wind energy growth. In addition, we find that a CZ with greater wind potential is less likely to expand in solar energy, and vice versa, a CZ with greater solar potential is less likely to expand in wind energy. These opposite coefficients suggest potential substitution effects between these two renewable energy sources in a location.

these energy sources, in particular, an increase of 1,143 jobs from a 10% solar capacity increase (about 12 MW) and 369 jobs from a 10% wind energy increase (about 41 MW) in 2019 for an average CZ, as reported in Table 1 Panel B.[7] One contributing factor for a stronger employment effect from solar over wind is that solar requires a lot of manual labor, with many tasks requiring minimal education and work experience, such as cleaners with only a 10-hour Occupational Safety and Health Administration (OSHA) card and no prior work experience and journeyman electricians with a 50-hour OSHA card with some work experience (see NREL, 2018).[8]

We re-estimate Equation (1) on labor force participation and total population to better understand the drivers of the employment increase. We present the results in Table 1 columns 2 and 3. The coefficients on labor force participation (column 2) closely mirror the estimates on employment (column 1). The coefficients on population (column 3) are in the same order of magnitudes as those in columns 1 and 2, specifically, with a smaller coefficient for solar and a slightly larger coefficient for wind. These findings imply the increase in employment is closely linked to existing working-age residents aged 16 to 64 staying in the locations and entering the workforce as well as an influx of migrant workers. The in-migration effect is also evident in Table 1 column 4 when we directly focus on the new resident population, although the coefficient for wind is not precisely estimated. In summary, these results show the positive effects of renewable growth on job opportunities and highlight their roles in retaining employable working-age workers and attracting new workers.

Wages and intensive margins. We proceed to analyze other margins, focusing on workers' wages and the extent to which they work. We infer weekly wages from annual wage income

[7] To offer an additional interpretation, we evaluate the effect of the overall cumulative change in solar and wind over the period 2005-2019 on employment for the year 2019. Over our sample period, an average CZ has witnessed a growth in solar capacity by 51 MW and wind capacity by 132 MW (see Appendix Table A.1 Panel B). Our results imply that the solar capacity expansion over 2005-2019 has led to a 3.8% increase in employment for an average CZ (or 15,000 jobs in 2019); the wind capacity expansion over our sample period has led to a 1.9% increase in employment on average, or 5,200 jobs in 2019.

[8] For additional examples, the US Bureau of Labor Statistics (BLS) provides examples of occupations relevant to solar power: https://www.bls.gov/green/solar_power/. This includes skilled workers in welding, glazing, and coating in manufacturing, equipment operators in construction and installation, high-wage workers such as civil engineers, and production and construction managers. In a recent study, Curtis & Marinescu (2023) also documented the spectrum of new jobs listed in the solar and wind industry as well as jobs in other industries with keywords associated with solar and wind energy.

and weeks worked per year, and compute hourly wages from annual wages, weeks worked per year, and hours worked per week. We re-estimate Equation (1) on these outcomes. Table 2 Panel A columns 1 to 3 present the wage effect. The expansion of solar energy consistently leads to positive effects on annual, weekly, and hourly wages, but the effects are small. Specifically, a 10% solar capacity expansion would increase weekly wages by 0.3% or \$1.9 (2005 US dollars) in the year 2019, as reported in Table 2 Panel B.

In addition to a positive wage effect, we also find a small decrease of 0.16% in weeks per work year (Table 2 column 4), and a negligible increase of 0.01% in hours worked per week (Table 2 column 5). These results together suggest that workers receive higher weekly and hourly wages and work fewer weeks in equilibrium. In contrast, we do not find any significant effects on wages or work extent resulting from wind expansion. The coefficients $\hat{\beta}_w$ are much smaller than $\hat{\beta}_s$ and they are not precisely estimated.

Throughout this paper, we use robust standard error clustered at the state level to allow correlation across CZs within a state. For robustness, we also produce the Conley standard errors to correct for spatial correlation in the error term (Conley, 1999, 2010) as well as the Newey-West heteroskedasticity and autocorrelation consistent (HAC) standard errors. Appendix Table A.3 presents the alternative standard errors for our employment and wage equations. Columns 2a to 2c show that our results are robust to generalizing spatial correlation. Columns 3a to 3c show that the standard errors tend to be greater when allowing for serial correlation, and our results are robust, especially for employment.

Temporal dynamics. While our baseline in Table 1 and 2 present the contemporaneous effect of utility-scale solar and wind expansion, it is of policy interest whether the short-run effect of renewable boom translates into a long-term effect. Previous studies on wind energy, in particular, suggest different stages of renewable projects may have different effects (e.g., ILO, 2011; Fabra et al., 2023). Therefore, we investigate the medium-run dynamics of the initial solar and wind investment using the recently developed local projections difference-in-differences (LP-DID) estimator proposed by Dube et al. (2023) adapted from the local projections estimator in Jordá (2005). To adapt the LP-DID estimator to our setting, we redefine our continuous variable of interest as a dummy variable of whether a CZ has first experienced any capacity increase in solar and wind, D_{it}^{solar} and D_{it}^{wind}, and take a first difference.[9]

Figure 6 shows the results for the LP-DID estimation for employment and weekly wage. Panels A and B show a positive and significant effect on both employment and wage for the initial increase in solar capacity at event time $h = 0$. This result is qualitatively similar to our short-run results in Tables 1 and 2. In the subsequent years following the initial solar capacity installation, we continue to observe a positive employment and wage effect, indicating an accumulative effect over time from the initial capacity installation.[10]

While Figure 6 appears to suggest a permanent positive effect from solar, we cannot conclusively determine whether the mechanism suggests a permanent long-run effect, an effect of repeated treatments, or both, since most treated CZs continue to grow their capacities. The potential repeated treatment also informs us of the appropriateness of specifying a 1-year FD in our main equation (1) as longer-term local projections (LP) require clean control across a longer time horizon, which is not plausible at the CZ level.

Figure 6 suggests a similar pattern for wind capacity installation, but we lack sufficient power for each individual post-event coefficient as the clean control condition further restricts our sample. Using a first-difference estimator, we find a short-run effect on employment but a null effect on wages, while the LP-DID estimator suggests an increasing slope after the initial event for both despite a lack of power.

[9] In particular, we estimate a modified equation based on our main specification:

$$\Delta Y_{it,t+h} = \gamma_{s,h} \Delta D_{it}^{solar} + \gamma_{w,h} \Delta D_{it}^{wind} + \mathbf{X}_{it}' \delta + \phi_t + \phi_s + \phi_s \cdot t + \varepsilon_{it} \tag{2}$$

where $h \in [-6, 6]$ is the event time, i.e., the number of years before or after the year when a CZ experiences its initial expansion in solar or wind energy. As it is still under development in the econometric literature how the LP-DID estimator behaviors for a continuous treatment that not only varies in magnitude cross-sectionally but also expands over time (i.e., repeated treated), we follow the base specification in Dube et al. (2023) and set the variable interest D_{it} being the dummy variable indicates whether a CZ i has first experienced any investment in solar or wind in year t, and we use the same clean control condition as in Dube et al. (2023). Equation (2) includes the same set of controls, fixed effects, and instruments as in the baseline equation (1). As identifying γ for solar and wind requires different clean control conditions, we estimate equation (2) separately when identifying $\gamma_{s,h}$ and $\gamma_{s,w}$ for solar and wind. Lastly, we normalize to two years before the first capacity increase to consider the construction stage as discussed in past studies (Fabra et al., 2023; Gilbert et al., 2023b).

[10] Our results also complement recent studies that analyze the long-run effect of coal phase-out, where Hanson (2023) find long-run negative effects of a shrinking coal industry on local workers' employment and wages.

Spatial spillover. We next explore the possibility that the changes in renewable energy in nearby locations may affect the labor market outcomes of workers in a CZ, resulting in spatial spillover. In Table 3 column 2, we include the changes in average utility-scale solar and wind capacity in adjacent CZs and in column 3, the changes in average solar and wind capacity in other CZs in the same state as control variables. We find that solar growth in nearby CZs tends to reduce a CZ's employment, with the order of magnitude being a small fraction of the main effect. These results suggest that a solar boom in close CZs may attract workers to relocate to those locations (as supportive evidence, we find a negative coefficient of adjacent CZs' solar capacity expansion on the population in a CZ). The effect of other CZs' wind energy has a statistically and economically insignificant effect on employment. As for wages, we find a negative effect from both solar and wind in nearby CZs, with small and only detectable effects for adjacent CZs' solar energy. The primary coefficients on solar and wind capacity are slightly smaller but remain similar to the baseline. Our weak evidence of geographical spillover aligns with Gilbert et al. (2023b), where authors find the effect of new wind turbines on local workers dampens as the distance increases. Overall, we do not find strong evidence of spatial spillover.

In summary, baseline estimates in Tables 1 and 2 indicate a positive impact of solar and wind energy growth on the overall workforce in affected CZs. Figure 6 shows that the effect of the initial investment is not short-lived. The expansion of solar and wind has translated into increased job opportunities, with solar also leading to wage increases. These gains in local labor markets are mostly localized as we observe (i) a weak spatial spillover effect and (ii) an in-migration effect.

4.2 Sectoral growth and implications for local businesses

This section delves into possible underlying factors contributing to the employment and wage gains for the overall workforce documented in Section 4.1. In particular, it is of policy interest whether most of the gains are concentrated in certain related sectors such as construction, or if they have a similar effect on other sectors in the local economy.

Sectoral effects on employment and wage. To address this question, we categorize workers into sub-populations based on their employment in the following four main sectors: manufacturing, service, public, and other sectors. We also examine specific sectors in the broad "other sectors" such as construction. We present the sectoral employment effects in Table 4 Panel A and the sectoral wage effects in Panel B.

As expected, we find some positive effects on labor market outcomes from renewable energy in directly affected sectors. Specifically for workers in the construction sector, column 4a in Table 4 in Panels A and B shows a notable positive employment effect from both solar (stronger than the baseline) and wind (with a magnitude similar to baseline), and a positive wage effect from solar (stronger than the baseline). Also, for workers in the utility sector, we observe a positive wage effect from solar with a magnitude similar to the baseline (see column 4a in Panel B).

More importantly, we also find renewable energy sources indirectly benefit workers in other sectors of the local economy. For example, we observe a sizable employment increase from solar energy expansion for service and other sectors (such as wholesale and retail trade, and transportation and warehousing). Notably, we find a substantial employment gain in the manufacturing sector, which is more than twice as large as the average effect. This is consistent with the examples of job creation in the manufacturing sector following solar energy installation, illustrated in the study by the BLS (see footnote 8). The employment growth across many sectors, in particular in manufacturing, is likely a combination outcome of (i) that energy-intensive industries in manufacturing sectors may move to locations with a lower energy price and efficient fuel source, (ii) a local agglomeration effect, and (iii) that manufacturing plants, in general, producing tradable goods, are relatively mobile in capital (see more discussions regarding manufacturing sector during energy transition in e.g., Hanson, 2023). To investigate the importance of the local agglomeration effect, we further break down manufacturing sectors into tradable and non-tradable sectors based on definitions used in Allcott & Keniston (2018) and Holmes & Stevens (2014). Consistent with such local multiplier effect, we find positive employment and wage effects from solar energy for both tradable and non-tradable sectors, rather than tradable sectors alone.[11]

[11]The results are available upon request.

As for wind energy, we find the strongest effects on the manufacturing and service sectors, although the estimate for the former lacks precision. Similar to employment, we find wage increases from solar energy growth in these sectors, although the wage outcomes exhibit less variation across sectors.

Third, while we find employment increases in all private sectors, we find a reduction in employment in the public sector from solar power, as shown in Table 4 Panel A column 5. Part of this result can be driven by the small wage increase, as the public sector experiences the lowest wage growth across all sectors, as shown in Table 4 Panel B. This possibility suggests a potential job displacement effect - workers leave the public sector for other jobs in affected locations or move to other locations as the public sector becomes less appealing in terms of wage profiles while other sectors and other locations present better job prospects.

In summary, our results indicate a growing local economy in locations that witness solar and wind growth, as the increases in employment and wages are not only restricted in directly affected sectors such as construction but also spilled over to many other sectors.[12] This local agglomeration effect has been observed in earlier work on oil and gas booms in the United States.[13] In our setting, we observe a strong employment and wage effect in manufacturing, which can come from a combination of (i) a greater demand for continuous manufacturing of parts needed for operation and maintenance, (ii) a propagated effect to other forms of manufacturing linked to solar and wind energy, and (iii) a local spillover effect through general equilibrium channels. The local growth is also evident in service, construction, utility, as well as other local industries (The sectoral distributional effects on employment for new residents resemble Table 4 Panel A).[14]

[12] Our finding is consistent with previous descriptive studies that examine solar- and wind-related job listings and find these jobs primarily concentrate in "blue collar" industries (construction, manufacturing, agriculture, transportation, etc.), followed by "white collar" industries (all service industries except for healthcare, arts and rec, and accommodations), then utilities and trade (Curtis & Marinescu, 2023).

[13] Specifically, Michaels (2011) studies the early 1940-1990 oil boom on manufacturing and agriculture, Allcott & Keniston (2018) study the 1969-2014 oil and gas boom on manufacturing, and Feyrer et al. (2017) and Kearney & Wilson (2018) study the recent shale gas boom on other sectors. Allcott & Keniston (2018) find both industrial linkage effects and local agglomeration effects can explain such agglomeration effects.

[14] While we find regional growth, our results may not extrapolate to economy-wide growth. One possibility is the growth in local industries, especially manufacturing, may represent a zero-sum re-distribution effect across locations as capital is relatively mobile. This is a phenomenon typically observed in the effects of place-based policies. The growth we observe in the manufacturing sector may come from the decline in other locations.

Sectoral growth in business establishments. To explore the drivers of the sectoral labor market growth and shift we document above, we examine the outcomes on local businesses. We repeat the baseline Equation (1) on the changes in the log number of business establishments using the County Business Pattern dataset. Table 5 column 1 shows no evidence that more businesses emerged due to the solar energy expansion in a CZ, and only weak evidence of a small positive effect for wind energy. This result suggests that the baseline employment gains discussed in Section 4.1 can be driven by the increasing scale of individual firms.

While the overall business count shows no evidence of notable change, we observe some sectoral shifts in business opportunities. In Table 5 columns 2 through 4, we analyze how the pattern in business establishments changes among the manufacturing, service, and other sectors. We find that an increase in solar energy capacity leads to more business establishments in manufacturing. The coefficient for manufacturing business establishments, despite moderate, is smaller than the coefficient for manufacturing employment (in Table 4 Panel A column 2). This result indicates that the growth in manufacturing jobs that we observe comes from both (i) an increasing number of firms brought by solar energy and (ii) an increasing size of these firms.[15]

We find an opposite pattern for businesses in service and other sectors. We find no evidence of increasing service and other businesses from solar, despite observing an increase in employment. These estimates suggest that although the service and other sectors did not expand in terms of the number of businesses, the increase in solar energy likely led to an increase in their scale. As for wind energy growth, we find a moderate coefficient for manufacturing, but the effect is not precisely estimated. Moreover, we find mostly small coefficients for other sectors, suggesting wind energy generally does not lead to a growth in business opportunities for local firms, despite its positive yet small effect on employment.

[15] The sectoral employment pattern closely resembles the pattern of annual payroll, which we report in Appendix Table A.4. A caveat is that there may be measurement errors associated with the annual payroll measure, as CBP does not report annual payrolls for industries with only a few establishments.

Taking all sectoral evidence together, the employment gains for the overall workforce come from (i) the increasing number and size of firms in manufacturing, and (ii) the increasing size of firms in service and other sectors brought by solar energy.

4.3 Distributional effects by demographics

In this section, we focus on studying the heterogeneous effects on various sub-populations of workers based on their demographics. While we studied various labor market outcomes for the overall workforce in Section 4.1, here we specifically focus on employment and weekly wage to highlight the differential effects across workers. We first begin by analyzing the employment and wage effects on different age groups, then we analyze workers with different levels of educational attainment to better understand the differential effects of renewable expansion between lower- and higher-skill workers, and finish this subsection by studying the effects across different racial groups and genders.

Effects by age. We find that the positive employment effects are concentrated among young workers. Table 6 Panel A presents the distributional employment effects. The most substantial positive employment effect is observed among the youngest group of workers aged 16 to 35 for both solar and wind energy: both coefficients are higher than the average effect, and both are precisely estimated. For workers aged 36 to 50, solar energy also exhibits a strong employment effect, with $\hat{\beta}_s$ being about 25% higher than the average. By contrast, the employment effects are notably weaker, almost negligible, for older workers aged 51 to 64.

We find a similar pattern in wages. Table 7 Panel A shows that the positive effect of wages from solar energy is the strongest for the youngest group of workers aged 16 to 35 and smaller for the rest of workers from 36 to 64. Consistent with the baseline, we do not find evidence of wage effect from wind energy expansion.

These strong positive effects observed among younger workers are likely attributable to their greater job mobility. Appendix Table A.5 Panel A shows the changes in population composition by age group, with patterns comparable to the employment effect in Table 6. Wind energy growth particularly raised the younger-age population from 16 to 35, and solar increased population groups for both from 36 to 50 and from 16 to 35. Comparing the effect to the decline of coal, studies have shown that the younger workers in those locations are affected more in extensive margins and less in terms of wages or other measures of well-being compared to their older counterparts, as younger workers are more likely to move to a different location or occupation (Hanson, 2023; Haywood et al., 2023).

Effects by educational attainment. We find that the gains are most pronounced among the least educated workers with less than a high school degree. Table 6 Panel B shows that both solar and wind energy have the strongest positive impact on workers with less than a high school degree: both $\hat{\beta}_s$ and $\hat{\beta}_w$ are approximately 4 times the average, although the latter is only statistically significant at the 10% level. Our finding of the pronounced effect of wind energy on unskilled workers is consistent with previous evidence of wind projects in Portugal (Costa & Veiga, 2021). Also, the employment effect is notably strong, although less pronounced, for the workers with a post-graduate degree, where $\hat{\beta}_w$ is almost twice the baseline.

Table 7 Panel B shows a similar pattern for the weekly wage. Column 2 highlights that $\hat{\beta}_s$ is almost three times the baseline for workers with less than a high school degree. Solar energy's wage effect remains sizable for workers with higher educational attainment (columns 4 through 6), although the estimates are less heterogeneous. Again, we find no wage effect observed from wind energy growth.

The sizable employment and wage benefits at both ends of the educational attainment spectrum suggest that the solar and wind growth leads to the greatest labor market opportunities for the lowest- and highest-skill workers. Again, this can come from a potential migration channel (see changes in population composition by education categories in Appendix Table A.5 Panel B). While less-educated workers have shown to be less responsive to negative shocks as they are less mobile (Autor et al., 2013; Hanson, 2023), these workers are found to respond to and gain from positive shocks in our context when the location they reside in experience the green energy boom. On the other hand, for higher-educated workers, our positive results are consistent with past studies as these workers are relatively mobile (Autor et al., 2013; Haywood et al., 2023).

Effects by race. We find consistent evidence of employment gains for non-Hispanic white workers, while the effects for other racial groups are mixed. Table 6 Panel C shows a positive and significant effect for non-Hispanic white workers from both solar and wind energy growth. We further compare the distributional employment effects versus changes in the population composition in Appendix Table A.5 Panel C. The overall patterns suggest that while white workers benefit from solar and wind growth, solar projects are likely to benefit existing local workers and wind projects may attract white workers to locate in this area.

The positive effect is absent for other racial groups. For Asian workers, the effect of solar energy is smaller and statistically insignificant, and the effect of wind energy is negligible and insignificant. The effect turns negative for both black and Hispanic workers, although only $\hat{\beta}_s$ for black workers is sizable and precisely estimated. Our estimation implies that a 10% increase in solar capacity would decrease black employment by 0.4%.

Table 7 Panel C shows a positive and significant wage effect of solar energy for non-Hispanic white, Hispanic white, and Asian workers (the last group is only significant at 10%). By contrast, no significant wage changes are found for black workers. For wind energy, we find minimum wage effects across racial groups except for a negative effect for Hispanic workers (only statistically significant at 10%).

Effects by gender. Table 6 Panel D shows that while both genders experience increases in employment from solar and wind energy expansion, the effect is slightly stronger for male workers and the difference between genders is not substantial. On the other hand, the gap between male and female wage gains is more notable. Table 7 Panel D shows that the positive wage effect from solar energy is twice as large for male workers as it is for female workers. It is yet unclear what drives the greater gains for male workers. This can be correlated with the type of jobs that solar and wind energy created, although past studies have documented that male workers experience a greater hit in employment and wage compared to female workers when facing a negative shock (e.g., Autor et al., 2019).

To gain further insight into effects across gender and educational attainment groups, we study the differential impacts of educational attainment for both male and female workers. Appendix

Table A.6 Panel A shows that both genders witness the greatest employment gains among workers with less than a high-school degree workers and the gains are of similar magnitude for both genders. However, the sizable gains for workers with a post-graduate degree that we previously found in Table 6 are only observed for male workers. Consistent with Table 6 Panel D, the gender disparities in employment gains are not notable on average.

For the wage effect, female workers with less than a high school degree experience the greatest gains compared to both (i) other women with higher education and (ii) male counterparts with the same educational attainment. While higher-educated male workers with a high-school degree or more still enjoy wage gains, their female counterparts do not appear to receive any gains except for college-educated women. These education-specific differences across genders contribute to the gap that we observe in Appendix Table 7 Panel D.

In summary, our demographic analysis shows that the positive employment and wage effects are predominantly concentrated on young, white, male workers with educational attainment at both ends of the spectrum, especially workers with less than a high school degree. Our analysis also highlights the groups that are left out of the renewable energy growth that policymakers may need to be aware of, such as older workers, black workers, and workers with some education.

4.4 Effects on transfer payments and other outcomes

Effects on public transfer payments. The positive labor market outcomes from solar and wind energy expansion for the overall workforce and regional economies likely reduce the welfare payments to local residents. To explore this directly, we study CZ-level transfer payments by aggregating county-level transfer data from the Regional Economic Accounts. Government transfers can provide valuable insights into the well-being of workers in a location and the overall health of the regional economy. We present our analysis in Table 8.

We find strong evidence of lower transfer payments due to solar energy expansion, with a smaller and less precise effect from wind energy expansion. Table 8 column 1 shows that a

10% increase in solar energy capacity would lower the total individual transfer payments by 0.2%. This reduction is at the same order of magnitude as the increase in wage income (Table 2, columns 1-3), suggesting the increasing wage income may be a contributing factor to the reduced transfer payments.

The reduction in the overall transfer payments comes from various sources, including a reduction in income maintenance benefits, medical benefits, and other benefits. Within income benefits, we see a notable reduction in the Supplemental Nutrition Assistance Program (SNAP, commonly referred to as the food stamps) and the Supplemental Security Income. Looking at medical benefits, the reduction is more pronounced for Medicaid and much weaker and inconclusive for Medicare. The reduction in income benefits and Medicaid is consistent with our findings of the employment and wage gains as these programs target low-income individuals. Our inconclusive findings for Medicare are consistent with weak employment and wage gains for the older workforce.[16] We also observe a lower expenditure on other safety nets such as social security, unemployment unsurance, and educational assistance, although the latter two are not precisely estimated. As for wind energy, the coefficients are mostly small and not statistically different from zero, except for a reduction in education assistance and training.

Combining these results and the demographics analysis in Section 4.3, we find that locations growing in renewable energy tend to (i) offer the working-age population more jobs with better pay and (ii) attract and retain younger workers. As a result, the population residing in these locations is more likely to be employed, better paid, younger, and consequently likely less dependent on government subsidies.

Effects on other outcomes. Finally, Table 9 shows the positive effects of solar energy on several additional outcomes, including total individual income, total household income and educational attainments. The expansion of solar energy not only contributes to the growth of regional economies by attracting younger workers with the lowest and highest levels of

[16] Although the eligible individuals for Medicare (65+) are not included in our sample, it is plausible our findings for older prime working-age workers (51 to 64) can be extrapolated to populations above 65 and explain why coefficients in Table 8 column 3a are small and imprecise.

education to stay or migrate, but also leads to an increase in the average educational attainment in the local community. This is consistent with our earlier findings on growth of employment and the number of business establishments. The effects of wind energy on these outcomes are negligible.

4.5 Effects on green jobs and their sectoral differences

Green jobs have been an interest of the US environmental and energy policy designs. Previous studies have documented growth in green jobs in response to stricter environmental policies and increased government investment in the green economy (e.g., Vona et al., 2018; Popp et al., 2021). It is plausible that some of the labor market gains we documented in Section 4.1 from solar and wind can be attributed to the increase in green jobs. However, studying the magnitude of such effects and their sectoral differences remains an empirical question.

To unpack the effect, we first identify "green tasks" for each occupation based on the textual description of each task provided by the O*NET database, and next define the "greenness" of an occupation based on the fraction of green tasks within that occupation following Vona et al. (2018) and Vona (2021).[17] We link the occupation greenness to the ACS microdata and construct outcome variables for three groups of workers depending on the greenness of their jobs: jobs with the least greenness level (greenness $= 0$, which constitute the majority of the jobs), jobs with a certain level of greenness (greenness ranging from 0 to 0.1), and jobs with the highest level of greenness (greenness > 0.1).

Table 10 Panel A reports the employment effects by occupation greenness. We find greater employment effects for workers with greener jobs from solar energy growth. This differential effect is also notable in the manufacturing sector and other sectors (see Table 11 estimates for $\hat{\beta}_s$), suggesting a possibility of greater demand for those jobs in these sectors. In contrast, Table 10 Panel A shows that the employment gains from wind energy are mostly concentrated in the least green jobs. This pattern is consistently observed in the manufacturing and other sectors

[17] As O*NET categorizes occupation in an 8-digit code while ACS only uses a 6-digit occupation code, we use the minimum operator similarly as in Vona et al. (2018), as the average operator is likely subject to greater bias. We calculate the greenness of an 8-digit occupation using the fraction of green tasks (e.g., 1) out of all tasks (e.g., 10), yielding a greenness of 0.1 in this example. We then compute the minimum greenness of all 8-digit occupations within an ACS 6-digit occupation.

(see Table 11 estimates for $\hat{\beta}_w$), which suggests that wind energy growth leads to a greater demand for less green jobs.

Furthermore, Table 10 Panel B reports the differential wage effect. The positive wage effect from solar falls mostly on brown occupations. Taking all results together, while solar leads to more jobs for green occupations, especially in manufacturing, there is no clear evidence that these jobs have become attractive in terms of payoff; meanwhile wind energy leads to more conventional, less green jobs.

5 Robustness and additional results

In this section, we perform robustness checks for our baseline analysis and produce additional results to further our discussions.[18]

Alternative measure of renewable energy. In our main analysis, we measure renewable energy penetration in each Commuting Zone using its aggregate generation capacity. However, the green energy transition may also affect local workers during the ongoing operation of existing renewable plants.

To explore this possibility, we examine the effect of solar and wind power generation (measured by net generation) in Appendix Table A.7. The results are qualitatively similar to our main findings. The effect of solar energy growth is slightly smaller: A 10% increase in solar energy generation would increase employment by 0.2% and weekly wage by 0.2%. The effect of wind is also smaller and not precisely estimated. The reduced impact observed with net generation indicates that the benefits identified from renewable energy are linked to the creation of support jobs, rather than deriving from operational benefits of these generators, such as decreased electricity prices.

[18] In addition to the robustness tests presented below, our baseline results also remain robust (i) under alternative sets of fixed effects, such as census division trends, census region trends, NERC region trends, or without any regional trends; and (ii) with additional controls for the spillover from the residential solar industry using data from Tracking the Sun. These results are available upon request.

Coal phasing-out as an additional shifter for the IV. Our baseline analysis employs two temporal shifters, the Renewable Portfolio Standards and the Production Tax Credit. However, it is plausible that the decline of coal also plays an important role in the renewable energy industry as the energy supply transitions away from fossil fuels toward alternative sources. Appendix Figure A.1 shows the retirement of coal-fired units from 2001 to 2019 across subregions of the North American Electric Reliability Corporation (NERC). We observe some correlation with the patterns seen in Figures 1 and 2.

To incorporate this possibility, we introduce an additional temporal shifter to capture the coal shock, resulting in a total of six instrumental variables. We measure the decline of coal by constructing the capacity-weighted vintage of coal-fired units in a NERC subregion, with the variation driven by both capacity changes and retirement timing, which Davis et al. (2021) document as exogenous for a unit. In Appendix Table A.8, we re-produce our analysis on employment and weekly wage with this additional shifter. The point estimates are very similar to the baseline results.

Longer first differences. Our main results are produced on stacked one-year first differences of outcome variables Y's and renewable energy RE's. We examine the robustness of our baseline using longer differences, which are commonly employed in many studies on local labor markets (e.g., Autor & Dorn, 2013; Autor et al., 2013, 2019) to study the medium-term effect of the energy transition. Appendix Table A.9 shows that our results are similar if we use two-year, three-year, five-year, and seven-year differences. In this specification, we are studying the effect of a medium-term change in renewable energy on medium-term changes in employment and wage, these results are still a reflection of a contemporaneous effect of renewable capacity expansion, but with a perspective of a longer time horizon.

6 Conclusion

In this paper, we provide a comprehensive study of the effects of the growth in solar and wind energy on local labor market outcomes in the United States. Our findings reveal substantial gains in employment, labor force participation, and wages resulting from the expansion in solar and wind energy between 2005 and 2019. Importantly, we find these job market gains are not just short-lived, confined to the construction phase, or exclusive to construction workers. Instead, they lead to the growth of manufacturing plants and an increase in employment across multiple sectors in the years following the completion of the installation. Alongside the increase in employment and business activities, we also observe a reduction in government transfer payments. This reduction in the public finance burden opens up an opportunity for policymakers to reallocate resources to assist sub-populations that have been left out or adversely affected by the expansion of solar and wind energy.

Our results suggest the types of jobs that the renewable energy boom creates. The growth in renewable energy has increased employment and wages for individuals with the lowest (with less than a high school degree) and the highest (with a post-graduate degree) levels of skills. We observe minimal employment benefits for older workers, mirroring the coal decline effect documented in Hanson (2023), and negative job prospects for black workers. This diverse range of effects highlights the gains and losses that policymakers must consider when designing green energy policies.

We find the benefits of the green energy transition tend to be localized, as we observe weak spatial spillover from neighboring commuting zones, accompanied by a strong in-migration effect that suggests jobs and higher wages are likely concentrated in the commuting zones experiencing growth in renewables. This finding aligns with past studies that find the effect of economy-wide industrial shocks tends to be localized (Autor & Dorn, 2013; Autor et al., 2013; Hanson, 2023). Given that both the negative shocks from the decline of coal industries (Hanson, 2023) and the positive gains from renewables that we find are localized, future research should explore how well the green energy shock replaces workers that experience job loss from the energy transition as well as the potential barriers preventing workers from capitalizing on the new opportunities created by the energy transition. Understanding the underlying mechanism of the transition dynamics can help ensure an efficient energy transition and equitable growth of the local economy.

Lastly, while this study examines the outcomes of workers in wage profiles and how workers move across sectors and infers potential migration patterns, our results cannot directly speak to labor market efficiency as a result of the renewable booms driven by both market forces and policy incentives. We leave room for future research to study labor productivity, allocative efficiency, and other challenges that the energy transition has led to.

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Figures

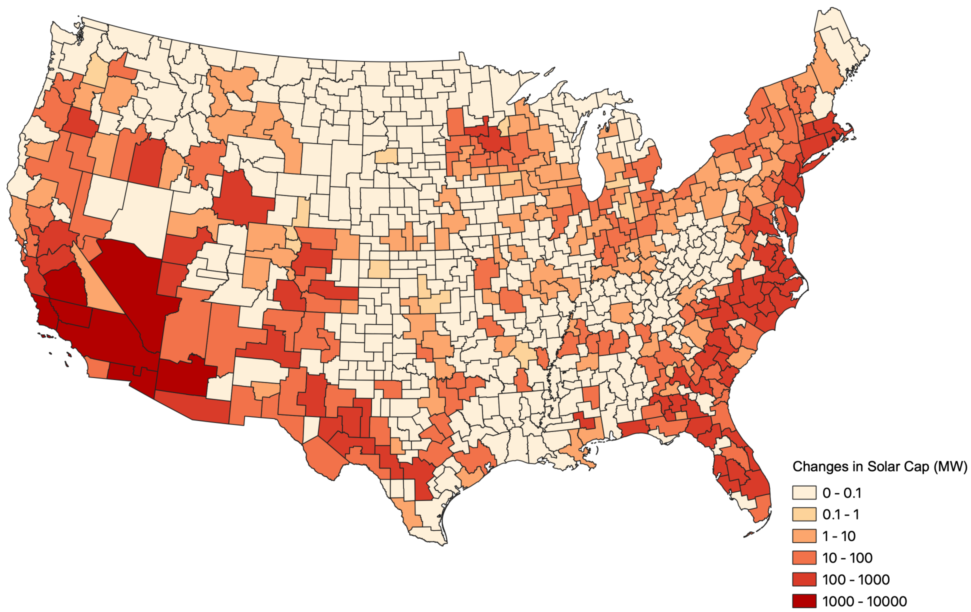


Figure 1: **Changes in Solar Energy Generation Capacities by Commuting Zone**

Notes: This map shows the changes in solar energy generation capacity (in Megawatts) from 2001 to 2019 using EIA data for the continental US.

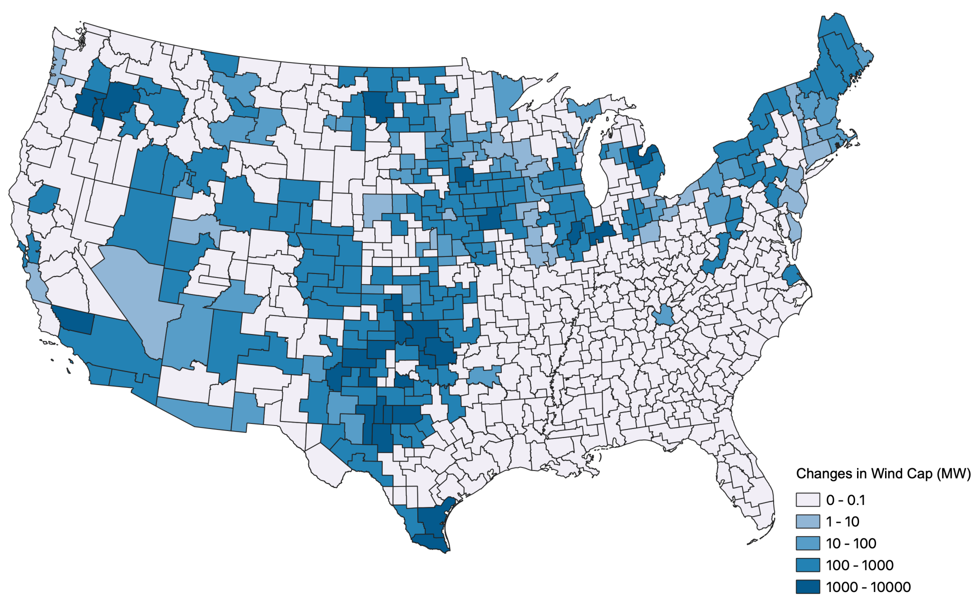


Figure 2: **Changes in Onshore Wind Energy Generation Capacities by Commuting Zone**

Notes: This map shows the changes in onshore wind energy generation capacity (in Megawatts) from 2001 to 2019 using EIA data for the continental US.

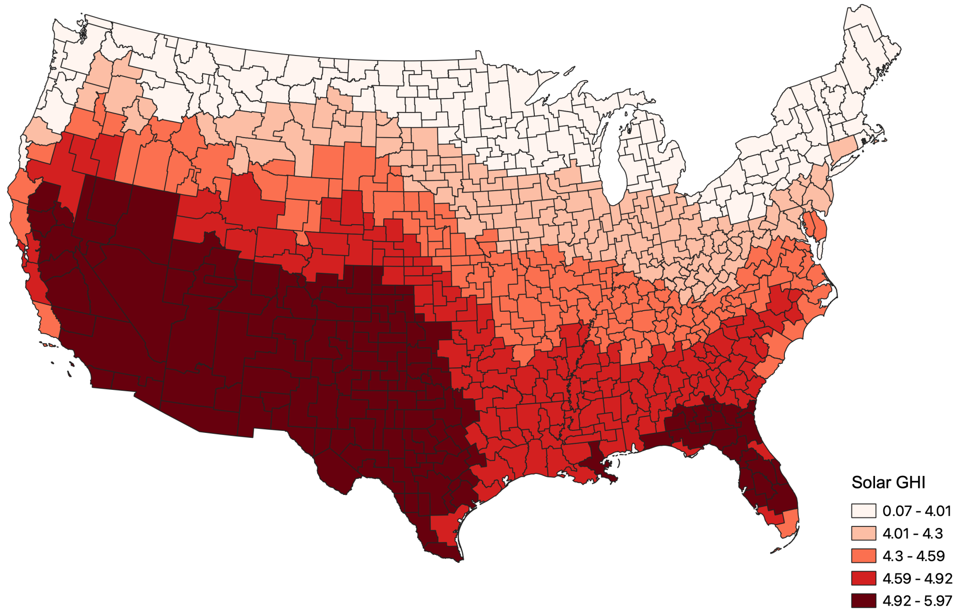


Figure 3: **Average Solar GHI by Commuting Zone**

Note: This map shows the average solar Global Horizontal Irradiance (GHI) by CZ using NREL data.

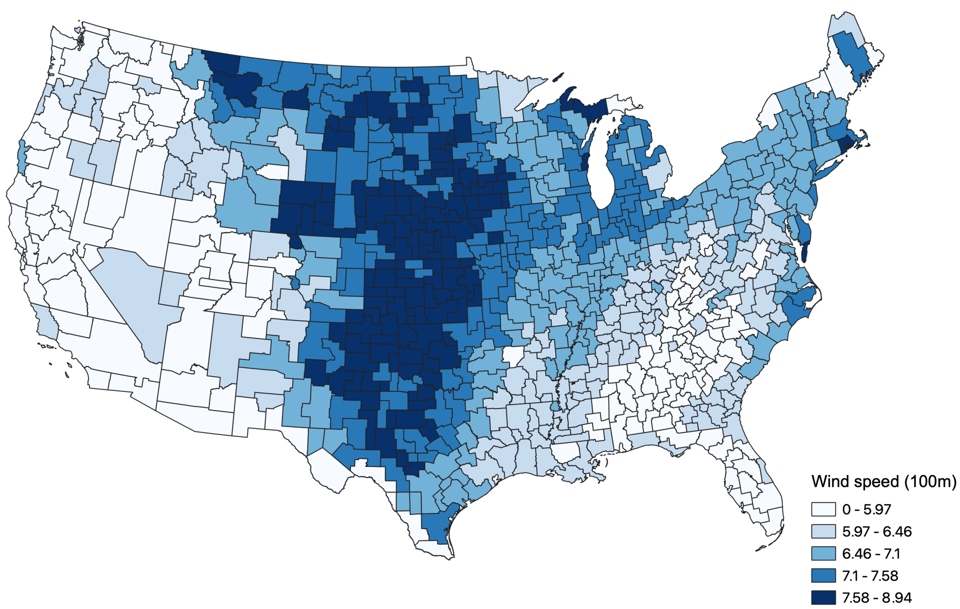


Figure 4: **Average Inland 120-meter Wind Speed by Commuting Zone**

Note: This map shows the average inland 120-meter wind speed by CZ using NREL data.

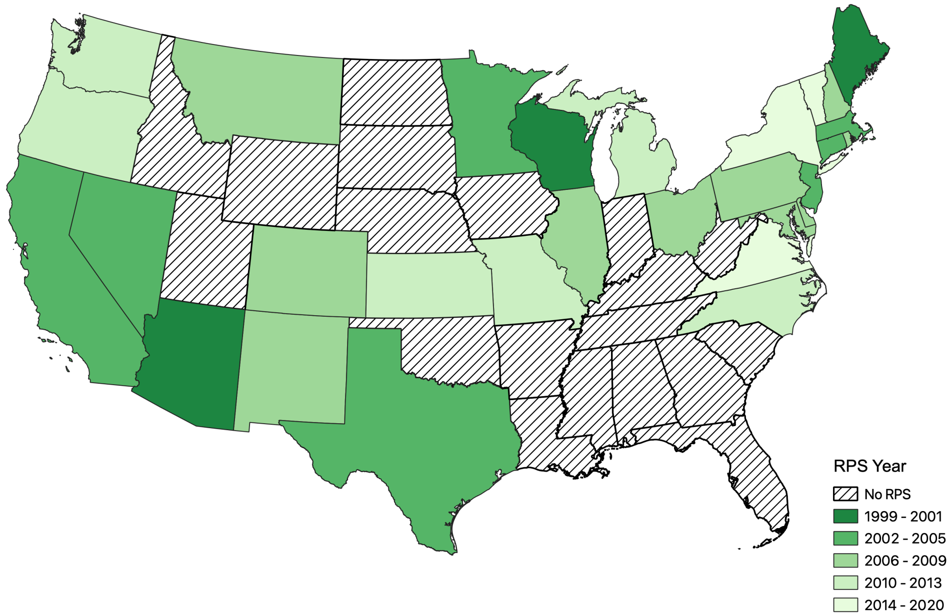
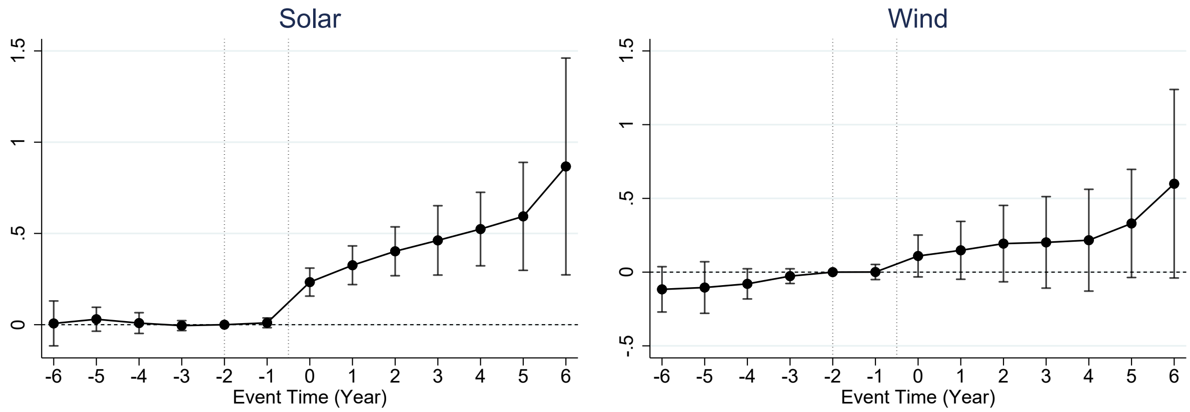


Figure 5: **Enacted Year of the Renewable Portfolio Standards (RPS)**

Note: This map shows the enacted year of the Renewable Portfolio Standards (RPS) by state using data from the Lawrence Berkeley National Laboratory (LBNL).

Panel A. Log Employment



Panel B. Log Weekly Wage

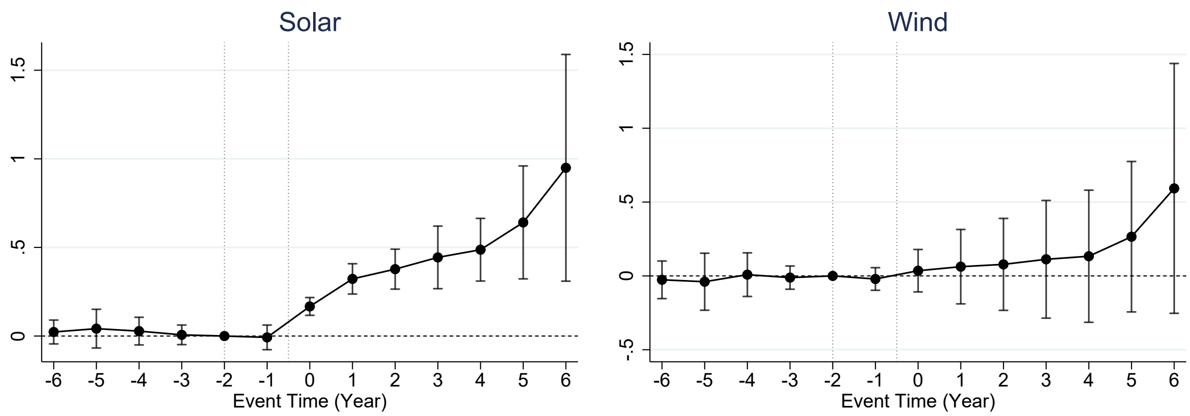


Figure 6: **Local Projection of the Initial Capacity Increase Event**

Note: This plot reproduces the baseline using the local projector estimator following Dube et al. (2023) inspired by Jordá (2005). We run our estimation separately for wind and solar shocks. We include the same controls and fixed effects, and we use the same instrumental variables as in Equation (1). We re-define the variable of interest as the first-differenced dummy variable if capacity increases from zero to a positive number. We define the clean control exactly following Dube et al. (2023).

Tables

Table 1: **Effects of Renewable Deployment on Extensive Margins of Work**

Dependent variable:	$\Delta \ln$ employment	$\Delta \ln$ labor force participation	$\Delta \ln$ population	$\Delta \ln$ new-resident population
	(1)	(2)	(3)	(4)
A. Estimates				
$\Delta \ln(\text{solar capacity})$	0.0287****	0.0277****	0.0120**	0.0349****
	(0.0031)	(0.0028)	(0.0049)	(0.0081)
$\Delta \ln(\text{wind capacity})$	0.0138**	0.0134**	0.0162*	0.0118
	(0.0066)	(0.0066)	(0.0095)	(0.0128)
$\ln(\text{population})_{t-1}$	X	X		
$\ln(\text{coal capacity retirement})_t$	X	X	X	X
Number of observations	10,094	10,094	10,094	10,094
Sargan over-id. p-value	1.00	1.00	1.00	1.00
B. Effect for a 10% increase in renewable capacity in 2019 (share in %)				
(for CZs with non-zero solar or wind capacity in 2019)				
B.1 Δ *solar cap.* $= 10\%$ ($\approx 12MW$):	1,143 (0.3%)	1,132 (0.3%)	511 (0.1%)	224 (0.4%)
B.2 Δ *wind cap.* $= 10\%$ ($\approx 41MW$):	369 (0.1%)	368 (0.1%)	464 (0.2%)	50 (0.1%)

Notes: Robust standard errors clustered at the state level in parenthesis. *, **, ***, and **** indicate statistical significance at 10, 5, 1, and 0.1 percent levels, respectively. All regressions are conducted at CZ by year level using first-differenced variables. All regressions include fixed effects of year, state, and a linear trend for each state. All regressions control for log coal retirement capacity in a CZ, a lag of log population, and dummy variables that represent whether the lagged solar or wind capacity in a CZ was zero.

Table 2: **Effects of Renewable Deployment on Other Margins of Work**

Dependent variable:	Δ ln wage annually	Δ ln wage weekly	Δ ln wage hourly	Δ ln weeks worked per year	Δ ln hours worked per week
	(1)	(2)	(3)	(4)	(5)
A. Estimates					
$\Delta \ln(\text{solar capacity})$	0.0150****	0.0246****	0.0291****	-0.0156****	0.0008*
	(0.0037)	(0.0044)	(0.0065)	(0.0019)	(0.0004)
$\Delta \ln(\text{wind capacity})$	-0.0013	-0.0004	-0.0091	0.0012	0.0013
	(0.0051)	(0.0073)	(0.0105)	(0.0030)	(0.0012)
Number of observations	10,094	10,094	10,094	10,094	10,094
Sargan over-id. p-value	1.00	1.00	1.00	1.00	1.00
B. Effect for a 10% increase in solar capacity ($\approx$ 12MW) in 2019 (with wages in 2005 USD) (for CZs with non-zero solar capacity in 2019)					
	\$50.6 (0.2%)	\$1.9 (0.3%)	\$0.06 (0.3%)	-0.07 (-0.02%)	0.03 (0.01%)

Notes: Number of observations = 10,094. Robust standard errors clustered at the state level in parenthesis. *, **, ***, and **** indicate statistical significance at 10, 5, 1, and 0.1 percent levels, respectively. All regressions in Panel A repeat the baseline as in Table 1 Panel A columns 1-2, i.e., all regressions fixed effects of year, state, a linear trend for each state, and the same sets of control variables. All calculations in Panels B to D repeat Table 1 Panel B to D and only evaluate on commuting zones with non-zero solar in 2019.

Table 3: **Potential Spillover from Local Locations**

Panel A. Dependent variable: $\Delta \ln$ employment

	(1)	(2)	(3)
	Base	Average capacity of local CZs: adjacent CZs	others in the state
$\Delta \ln$ (solar capacity)	0.0287****	0.0283****	0.0271****
	(0.0031)	(0.0031)	(0.0034)
$\Delta \ln$ (wind capacity)	0.0138**	0.0131**	0.0138**
	(0.0066)	(0.0065)	(0.0066)
$\Delta \ln$ (solar capacity for local CZs)		-0.0033**	-0.0031***
		(0.0013)	(0.0010)
$\Delta \ln$ (wind capacity for local CZs)		0.0010	0.0013
		(0.0011)	(0.0015)

Panel B. Dependent variable: $\Delta \ln$ weekly wage

	(1)	(2)	(3)
	Base	Average capacity of local CZs: adjacent CZs	others in the state
$\Delta \ln$ (solar capacity)	0.0246****	0.0231****	0.0231****
	(0.0044)	(0.0044)	(0.0041)
$\Delta \ln$ (wind capacity)	-0.0004	-0.0002	-0.0004
	(0.0073)	(0.0067)	(0.0072)
$\Delta \ln$ (solar capacity for local CZs)		-0.0037**	-0.0027
		(0.0015)	(0.0016)
$\Delta \ln$ (wind capacity for local CZs)		-0.0018	-0.0005
		(0.0015)	(0.0031)

Notes: Number of observations = 10,094. Robust standard errors clustered at the state level in parenthesis. *, **, ***, and **** indicate statistical significance at 10, 5, 1, and 0.1 percent levels, respectively. Column 1 repeats the baseline from Table 1 column 1 and Table 2 column 2. In columns 4 and 5, we control for renewable capacity in local CZs.

Table 4: **Sectoral Outcomes on Employment and Wage**

Panel A. Dependent variable: Δ ln employment

A.1 Main sectors:	All workers (1)	Manufacturing sector (2)	Service sector (3)	Other sectors (4)	Public and government (5)
$\Delta \ln(\text{solar capacity})$	0.0287****	0.0745****	0.0228****	0.0210****	-0.0190***
	(0.0031)	(0.0086)	(0.0030)	(0.0040)	(0.0068)
$\Delta \ln(\text{wind capacity})$	0.0138**	0.0180	0.0166**	0.0075	-0.0166
	(0.0066)	(0.0150)	(0.0071)	(0.0059)	(0.0151)
A.2 Selected sectors in "other sectors":	Agriculture (4a)	Utility (4b)	Construction (4c)	Wholesale & retail (4d)	Transport. & warehousing (4e)
$\Delta \ln(\text{solar capacity})$	0.0429	-0.0081	0.0480****	0.0109***	0.0234***
	(0.0263)	(0.0158)	(0.0102)	(0.0036)	(0.0071)
$\Delta \ln(\text{wind capacity})$	-0.0008	0.0010	0.0113	0.0010	-0.0119
	(0.0263)	(0.0273)	(0.0114)	(0.0079)	(0.0213)

Panel B. Dependent variable: Δ ln weekly wage

B.1 Main sectors:	All workers (1)	Manufacturing sector (2)	Service sector (3)	Other sectors (4)	Public and government (5)
$\Delta \ln(\text{solar capacity})$	0.0246****	0.0195***	0.0190****	0.0396****	0.0134***
	(0.0044)	(0.0070)	(0.0039)	(0.0073)	(0.0042)
$\Delta \ln(\text{wind capacity})$	-0.0004	-0.0040	0.0092	-0.0115	-0.0033
	(0.0073)	(0.0171)	(0.0082)	(0.0096)	(0.0103)
B.2 Selected sectors in "other sectors":	Agriculture (4a)	Utility (4b)	Construction (4c)	Wholesale & retail (4d)	Transport. & warehousing (4e)
$\Delta \ln(\text{solar capacity})$	-0.0373	0.0262***	0.0178**	0.0410****	0.0402****
	(0.0295)	(0.0095)	(0.0072)	(0.0104)	(0.0104)
$\Delta \ln(\text{wind capacity})$	0.0089	-0.0154	-0.0273*	0.0068	-0.0225
	(0.0376)	(0.0171)	(0.0154)	(0.0121)	(0.0221)

Notes: Number of observations = 10,094. Robust standard errors clustered at the state level in parenthesis. *, **, ***, and **** indicate statistical significance at 10, 5, 1, and 0.1 percent levels, respectively. All regressions repeat the baseline as in Table 1 column 1 using the outcome on various sub-populations. The "other sectors", as in column 4, include all sectors excluding manufacturing, service, and the public sector, i.e., all sectors with the first-digit North American Industry Classification System (NAICS) code being 1, 2, and 4. Specifically, they are agriculture, forestry, fishing, and hunting; mining; utilities; construction; wholesale and retail trade; and transportation.

Table 5: **Sectoral Effects on Local Business Establishments**

Dependent variable: $\Delta \ln$ *business establishments for*

A. Main sectors:	All sectors (1)	Manufacturing sector (2)	Service sector (3)	Other sectors (4)	
$\Delta \ln$(solar capacity)	0.0025	0.0372****	-0.0037	-0.0016	
	(0.0020)	(0.0067)	(0.0028)	(0.0024)	
$\Delta \ln$(wind capacity)	0.0076*	0.0166	0.0058	0.0051	
	(0.0040)	(0.0133)	(0.0041)	(0.0042)	

B. Selected sectors in "other sectors":	Agriculture (4a)	Utility (4b)	Construction (4c)	Wholesale & retail (4d)	Transport. & warehousing (4e)
$\Delta \ln$(solar capacity)	0.0505***	0.0971****	0.0035	-0.0103****	0.0108
	(0.0156)	(0.0193)	(0.0051)	(0.0024)	(0.0101)
$\Delta \ln$(wind capacity)	0.0306	0.0223	0.0058	0.0041	-0.0005
	(0.0239)	(0.0219)	(0.0058)	(0.0047)	(0.0114)

Notes: Number of observations = 10,094. Robust standard errors clustered at the state level in parenthesis. *, **, ***, and **** indicate statistical significance at 10, 5, 1, and 0.1 percent levels, respectively. All regressions repeat the baseline as in Table 1 columns 1-2 and Table 2 on alternative outcome variables. The "other business establishments", as in column 4, include business establishments in all sectors excluding manufacturing and service sectors. All columns exclude the public sector as we only include business establishments.

Table 6: **Distributional Employment Effects by Demographics**

Dep. var.: $\Delta \ln employment$	(1)	(2)	(3)	(4)	(5)	(6)
A. Effects by Age						
	All workers	16–35	36–50	51–64		
$\Delta \ln$ (solar cap.)	0.0287****	0.0377****	0.0358****	0.0061**		
	(0.0031)	(0.0058)	(0.0038)	(0.0026)		
$\Delta \ln$ (wind cap.)	0.0138**	0.0230**	0.0106	0.0012		
	(0.0066)	(0.0113)	(0.0086)	(0.0062)		
B. Effects by Educational Attainment						
	All workers	Less than high school	High school degree	Some college	College degree	Post-grad degree
$\Delta \ln$ (solar cap.)	0.0287****	0.1159****	0.0049	0.0179***	0.0064*	0.0184***
	(0.0031)	(0.0149)	(0.0031)	(0.0063)	(0.0036)	(0.0052)
$\Delta \ln$ (wind cap.)	0.0138**	0.0584*	0.0063	-0.0224**	0.0046	0.0260**
	(0.0066)	(0.0292)	(0.0066)	(0.0104)	(0.0086)	(0.0120)
C. Effects by Race						
	All workers	Non-hispanic white	Hispanic white	Black	Asian	
$\Delta \ln$ (solar cap.)	0.0287****	0.0164****	-0.0180	-0.0408**	0.0121	
	(0.0031)	(0.0035)	(0.0150)	(0.0190)	(0.0112)	
$\Delta \ln$ (wind cap.)	0.0138**	0.0222**	-0.0224	-0.0249	-0.0008	
	(0.0066)	(0.0095)	(0.0331)	(0.0369)	(0.0206)	
D. Effects by Gender						
	All workers	Male	Female			
$\Delta \ln$ (solar cap.)	0.0287****	0.0318****	0.0249****			
	(0.0031)	(0.0032)	(0.0029)			
$\Delta \ln$ (wind cap.)	0.0138**	0.0157**	0.0111*			
	(0.0066)	(0.0073)	(0.0061)			

Notes: Number of observations = 10,094. Robust standard errors clustered at the state level in parenthesis. *, **, ***, and **** indicate statistical significance at 10, 5, 1, and 0.1 percent levels, respectively. All regressions repeat the baseline as in Table 1 column 1 using the outcome on various sub-populations.

Table 7: **Distributional Wage Effects by Demographics**

Dep. var.: $\Delta \ln$ *weekly wage*	(1)	(2)	(3)	(4)	(5)	(6)
A. Effects by Age						
	All workers	16–35	36–50	51–64		
$\Delta \ln$ (solar cap.)	0.0246****	0.0407****	0.0216****	0.0197***		
	(0.0044)	(0.0060)	(0.0036)	(0.0057)		
$\Delta \ln$ (wind cap.)	-0.0004	0.0019	0.0032	-0.0007		
	(0.0073)	(0.0121)	(0.0084)	(0.0115)		
B. Effects by Educational Attainment						
	All workers	Less than high school	High school degree	Some college	College degree	Post-grad degree
$\Delta \ln$ (solar cap.)	0.0246****	0.0722****	0.0119*	0.0260****	0.0300****	0.0292****
	(0.0044)	(0.0119)	(0.0062)	(0.0066)	(0.0075)	(0.0059)
$\Delta \ln$ (wind cap.)	-0.0004	0.0300	0.0034	-0.0043	-0.0018	0.0034
	(0.0073)	(0.0361)	(0.0093)	(0.0097)	(0.0132)	(0.0098)
C. Effects by Race						
	All workers	Non-hispanic white	Hispanic white	Black	Asian	
$\Delta \ln$ (solar cap.)	0.0246****	0.0196****	0.0420****	-0.0019	0.0244*	
	(0.0044)	(0.0038)	(0.0071)	(0.0116)	(0.0135)	
$\Delta \ln$ (wind cap.)	-0.0004	-0.0020	-0.0294*	0.0178	0.0319	
	(0.0073)	(0.0066)	(0.0155)	(0.0162)	(0.0254)	
D. Effects by Gender						
	All workers	Male	Female			
$\Delta \ln$ (solar cap.)	0.0246****	0.0304****	0.0159****			
	(0.0044)	(0.0055)	(0.0033)			
$\Delta \ln$ (wind cap.)	-0.0004	-0.0059	0.0069			
	(0.0073)	(0.0096)	(0.0054)			

Notes: Number of observations = 10,094. Robust standard errors clustered at the state level in parenthesis. *, **, ***, and **** indicate statistical significance at 10, 5, 1, and 0.1 percent levels, respectively. All regressions repeat the baseline as in Table 2 column 2 using the outcome on various sub-populations.

Table 8: **Effects on Regional Government Transfer Receipts**

Dependent variable: $\Delta \ln$ *Government transfer per capita*

	1. Total	*2. Income maintenance benefits*			
	Total individual transfer	Total individual income benefits	Supplemental security income (SSI)	SNAP	EITC
	(1)	(2)	(2a)	(2b)	(2c)
$\Delta \ln(\text{solar cap.})$	-0.0172****	-0.0471****	-0.0145*	-0.0269***	0.0115
	(0.0039)	(0.0066)	(0.0077)	(0.0080)	(0.0070)
$\Delta \ln(\text{wind cap.})$	-0.0026	-0.0037	0.0038	-0.0134	0.0059
	(0.0098)	(0.0145)	(0.0137)	(0.0151)	(0.0085)

	3. Medical benefits			*4. Other programs*		
	Total medical	Medicare	Medicaid	UI	Social security (SS)	Education assistance
	(3)	(3a)	(3b)	(4a)	(4b)	(4c)
$\Delta \ln(\text{solar cap.})$	-0.0126*	-0.0077	-0.0186***	-0.0110	-0.0085**	-0.0066
	(0.0071)	(0.0076)	(0.0064)	(0.0317)	(0.0041)	(0.0066)
$\Delta \ln(\text{wind cap.})$	-0.0003	0.0007	-0.0023	-0.0360	0.0000	-0.0337***
	(0.0107)	(0.0128)	(0.0107)	(0.0219)	(0.0078)	(0.0167)

Notes: Number of observations = 10,094. Robust standard errors clustered at the state level in parenthesis. *, **, ***, and **** indicate statistical significance at 10, 5, 1, and 0.1 percent levels, respectively. All regressions repeat the baseline as in Table 1 column 1 on alternative outcome variables.

Table 9: **Effects on Other Outcomes**

Dependent variable:	$\Delta \ln$ total personal annual income	$\Delta \ln$ total household annual income	$\Delta \ln$ years of educational attainment
	(1)	(2)	(3)
$\Delta \ln(\text{solar capacity})$	0.0162****	0.0210****	0.0286****
	(0.0031)	(0.0029)	(0.0028)
$\Delta \ln(\text{wind capacity})$	-0.0018	0.0018	0.0130*
	(0.0050)	(0.0066)	(0.0067)

Notes: Number of observations = 10,094. Robust standard errors clustered at the state level in parenthesis. *, **, ***, and **** indicate statistical significance at 10, 5, 1, and 0.1 percent levels, respectively. All models repeat the baseline as in Table 1 column 1.

Table 10: **Distributional Employment Effects by Occupation Greenness**

	All workers	*Least green:* If minimum occupation greenness $= 0$	*Somewhat green:* If minimum occupation greenness $\in (0,\ 0.1]$	*The greenest:* If minimum occupation greenness > 0.1
	(1)	(2)	(3)	(4)
A. Dependent variable: $\Delta \ln$ *employment*				
$\Delta \ln(\text{solar capacity})$	0.0287****	0.0263****	0.1246****	0.0333***
	(0.0031)	(0.0031)	(0.0097)	(0.0073)
$\Delta \ln(\text{wind capacity})$	0.0138**	0.0154***	0.0249	-0.0109
	(0.0066)	(0.0066)	(0.0269)	(0.0103)
B. Dependent variable: $\Delta \ln$ *weekly wage*				
$\Delta \ln(\text{solar capacity})$	0.0246****	0.0256****	-0.0133	0.0153
	(0.0044)	(0.0039)	(0.0120)	(0.0164)
$\Delta \ln(\text{wind capacity})$	-0.0004	0.0026	0.0101	-0.0179
	(0.0073)	(0.0074)	(0.0158)	(0.0221)
Share of workers		93.2%	1.6%	5.1%

Notes: Number of observations = 10,094. Robust standard errors clustered at the state level in parenthesis. *, **, ***, and **** indicate statistical significance at 10, 5, 1, and 0.1 percent levels, respectively. All regressions repeat the baseline as in Table 1 column 1 using the outcome on various sub-populations. We calculate the greenness for an 8-digit occupation in the O*NET using the fraction of green tasks out of all tasks, and construct the greenness for a 6-digit occupation in the ACS data using the minimum greenness of all 8-digit occupations within a 6-digit occupation as following Vona et al. (2018).

Table 11: **Distributional Employment Effects by Sector and Occupation Greenness**

Dependent variable: $\Delta \ln employment$	Manufacturing sector			Other sectors (excl. service and gov't.)		
	All occp.:	*Other occp.:* $\min green = 0$	*Green occp.:* $\min green > 0$	*All occp.:*	*Other occp.:* $\min green = 0$	*Green occp.:* $\min green > 0$
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
$\Delta \ln(\text{solar cap.})$	0.0745****	0.0676****	0.1177****	0.0210****	0.0201****	0.0295***
	(0.0086)	(0.0081)	(0.0198)	(0.0040)	(0.0040)	(0.0089)
$\Delta \ln(\text{wind cap.})$	0.0180	0.0162	-0.0007	0.0075	0.0107*	-0.0136
	(0.0150)	(0.0136)	(0.0297)	(0.0059)	(0.0061)	(0.0106)
Share of workers in a sector		87.6%	12.4%		89.4%	10.6%

Notes: Number of observations = 10,094. Robust standard errors clustered at the state level in parenthesis. *, **, ***, and **** indicate statistical significance at 10, 5, 1, and 0.1 percent levels, respectively. All regressions repeat the baseline as in Table 1 column 1 using the outcome on various sub-populations. The greenness for an occupation is constructed as in Table 10. Green occupations in this table are defined as occupations with greenness greater than 0. We exclude the service and public sectors from this analysis as they have fewer green occupations.

Online Appendix

Appendix A. Additional Figures and Tables

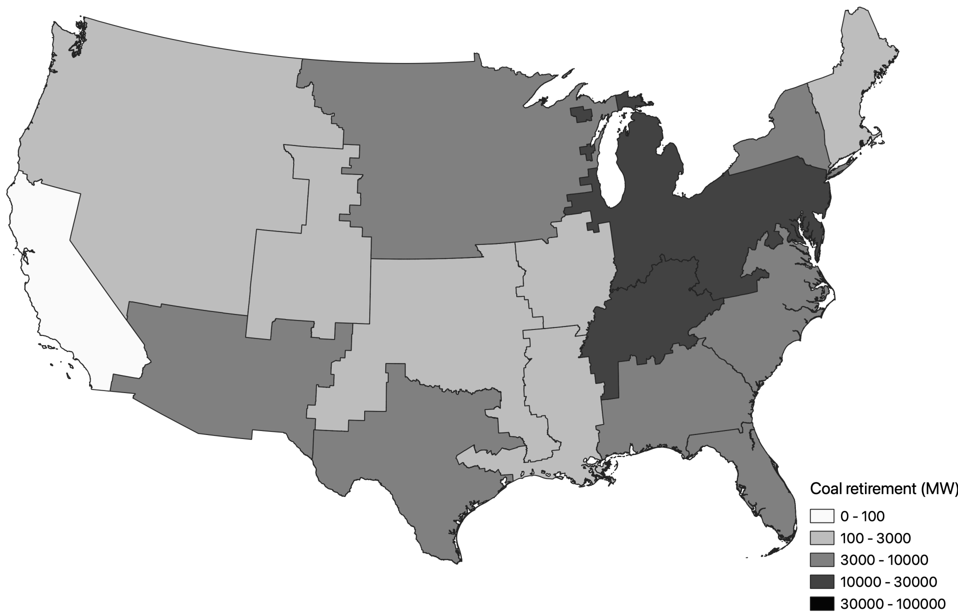


Figure A.1: **Changes in Coal-fired Power Generation Capacity**

Notes: This map displays the retirements in coal-fired generation capacity (in Megawatts) from 2001 to 2019 for each NERC subregion in the continental US. We thank Erin Mansur for his generosity in sharing his code and shapefiles, which allowed us to match utilities to each county and the balancing authority.

Table A.1: **Summary Statistics for Key Variables**

Panel A. Annual Changes in Key Variables

Variable name:	Mean	St. Dev.	Variable name:	Mean	St. Dev.
A.1 Outcome variables			A.2 Variables of interest		
$\Delta \ln(\text{employment})$	0.002	0.044	$\Delta \ln(\text{solar capacity})$	0.092	0.435
$\Delta \ln(\text{labor force part.})$	0.001	0.040	$\Delta \ln(\text{wind capacity})$	0.099	0.609
$\Delta \ln(\text{population})$	-0.002	0.037	$\Delta \ln(\text{solar net gen.})$	0.101	0.586
$\Delta \ln(\text{annual wage})$	0.009	0.058	$\Delta \ln(\text{wind net gen.})$	0.120	0.690
$\Delta \ln(\text{weekly wage})$	0.008	1.403			
$\Delta \ln(\text{hourly wage})$	0.011	1.378			
$\Delta \ln(\text{weeks worked/year})$	-0.001	0.019			
$\Delta \ln(\text{hours worked/week})$	0.004	1.220			
Number of observations					10,094

Panel B. Cumulative Changes in Renewable Energy in a CZ from 2005 to 2019

Variable name:	Mean	St. Dev.	Variable name:	Mean	St. Dev.
B.1 Solar			B.2 Wind		
Capacity (MW) in 2005	0.6	14.9	Capacity (MW) in 2005	12.0	61.9
Capacity (MW) in 2019	51.8	253.7	Capacity (MW) in 2019	144.0	375.0
$\Delta \ln(\text{capacity})_{2019-2005}$	1.29	1.93	$\Delta \ln(\text{capacity})_{2019-2005}$	1.39	2.31
Net gen. (GWh) in 2005	0.8	19.9	Net gen. (GWh) in 2005	24.5	136.2
Net gen. (GWh) in 2019	99.3	561.4	Net gen. (GWh) in 2019	409.1	1,053.7
$\Delta \ln(\text{net gen})_{2019-2005}$	1.42	2.15	$\Delta \ln(\text{net gen})_{2019-2005}$	1.68	2.74

Table A.2: **First-stage Regressions**

Dependent variable:	Δ ln (solar capacity) (1)	Δ ln (wind capacity) (2)
State-level RPS Obligation (TWh)	0.0712**	0.0230
$\times$ CZ Area $\times$ Solar GHI	(0.0268)	(0.0270)
State-level RPS Obligation (TWh)	-0.0022****	-0.0005
$\times$ CZ Area $\times$ 120-meter wind speed^3	(0.0005)	(0.0007)
PTC (Dollar-per-MWh)	-0.0460	-0.1894***
$\times$ CZ Area $\times$ Solar GHI	(0.0593)	(0.0546)
PTC (Dollar-per-MWh)	0.0008	0.0045****
$\times$ CZ Area $\times$ 120-meter wind speed^3	(0.0008)	(0.0012)
Number of observations	10,094	10,094
R-squared	0.13	0.08
Joint-sig. Wald-stat (IVs)	77.5	12.0
Joint-sig. Wald-stat p-value (IVs)	0.000	0.000

Notes: Robust standard errors clustered at the state level in parenthesis. *, **, ***, and **** indicate statistical significance at 10, 5, 1, and 0.1 percent levels, respectively. This table reports the first-stage regression for the baseline regression as in Table 1 columns 1-2 and Table 2.

Table A.3: **Alternative Standard Errors**

	Base	Conely spatial SE			HAC SE		
	robust SE	cutoff distance at:			serial correlation:		
	cluster at state (1)	165 mile (265 km) (2a)	250 mile (400 km) (2b)	375 mile (600 km) (2c)	2 years (3a)	10 years (3b)	14 years (3c)
A. Dependent variable: $\Delta \ln$ *employment*							
$\Delta \ln(\text{solar cap.})$	0.0287****	0.0287****	0.0287****	0.0287****	0.0287**	0.0287**	0.0287**
	(0.0031)	(0.0051)	(0.0048)	(0.0031)	(0.0130)	(0.0110)	(0.0102)
$\Delta \ln(\text{wind cap.})$	0.0138**	0.0138**	0.0138***	0.0138***	0.0138	0.0138*	0.0138*
	(0.0066)	(0.0063)	(0.0053)	(0.0050)	(0.0086)	(0.0074)	(0.0072)
B. Dependent variable: $\Delta \ln$ *weekly wage*							
$\Delta \ln(\text{solar cap.})$	0.0246****	0.0246****	0.0246****	0.0246****	0.0246	0.0246*	0.0246*
	(0.0044)	(0.0056)	(0.0026)	(0.0027)	(0.0154)	(0.0138)	(0.0125)
$\Delta \ln(\text{wind cap.})$	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004
	(0.0073)	(0.0071)	(0.0079)	(0.0069)	(0.0093)	(0.0083)	(0.0078)

Notes: Number of observations = 10,094. Standard errors in parenthesis. *, **, ***, and **** indicate statistical significance at 10, 5, 1, and 0.1 percent levels, respectively. Panel A repeats Table 1 column 1 and Panel B repeats 2 column 2 using alternative standard errors. In column 1, we report the baseline standard error, the robust standard errors clustered at the state level. In columns 2a through 2c, we use the Conley standard error. For reference, 165 miles are roughly the mean distance of the nearest 5 neighboring commuting zones (CZs). In columns 3a through 3c, we compute the Newey-West heteroskedasticity and autocorrelation consistent (HAC) standard errors. For reference, 14 years is the panel length of the stacked 1-year first-differenced data.

Table A.4: **Sectoral Effects on Annual Payroll for Local Business Establishment**

Dependent variable: $\Delta \ln$ *annual payroll in establishments for*	All businesses (1)	Manufacturing sector (2)	Service sector (3)	Business in other sectors (4)
$\Delta \ln(\text{solar capacity})$	0.0357***	0.0505****	0.0560****	0.0235
	(0.0121)	(0.0153)	(0.0071)	(0.0178)
$\Delta \ln(\text{wind capacity})$	-0.0134	0.0115	0.0186	-0.0297
	(0.0272)	(0.0215)	(0.0120)	(0.0296)

Notes: Number of observations = 10,094. Robust standard errors clustered at the state level in parenthesis. *, **, ***, and **** indicate statistical significance at 10, 5, 1, and 0.1 percent levels, respectively. All regressions repeat the baseline as in Table 1 columns 1 on alternative outcome variables.

Table A.5: **Changes in Population Composition**

Dep. var.: $\Delta \ln$ *population*	(1)	(2)	(3)	(4)	(5)	(6)
A. Effects by Age						
	All workers	16–35	36–50	51–64		
$\Delta \ln$ (solar cap.)	0.0120**	0.0161**	0.0219****	-0.0095*		
	(0.0049)	(0.0074)	(0.0043)	(0.0048)		
$\Delta \ln$ (wind cap.)	0.0162*	0.0243*	0.0130	0.0043		
	(0.0095)	(0.0141)	(0.0106)	(0.0082)		
B. Effects by Educational Attainment						
	All workers	Less than high school	High school degree	Some college	College degree	Post-grad degree
$\Delta \ln$ (solar cap.)	0.0120**	0.0642****	-0.0058	0.0229***	-0.0025	0.0009
	(0.0049)	(0.0149)	(0.0051)	(0.0070)	(0.0042)	(0.0057)
$\Delta \ln$ (wind cap.)	0.0162*	0.0551*	0.0078	-0.0196*	0.0064	0.0289**
	(0.0095)	(0.0286)	(0.0095)	(0.0100)	(0.0092)	(0.0127)
C. Effects by Race						
	All workers	Non-hispanic white	Hispanic white	Black	Asian	
$\Delta \ln$ (solar cap.)	0.0120**	0.0062	0.0123	0.0155	0.0374****	
	(0.0049)	(0.0045)	(0.0172)	(0.0181)	(0.0068)	
$\Delta \ln$ (wind cap.)	0.0162*	0.0234**	-0.0222	-0.0369	-0.0004	
	(0.0095)	(0.0108)	(0.0365)	(0.0431)	(0.0195)	
D. Effects by Gender						
	All workers	Male	Female			
$\Delta \ln$ (solar cap.)	0.0120**	0.0166****	0.0066			
	(0.0049)	(0.0045)	(0.0053)			
$\Delta \ln$ (wind cap.)	0.0162*	0.0177*	0.0143			
	(0.0095)	(0.0090)	(0.0105)			

Notes: Number of observations = 10,094. Robust standard errors clustered at the state level in parenthesis. *, **, ***, and **** indicate statistical significance at 10, 5, 1, and 0.1 percent levels, respectively. All regressions repeat the baseline as in Table 2 column 2 using the outcome on various sub-populations.

Table A.6: **Distributional Effects by Gender and Educational Attainment**

Panel A. Dependent variable: $\Delta \ln$ employment

	(1)	(2)	(3)	(4)	(5)	(6)
A.1 For male	All male workers	Less than high school	High school degree	Some college	College degree	Post-grad degree
$\Delta \ln(\text{solar cap.})$	0.0318****	0.1130****	0.0101***	0.0078	0.0139****	0.0330***
	(0.0032)	(0.0167)	(0.0029)	(0.0083)	(0.0038)	(0.0092)
$\Delta \ln(\text{wind cap.})$	0.0157**	0.0585**	0.0072	-0.0301**	0.0076	0.0368**
	(0.0073)	(0.0273)	(0.0063)	(0.0138)	(0.0113)	(0.0162)
A.2 For female	All female workers	Less than high school	High school degree	Some college	College degree	Post-grad degree
$\Delta \ln(\text{solar cap.})$	0.0249****	0.1181****	-0.0012	0.0278****	-0.0009	0.0116**
	(0.0029)	(0.0122)	(0.0037)	(0.0064)	(0.0044)	(0.0054)
$\Delta \ln(\text{wind cap.})$	0.0111*	0.0574	0.0051	-0.0143	0.0005	0.0180
	(0.0061)	(0.0328)	(0.0085)	(0.0119)	(0.0088)	(0.0137)

Panel B. Dependent variable: $\Delta \ln$ weekly wage

	(1)	(2)	(3)	(4)	(5)	(6)
B.1 For male	All male workers	Less than high school	High school degree	Some college	College degree	Post-grad degree
$\Delta \ln(\text{solar cap.})$	0.0304****	0.0652****	0.0198***	0.0477****	0.0344****	0.0503****
	(0.0055)	(0.0099)	(0.0065)	(0.0060)	(0.0090)	(0.0078)
$\Delta \ln(\text{wind cap.})$	-0.0059	0.0234	0.0043	-0.0076	-0.0143	0.0034
	(0.0096)	(0.0351)	(0.0118)	(0.0124)	(0.0174)	(0.0123)
B.2 For female	All female workers	Less than high school	High school degree	Some college	College degree	Post-grad degree
$\Delta \ln(\text{solar cap.})$	0.0159****	0.0911****	-0.0020	0.0021	0.0186***	0.0066
	(0.0033)	(0.0174)	(0.0059)	(0.0086)	(0.0069)	(0.0069)
$\Delta \ln(\text{wind cap.})$	0.0069	0.0453	0.0020	0.0066	0.0119	0.0081
	(0.0054)	(0.0432)	(0.0067)	(0.0104)	(0.0105)	(0.0115)

Notes: Number of observations = 10,094. Robust standard errors clustered at the state level in parenthesis. *, **, ***, and **** indicate statistical significance at 10, 5, 1, and 0.1 percent levels, respectively. All regressions repeat the baseline as in Table 4 column 2 using the outcome on various sub-populations.

Table A.7: **Effects of Renewable Generation**

Panel A. Effect on extensive margins of work

Dependent variable:	Δ ln(Employment)	Δ ln(Labor force participation)	Δ ln(Population)
	(1)	(2)	(3)
Δ ln(solar net generation)	0.0168***	0.0159***	0.0013
	(0.0053)	(0.0056)	(0.0055)
Δ ln(wind net generation)	0.0088	0.0087	0.0203
	(0.0114)	(0.0116)	(0.0141)
Number of observation	10,094	10,094	10,094

Panel B. Effect on other margins of work

Dependent variable:	Δ ln wage annually	Δ ln wage weekly	Δ ln wage hourly	Δ ln weeks worked per year	Δ ln hours worked per week
	(1)	(2)	(3)	(4)	(5)
Δ ln(solar net generation)	0.0120**	0.0160**	0.0219**	-0.0007	0.0015*
	(0.0047)	(0.0071)	(0.0089)	(0.0026)	(0.0007)
Δ ln(wind net generation)	-0.0092	-0.0093	-0.0243	-0.0021	0.0003
	(0.0085)	(0.0128)	(0.0191)	(0.063)	(0.0016)
Number of observation	10,094	10,094	10,094	10,094	10,094

Notes: Robust standard errors clustered at the state level in parenthesis. *, **, ***, and **** indicate statistical significance at 10, 5, 1, and 0.1 percent levels, respectively. Panel A repeats Table 1 and Panel B repeats Table 2 with different endogenous variables, net generation, while keeping the same fixed effects and sets of controls, except we include dummy variables that represent whether the lagged solar or wind net generation in a CZ was non-positive (instead of zero as net generation can be negative).

Table A.8: **Additional Temporal Shifters for the IVs Using Coal Phase-out**

Dependent variable:	Δ ln employment		Δ ln weekly wage	
	base	3 temporal shifters	base	3 temporal shifters
	(1a)	(1b)	(2a)	(2b)
$\Delta \ln(\text{solar capacity})$	0.0287****	0.0295****	0.0255****	0.0230****
	(0.0031)	(0.0044)	(0.0038)	(0.0041)
$\Delta \ln(\text{wind capacity})$	0.0138**	0.0168**	-0.0011	-0.0001
	(0.0066)	(0.0066)	(0.0076)	(0.0067)
Number of observation	10,094	10,094	10,094	10,094
Sargan over-id. p-value	1.00	1.00	1.00	1.00

Notes: Number of observations = 10,094. Robust standard errors clustered at the state level in parenthesis. *, **, ***, and **** indicate statistical significance at 10, 5, 1, and 0.1 percent levels, respectively. Columns 1a and 2a repeat the baseline as in Tables 1 and 2. In columns 1b and 2b, we include the average vintage of coal-fired units at the NERC subregions as an additional temporal shifter (making a total of 6 IVs).

Table A.9: **Alternative Time Intervals for the First-Difference Estimator**

Panel A. Dependent variable: $\Delta \ln$ employment

Time interval:	Every year (base) (1)	Every 2 years (2)	Every 3 years (3)	Every 5 years (4)	Every 7 years (5)
$\Delta \ln(\text{solar capacity})$	0.0287****	0.0272****	0.0268****	0.0251****	0.0355****
	(0.0031)	(0.0025)	(0.0027)	(0.0035)	(0.0044)
$\Delta \ln(\text{wind capacity})$	0.0138**	0.0138**	0.0163**	0.0174**	0.0218**
	(0.0066)	(0.0063)	(0.0077)	(0.0080)	(0.0082)
Number of obs.	10,094	5,047	3,605	2,163	1,442

Panel B. Dependent variable: $\Delta \ln$ weekly wage

Time interval:	Every year (base) (1)	Every 2 years (2)	Every 3 years (3)	Every 5 years (4)	Every 7 years (5)
$\Delta \ln(\text{solar capacity})$	0.0246****	0.0226****	0.0239****	0.0179****	0.0214***
	(0.0044)	(0.0036)	(0.0043)	(0.0045)	(0.0065)
$\Delta \ln(\text{wind capacity})$	-0.0004	0.0024	0.0056	0.0067	0.0095
	(0.0073)	(0.0076)	(0.0096)	(0.0100)	(0.0100)
Number of obs.	10,094	5,047	3,605	2,163	1,442

Notes: Robust standard errors clustered at the state level in parenthesis. *, **, ***, and **** indicate statistical significance at 10, 5, 1, and 0.1 percent levels, respectively. Panel A repeats Table 1 column 1, and Panel B repeats Table 2 column 2 on alternative samples. In column 2, we take the first difference over sample years 2005, 2007, 2009, 2011, 2013, 2015, 2017, and 2019. In column 3, we take the first difference over sample years 2005, 2008, 2011, 2014, 2017, and 2019. In column 4, we take the first difference over sample years 2005, 2010, 2015, and 2019. In column 5, we take the long first difference over sample years 2005, 2012, and 2019.