Princeton's Net-Zero America study
Annex R: Employment Transition (Methods)

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Note to reader: All findings and modeling details in Annex R are preliminary. Annex R details the methods consistent with and provided as supporting information for *Net-Zero America: Potential Pathways, Infrastructure, and Inputs* (Larson *et al.* 2021). A manuscript which details the labor modeling methods and results, titled *Labor pathways to achieve net zero emissions in the United States by mid-Century* by, E. Mayfield, J. Jenkins, E. Larson, and C. Greig, is currently undergoing peer review.

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1 Scope of analysis and conceptual model structure

Here, we describe the development of the Decarbonization Employment and Energy Systems (DEERS) model – a data-driven modeling framework for estimating labor market pathways of large-scale, low-carbon energy-supply infrastructure development. The model is designed as a tool to inform regional and national workforce and infrastructure planning and policy-making in the U.S. Figure 1 is a conceptual model of DEERS.

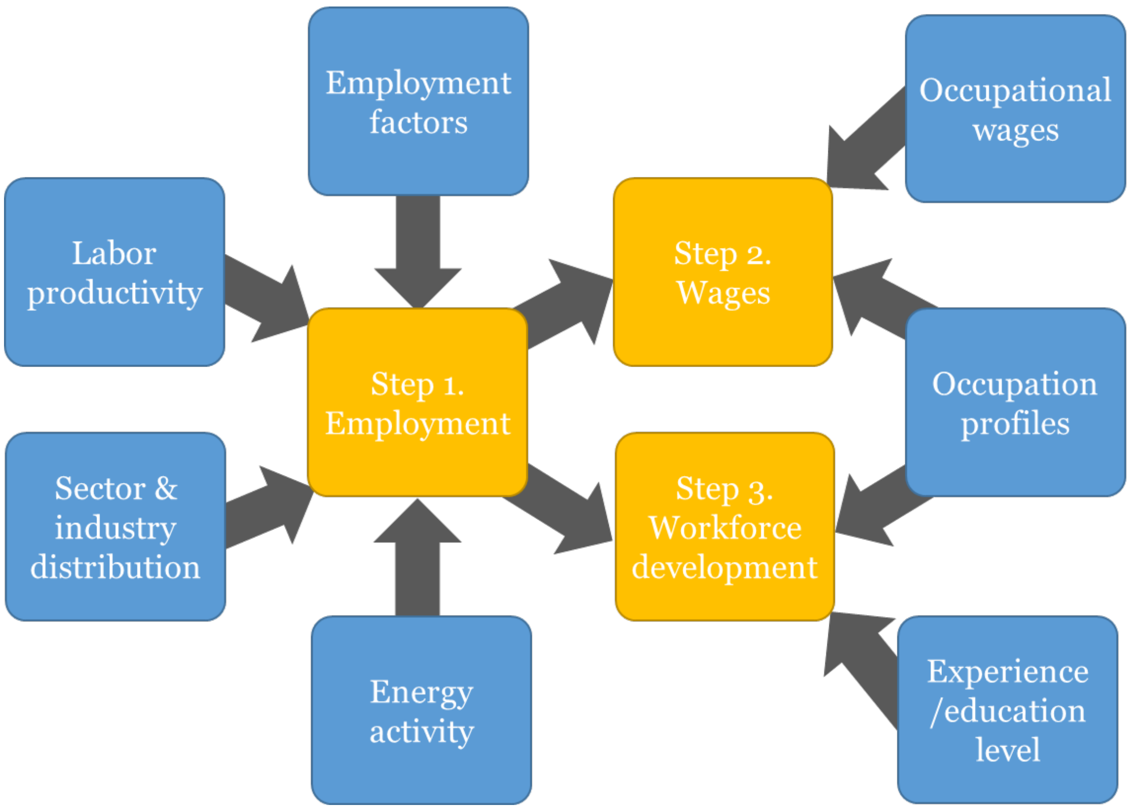

Figure 1. Conceptual model of the DEERS model.

The DEERS model simulates the distribution of labor effects over time and across economic sectors, resource sectors, occupations, and geography for multi-decadal energy-supply system transition scenarios. The model is used to estimate employment and wages, as well as experience, education, and training requirements, across domestic energy supply chains. Leveraging current, publicly-available energy activity and labor market data, we apply a combination of simulation, regression-based, and bottom-up estimation approaches for incumbent fossil fuel resources and emerging low carbon resources. We also incorporate time-variant factors, such as labor productivity and wage inflation, which are especially important in the context of emerging labor markets and long-term transitions. The DEERS model is adaptable to different energy system contexts and readily coupled with regional and downscaled macro-energy system modeling outputs. It can also be used to explore modifiable workforce and infrastructure planning and policy decisions, such as siting domestic manufacturing facilities, creating just transition funds, and changing fossil fuel exports over time.

We apply the DEERS model to estimate employment, wages, and education, experience, and training requirements associated with alternative energy system pathways that achieve the goal of net-zero emissions by 2050 in the U.S. The model framework is structured to balance the long temporal horizon of decarbonization, with spatial, sectoral, industrial, occupational, and technology details that are useful for infrastructure and workforce planning and policy. We further structure DEERS to pair well with macro-energy system optimization models, the predominant class of models used to develop technoeconomic decarbonization pathways. This analytical modeling approach is structurally distinct from and offers complementary insight to other *ex-ante* approaches for estimating employment impacts, such as input-output and general equilibrium models which assess the broader economy as well as bottom-up models that typically focus on a specific resource or technology [1,2]. Each of these approaches has differing application domains, strengths, and limitations, which are well-reviewed in the literature [1,2]. More recently, these traditional estimation approaches have been applied to determine the near-term labor effects associated with a suite of policies associated with deep decarbonization of the U.S. economy [3]. However, existing studies do not model labor pathways associated with long-term, economy-wide decarbonization to achieve net-zero emissions and with a focus on the distribution of labor effects.

We estimate the distribution of labor effects by state from 2020 to 2050, as well as the distribution of labor effects across multiple economic sectors, including agriculture, construction, manufacturing, mining, professional services, utility, and wholesale trade. We model the following resource supply chains: biomass feedstock production, transport, and conversion/generation; CO_2 transmission and injection; coal production, transport, and generation; electricity transmission and distribution; natural gas production, transmission, distribution, and generation; nuclear generation; oil production, transport, and consumption; solar manufacturing and generation; and wind manufacturing and generation. We focus on energy supply-related sectors, and do not model employment associated with energy efficiency, appliances, vehicles and industrial processes. We additionally omit several low-carbon technologies, such as direct air capture, geothermal energy, and hydropower, which do not result in significant new capacity in most of our modeled results. Specific energy activity processes reflected in the employment modeling are summarized Table 1.

Table 1. Coverage of energy activity processes in employment model.

Resource	Energy Activity Processes
Biomass	**Production** (i.e., woody, nonwoody, and corn crop production; trade & distribution of agriculture products) and **electric power generation / fuel conversion** (i.e., operation & maintenance of generation infrastructure; construction & associated contracting of generation infrastructure; manufacture of generation equipment; professional, scientific, and technical services; marketing of electricity transactions from generator to grid)
Coal	**Production** (i.e., mining, developing, & beneficiating coal), **transport** (i.e., transport of coal from mine to end user), and **electric power generation** (i.e., operation & maintenance of generation infrastructure; construction & associated contracting of generation infrastructure; manufacture of generation equipment; professional, scientific, and technical services; marketing of electricity transactions from generator to grid)
CO_2 transmission & storage	**Transmission** (i.e., transmission & storage of CO_2 from sources to wellhead, operation & maintenance of gas feeder and trunk pipelines, marketing & brokerage of CO_2 transactions from source to wellhead, construction & associated trade contracting of pipeline infrastructure), and **storage** (i.e., construction & associated contracting of wellhead & storage infrastructure; injection, storage, and monitoring of CO_2; exploration of CO_2 storage)
Electricity transmission	**Transmission** (i.e., transmission from plants to distribution systems, operation & maintenance of transmission infrastructure, marketing & brokerage of electricity transactions, construction & associated trade contracting of natural gas transmission infrastructure), and **distribution** (i.e., operation & maintenance of distribution systems, marketing & brokerage of transactions to final consumers, construction & associated trade contracting of distribution infrastructure),
Natural gas	**Production** (i.e., exploration, development, and production of gas; marketing & brokerage of gas transactions from upstream to midstream/local distribution systems), **transmission** (i.e., storage and transmission of gas from processing plants to local distribution systems, operation & maintenance of gas transmission pipelines, marketing & brokerage of gas transactions from wellhead to local distribution systems, construction & associated trade contracting of natural gas transmission infrastructure), **distribution** (i.e., operation & maintenance of distribution systems, marketing & brokerage of gas transactions from upstream/midstream to final consumers, construction & associated trade contracting of natural gas distribution infrastructure), and **electric power generation** (i.e., operation & maintenance of generation infrastructure; construction & associated contracting of generation infrastructure; manufacture of generation equipment; professional, scientific, and technical services; marketing of electricity transactions from generator to grid)
Nuclear	**Electric power generation** (i.e., operation & maintenance of generation infrastructure; construction & associated contracting of generation infrastructure; manufacture of generation equipment; professional, scientific, and technical services; marketing of electricity transactions from generator to grid)
Oil	**Production** (i.e., exploration, development, and production of crude oil), **transport** (i.e., operation & maintenance of crude oil & refined product pipelines, construction & associated trade contracting of oil pipeline infrastructure), **refining** (i.e., operation & maintenance of crude oil & refined product pipelines, construction & associated trade contracting of refinery infrastructure), and **storage** (i.e., wholesale trade of crude oil and refined products; operation & maintenance of bulk liquid storage facilities; construction & associated contracting of pump stations & storage facilities)
Solar	**Electric power generation** (operation & maintenance of generation infrastructure; construction & associated contracting of generation infrastructure; professional, scientific, and technical services; marketing of electricity transactions from generator to grid) and **manufacturing** (manufacture of generation equipment)
Wind	**Electric power generation** (operation & maintenance of generation infrastructure; construction & associated contracting of generation infrastructure; professional, scientific, and technical services; marketing of electricity transactions from generator to grid) and **manufacturing** (manufacture of generation equipment)

2 Employment modeling

To simulate employment, we formulate and parameterize a series of equations that relate employment factors and energy activity estimates. The derivation of employment factors – measures of the average additional jobs per unit of energy consumption, production, or other activity [e.g., jobs per gigawatt (GW)] – are described in 2.1. Employment equations for each resource sector are detailed in Section 2.2.

Throughout this study, we use the metric job, which is a full-time equivalent job over a single year, rather than a sustained job over multiple years or a career. We alternatively use job-years, a time-weighted metric that is contextually useful for reporting cumulative employment impacts over long time horizons. This analysis reflects energy-related employment impacts only and does not assess general equilibrium impacts or induced effects; equilibrium effects are more ambiguous and uncertain over long time horizons as there may be structural changes in the economy. Throughout the paper, we report employment estimates in units of million (M) or thousand (k) jobs.

2.1 Employment factors

To formulate the employment equations and estimate marginal employment effects for existing resource sectors, we apply regression-based approaches to recent energy activity and employment data. There are several benefits of this approach, rather than relying on other literature values of marginal employment factors; we can develop employment factors that 1) are reflective of the most recent labor intensity of different processes, 2) can readily be paired to spatially-explicit energy system activity data, and 3) are internally consistent to the extent possible. For most existing resources (i.e., coal, natural gas, nuclear, oil, wind), we compile state-level data from 2016 to 2018. For electricity transmission and distribution, we compile data for eight North American Electric Reliability Corporation (NERC) regions from 2012 to 2019. For solar, we compile state-level data from 2012 to 2019. Employment data are from the Quarterly Census on Employment and Wages (QCEW) published by the U.S. Bureau of Labor Statistics (BLS), the National Solar Jobs Census by the Solar Foundation, the annual *U.S. Energy and Employment Reports* (USEER) by the U.S. Department of Energy, Energy Futures Initiative, and National Association of State Energy Officials [4–8]. USEER data are a compilation of the QCEW employment statistics that have been supplemented by annual survey data of approximately 30,000 employers. Energy activity data are reported by the Energy Information Administration (EIA) [9–22], NERC [23], and other sources [24]. For most resources, datasets include observations for each state (including the District of Columbia) from 2016 to 2018 (n = 153 observations). For electricity transmission, the dataset is comprised of observations for regions from 2012 to 2018. These datasets are not treated as panel data and do not account for county and time fixed effects and temporal lags. Summary statistics for the datasets are provided in Table 2.

We specify multivariate regressions measuring the contemporaneous employment effects of energy activity. The general form of the multivariate regression specification is as follows:

$$Y = \beta_1 \cdot EnergyActivity_1 + \cdots + \beta_n \cdot EnergyActivity_n + \varepsilon \quad (1)$$

Where Y is a measure of employment, $EnergyActivity_n$ is the associated energy activity for a given type of activity for a resource n (e.g., oil production), and ε is the random error term. The regression coefficients (β_n) represent the marginal employment effect associated with that energy activity for a given resource. For example, a regression coefficient for coal production may represent the average additional jobs associated with an increase in coal production by one thousand short tons. For each resource, we specify various regression models with alternative energy activity variables. We select between alternative models based on goodness-of-fit metrics, the compatibility of regression formulations with macro-energy system modeling outputs, and the capacity to spatially allocate employment. Table 3 provides the employment effects for the selected regression models for each resource. We compare the actual versus predicted employment for the selected models, as shown in Figure 2.

For resources that have established industries and at-scale operations, the marginal employment effects derived using regression-based approaches may reasonably approximate future employment factors associated with the same type of activity, notwithstanding additional changes in labor productivity. For example, coal power generation employment is assumed to be a function of total capacity and retired capacity, which captures the primary components of future activity. However, for incumbent resources, future marginal employment factors may diverge from empirically-derived employment effects because the associated technologies and nature of activity are evolving. For example, natural gas transmission & distribution infrastructure will retire, the composition of the natural gas generation fleet will change and include plants with CCS, and production technologies may change. Also, the empirically-derived nuclear employment regression does not capture employment related to nuclear capacity additions, and the marginal effects associated with existing and advanced nuclear capacity may be very different. With respect to wind and solar employment effects, labor productivity may (vastly) increase across the supply chain, and the composition of domestic manufacturing activity may change.

For resources where historical data are limited, unrepresentative, or unavailable to apply a regression-based approach, we supplement and specify employment factors based on analogue supply chains and other sources. We also modify some of the regression-based employment factors to more readily pair with downscaled energy activity estimates.

To estimate employment factors associated with the production of biomass feedstock, we use historical data of employment by type of feedstock, waste biomass consumption, and ethanol, woody, and non-woody biomass production from 2016 to 2018 for the U.S. [4–6,9]. Although we derive regression-based factors for woody biomass and ethanol, we defer to the employment factors derived based on aggregate U.S. data for consistency. We also estimate employment associated with biomass power generation and fuel conversion based on historical woody and waste biomass generation and employment from 2016 to 2018 for the U.S. [4–6,15,16.] As biomass power generation and hydrogen conversion principally rely on gasification in macro-energy system model results, we adopt the natural gas generation employment factors associated with capacity additions and retirements.

For the CO_2 resource sector, we derive employment factors based on upstream and midstream natural gas processes, which serve as analogues (albeit imperfect) for CO_2 transmission and storage. Given that activity data for CO_2 processes are in the form of capital and operating costs, we derive employment factors as a function of costs. To derive employment factors associated with storage processes, we use regression-based employment factors from the literature associated with upstream natural gas construction and operations, paired with historical construction and operating costs [25,26]. For construction and operations of trunk and spur lines, we use a study of employment effects associated with the construction and operations of natural gas distribution, gathering, and transmission lines [27].

For the electricity grid sector, we use the previously described regression-based approach to represent ongoing operations, maintenance, and trade related to transmission and distribution systems. Historical data do not effectively capture employment associated with investment and construction of new transmission and distribution infrastructure. Therefore, we use the National Renewable Energy Laboratory (NREL) Jobs and Economic Development Impact (JEDI) model, which estimates employment for different lengths and voltages of new grid infrastructure [28]. We derive an employment factor, which is a composite estimate that combines JEDI model output with the downscaled voltage and length distributions from the NZA study.

Since the total U.S. nuclear capacity has been flat over that past three decades, regression model coefficients are not reflective of employment associated with capacity additions. Therefore, we compute an employment factor based on the average direct on-site workforce associated with the construction of four Westinghouse AP1000 reactors built in the U.S. and the indirect construction-related workforce associated with a generic Generation II reactor [29].

We also estimate the distribution of employment across economic sectors based on 2018 employment data[4]. In addition, we match each combination of economic sector and resource (156 combinations) to associated 2-, 3-, 4-, and 6-digit NAICS codes. We also find the 2018 historical distribution of employment across over 1000 different occupations for each sector and industry (~5000 combinations) [30]. The industry classifications and occupation distributions are used in subsequent modeling of productivity, wages, and education, experience, & training requirements.

Table 2. Descriptive statistics of historical employment and energy activity data used in regression analysis.

Resource	Variable	Units	Mean	Std. dev.	Sample Size	Sources
Coal	Underground production	thousand short tons	5,337	13,515	153	[10]
Coal	Surface production	thousand short tons	9,708	42,977	153	[10]
Coal	Capacity	MW	5,558	5,460	153	[15]
Coal	Retired capacity	MW	187	540	153	[16]
Coal	Production employment	jobs	1,486	2,703	153	[4–6]
Coal	Generation employment	jobs	1,766	2,409	153	[4–6]
Grid	Capacity	GW	153	102	60	[15]
Grid	Generation	GWh	293,141	205,614	60	[15]
Grid	Employment	jobs	69,561	43,051	60	[7]
Natural gas	Production	mmcf	499,324	1,217,644	153	[17]
Natural gas	Consumption	mmcf	536,243	670,691	153	[18]
Natural gas	Capacity	MW	10,050	13,340	153	[15]
Natural gas	New capacity	MW	181	533	153	[16]
Natural gas	Retired capacity	MW	151	494	153	[16]
Natural gas	Upstream employment	jobs	6,078	20,399	153	[4–6]
Natural gas	T&D employment	jobs	2132	3038	153	[7]
Natural gas	Generation employment	jobs	1,730	2,971	153	[4–6]
Nuclear	Capacity	MW	2,050	2,727	153	[15]
Nuclear	Retired capacity	MW	5	54	153	[16]
Nuclear	Employment	jobs	1,252	1,476	153	[4–6]
Oil	Production	thousand bbls	69,674	275,864	153	[19]
Oil	Consumption	thousand bbls	110,974	130,776	153	[11–13,20–22]
Oil	Fuel transport employment	jobs	2,145	3,601	153	[7]
Oil	Production employment	jobs	10,878	27,178	153	[4–6]
Solar	Distributed capacity	MW	317	978	255	[9]
Solar	Utility capacity	MW	528	1567	255	[15]
Solar	New distributed capacity	MW	67	196	255	[14]
Solar	New utility capacity	MW	108	271	255	[16]
Solar	Manufacturing capacity	MW	1220	592	8	[33]
Solar	Installation employment	jobs	2758	6563	255	[8]
Solar	Trade employment	jobs	572	1581	255	[8]
Solar	Other non-manufacturing employment	jobs	284	762	255	[8]
Solar	Manufacturing employment	jobs	32,876	4,492	8	[8]
Wind	Capacity	MW	1,704	3,353	153	[15]
Wind	New capacity (1-yr lag)	MW	129	341	153	[16]
Wind	Manufacturing facilities	facilities	3	4	153	[24]
Wind	Employment	jobs	2,090	3,772	153	[4–6]

Table 3. Employment effects for different energy resources.

(1) Coal - production					(2) Coal - generation				
Variables	**Estimate**	**Std. Error**	**P(>|t|)**		**Variables**	**Estimate**	**Std. Error**	**P(>|t|)**	
Underground production	0.15125	0.007403	< 2e-16	***	Capacity	0.26558	0.02323	<2e-16	***
Surface production	0.01915	0.002057	< 2e-16	***	Retired capacity	0.6896	0.31716	0.0313	*
Capacity	0.08755	0.014153	5.8E-09	***					
Sample size	153				Sample size	153			
R-squared	0.8812				R-squared	0.5881			
Adjusted R-squared	0.8788				Adjusted R-squared	0.5826			
(3) Electricity transmission					(4) Nuclear - generation				
Variables	**Estimate**	**Std. Error**	**P(>|t|)**		**Variables**	**Estimate**	**Std. Error**	**P(>|t|)**	
GW	426.1	10.43	<2e-16	***	Capacity	0.513	0.02375	<2e-16	***
GWh	0.01136	0.005347	0.038	*	Retired capacity	1.51172	1.4831	0.311	
Sample size	60				Sample size	101			
R-squared	0.9845				R-squared	0.8269			
Adjusted R-squared	0.9839				Adjusted R-squared	0.8234			
(5) Natural gas - T&D					(6) Natural gas - generation				
Variables	**Estimate**	**Std. Error**	**P(>|t|)**		**Variables**	**Estimate**	**Std. Error**	**P(>|t|)**	
Production	0.0008	0.000119	3.2E-10	***	Capacity	0.12274	0.02465	9E-06	***
Consumption	0.00278	0.000189	< 2e-16	***	New capacity	0.34553	0.32945	0.2995	
					Retired capacity	1.58812	0.72408	0.0332	*
Sample size	153				Sample size	153			
R-squared	0.8494				R-squared	0.6687			
Adjusted R-squared	0.8474				Adjusted R-squared	0.648			
(7) Natural gas - upstream					(8) Oil - upstream				
Variables	**Estimate**	**Std. Error**	**P(>|t|)**		**Variables**	**Estimate**	**Std. Error**	**P(>|t|)**	
Appalachian basin production	0.00183	0.000315	3.7E-08	***	Andarko basin production	0.392749	0.121074	0.0015	**
Bakken basin production	0.00916	0.00362	0.01248	*	Appalachian basin production	0.184749	0.016179	< 2e-16	***
Niobrara basin production	0.00501	0.000787	2.4E-09	***	Bakken basin production	0.030251	0.006883	2E-05	***
New Mexico production	0.00535	0.001426	0.00025	***	Niobrara basin production	0.083535	0.016969	2E-06	***
Texas production	0.01847	0.000391	< 2e-16	***	Alaska basin production	0.037871	0.015664	0.0169	*
Other production	0.00947	0.00057	< 2e-16	***	New Mexico production	0.059794	0.014618	7E-05	***
Consumption	0.00268	0.00045	1.8E-08	***	Texas production	0.083207	0.002248	< 2e-16	***
					Other production	0.231154	0.019836	< 2e-16	***
					Consumption	0.033435	0.004296	1E-12	***
Sample size	153				Sample size	153			
R-squared	0.9771				R-squared	0.9734			
Adjusted R-squared	0.976				Adjusted R-squared	0.9717			
(9) Oil - transport					(10) Solar - Manufacturing				
Variables	**Estimate**	**Std. Error**	**P(>|t|)**		**Variables**	**Estimate**	**Std. Error**	**P(>|t|)**	
Production	0.00663	0.00023	<2e-16	***	Manufacturing capacity	21.37	3.813	0.0008	***
Consumption	0.01531	0.000381	<2e-16	***	Consumption	0.060639	0.004427	<2e-16	***
Sample size	153				Sample size	8			
R-squared	0.9804				R-squared	0.8178			
Adjusted R-squared	0.9802				Adjusted R-squared	0.7917			
(11) Solar - Installation					(12) Solar - Trade				
Variables	**Estimate**	**Std. Error**	**P(>|t|)**		**Variables**	**Estimate**	**Std. Error**	**P(>|t|)**	
New distributed capacity	28.1122	0.726	<2e-16	***	New distributed capacity	5.59045	0.21811	< 2e-16	***
New utility capacity	4.9776	0.5177	<2e-16	***	New utility capacity	0.93741	0.12344	6E-13	***
					Utlity capacity	0.18568	0.03228	3E-08	***
Sample size	255				Sample size	255			
R-squared	0.947				R-squared	0.9612			
Adjusted R-squared	0.9466				Adjusted R-squared	0.9607			
(13) Solar - Other					(14) Wind				
Variables	**Estimate**	**Std. Error**	**P(>|t|)**		**Variables**	**Estimate**	**Std. Error**	**P(>|t|)**	
New distributed capacity	1.63441	0.22933	1.1E-11	***	Capacity	0.8943	0.1003	3E-14	***
New utility capacity	0.55287	0.10487	2.9E-07	***	New capacity (1-yr lag)	0.2634	1.0126	0.795	
Distributed capacity	0.21443	0.05607	0.00017	***	Manufacturing facilities	193.641	39.4187	4E-06	***
Utlity capacity	0.0657	0.0318	0.03985	*					
Sample size	255				Sample size	153			
R-squared	0.911				R-squared	0.978			
Adjusted R-squared	0.9096				Adjusted R-squared	0.9774			
Significance codes: ***p<0.001, **p<0.01, *p<0.05, .p<0.1									

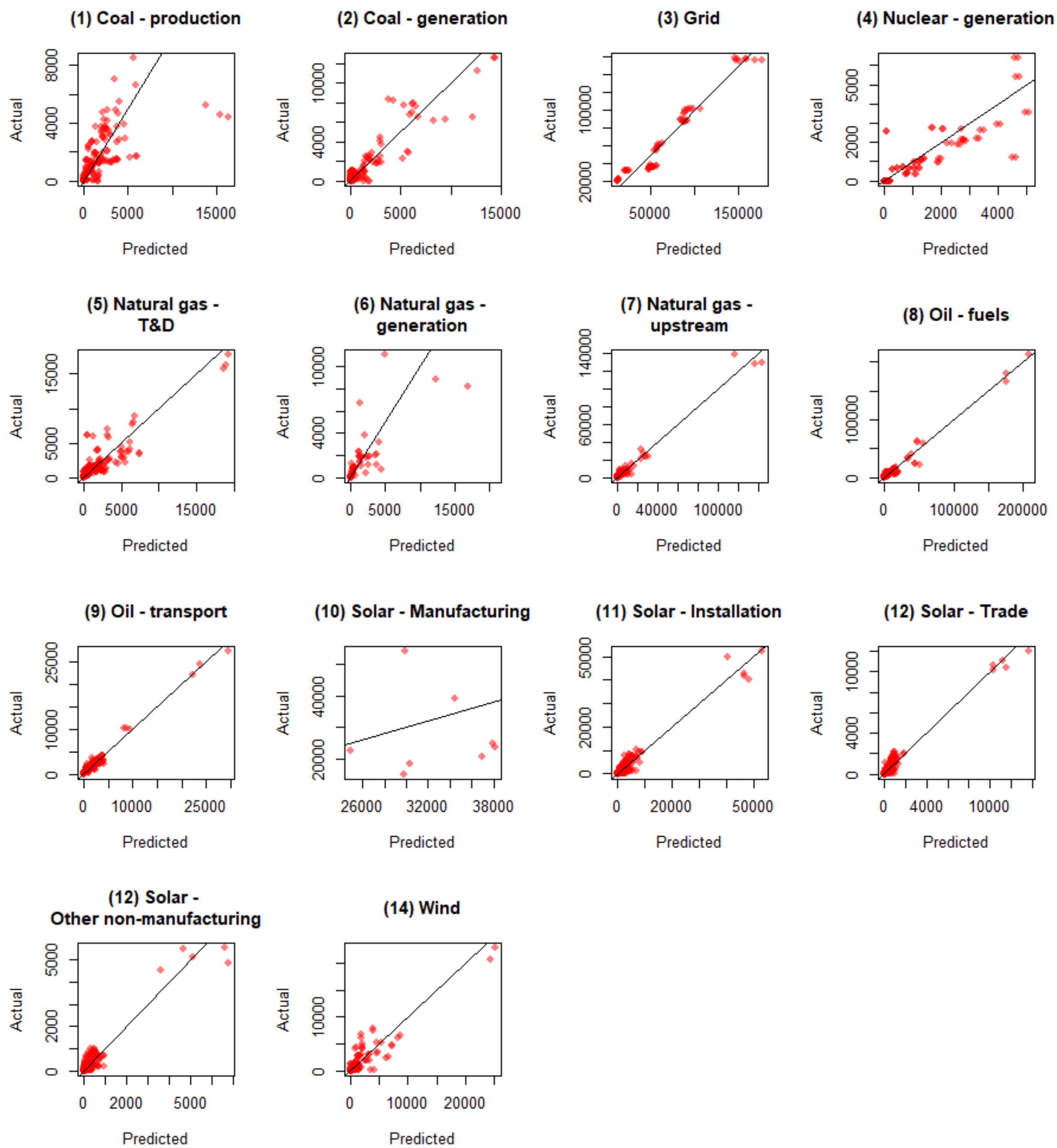

Figure 2. Actual versus predicted employment for regression model specifications.

2.2 Employment model specification

The set of equations used to estimate employment for each resource are summarized in the following subsections. Marginal employment parameter values are provided in Table 4, and energy activity parameter definitions are provided in Table 5. Note that energy activity parameters and employment variables are estimated for each state and year, which we do not reflect in the following equations for simplicity. Figure 3 compares actual versus modeled employment by resource sector in 2018 to validate the model.

Biomass

We estimate employment associated with biomass feedstock production ($E_{bio,feedstock}$) as follows:

$$E_{bio,feedstock} = PROD_{bio,ethanol} \cdot EF_{bio,ethanol} + PROD_{bio,woody} \cdot EF_{bio,woody} + PROD_{bio,nonwoody} \cdot EF_{bio,nonwoody} + CON_{bio,other} \cdot EF_{bio,other} \quad (2)$$

where $PROD_{bio,ethanol}$, $PROD_{bio,woody}$, and $PROD_{bio,nonwoody}$ are corn ethanol, woody biomass, and nonwoody biomass feedstock production, respectively, and $CON_{bio,other}$ is the consumption of other biomass (e.g., waste biomass). $EF_{bio,ethanol}$, $EF_{bio,woody}$, $EF_{bio,nonwoody}$, and $EF_{bio,other}$ are the marginal employment factors per unit of consumption or production.

We estimate employment associated with biomass electricity generation ($E_{bio,generation}$) as follows:

$$E_{bio,generation} = CAP_{bio} \cdot EF_{bio,cap} + RETCAP_{bio} \cdot EF_{bio,ret\ cap} + NEWCAP_{bio} \cdot EF_{bio,new\ cap} \quad (3)$$

where CAP_{bio}, $RETCAP_{bio}$, and $NEWCAP_{bio}$ is biomass capacity, retired capacity, and capacity additions, respectively. $EF_{bio,cap}$, $EF_{bio,ret\ cap}$, and $EF_{bio,new\ cap}$ is the marginal employment per unit of biomass capacity, retired capacity, and added capacity.

Coal

We estimate employment associated with coal production ($E_{coal,mining}$) as follows:

$$E_{coal,production} = CAP_{coal} \cdot EF_{coal,fuels,cap} + PROD_{coal,under} \cdot EF_{coal,under\ prod} + PROD_{coal,surf} \cdot EF_{coal,surf\ prod} \quad (4)$$

where CAP_{coal} is coal generation capacity, and $PROD_{coal,under}$ and $PROD_{coal,surf}$ are underground and surface coal mining, respectively. $EF_{coal,mining,cap}$, $EF_{coal,under\ prod}$, and $EF_{coal,surf\ prod}$ are the marginal employment factors per unit of coal generation capacity or production.

We estimate employment associated with coal electricity generation ($E_{coal,generation}$) as follows:

$$E_{coal,generation} = CAP_{coal} \cdot EF_{coal,gen,cap} + RETCAP_{coal} \cdot EF_{coal,ret\ cap} \quad (5)$$

where CAP_{coal} is coal generation capacity, $RETCAP_{coal}$ is retired coal capacity, $EF_{coal,cap}$ is the marginal employment per unit of coal capacity, and $EF_{coal,ret\ cap}$ is the marginal employment per unit of coal capacity retired.

We estimate employment associated with coal transport ($E_{coal,trans}$) as follows:

$$E_{coal,trans} = CAP_{coal} \cdot EF_{coal,trans,cap} + PROD_{coal} \cdot EF_{coal,trans,prod} \quad (6)$$

where $PROD_{coal}$ is coal production, $EF_{coal,trans,cap}$ is the marginal employment per unit of coal capacity, and $EF_{coal,trans,prod}$ is the marginal employment per unit of coal production.

CO_2 transmission & storage

We estimate employment associated with CO_2 transmission ($E_{CO2,trans}$) as follows:

$$E_{CO2,trans} = OPEX_{CO2,trans} \cdot EF_{CO2,trans,opex} + CAPEX_{CO2,trans} \cdot EF_{CO2,trans,capex} \quad (7)$$

where $OPEX_{CO2,trans}$ and $CAPEX_{CO2,trans}$ are the CO_2 transmission operating and capital costs, respectively. $EF_{CO2,trans,opex}$ and $EF_{CO2,trans,capex}$ are the marginal employment factors per unit of CO_2 transmission operating and capital costs.

We estimate employment associated with CO_2 injection and storage ($E_{CO2,inj}$) as follows:

$$E_{CO2,inj} = OPEX_{CO2,inj} \cdot EF_{CO2,inj,opex} + CAPEX_{CO2,inj} \cdot EF_{CO2,inj,capex} \tag{8}$$

where $OPEX_{CO2,inj}$ and $CAPEX_{CO2,inj}$ are the CO_2 injection and storage operating and capital costs, respectively. $EF_{CO2,inj,opex}$ and $EF_{CO2,inj,capex}$ are the marginal employment factors per unit of CO_2 injection and storage operating and capital costs.

Electricity transmission & distribution

We estimate employment associated with electricity transmission and storage (E_{grid}) as follows:

$$E_{grid} = CAP_{grid} \cdot EF_{grid,cap} + CAPEX_{grid,trans} \cdot EF_{grid,trans} + CAPEX_{grid,dist} \cdot EF_{grid,dist} \tag{9}$$

where CAP_{grid}, $CAPEX_{grid,trans}$, and $CAPEX_{grid,dist}$ are the electricity generation, capital costs for transmission expansion, and capital costs for distribution expansion, respectively. $EF_{grid,cap}$, $EF_{grid,trans}$, and $EF_{grid,dist}$ are the marginal employment factors per unit of electricity generation, transmission capital costs, and distribution capital costs, respectively.

Natural gas

We estimate employment associated with natural gas upstream activities ($E_{ng,upstream}$) as follows:

$$E_{ng,upstream} = PROD_{ng} \cdot EF_{ng,upsteam,prod} + CON_{ng} \cdot EF_{ng,upstream,con} \tag{10}$$

where $PROD_{ng}$ is natural gas production and CON_{ng} is natural gas consumption. $EF_{ng,upsteam,prod}$ and $EF_{ng,upstream,con}$ are the marginal employment factors per unit of natural gas production and consumption, respectively.

We estimate employment associated with natural gas transmission, distribution, and storage ($E_{ng,tds}$) as follows:

$$E_{ng,tds} = PROD_{ng} \cdot EF_{ng,tds,prod} + CON_{ng} \cdot EF_{ngtds,con} + PROD_{ng} \cdot EF_{ng,tds\ construction,prod} + CON_{ng} \cdot EF_{ng,tds\ construction,con} \tag{11}$$

where $PROD_{ng}$ is natural gas production and CON_{ng} is natural gas consumption. $EF_{ng,tds,prod}$ and $EF_{ng,tds,con}$ are the marginal employment factors (associated with activity other than construction) per unit of natural gas production and consumption, respectively. $EF_{ng,tds\ construction,prod}$ and $EF_{ng,tds\ construction,con}$ are the marginal employment factors (associated with construction activity) per unit of natural gas production and consumption, respectively.

We estimate employment associated with natural gas electricity generation ($E_{ng,generation}$) as follows:

$$E_{ng,generation} = CAP_{ng} \cdot EF_{ng,cap} + NEWCAP_{ng} \cdot EF_{ng,new\ cap} + RETCAP_{ng} \cdot EF_{ng,ret\ cap} \tag{12}$$

where CAP_{ng}, $NEWCAP_{ng}$, and $RETCAP_{ng}$ are natural gas capacity, capacity additions, and retired capacity, respectively. $EF_{ng,cap}$, $EF_{ng,new\ cap}$, and $EF_{ng,ret\ cap}$ are the marginal employment factors per unit of natural gas capacity, capacity additions, and retired capacity, respectively.

Nuclear

We estimate employment associated with nuclear electricity generation ($E_{nuclear}$) as follows:

$$E_{nuclear} = CAP_{nuclear} \cdot EF_{nuclear,cap} + NEWCAP_{nuclear} \cdot EF_{nuclear,new\ cap} + RETCAP_{nuclear} \cdot EF_{nuclear,ret\ cap} \tag{13}$$

where $CAP_{nuclear}$, $NEWCAP_{nuclear}$, and $RETCAP_{nuclear}$ are nuclear capacity, capacity additions, and retired capacity, respectively. $EF_{nuclear,cap}$, $EF_{nuclear,new\ cap}$, and $EF_{nuclear,ret\ cap}$ are the marginal employment factors per unit of nuclear capacity, capacity additions, and retired capacity, respectively.

Oil

We estimate employment associated with oil production (E_{oil}) as follows:

$$E_{oil} = PROD_{oil} \cdot EF_{oil,prod} + CON_{oil} \cdot EF_{oil,con} \tag{14}$$

where $PROD_{oil}$ and CON_{oil} are oil production and consumption, respectively. $EF_{oil,prod}$ and $EF_{oil,con}$ are the marginal employment factors per unit of oil production and consumption, respectively.

We estimate employment associated with oil transport and trade ($E_{ng,transport}$) as follows:

$$E_{oil,transport} = PROD_{oil} \cdot EF_{oil,trans,prod} + CON_{oil} \cdot EF_{oil,trans,con} + PROD_{oil} \cdot EF_{oil,trans\ construction,prod} \tag{15}$$

where $PROD_{oil}$ and CON_{oil} are oil production and consumption, respectively. $EF_{oil,trans,prod}$ and $EF_{oil,trans,con}$ are the marginal employment factors (associated with activity other than construction) per unit of oil production and consumption, respectively. $EF_{oil,trans\ construction,prod}$ is the marginal employment factors (associated with construction activity) per unit of natural gas production.

Solar

We estimate employment associated with solar generation (E_{solar}) as follows:

$$E_{solar} = CAP_{solar} \cdot EF_{solar,cap} + NEWCAP_{solar} \cdot EF_{solar,new\ cap} + MAN_{solar} \cdot EF_{solar,man} \tag{16}$$

where CAP_{solar} is solar capacity, $NEWCAP_{solar}$ is solar capacity additions, and MAN_{solar} is the number of manufacturing facilities. $EF_{solar,cao}$, $EF_{solar,new\ cap}$, and $EF_{solar,man}$ are the marginal employment factors per unit of solar generation, capacity additions, and manufacturing facilities, respectively.

Wind

We estimate employment associated with wind generation (E_{wind}) as follows:

$$E_{wind} = CAP_{wind} \cdot EF_{wind,cap} + NEWCAP_{wind} \cdot EF_{wind,new\ cap} + MAN_{wind} \cdot EF_{wind,man} \tag{17}$$

where CAP_{wind} is wind generation, $NEWCAP_{wind}$ is wind capacity additions, and MAN_{wind} is the number of manufacturing facilities. $EF_{wind,cap}$, $EF_{wind,new\ cap}$, and $EF_{wind,man}$ are the marginal employment factors per unit of wind generation, capacity additions, and manufacturing facilities, respectively.

Table 4. Employment factor parameter definitions and values.

Resource	Parameter	Value	Units
Biomass	$EF_{bio,ethanol}$	0.0244	jobs/Bbtu ethanol production
Biomass	$EF_{bio,woody}$	0.0129	jobs/Bbtu woody biomass production
Biomass	$EF_{bio,nonwoody}$	0.0211	jobs/Bbtu nonwoody biomass production
Biomass	$EF_{bio,other}$	0.0399	jobs/Bbtu other biomass consumption
Biomass	$EF_{bio,cap}$	123	jobs/GW biomass capacity
Biomass	$EF_{bio,new\ cap}$	346	jobs/GW biomass capacity additions
Biomass	$EF_{bio,ret\ cap}$	1588	jobs/GW biomass retired capacity
Coal	$EF_{coal,under\ prod}$	0.151	jobs/thousand short tons underground mining production
Coal	$EF_{coal,surf\ prod}$	0.0191	jobs/thousand short tons surface mining production
Coal	$EF_{coal,mining,cap}$	87.6	jobs/GW coal capacity
Coal	$EF_{coal,cap}$	266	jobs/GW coal capacity
Coal	$EF_{coal,ret\ cap}$	690	jobs/GW retired coal capacity
Coal	$EF_{coal,trans,prod}$	0.024	jobs/thousand short tons production
Coal	$EF_{coal,tran,cap}$	68.9	jobs/GW coal capacity
CO_2	$EF_{CO2,inj,opex}$	5.70	jobs/million \$ CO_2 injection operating cost
CO_2	$EF_{CO2,inj,capex}$	2.42	jobs/million \$ CO_2 injection capital cost
CO_2	$EF_{CO2,trans,opex}$	4.80	jobs/million \$ CO_2 transmission operating cost
CO_2	$EF_{CO2,trans,capex}$	10.8	jobs/million \$ CO_2 transmission capital cost
Electricity transmission	$EF_{grid,cap}$	444	jobs/GW grid transmission capacity
Electricity transmission	$EF_{grid,trans,new\ cap}$	4.99	jobs/million $ grid transmission capital cost
Electricity transmission	$EF_{grid,dist,new\ cap}$	4.45	jobs/million $ grid distribution capital cost
Natural gas	$EF_{ng,upstream,prod\ Niobrara}$	0.00501	jobs/mmcf natural gas production in Niobrara basin
Natural gas	$EF_{ng,upstream,prod\ Appalachia}$	0.00183	jobs/mmcf natural gas production in Appalachian basin
Natural gas	$EF_{ng,upstream,prod\ Bakken}$	0.00916	jobs/mmcf natural gas production in Bakken basin
Natural gas	$EF_{ng,upstream,prod\ New\ Mexico}$	0.00535	jobs/mmcf natural gas production in New Mexico
Natural gas	$EF_{ng,upstream,prod\ Texas}$	0.018467	jobs/mmcf natural gas production in Texas
Natural gas	$EF_{ng,upstream,prod\ Other}$	0.00947	jobs/mmcf natural gas production Other
Natural gas	$EF_{ng,upstream,con}$	0.00268	jobs/mmcf natural gas consumption
Natural gas	$EF_{ng,cap}$	123	jobs/GW natural gas capacity
Natural gas	$EF_{ng,new\ cap}$	346	jobs/GW natural gas capacity additions
Natural gas	$EF_{ng,ret\ cap}$	1588	jobs/GW natural gas retired capacity
Natural gas	$EF_{ng,tds,prod}$	0.00191	jobs/mmcf natural gas production
Natural gas	$EF_{ng,tds,con}$	0.00661	jobs/mmcf natural gas consumption
Nuclear	$EF_{nuclear,cap}$	513	jobs/GW nuclear capacity
Nuclear	$EF_{nuclear,new\ cap}$	9,930	jobs/GW nuclear capacity additions
Nuclear	$EF_{nuclear,ret\ cap}$	1510	jobs/GW nuclear retired capacity

Oil	$EF_{oil,prod\ Appalachian}$	0.392	jobs/thousand bbls of production in Appalachian basin
Oil	$EF_{oil,prod\ Andarko}$	0.185	jobs/thousand bbls of production in Andarko basin
Oil	$EF_{oil,prod\ Bakken}$	0.0303	jobs/thousand bbls of production in Bakken basin
Oil	$EF_{oil,prod\ Texas}$	0.0832	jobs/thousand bbls of production in Texas
Oil	$EF_{oil,prod\ New\ Mexico}$	0.0600	jobs/thousand bbls of production in New Mexico
Oil	$EF_{oil,prod\ Niobrara}$	0.0835	jobs/thousand bbls of production in Niobrara basin
Oil	$EF_{oil,prod\ Alaska}$	0.0379	jobs/thousand bbls of production in Alaska
Oil	$EF_{oil,prod\ Other}$	0.231	jobs/thousand bbls of production Other
Oil	$EF_{oil,con}$	0.0334	jobs/thousand bbls of consumption
Oil	$EF_{oil,trans,prod}$	0.00664	jobs/thousand bbls of production
Oil	$EF_{oil,trans,con}$	0.0184	jobs/thousand bbls of consumption
Oil	$EF_{oil,trans\ construction,prod}$	0.0153	jobs/thousand bbls of production
Solar	$EF_{solar,distributed\ cap}$	541	jobs/GW distributed solar capacity
Solar	$EF_{solar,utility\ cap}$	448	jobs/GW utility-scale solar capacity
Solar	$EF_{solar,distributed\ new\ cap}$	35,337	jobs/GW distributed solar capacity additions
Solar	$EF_{solar,utility\ new\ cap}$	6468	jobs/GW utility-scale solar capacity additions
Solar	$EF_{solar,man}$	21,370	jobs/GW solar manufacturing capacity
Wind	$EF_{wind,cap}$	894	jobs/GW wind capacity
Wind	$EF_{wind,new\ cap}$	263	jobs/GW wind capacity additions
Wind	$EF_{wind,man}$	194	jobs/wind manufacturing facility

Table 5. Energy activity modeling parameter definitions.

Resource	Parameter	Parameter Definition	Units
Biomass	$PROD_{bio,ethanol}$	ethanol feedstock production	billion btu
Biomass	$PROD_{bio,woody}$	woody biomass feedstock production	billion btu
Biomass	$PROD_{bio,nonwoody}$	nonwoody biomass feedstock production	billion btu
Biomass	$CON_{bio,other}$	other biomass (e.g., waste) consumption	billion btu
Biomass	CAP_{bio}	biomass capacity	GW
Biomass	$RETCAP_{bio}$	retired biomass capacity	GW
Biomass	$NEWCAP_{bio}$	biomass capacity additions	GW
Coal	$PROD_{coal,under}$	coal underground production	thousand short tons
Coal	$PROD_{coal,surf}$	coal surface production	thousand short tons
Coal	$PROD_{coal}$	coal underground and surface production	thousand short tons
Coal	CAP_{coal}	coal capacity	GW
Coal	$RETCAP_{coal}$	retired coal capacity	GW
CO_2 transmission	$OPEX_{CO2,trans}$	CO_2 transmission operating costs	million $
CO_2 transmission	$CAPEX_{CO2,trans}$	CO_2 transmission capital costs	million $
CO_2 transmission	$OPEX_{CO2,dist}$	CO_2 injection & storage operating costs	million $
CO_2 transmission	$CAPEX_{CO2,dist}$	CO_2 injection & storage capital costs	million $
Electricity transmission	CAP_{grid}	Generation capacity	GW
Electricity transmission	$CAPEX_{grid,trans}$	Electricity transmission capital costs	million $
Electricity transmission	$CAPEX_{grid,dist}$	Electricity distribution capital costs	million $
Natural gas	$PROD_{ng}$	natural gas production	mmcf
Natural gas	CON_{ng}	natural gas production	mmcf
Natural gas	CAP_{ng}	natural gas capacity	GW
Natural gas	$RETCAP_{ng}$	retired natural gas capacity	GW
Natural gas	$NEWCAP_{ng}$	natural gas capacity additions	GW
Nuclear	$CAP_{nuclear}$	nuclear capacity	GW
Nuclear	$RETCAP_{nuclear}$	retired nuclear capacity	GW
Nuclear	$NEWCAP_{nuclear}$	nuclear capacity additions	GW
Oil	$PROD_{oil}$	oil production	thousand bbls
Oil	CON_{oil}	oil consumption	thousand bbls
Solar	CAP_{solar}	solar capacity	GW
Solar	$NEWCAP_{solar}$	solar capacity additions	GW
Solar	MAN_{solar}	solar manufacturing facilities	facilities
Wind	CAP_{wind}	wind capacity	GW
Wind	$NEWCAP_{wind}$	wind capacity additions	GW
Wind	MAN_{wind}	wind manufacturing facilities	facilities

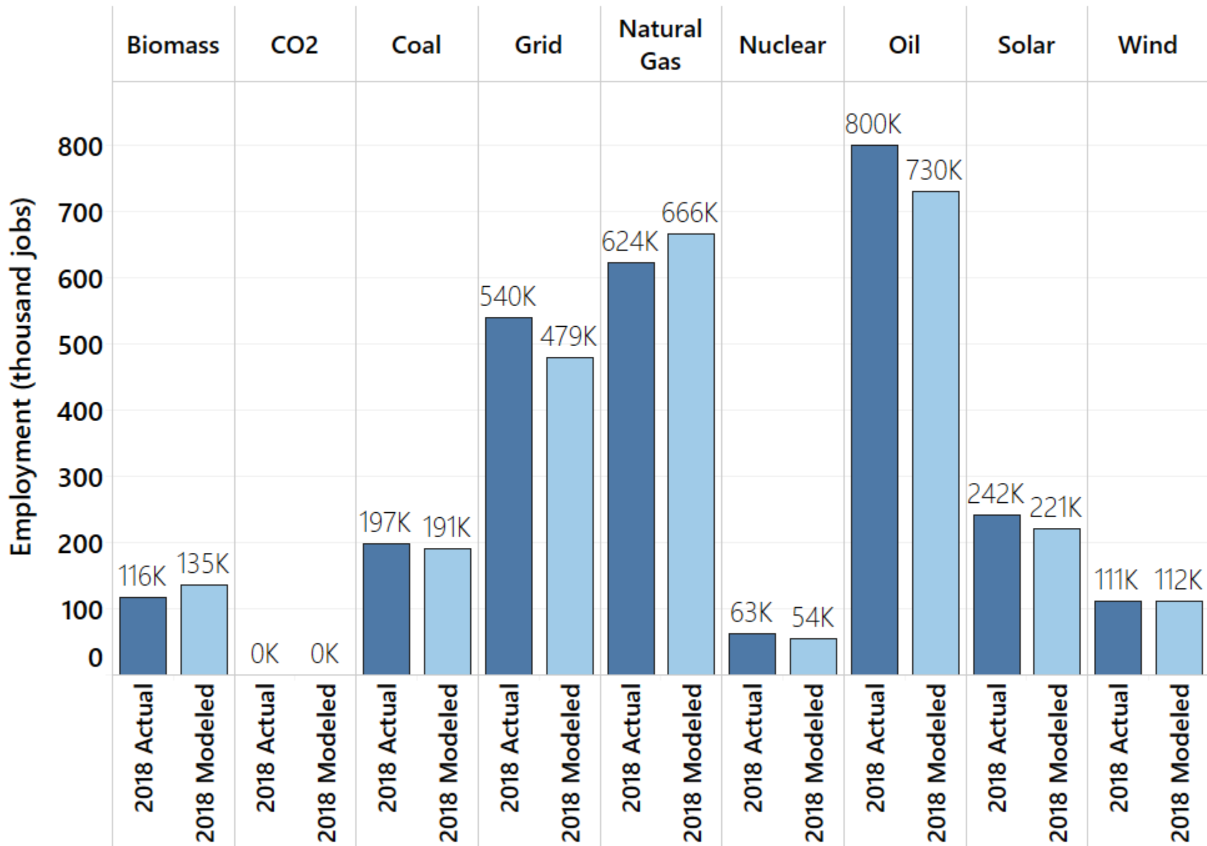

Figure 3. 2018 Actual versus modeled employment by resource sector.

3 Labor force projection

To contextualize energy-related employment, we compare energy workforce estimates to the size of the U.S. labor force – the number of people that are employed and unemployed, and who are either working or actively looking for work. We estimate the future labor force based on the 2019 labor force by state and 2008-2018 U.S. average annual labor force growth rate (0.5%/yr) (Figure 4) [31,32].

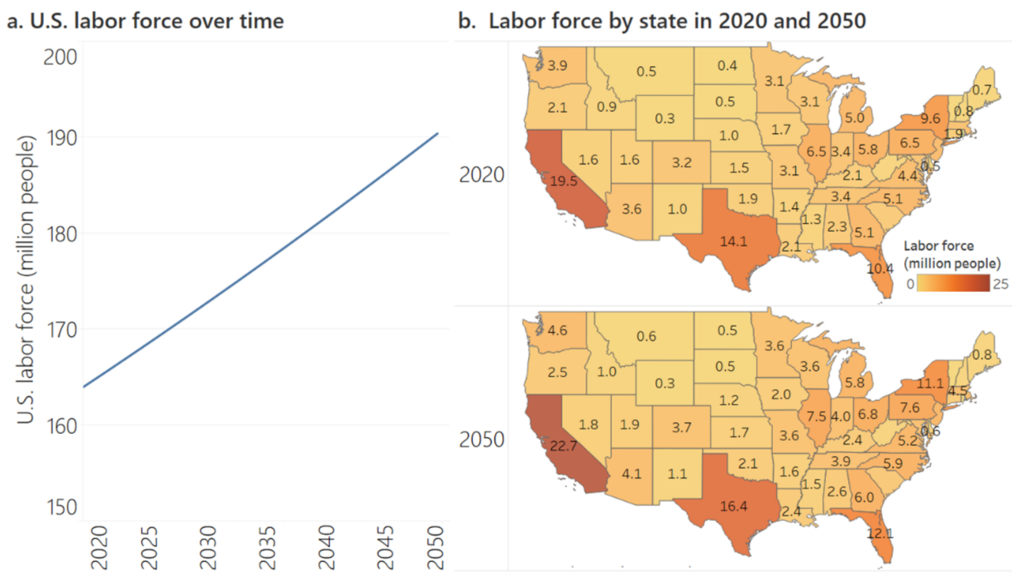

Figure 4. Labor force projection over time and by state.

4 Energy activity simulation

A primary input into the DEERS modeling is energy activity by resource, supply chain segment, spatial unit, and year. Here, we use and develop state-level and US-wide activity data associated with multiple net-zero emission pathway scenarios. Most of the energy activity inputs are based on the NZA study, which reports capacity, generation, fuel consumption, and other types of energy activity for each state and region in 5-year increments. Results from the NZA study are further converted, spatially allocated, and interpolated over time for use as input into the employment modeling. Additionally, we derive energy activity estimates for other segments of the supply chain (e.g., fossil fuel production, solar & wind manufacturing capacity) that are not modeled by the NZA study. Figure 5 through Figure 13 provide U.S.-wide energy activity over time for each scenario, and Figure 14 through Figure 22 provide the state-level distribution of energy activity for the E+ scenario by decade. The following provides an overview of energy activity for each resource.

With respect to surface and underground coal mining, we assume that the US continues to produce coal to meet domestic industrial and coking demand as reported in the NZA study as well as projected exports [34]. We assume that continued coal production to meet export demand occurs in states that have historically produced coal for export; we use the 2019 historical state origin of exports to spatially allocate future production [10].

We estimate the 2018 historical spatial distribution of natural gas extraction by state or resource basin [17]. We then convert projected U.S.-wide natural gas consumption, as reported in the NZA study, to production, accounting for methane supply chain losses [35]. We assume that the US produces sufficient gas to meet domestic demand and projected export demand [34]. With respect to residential, commercial, and industrial gas consumption, we use US-wide fuel consumption estimates reported in the NZA study, and then spatially allocate based on the 2018 historical state distribution [18]. We also existing, new, and retired natural gas capacity from the NZA study, which report information for multiple thermal technologies; this includes spatially downscaled data from a detailed siting model.

We estimate the 2018 historical distribution of petroleum product consumption and crude oil production by state or resource basin [11–13,19–22]. We then convert projected U.S.-wide production and consumption, as reported in the NZA report, to states based on the historical spatial distribution. We assume that the U.S. will continue to export oil at a rate consistent with the EIA AEO reference case projection [34]. As domestic oil consumption declines, we assume that the U.S. will import less and a higher share of oil will be produced domestically, but not in excess of projected domestic crude production [34].

For the biomass sector, we use spatially downscaled activity data for new biomass generation and conversion capacity for technologies (i.e. power, gasification, and pyrolysis) based on a detailed siting exercise reported in the NZA study. For biomass feedstock production, we convert and spatially allocate regional NZA estimates by type (i.e., corn, woody, nonwoody, other biomass), assuming that consumption and production are co-located in the same state. For existing capacity and feedstock production, we use the 2018 data regarding the spatial distribution of activity [9,16].

For CO_2 activity, we use spatially downscaled capital and operating costs from the NZA study; these cost estimates are based on an investment model paired with a geospatial analysis that sites trunk and spur lines along existing gas transmission corridors and least cost paths connecting CO_2 source locations to injection basins.

For solar and wind capacity, we use US-wide estimates of existing and new capacity from the NZA study. The NZA study further reports spatially-resolved data of new utility-scale solar, onshore, and offshore wind capacity based on a detailed geospatial model that identifies least-cost sites for renewable infrastructure under various land use constraints. We assume new distributed (i.e., rooftop) solar follows the same state-level spatial distribution as existing distributed solar capacity [9]. With respect to solar and wind manufacturing, we estimate domestic manufacturing capacity over time, assuming that capacity grows to keep pace with increasing demand for renewable products, but the domestic share of manufacturing stays constant. For solar manufacturing, the current domestic share of manufacturing (11%) is based on the 2019 domestic share of photovoltaic shipments [33,36]. For wind manufacturing, we estimate the current domestic share of wind manufacturing (77%) based on 2017 nacelle, blade, and tower domestic content and sales, in addition to the number of domestic wind manufacturing facilities [37–39]. To spatially allocate facilities, we assume that manufacturing capacity must be sited within defined logistical regions to meet demand for new generation capacity within that region (Figure 23); this assumption generally accounts for the constraints related to transport between manufacturing and generation. We further spatially allocate from logistic regions to states based on the 2018 historical distribution of the energy workforce[5].

For the electric grid, we use capital cost estimates associated with new transmission and distribution infrastructure from the NZA study, which uses a geospatial model to site linear infrastructure along existing transmission corridors and least-cost paths. We further use spatially downscaled thermal and renewable capacity from the NZA study, which correlates at state-level with existing and expanding grid infrastructure.

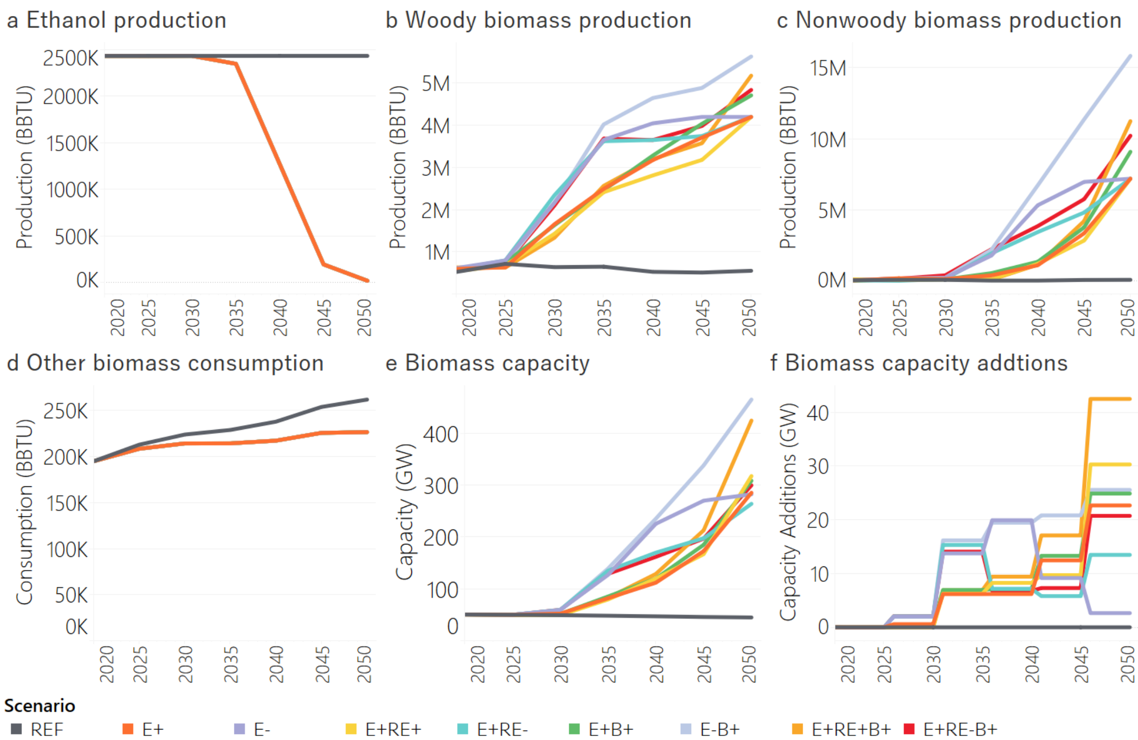

Figure 5. Future U.S.-wide biomass activity by scenario.

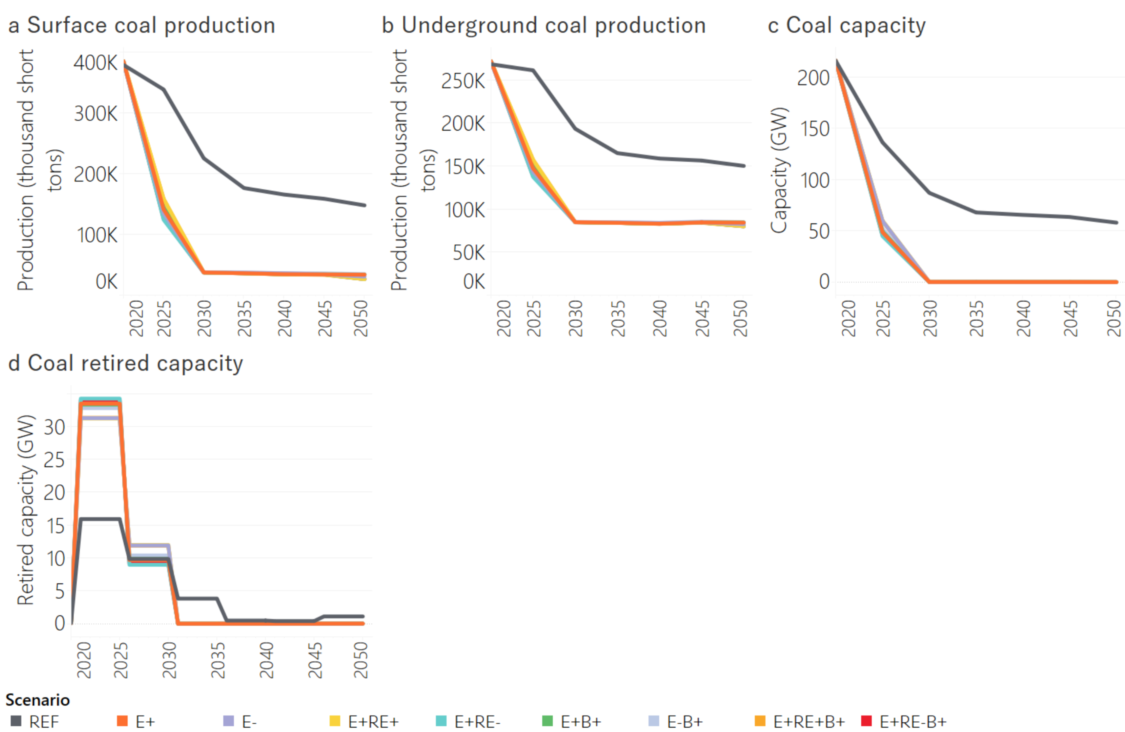

Figure 6. Future U.S.-wide coal activity by scenario.

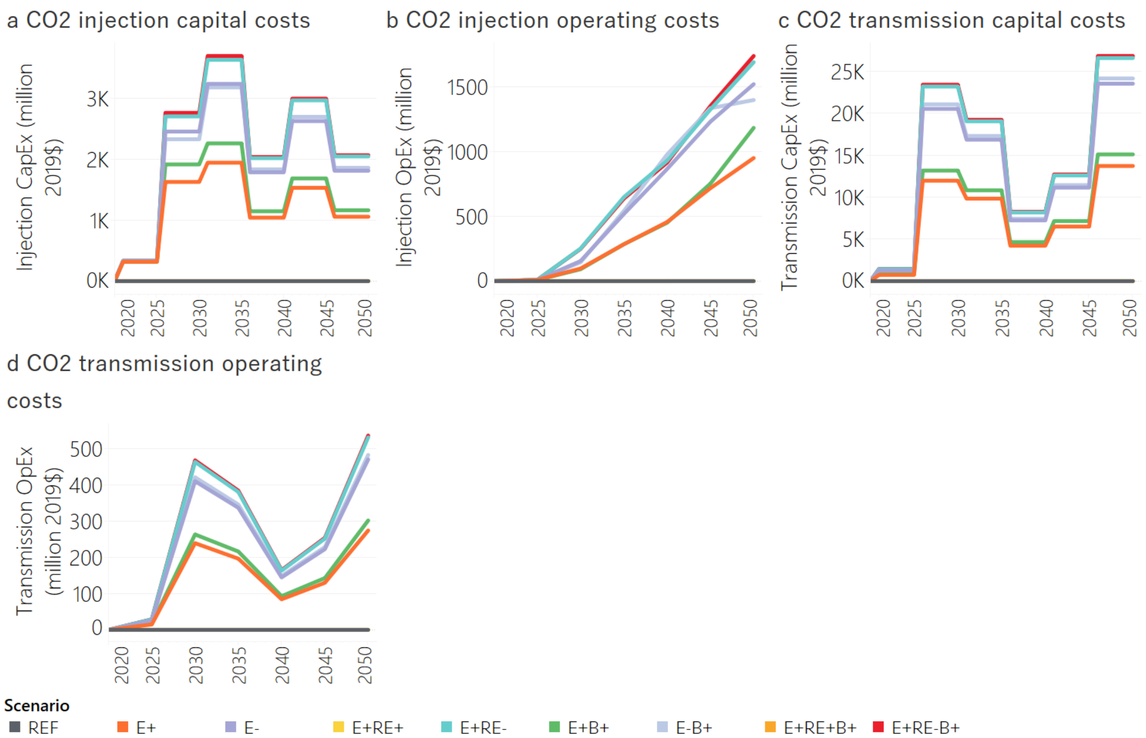

Figure 7. Future U.S.-wide CO2 activity by scenario.

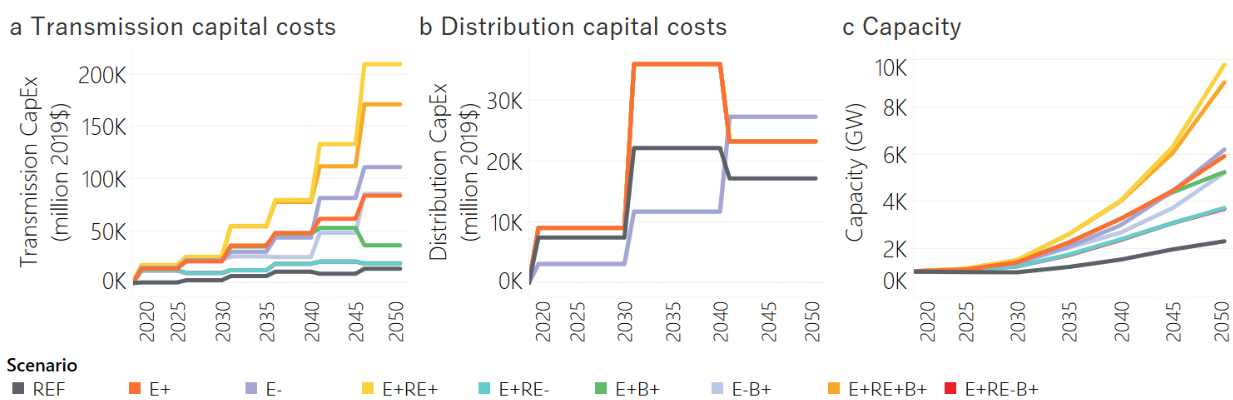

Figure 8. Future U.S.-wide grid activity by scenario.

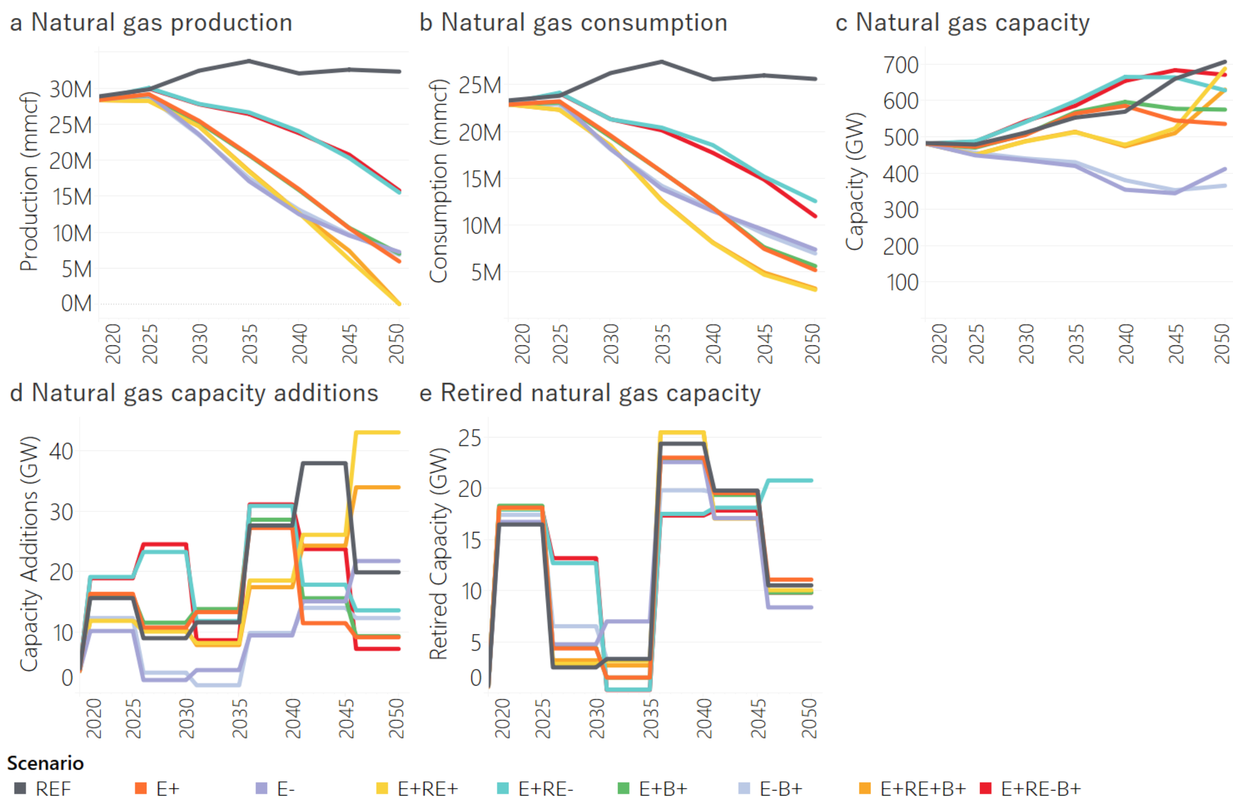

Figure 9. Future U.S.-wide natural gas activity by scenario.

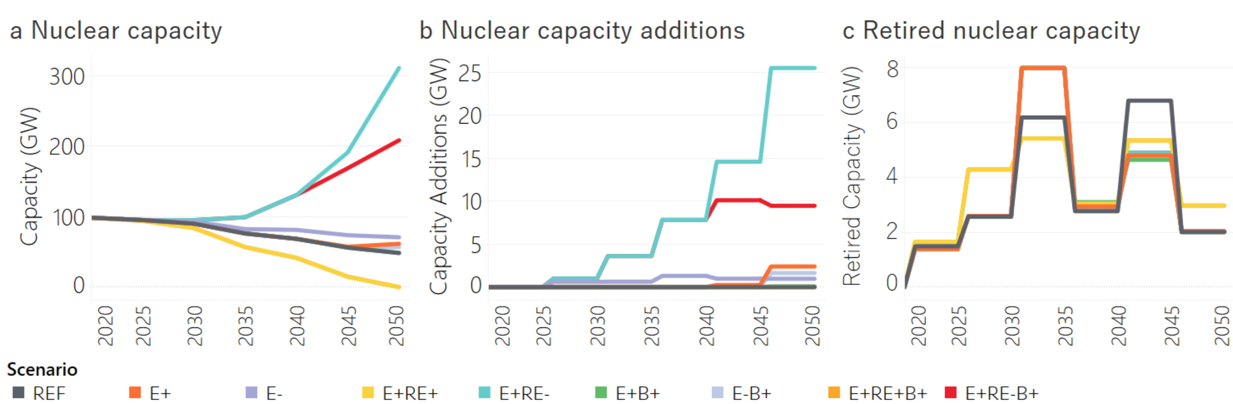

Figure 10. Future U.S.-wide nuclear activity by scenario.

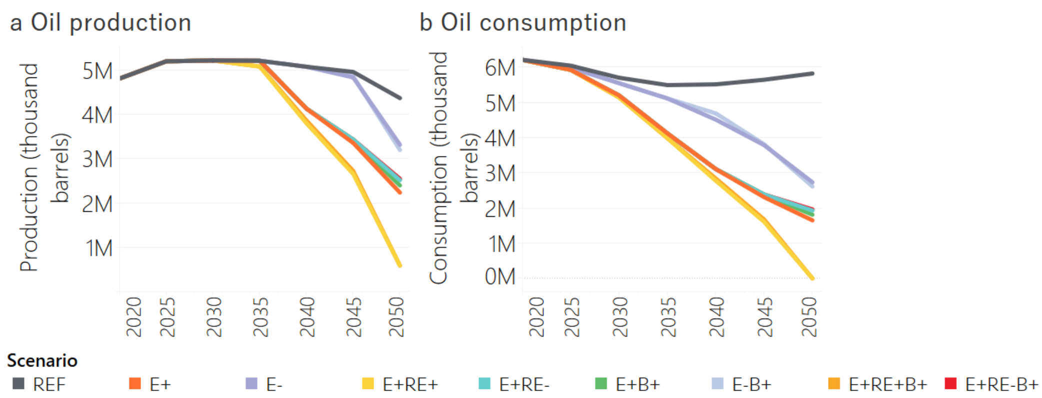

Figure 11. Future U.S.-wide oil activity by scenario.

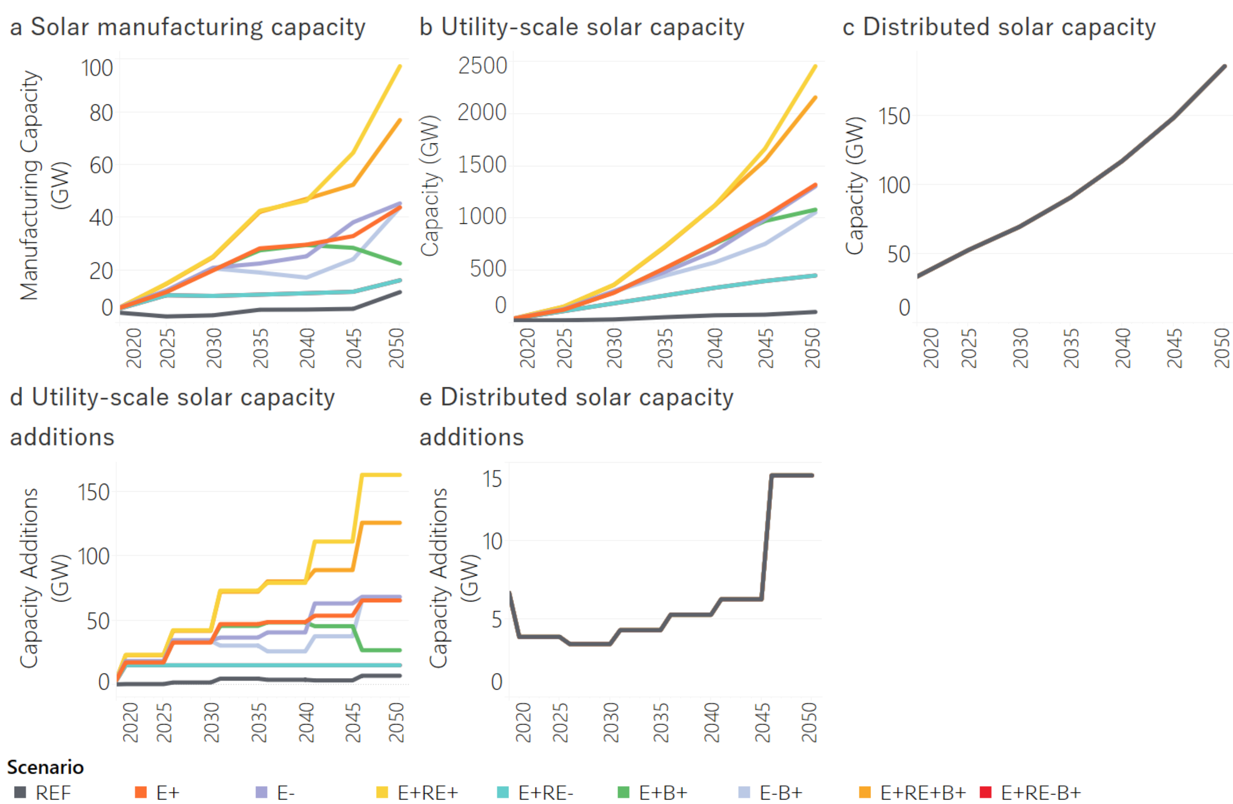

Figure 12. Future U.S.-wide solar activity by scenario.

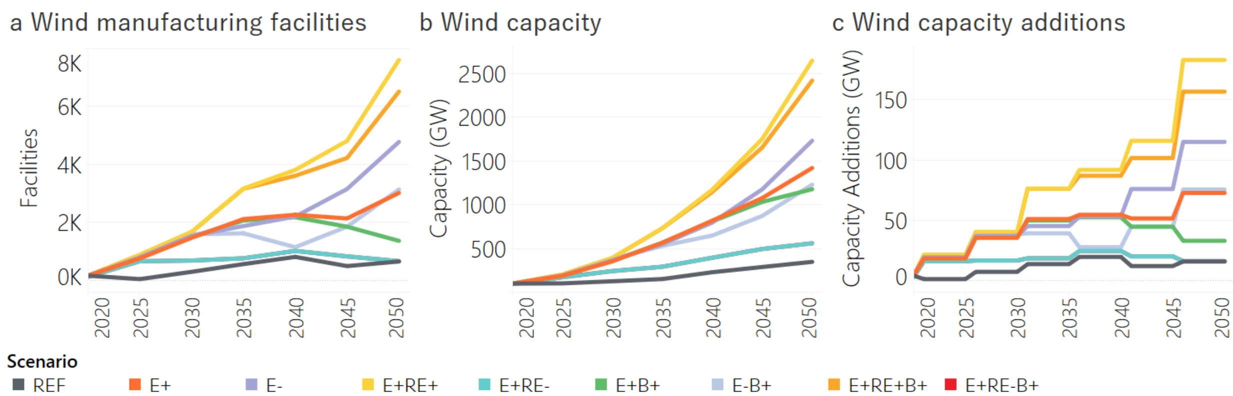

Figure 13. Future U.S.-wide wind activity by scenario.

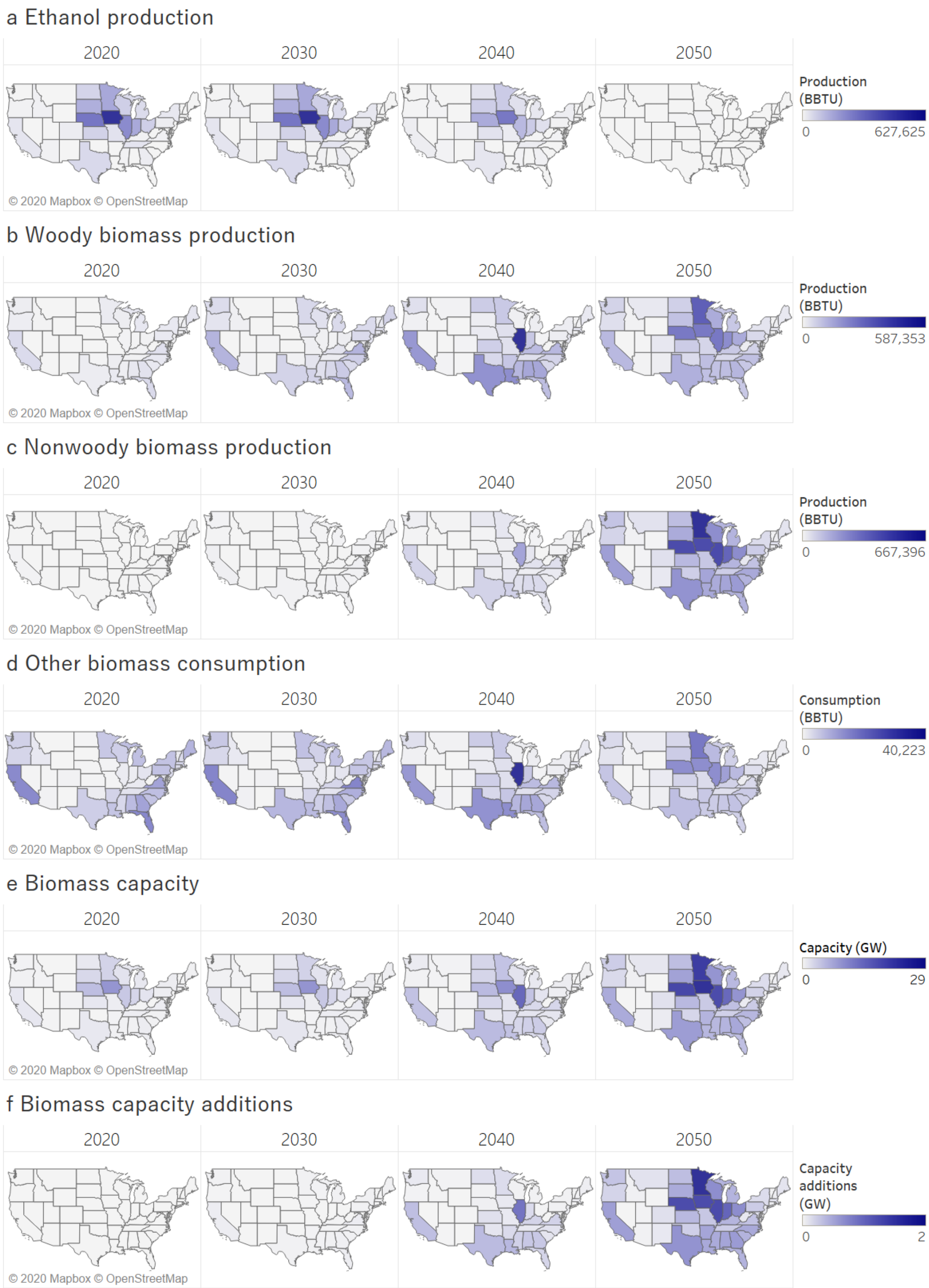

Figure 14. State-level biomass activity for the E+ scenario for 2020, 2030, 2040, and 2050.

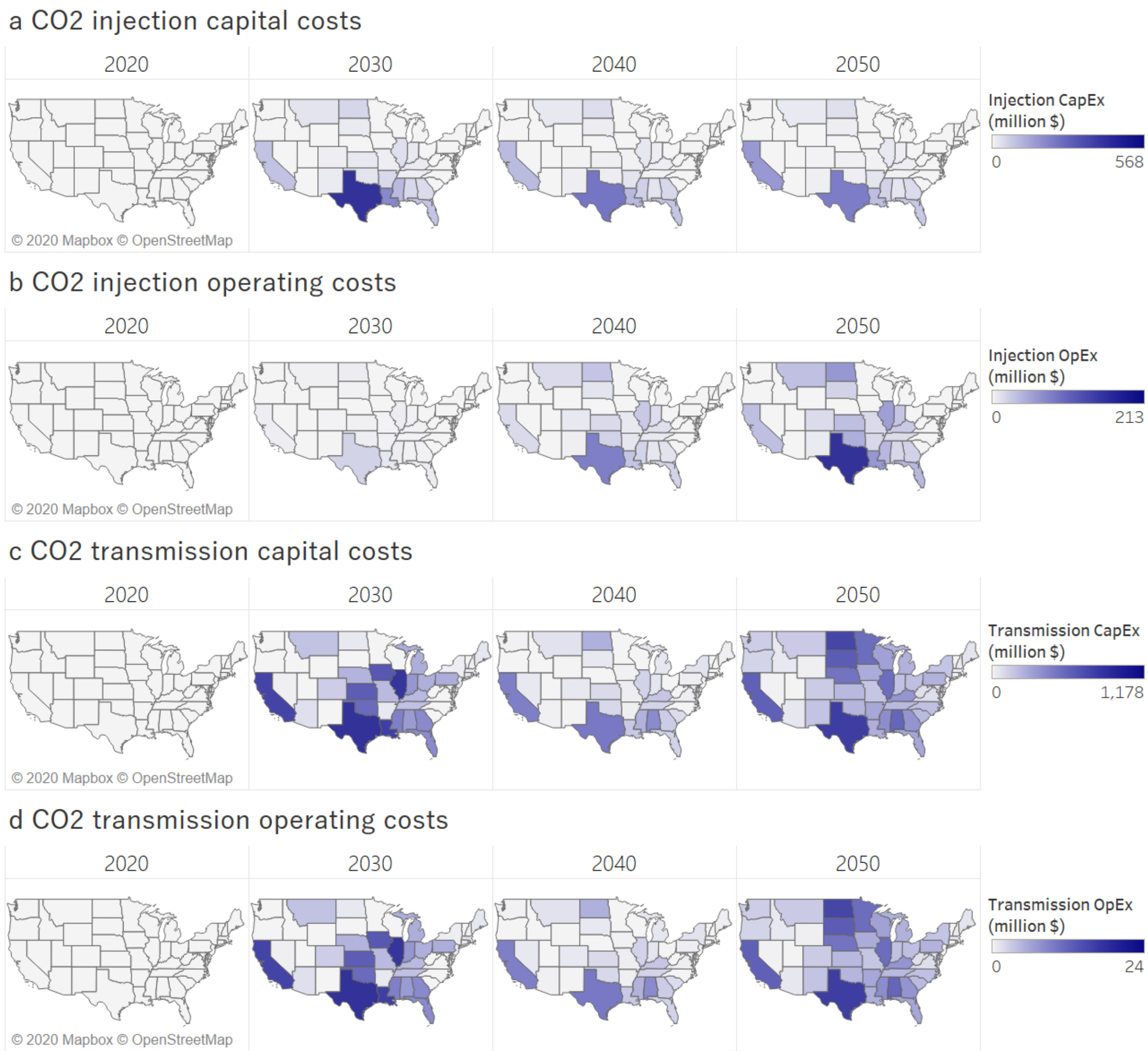

Figure 15. State-level CO2 activity for the E+ scenario for 2020, 2030, 2040, and 2050.

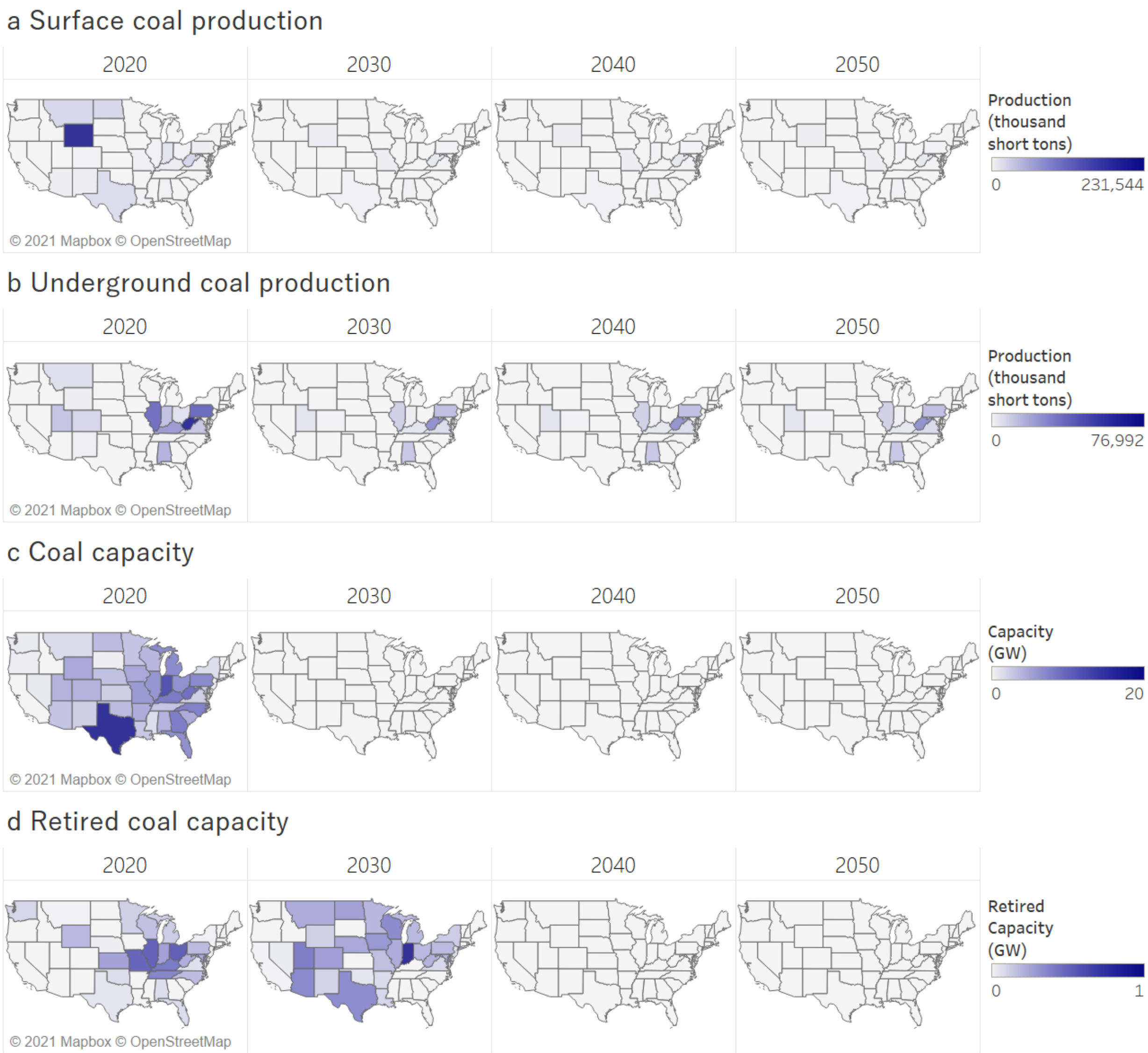

Figure 16. State-level coal activity for the E+ scenario for 2020, 2030, 2040, and 2050.

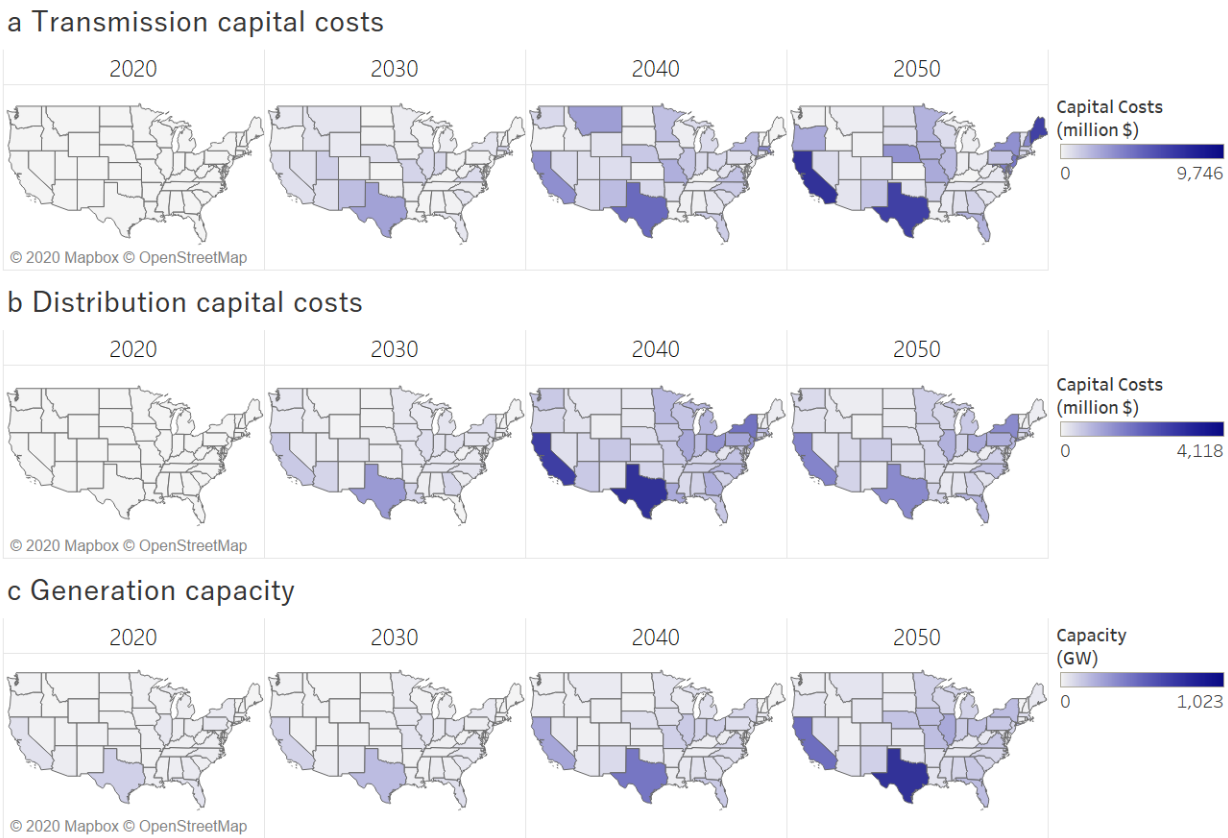

Figure 17. State-level grid activity for the E+ scenario for 2020, 2030, 2040, and 2050.

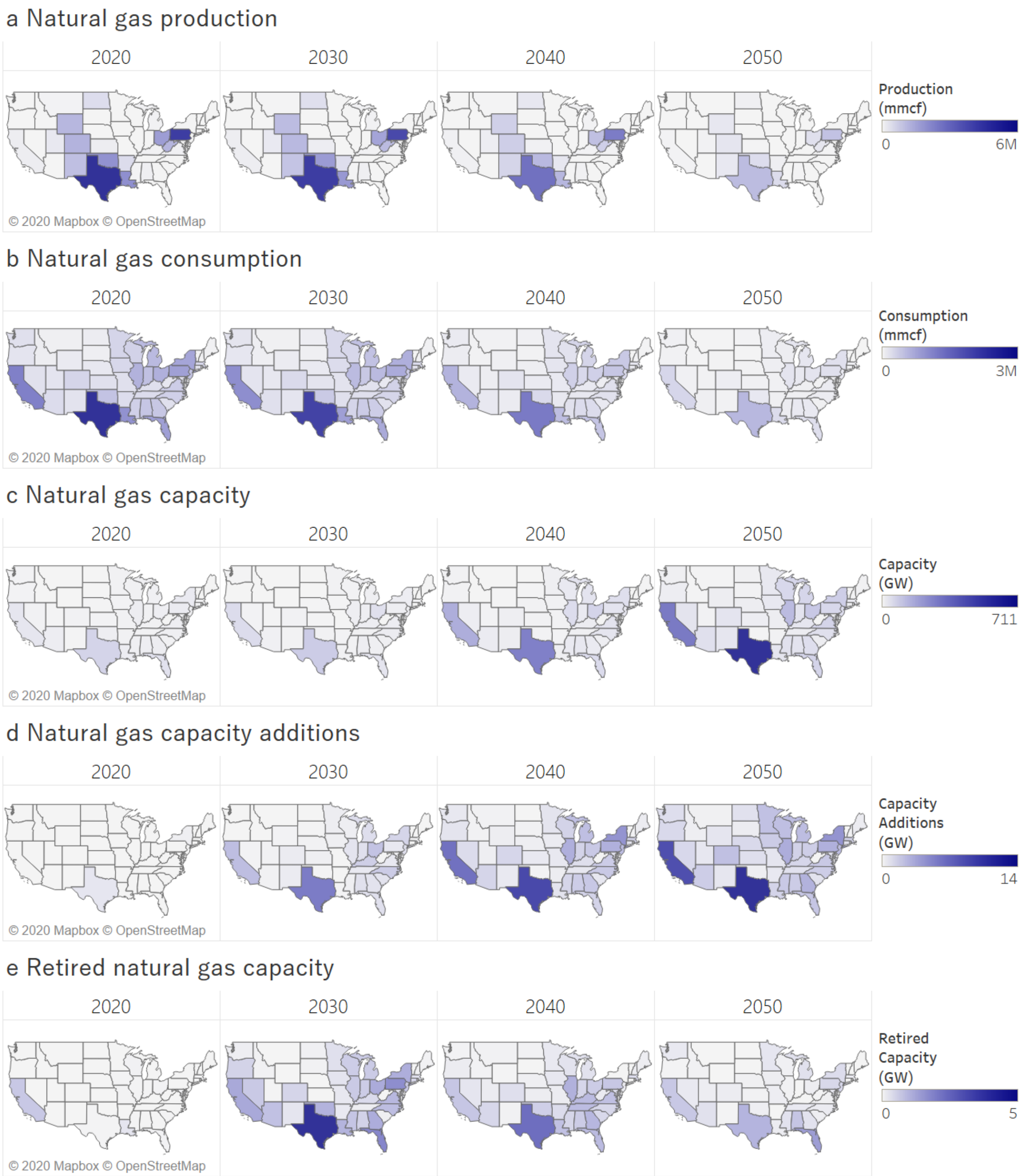

Figure 18. State-level natural gas activity for the E+ scenario for 2020, 2030, 2040, and 2050.

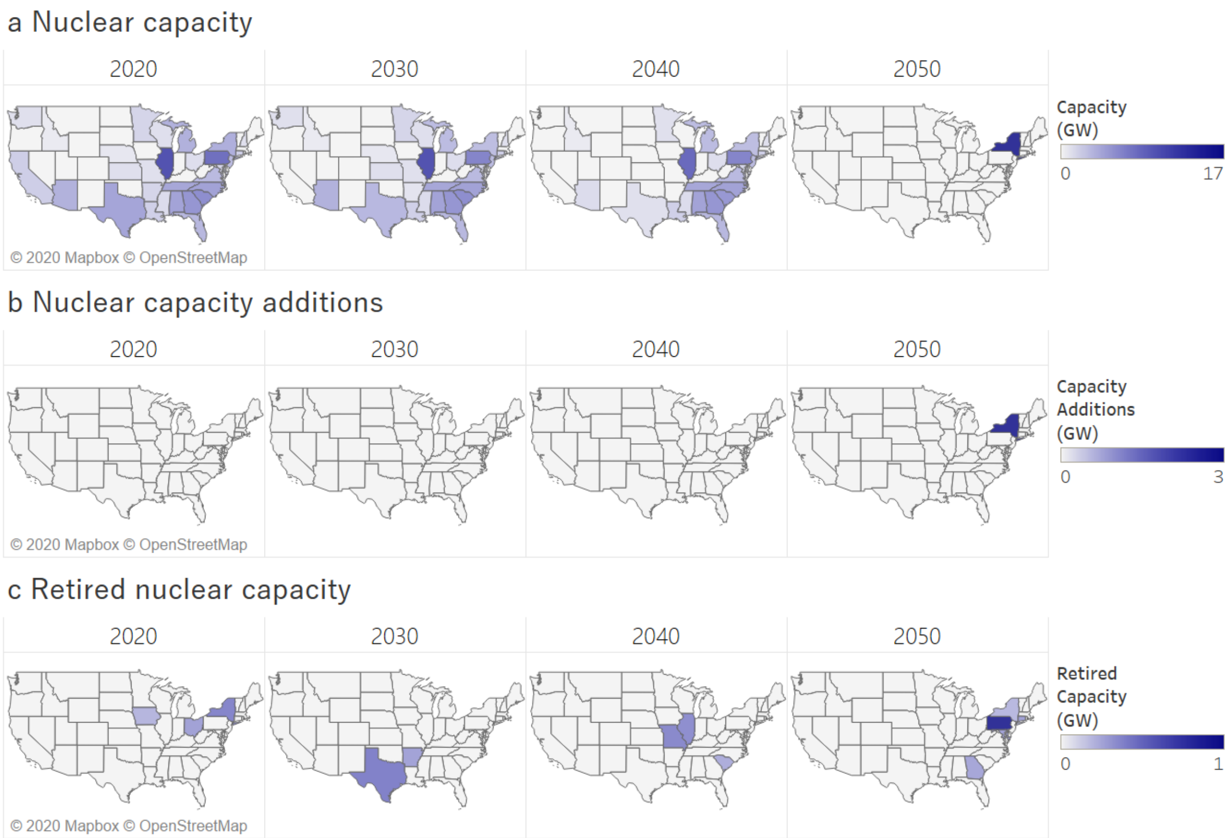

Figure 19. State-level nuclear activity for the E+ scenario for 2020, 2030, 2040, and 2050.

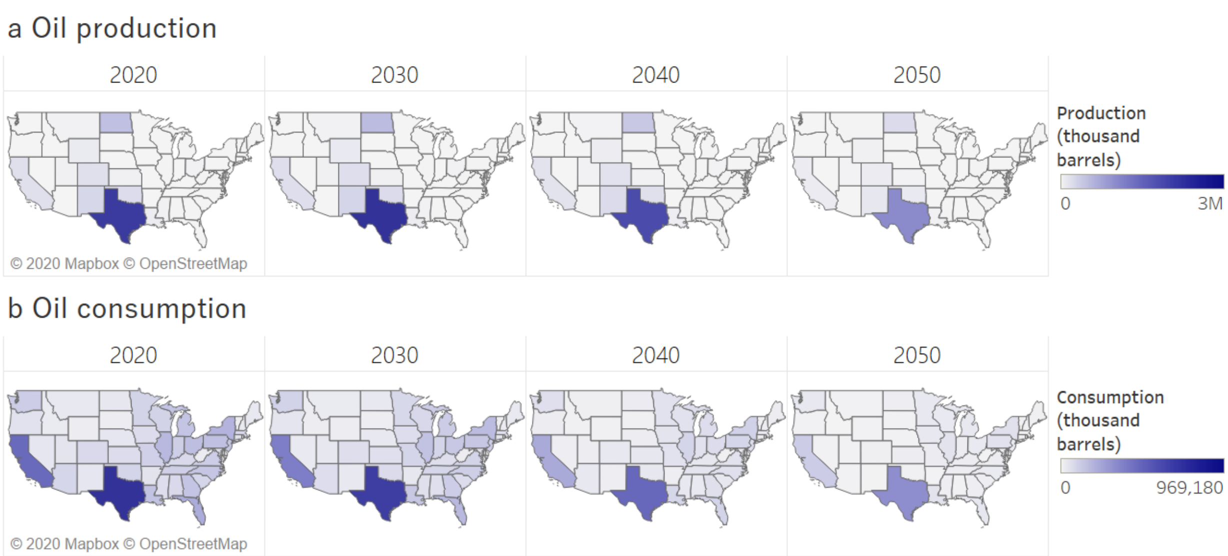

Figure 20. State-level oil activity for the E+ scenario for 2020, 2030, 2040, and 2050.

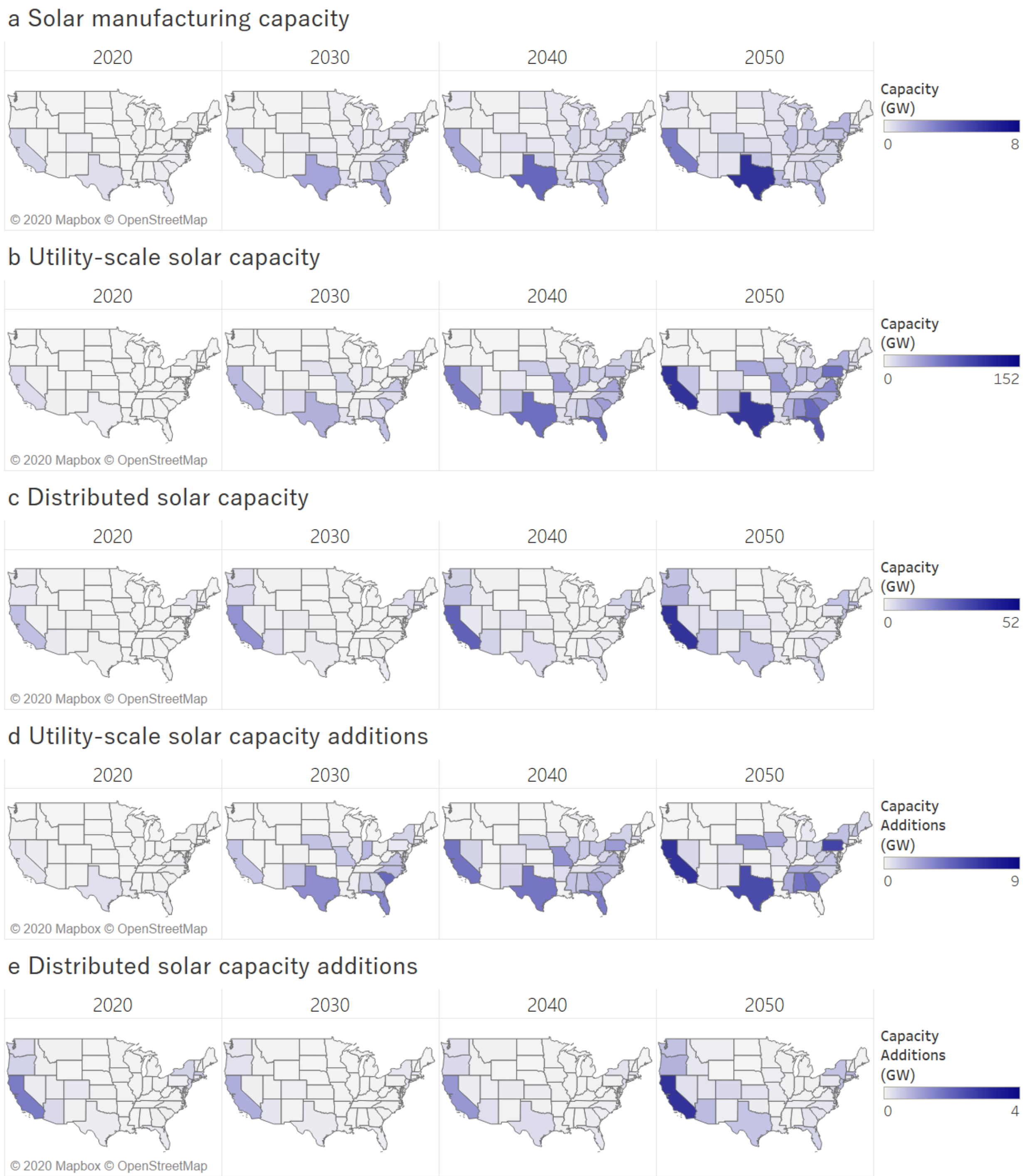

Figure 21. State-level solar activity for the E+ scenario for 2020, 2030, 2040, and 2050.

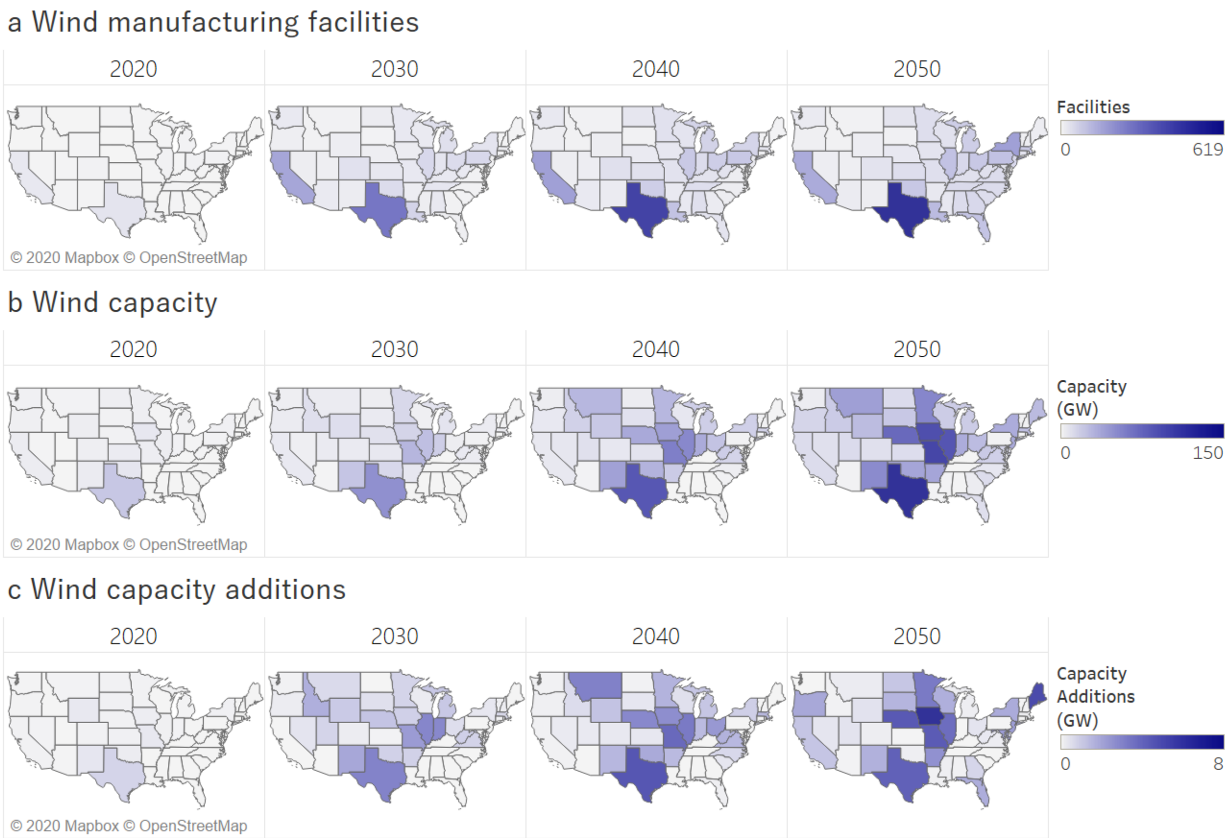

Figure 22. State-level wind activity for the E+ scenario for 2020, 2030, 2040, and 2050.

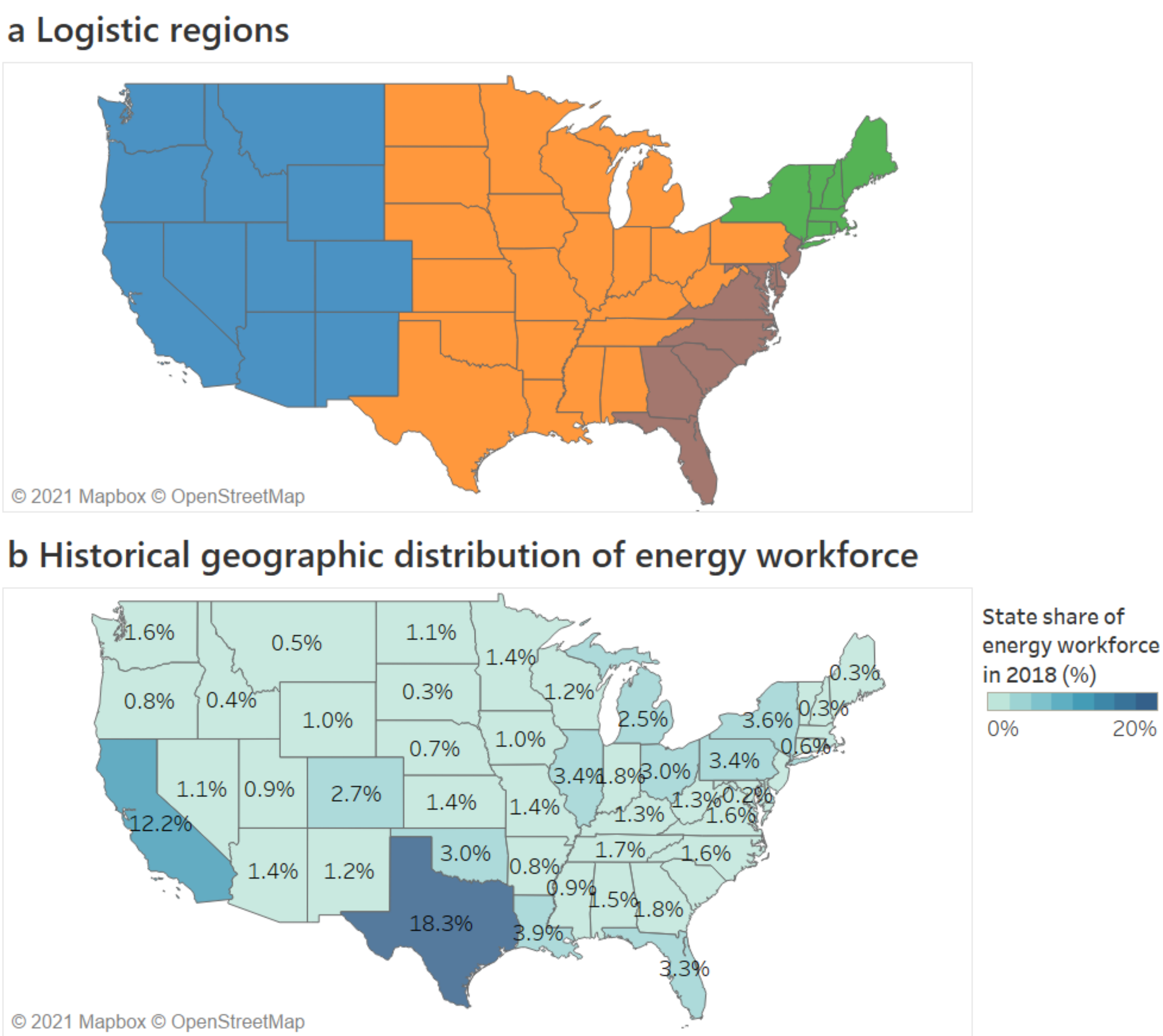

Figure 23. Logistic regions and 2018 historical energy-related employment distribution used in the spatially allocating renewable manufacturing capacity.

5 Sector, industry, and occupation classification

The historical sectoral distribution by resource and supply chain segment are provided in Figure 24.

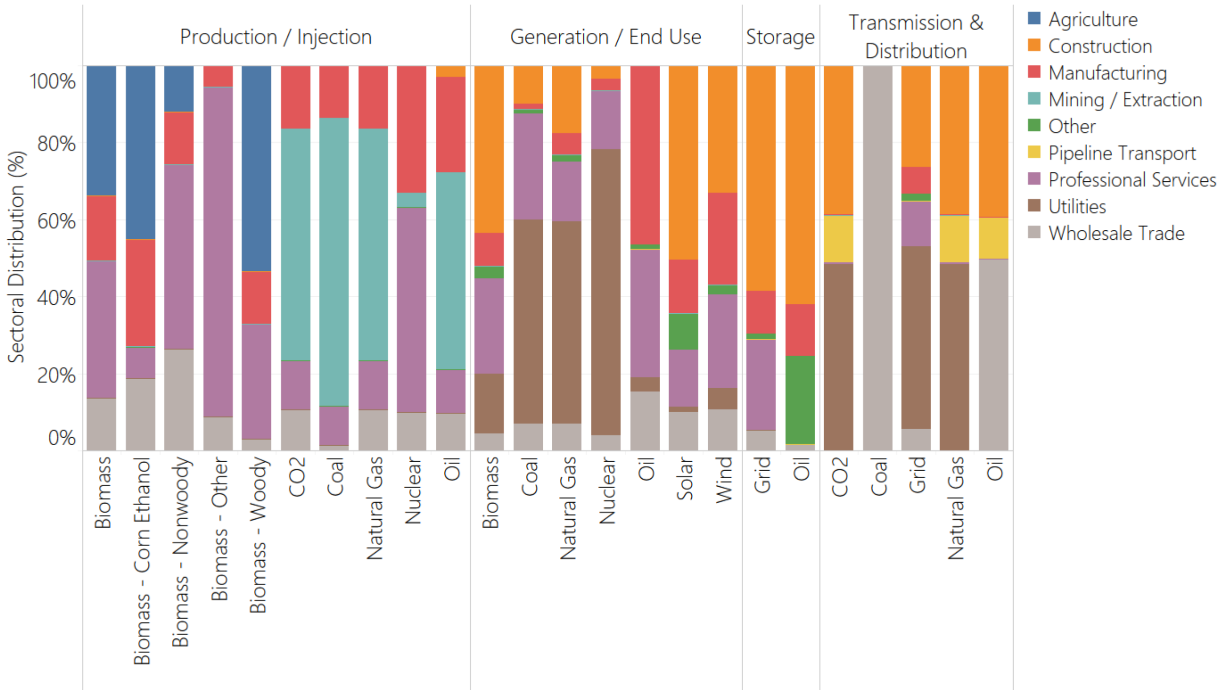

Figure 24. Historical distribution of employment by sector and supply chain segment.

6 Productivity modeling

In addition, we model the effects of changes in labor productivity – a measure of the efficiency at which labor is used to produce output of goods and services (e.g., GWh/job). For most economic sectors with energy-related employment, productivity has generally increased in both the long- and short-terms (Figure 25). At an industry-level, there is also evidence of rapid increases in labor productivity (Figure 26). For example, there were very rapid increases in labor productivity in the oil & gas extraction industry and moderate increases in the natural gas distribution industry during the shale gas boom. Existing models that estimate labor demand associated with low carbon energy transitions often adopt static assumptions with respect to the marginal labor required to produce energy-related goods and services and do not account for changing labor productivity over time. As a result, models may overestimate near- and long-term employment. Incorporating changes in labor productivity is especially important in the context of multi-decade economy-wide decarbonization pathways in which a non-trivial portion of the total labor force will be employed in energy-related jobs. In addition to sector-level productivity gains (even absent a large-scale energy transition), there are likely to be increasing labor economies of scale associated with scaling up energy-related industries that are currently relatively small and/or nascent (e.g., wind-related construction, solar manufacturing). Moreover, employment estimates reflecting labor productivity changes are better suited for identifying potential labor supply bottlenecks, organizing labor to meet demand, and long-term planning and policy design. Therefore, we develop an approach for modeling future changes in labor productivity at both the sector- and industry-levels. We develop empirical models of historical productivity changes for each economic sector, as well as estimate industry-level changes in productivity based on historical, time-series energy activity and employment data for 18 analogue industries. Then we develop future proration factors for each economic sector and industry, which reflect how productivity changes over time. We use sector-level factors to discount all employment projections, and we apply the industry-level factors to discount employment estimates for select industries that are relatively nascent or small and will likely experience rapid gains in productivity in excess of broader sector-level increases. Given large uncertainties in future productivity, we also perform extensive sensitivity analyses.

The following section outlines an approach for modeling future changes in labor productivity at both the sector- and industry-levels. We specify multiple productivity sensitivity scenarios, as summarized in Table 6.

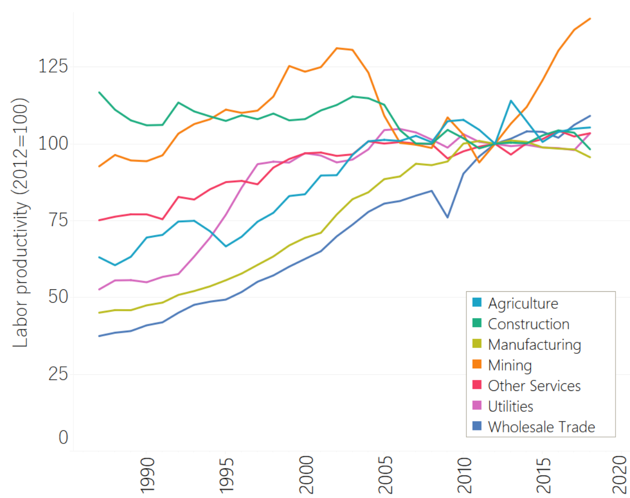

Figure 25. Historical productivity over time by sector.

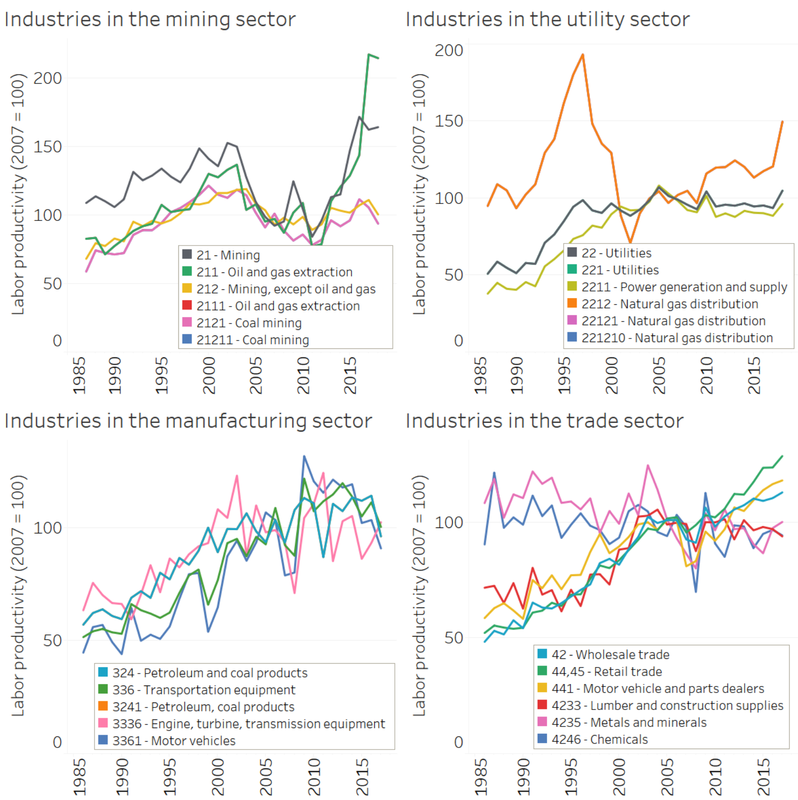

Figure 26. Historical productivity over time for select industries.

Table 6. Productivity sensitivity scenarios.

Scenario	Sector productivity change model	Industry productivity change model
1	No change	No change
2a	Linear	No change
2b	Log-linear	No change
2c	Elasticity	No change
2d	Long-term percent change	No change
2e	Short-term percent change	No change
3a	Linear	Long-term percent change
3b	Log-linear	Long-term percent change
3c	Elasticity	Long-term percent change
3d	Long-term percent change	Long-term percent change
3e	Short-term percent change	Long-term percent change
4a	Linear	Short-term percent change
4b	Log-linear	Short-term percent change
4c	Elasticity	Short-term percent change
4d	Long-term percent change	Short-term percent change
4e (base case assumption)	Short-term percent change	Short-term percent change

Sector-level productivity modeling

We develop empirical models of historical sector-level productivity changes as a function of gross domestic product (GDP) or sector output based on historical time-series data from 1980 to 2019. Specifically, we estimate five models: a) elasticity between GDP and productivity, b) linear model based on GDP and productivity, c) log-linear model based on GDP and productivity, d) long-term (10-yr) average annual productivity rate of change, and e) short-term (30-yr) average annual productivity rate of change. Productivity is measured as a function of GDP for models (a)-(c) and sector output for models (d)-(e). Based on these five models, we estimate future productivity, incorporating GDP projections reported in the 2019 EIA AEO. Then we develop a future proration factor for each sector which reflects how productivity changes over time, and finally use these factors to discount employment projections.

For model (a), we calculate the elasticity between GDP and productivity, which is a measure of the sensitivity between these parameters. We first regress productivity (y) on GDP (x) to determine the marginal effect (β), as follows:

$$y = \beta_0 + \beta x \tag{18}$$

Then, we calculate elasticity (ε) based on the following equation:

$$\varepsilon = \frac{\bar{x}}{\bar{y}} \cdot \frac{\Delta y}{\Delta x} = \frac{\bar{x}}{\bar{y}} \cdot \beta \tag{19}$$

where $\bar{x}$ and $\bar{y}$ are average GDP and productivity, respectively. We estimate elasticities for each relevant economic sector. For example, we find that an increase in GDP by 1% is associated with a 1.45% increase in productivity for the manufacturing sector (NAICS 32 & 33).

For models (b) and (c), we similarly formulate log and log-linear regression models to determine the marginal effect of GDP on productivity. For models (a)-(c), we estimate future productivity based on the EIA AEO GDP projections, as shown in Figure 27. For models (d) and (e), we estimate the short- and long-term annual rates of change, as shown in Figure 28. Finally, we estimate a productivity index relative to 2020 (

Figure 29) and estimate a proration factor which we use to discount employment estimates (Figure 30).

Industry-level productivity modeling

We estimate productivity based on historical, time-series energy activity and employment data for 18 analogue industries. We then estimate short-and long-term (10-and 30-yr, respectively) average annual rates of change, and project future productivity and annual prorate factors. Based on the prorate factors for the analogue industries, we discount employment estimates for select industries that are nascent or small and will likely experience rapid gains in productivity in excess of broader sector-level increases in productivity.

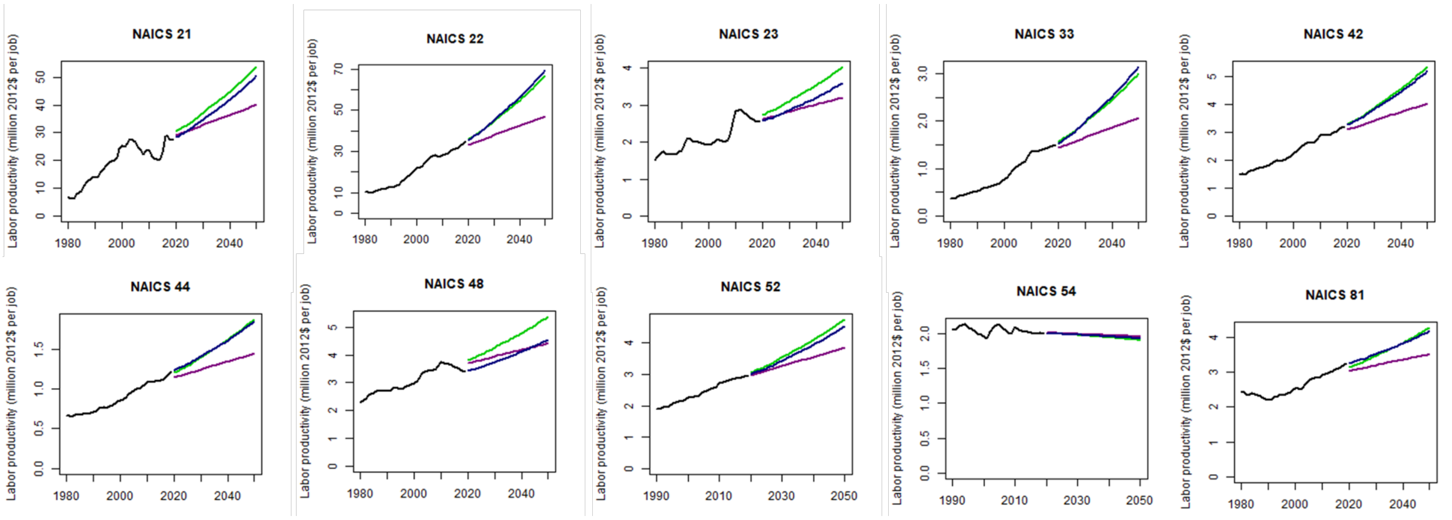

Figure 27. Projected labor productivity by sector. Black lines are historical productivity, and blue, green, and purple lines are projected productivity for models (a)-(c), respectively. The following are the sector names (NAICS): Sector name (NAICS): mining (21), utilities (22), construction (23), manufacturing (32 & 33), wholesale trade (42), retail trade (44), transportation & warehousing (48), finance & insurance (52), professional & technical services (54), other services (81).

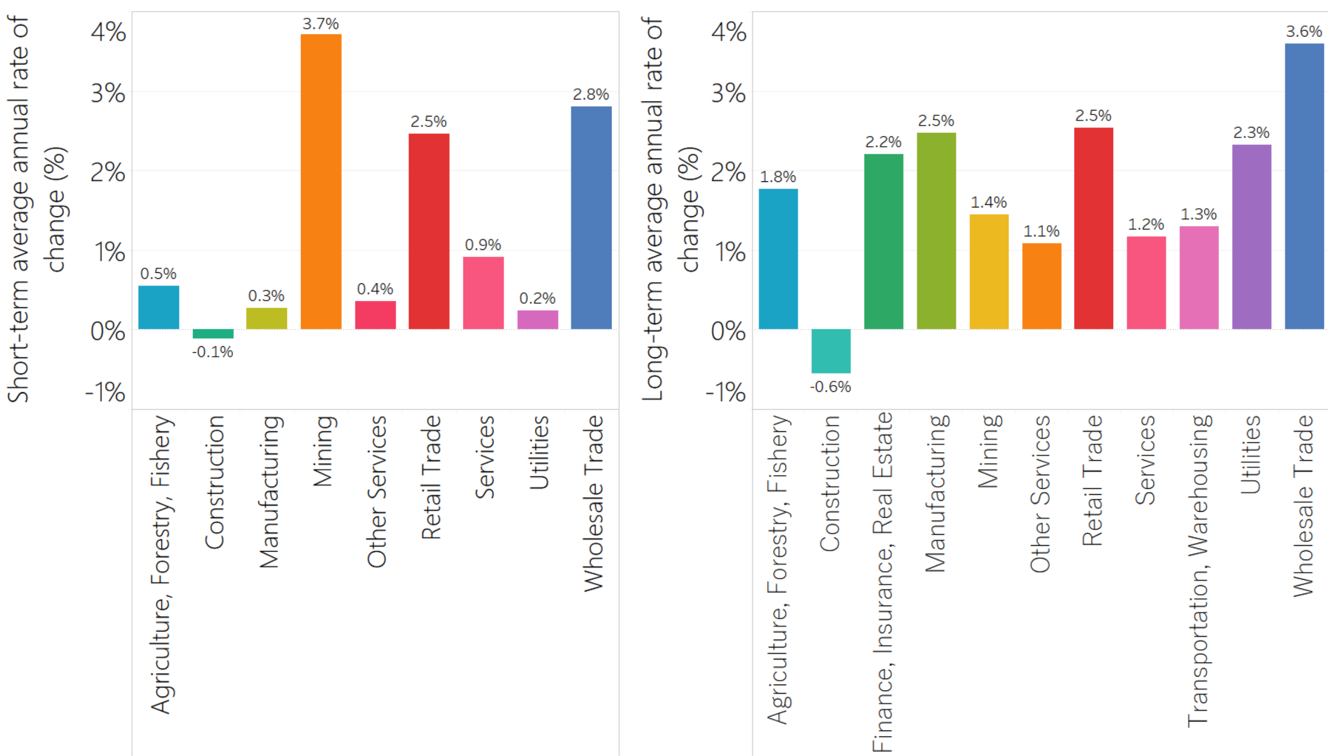

Figure 28. Short- and long-term historical rates of change by sector.

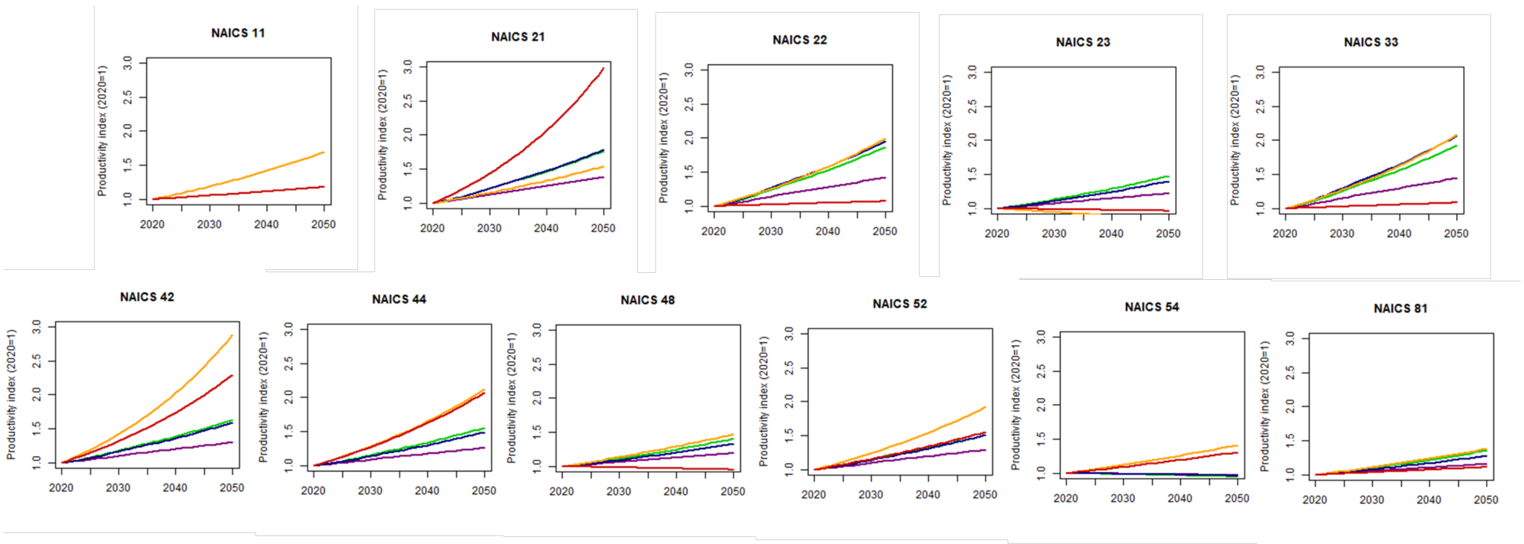

Figure 29. Productivity index by sector. Blue, green, purple, orange, and red lines are productivity indices for models (a)-(e), respectively. The following are the sector names (NAICS): Sector name (NAICS): agriculture (11), mining (21), utilities (22), construction (23), manufacturing (32 & 33), wholesale trade (42), retail trade (44), transportation & warehousing (48), finance & insurance (52), professional & technical services (54), other services (81).

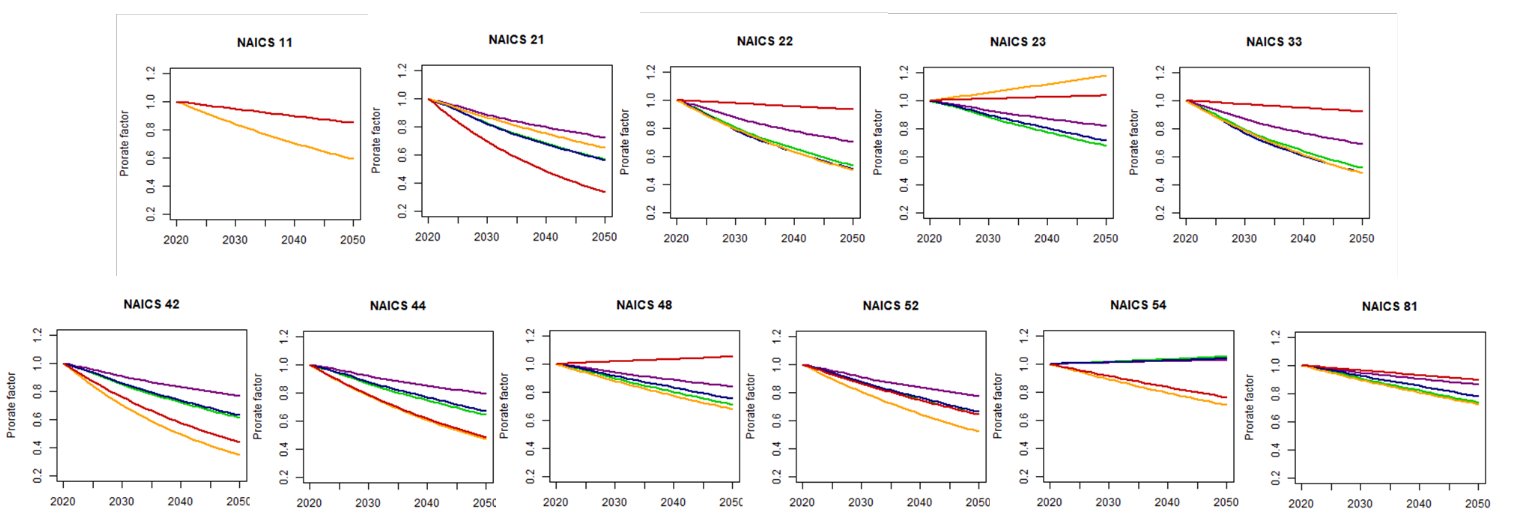

Figure 30. Proration factor by sector. Blue, green, purple, orange, and red lines are proration factors for models (a)-(e), respectively. The following are the sector names (NAICS): Sector name (NAICS): agriculture (11), mining (21), utilities (22), construction (23), manufacturing (32 & 33), wholesale trade

(42), retail trade (44), transportation & warehousing (48), finance & insurance (52), professional & technical services (54), other services (81).

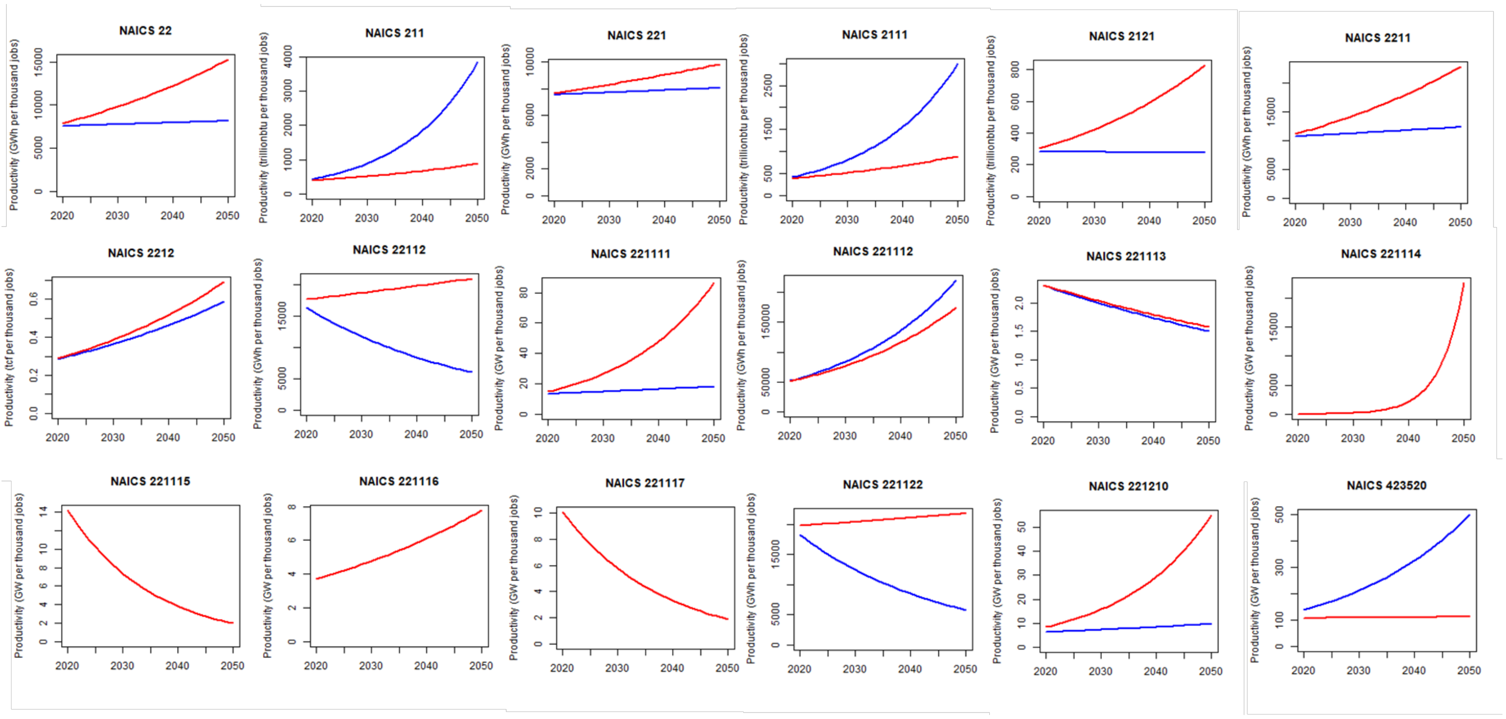

Figure 31. Projected productivity for 18 analogue industries. Red and blue lines are productivity based on the short- and long-term rates of change, respectively. The following are the industry names (NAICS): utilities (22), oil & gas extraction (211), electric power transmission, distribution, and generation (221), oil & gas extraction (2111), coal mining (2121), power generation and supply (2211), natural gas distribution (2212), electric power transmission and distribution (22112), hydro generation (221111), fossil fuel electric power generation (221112), nuclear generation (221113), solar generation (221114), wind generation (221115), geothermal generation (221116), biomass generation (221117), electric power distribution (221122), natural gas distribution (221210), coal and other mineral and ore merchant wholesalers (423520).

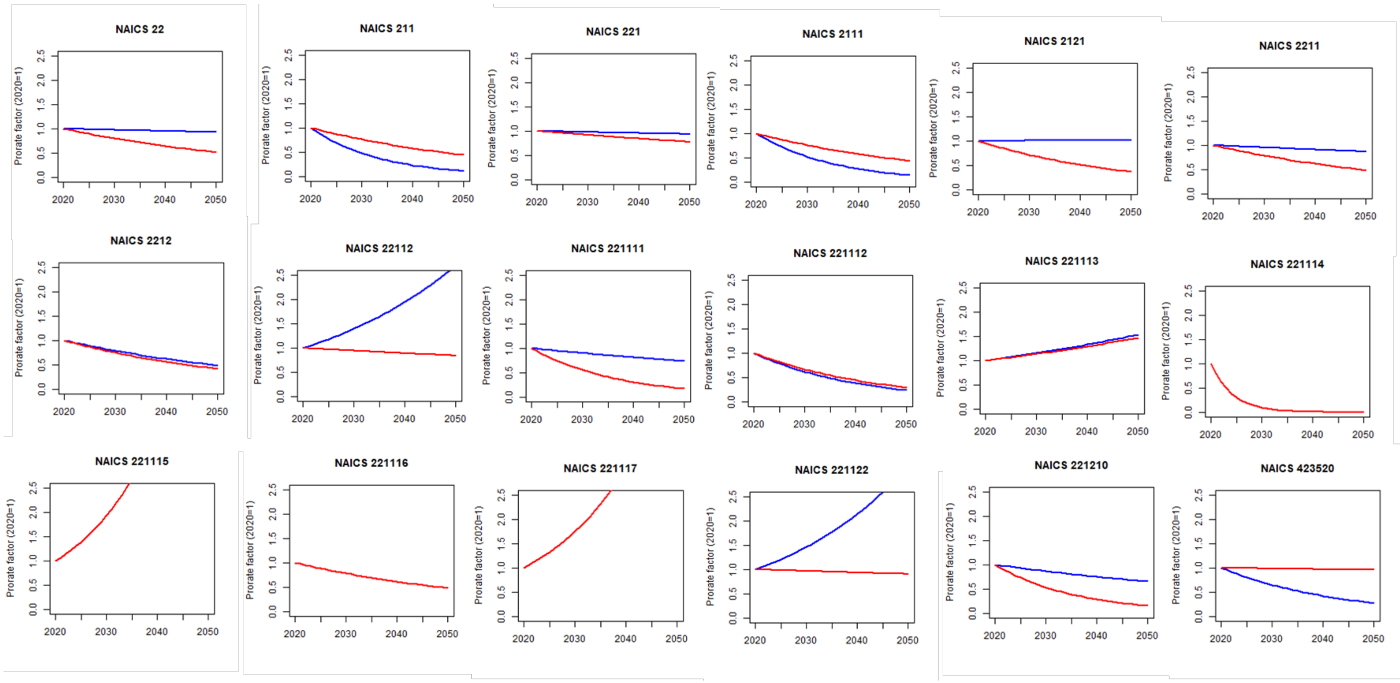

Figure 32. Prorate factors for 18 analogue industries. Red and blue lines are productivity based on the short- and long-term rates of change, respectively. The following are the industry names (NAICS): utilities (22), oil & gas extraction (211), electric power transmission, distribution, and generation (221), oil & gas extraction (2111), coal mining (2121), power generation and supply (2211), natural gas distribution (2212), electric power transmission and distribution (22112), hydro generation (221111), fossil fuel electric power generation (221112), nuclear generation (221113), solar generation (221114), wind generation (221115), geothermal generation (221116), biomass generation (221117), electric power distribution (221122), natural gas distribution (221210), coal and other mineral and ore merchant wholesalers (423520).

7 Education, experience, and education modeling

We model the education, experience, and training requirements associated with employment pathways. We use occupational data from the Occupational Information Network (O*NET) database, which contains information regarding the nature of work for approximately 1,000 occupations in the U.S. Specifically, we model employment across four education, experience, and training metrics, each of which are subdivided into five categories: required level of education, related work experience, on-site or in-plant training, and on-the-job training. O*NET reports the frequency of jobs for a given occupation that are within a specific category (e.g., 57% of civil engineer jobs require a bachelor's degree). To compute the education, experience, and training requirements, we combine the employment estimates by occupation with the frequency distributions.

An example of the education, experience, and training distribution of jobs for a given occupation across is provided in Figure 33.

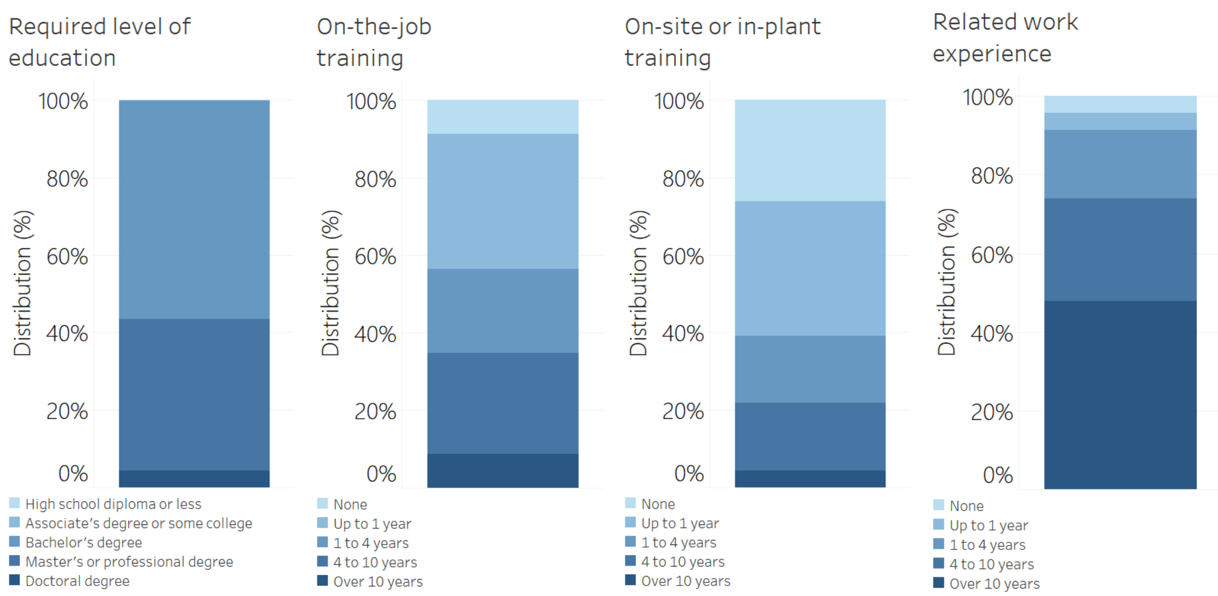

Figure 33. Example of education, experience, and training distribution for civil engineers.

8 Wage modeling

We project real (2019$) median wages for approximately 1500 occupations, based on historical nominal wages from 2000 to 2019 (which we adjust for inflation), and estimates of long-term, historical real wage inflation/deflation rates for each occupation [30,40]. Combining median wage and employment estimates for each occupation, we project total wages for each pathway.

We simulate total and average wages over time by state and resource. Specifically, we estimate future total wages for each occupation o and year t ($Total\ wages_{o,t}$) as follows:

$$Total\ wages_{o,t} = Wages\ per\ job_{o,t} \cdot E_{o,t} \tag{20}$$

where $E_{o,t}$ is the total employment, and $Wages\ per\ job_{o,t}$ is the future annual median wage per job.

We estimate future wages per job for approximately 1500 occupations, based on historical wages and estimates of wage inflation. Nominal historical wages are reported by the U.S. Bureau of Labor Statistics[30] and adjusted for inflation based on the Consumer Price Index for all urban consumers[40]. We estimate long-term average wage inflation rates for each occupation based on historical real (2019$), median wages from 2000 to 2019, as shown in Figure 34 shows the long-term average wage inflation by occupation, and an example of future median wages is provided in Figure 35.

To contextualize energy-related wages, we compare wages associated with the energy workforce to total wages across the entire employed labor force. We estimate future total wages based on state-level employed labor force projections paired with median wage projections for all occupations.

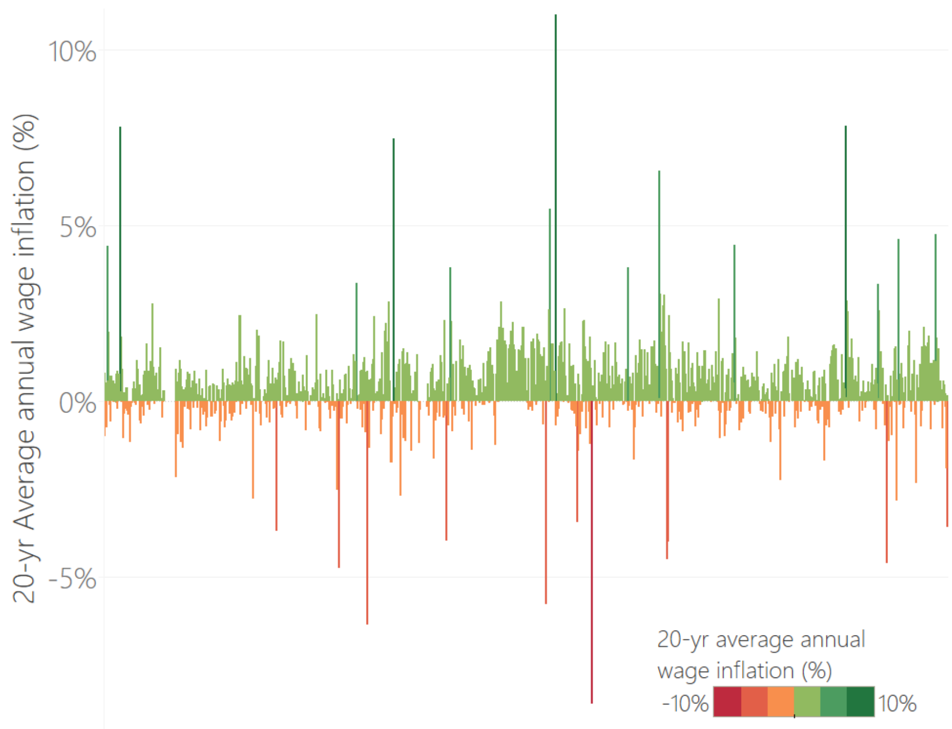

Figure 34. Long-term average wage inflation by occupation. Each bar represents an occupation.

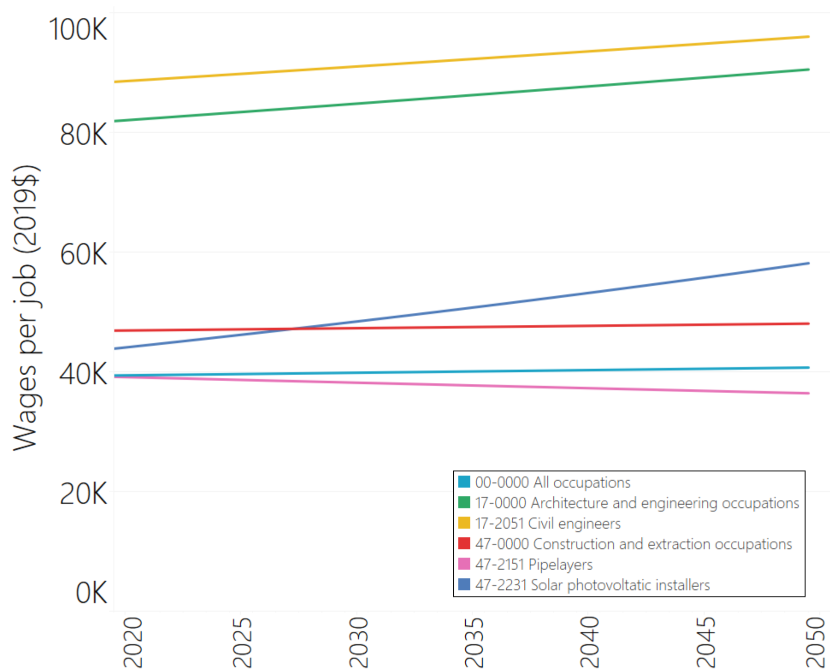

Figure 35. Example of future wages for specific occupations.

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