Working Paper No. 2023-28

INET Oxford Working Paper Series
30th November 2023

UNIVERSITY OF OXFORD

INSTITUTE FOR NEW ECONOMIC THINKING AT THE OXFORD MARTIN SCHOOL

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Joris Bücker, R. Maria del Rio-Chanona, Anton Pichler,
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Joris Bücker[1,2,*], R. Maria del Rio-Chanona[3,4,5], Anton Pichler[3,6], Matthew C. Ives[1,2], and J. Doyne Farmer[1,2,7]

[1] *Institute for New Economic Thinking at the Oxford Martin School, University of Oxford, Oxford, UK*
[2] *Smith School of Enterprise and the Environment, University of Oxford, Oxford, UK*
[3] *Complexity Science Hub, Vienna, Austria*
[4] *University College London, Univesity of London*
[5] *Bennett Institute for Public Policy, University of Cambridge*
[6] *Vienna University of Economics and Business, Vienna, Austria*
[7] *Santa Fe Institute, Santa Fe, NM, US*
[*] *Correspondence: joris.bucker@seh.ox.ac.uk*

November 30, 2023

Abstract

Transitioning to a net-zero emissions power system will create and destroy jobs in different occupations, creating skill mismatches and labor mobility frictions. We analyze the employment dynamics of a fast transition scenario for the US electricity sector that reaches 95% decarbonization by 2035, using an input-output model coupled to an occupational mobility network. We find three distinct labor market phases during the transition: 'scale-up', 'scale-down', and a long-term steady state. During the scale-up phase, from 2023–2034, for every job lost in a given industry, twelve new jobs are created elsewhere. But only a few occupations experience a consistent increase in demand throughout the transition. We predict that skill mismatches will create labor frictions during the transition, especially in the scale-down phase. Without proper planning, rapidly growing industries will struggle to find skilled labor in the scale-up phase, and displaced workers will have difficulty finding jobs during the scale-down phase.

Introduction

An immediate and accelerated decarbonization of the global economy is required to limit global warming to less than 1.5°C above pre-industrial levels (IPCC, 2018; Armstrong McKay et al., 2022). Since the majority of greenhouse gas emissions (around 75%) are energy related, the rapid expansion of renewables and the phase-out of fossil fuels has become a key focus in near-term mitigation strategies (IEA, 2021). While a fast transition to a net zero energy system could end up being economically beneficial (Way et al., 2022; IEA, 2023), it will still have profound impacts on countries' economies, including their labor markets.

The net-zero energy transition will create and destroy jobs. On the one hand, the transition will lead to a downscaling or removal of fossil fuel energy generation with an associated displacement of workers. Past experiences of long-term depressions from shrinking industries and mine closures in North England, the US Appalachians, and the German Ruhr areas (Oei et al., 2020; Gore and Hollywood, 2009; Olson-Hazboun, 2018; Beatty et al., 2007; Carley and Konisky, 2020) underscore the importance of managing such transitions and finding ways to alleviate the negative impacts of stranded labor on displaced workers and communities.

On the other hand, a net-zero transition will create a demand for many new workers to build and manage the new clean energy infrastructure, leading to the possibility of skill shortages and unfilled vacancies. This will be exacerbated if the overall labor market is tight[1], as it currently is in many countries in Europe and North America (Domash and Summers, 2022). A shortage of workers with the right skills could slow down the energy transition.

Previous literature broadly aligns in concluding there will be a net gain of jobs in the US during a clean energy transition. For example, Jacobson et al. (2015) find almost 2 million net jobs created

[1] The labor market is tight if the ratio between unemployment and vacancies is significantly larger than one.

in the US (6 million gained, 4 million lost), whereas an IEA report finds a 0.45% economy-wide net increase in employment, representing around 700,000 jobs[2] (Kuhn et al., 2018). Mayfield et al. (2021) project that the fraction of the US workforce that is part of the energy supply chain grows from 1.5% in 2020 to 2.5–5% in 2050, representing a 1.6–3.6 million increase in workers. Ram et al. (2022) find a 4 million net increase in energy-related jobs between 2020 and 2050 for the US. Xie et al. (2023) find an increase of 439,000 jobs by the 2040s if the power sector reaches net zero emissions by 2035. Other studies finding job growth include Dell'Anna (2021), Lehr et al. (2008) and Černý et al. (2022). Only few studies find a negative impact on job creation. For an overview see, e.g., Stavropoulos and Burger (2020).

Most of these studies focus on aggregate job numbers in the initial transition phase and do not address the heterogeneity of impacts across workers. Workers' occupations, skills, experience, geographic location, available alternative employment options, and their perceived socio-economic status can affect their employment prospects (Hollywood, 2002; Schmutte, 2014; Diodato and Weterings, 2015; Nedelkoska et al., 2018; Neffke et al., 2022). Workers are more likely to transition to jobs in industries and occupations related to their previous job (Mealy et al., 2018; Neffke and Henning, 2013; Hausmann and Neffke, 2019). This can have significant implications for employment. When new vacancies are opened in occupations that are very unrelated to occupations where workers lose their job, a skill mismatch is created, rendering it challenging for displaced workers to find new roles as their usual job alternatives are not available (Del Rio-Chanona et al., 2021).

The net-zero transition has the potential to generate skill mismatches. To assess the employment implications of the net-zero transition, it is important to consider the heterogeneous effects across all occupations. Traditional global process integrated assessment models rarely analyze the evolving labor structure or categorize households by occupation, lacking information on employment shifts linked to specific mitigation scenarios (Rao et al., 2017). Although some macroeconomic models have begun to explore labor market impacts at a detailed level and consider different skills and occupations (ILO, 2018; Mayfield et al., 2021), most of these studies overlook potential skill mismatches that result from correlated displacement shocks across occupations.

The skill mismatch literature often builds on network models. Three studies stand out in examining potential skill mismatches resulting from the net-zero transition: Lankhuizen et al. (2022) apply an industry and geography mobility model to the Netherlands, and Berryman et al. (2023) use a computable general equilibrium model linked with an occupational mobility model for Brazil. These studies identify potential skill mismatches that could lead to higher rates of unemployment or unfilled vacancies. Additionally, Xie et al. (2023) look at the distributional effects of a US power sector decarbonization across states for workers by skill level and gender.

To understand the potential for skill mismatch in the net-zero transition, previous work classifies occupations into 'green' and 'brown' categories depending on their skills, industry employment, or future outlook in a decarbonizing economy, sometimes with sub-classifications for green jobs (e.g., Dierdorff et al., 2009). For example, O*NET classifies occupations as 'Green New & Emerging' if they are likely to see a demand increase when shifting to a 'greener' economy. Vona et al. (2018) analyzes the characteristics of green and brown occupations in a labor market network. The labor transition is complicated by the fact that green jobs tend to require higher skills, are more often located in urban areas and are less prone to automation than brown jobs (Bergant et al., 2022; Bowen et al., 2018; Saussay et al., 2022). Nevertheless, more transitions from brown to green jobs can be expected as the availability of green jobs increases (Curtis et al., 2023).

Temporal effects also play a crucial role in the net-zero transition. The classification of occupations as 'green' or 'brown' overlooks the fact that some roles may be crucial for only part of the transition. While some macroeconomic models can deal with temporal changes in demand, their focus is often restricted to the initial scale-up phase. This approach neglects the later stages when generation capacity has shifted to renewables, and worker demand, particularly in construction and manufacturing, may decline. The narrow focus on job growth in the initial transition phase can lead to misunderstandings of the complexities involved in the full trajectory to a net-zero economy.

We develop a novel framework for analyzing skill mismatches during the clean energy transition. We quantify the temporal dynamics of labor market frictions at a granular occupation level during power sector decarbonization and identify occupation-specific impacts and skill-mismatch frictions as they evolve through time. If the demand for occupations with similar skills rises in tandem, it becomes relatively harder for employers to fill vacancies, and if it falls in tandem, it becomes harder for workers to find new jobs. Our goal is to alert policymakers to these problems so they can make targeted interventions to mitigate them.

We follow a four-step procedure (see Methods, Fig. 7). First, we translate the different cost

[2]In June 2023, about 161 million people were employed in the US (BLS, 2023).

components (capital expenditure, operational expenditure and fuel cost) of power sector decarbonization scenarios into annual demand shocks and intermediate consumption changes. Second, we use these shocks to initialize a simple demand-driven input-output (IO) model to estimate direct and upstream industry output changes in the electricity generation sector as a consequence of the changing energy mix. To do this, we disaggregate the IO data to include ten different electricity technologies. Our model is dynamic: in each year of the analysis, we update the links in the IO network to represent the change in the deployment of energy technologies (e.g., when the coal power share of electricity production is reduced in favor of wind energy, industries and households switch part of their demand from coal power to wind). Third, we calculate annual labor demand profiles for all occupations and industries, assuming fixed employment and occupation inputs per constant-dollar output. This assumption allows for any energy technology cost reductions to be translated into decreased labor demand for the same product, accounting for automation and innovation through the electricity supply chain.[3] Finally, by linking occupational demand trajectories to an occupational mobility network, we quantify potential skill-mismatch frictions. All such 'skill mismatch' or labor market frictions identified by this study relate to the difficulty of changing one's occupation at different stages of the clean energy transition. To test the robustness of our results, we engage in extensive sensitivity analysis of key assumptions and data sources.

We apply our method to the United States using the National Renewable Energy Laboratory (NREL)'s standard scenarios, focusing on their fast transition scenario that reaches 95% decarbonization in the power sector by 2035 (Cole et al., 2021). We are interested in this scenario partly because accelerated climate action is required to meet the US's Paris pledge to keep global warming well below 2 °C. A faster scenario might also be financially beneficial (Way et al., 2022; IEA, 2023; Creutzig et al., 2023) and thus accelerated by economic forces. Additionally, NREL is a US Department of Energy sponsored research center that produces scenarios that are closely examined by US policymakers and has high credibility in the research community. Finally, NREL's fast transition scenario covers both the transition phase and a subsequent low carbon power system phase of an energy sector that is decarbonized by 2050, enabling us to assess the full occupational implications of the transition.

Our model works with national-level data and thus neglects regional differences. As shown in Lim et al. (2023), green jobs are likely to arise in different locations than fossil fuel jobs, which can amplify skill mismatches. Vice versa, locations without any green or brown energy-related jobs may not be affected at all. We discuss how our analysis can be extended to include geography in the Supplementary Material (SM) Section B.1.

Since we are concerned with the labor impacts of decarbonizing the power sector and its upstream industries, an IO network provides a straightforward way to convert the scenario's annual energy system spending into changes in direct and upstream labor demand. This should not be interpreted as a macroeconomic model, as it lacks mechanisms such as prices and substitutability; any additional energy demand effects caused by electrification or changes to the costs of energy services from the scenario spending are assumed to have already been included in the energy scenarios that we apply. While it is beyond the scope of this work, the extent of electrification will be an important factor. To focus specifically on the labor impacts of the low carbon transition all of our results are shown as relative to a second NREL no-new-policies reference scenario. We apply our method to the US transition, but with sufficient data this approach could be applied to virtually any modeled energy-economy transition scenario for any country or region.

Temporal heterogeneity in labor demand during the transition

The two NREL scenarios we use are shown in Fig. 1. The left panels display the capacity and generation profile of the reference scenario, representing "no new policies". The right panels depict the fast transition scenario, where the model is required to reach a 95% decarbonized system from 2035 onward. The corresponding emission pathways are shown in the Supplementary Material (SM) Fig. 8.[4]

[3] When we refer to 'jobs' gained (lost), we refer to the net increase (decrease) in demand within industries or occupations relative to a reference scenario. See Methods for more information.

[4] The 95% by 2035 scenario results in slightly higher total generation because of higher losses during transmission and storage, and energy used for carbon capture, which we model as (more expensive) gas capacity.

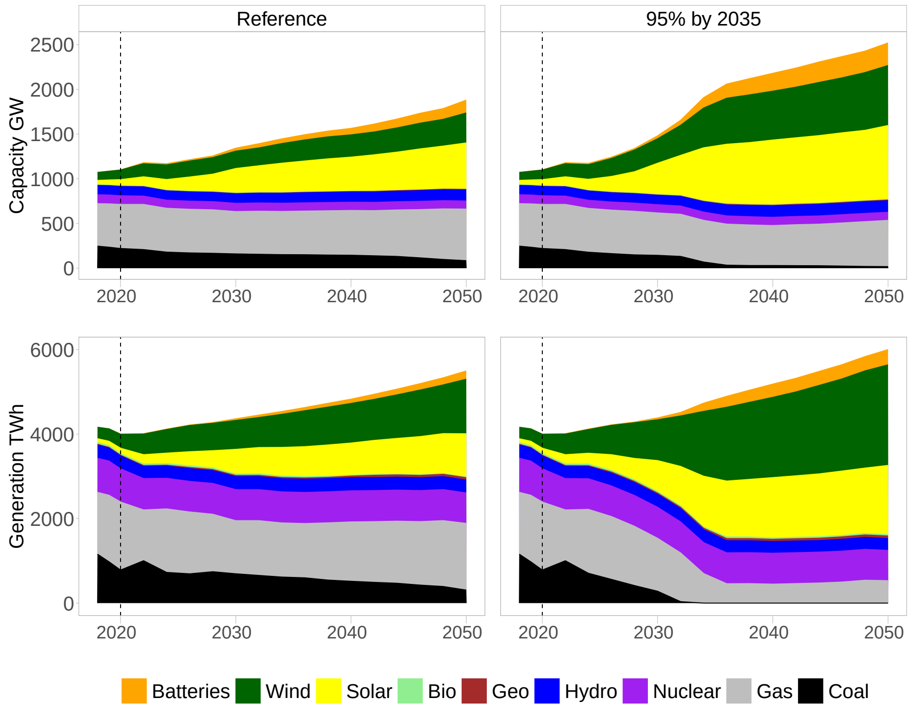
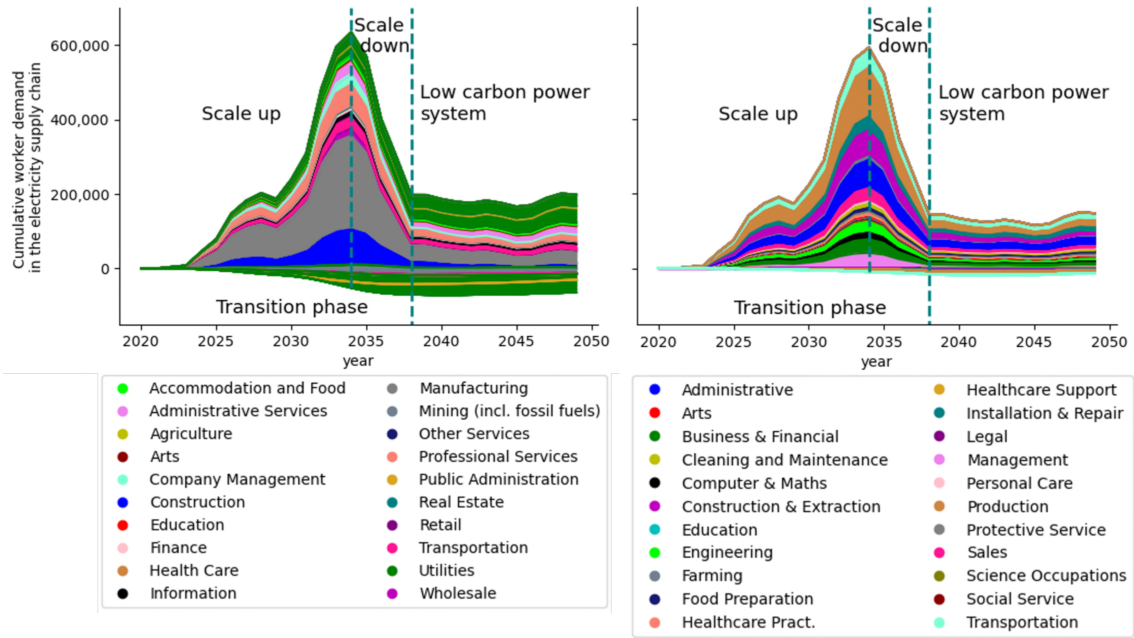


Figure 1: The US power sector scenarios we use in this study. The upper panels show the capacities in GW and the lower panels the electricity generation in TWh in yearly resolution. On the left, we show NREL's no-new-policies scenario that we use as a reference and on the right NREL's fast 95% by 2035 scenario (Cole et al., 2021). Up to 2020, the figures show historical data from the Electric Power Annual 2020 (EIA, 2022). Technological categories are aggregated according to SM Table 2.

In Fig. 2 we present our model's estimates of the cumulative difference in labor demand relative to the reference scenario for industries and occupations between 2020 and 2050. For visualization purposes, the labels indicate 2-digit NAICS industry classification codes (20 industries) and 22 high-level occupational categories, but this is an aggregation of results using a more detailed classification of 82 industries and 539 occupations. Across all industries with a labor demand growth, we predict an increase in demand of about 634,000 workers by 3034. In the same time period, 52,000 jobs are lost in industries with a decrease in demand. In testing the sensitivity of our analysis against some of the key uncertainties in the modeling (see SM Section D.4) we find that the net growth in the number of workers at the peak in 2034 can be between 450,000 and 800,000, with around 580,000 being our base case. Our estimates are roughly an order of magnitude lower than reported by Jacobson et al. (2015), Mayfield et al. (2021), or Ram et al. (2022). This discrepancy is in part due to the fact that these studies include the entire energy sector, rather than just the electricity sector. Some also aggregate over a longer time period. Our results are more in line with Xie et al. (2023)'s estimate of employment changes due to power sector decarbonization and the ILO's estimate of an IEA scenario to keep warming below 2°C (ILO, 2018).

To put our estimates in perspective, 680,000 jobs account for 0.4% of the current US employment and roughly 0.15% of the average annual US labor market flux within 15 years.[5] Not all job transitions are occupational transitions: Vom Lehn et al. (2022) calculates that approximately 6.7% of US workers switched occupations per year between 2011–2019, although in recent times occupational switching appears to have slowed down. While a change of 680,000 workers may seem small with respect to total employment and labor flows, job changes caused by the energy transition could be highly geographically concentrated (Lim et al., 2023). Therefore, there may be skill shortages within regions where jobs are created and a concentration of displaced workers where jobs are lost. While the former may slow down the transition, the latter can lead to local economic decline and rising political discontent (Dijkstra et al., 2020). To understand possible employment outcomes of the transition, we study these temporal aspects in detail and their implications for industries and occupations.

[5]There are currently (2023) 161 million employed workers in the US, and the annual job reallocation rate is roughly 20% (final year (2011) data from Davis and Haltiwanger, 2014).



(a) Industries

(b) Occupations

Figure 2: Cumulative demand for workers in the 95% decarbonization by 2035 scenario per industry (a) and per occupation category (b). The change is shown as relative to the NREL no-new-policy reference scenario. Industries are plotted at the detailed level used in the analysis (82 industries) but colored by their 2-digit aggregated categories. Occupations are plotted at the detailed level used in the analysis (539 occupations) and colored by their 2-digit level aggregation (22 occupation groups). Different phases of the transition are demarcated with dotted vertical lines and labeled.

Our temporal analysis shows three distinct phases in the demand for labor in the electricity supply chain over the full transition. The first phase, before 2034, is the scale-up phase where the work is done to reach the goal of a 95% decarbonized generation capability by 2035. It includes an increase in overall demand for labor, mainly driven by the need to replace existing fossil fuel generation infrastructure with renewables and additional electrification. The next phase, between 2034 and 2038, is the scale-down phase of decreasing labor demand after most of the new replacement infrastructure is built. Together, the scale-up and scale-down phases make up what we refer to as the 'transition phase'.

Such fluctuations are not new and to be expected in large-scale infrastructure projects or technological transitions. For example, railway construction started in Ireland in 1833 and employment grew to over 30,000 workers in 1847 during the *railway mania*. By 1849, the number of workers had fallen back to 10,000–15,000, where it remained until 1960 (Lee, 1979). In a more modern example, BT Group in the UK announced job cuts in 2023 when its fiberglass cable expansion was finished. One labor union representative acknowledged that such job cuts were 'no surprise' given the infrastructure changes (Sandle, 2023).

After the transition phase, we observe the low-carbon power system phase. While grid expansion continues in this phase until at least 2050, the demand for labor is relatively stable. We estimate the new low carbon power system will have about 117,000 net more employed workers compared to a no-new-policies reference scenario (see SM Section D.4 for a sensitivity analysis on this estimate).

When we dive deeper into the industry profile details (Fig. 2a), we find that the largest contributors to the peak in 2034 are the manufacturing and construction sectors, which are crucial for producing renewable energy technologies and developing the necessary infrastructure. Smaller industries, such as Professional, Scientific, and Technical Services, and Wholesale Trade, also fit within this group. Other industries behave in different ways. Fossil-fuel industries, including some utility industries and Mining, see a net loss of worker demand over the entire period. Utilities that are based on renewables experience a net gain in labor demand.

We map sectoral labor demand changes to 539 occupations, assuming a fixed occupational compositions per sector. Fig. 2b shows the labor requirement dynamics per aggregate occupation category. We highlight two results: First, as seen by the differences in the mass of color below the x-axis, occupations experience much fewer job losses than industries. This is due to the fact that the same occupations are needed in many different industries. For workers in such occupations, the transition might involve a change of firm and sector, but not necessarily a change in occupation.

Second, while it is apparent that industries experience different temporal employment dynamics (e.g., compare manufacturing vs. utilities vs. mining), most of the 22 occupational categories move through the transition more or less in tandem. In the next section, however, the heterogeneity becomes apparent at the detailed occupation level.

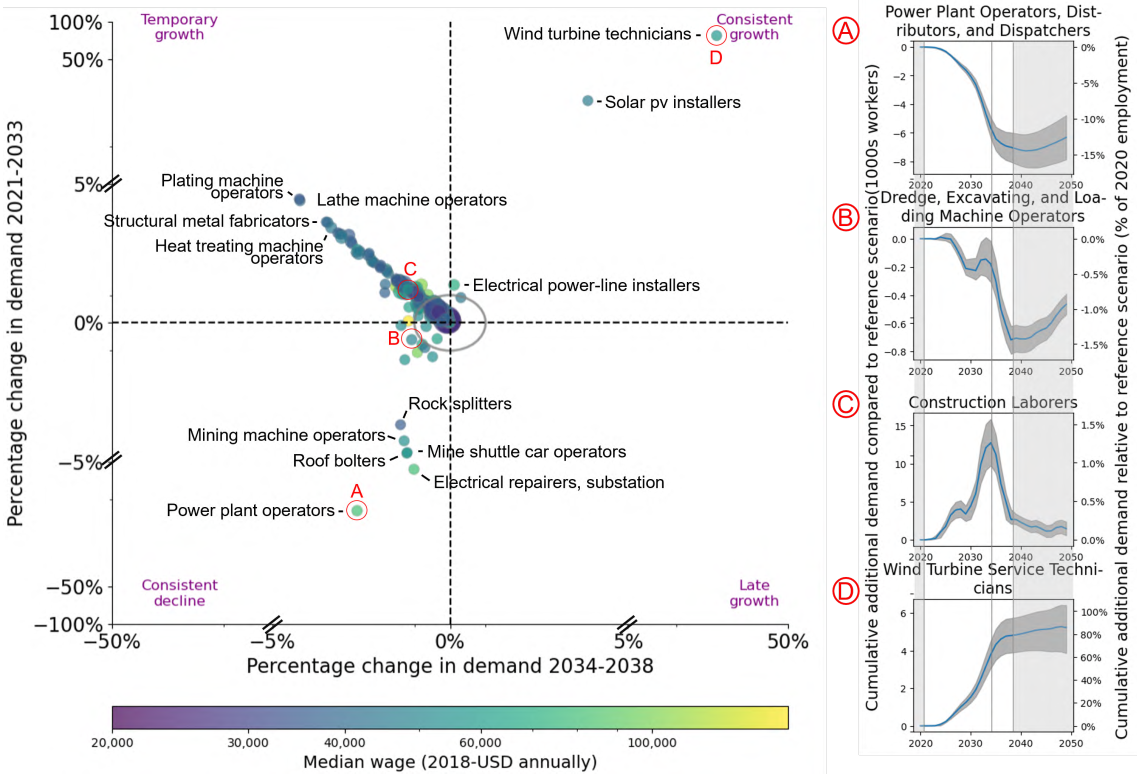


Figure 3: Occupation demand change relative to employment in the *95% by 2035* scenario. On the vertical axis, the net demand change between 2021–2034 (scale-up phase), and on the horizontal axis, the change between 2034–2048 (scale-down phase). Occupations within the grey circle indicating less than 1% demand change are considered minimally affected; all others are categorized in the labor transition typology that is formed by the four quadrants. The axes are in a linear scale from -5% to +5% and a log scale beyond that. Occupations are colored according to their mean wage. The occupational profiles on the right show the full temporal dynamics for four selected occupations. Grey error bars are constructed via the sensitivity analysis on the trajectory calculation (See SM Section D.4).

Typology of temporal heterogeneity in occupational demand change

To better understand skill mismatches, we study the temporal dynamics of different occupations. In Fig. 3, we plot the change in demand for all occupations during the initial scale-up phase against the change in demand during the later scale-down phase of the power system transition. We classify occupations into five types based on the dynamics of their demand.[6] We classify occupations that lie within the grey circle as 'minimally affected'. The combined demand change of these occupations in the scale-up and scale-down phases is less than 1% of their 2020 employment level.[7] This group consists of 423 out of the 539 occupations, or 88% of total US employment in 2020. The minimally affected occupations include all legal, healthcare and education occupations, and the vast majority of sales, administrative support, management and business workers, among others.

The remaining occupations are classified based on the quadrants in Fig. 3 they are positioned in. The top-right quadrant corresponds to the 'Consistent growth' occupations that experience a demand *increase* during *both* the scale-up and scale-down of the electricity transition. This group has only three occupations: solar PV installers, wind turbine service technicians and power line installers. Relative to the no-new-policies baseline, the demand for solar PV installers is expected to increase by 20% between 2020 and 2038, and the demand for wind power technicians is expected

[6]The formal definitions of the typology can be found in SM Section B.7. A full list of occupations in each group can be found in SM Section C.10.

[7]We calculate the combined demand change by taking the square root of the sum of squared changes in demand in the scale-up and scale-down phases.

to increase by 80%. To achieve the fast transition scenario, we will need to train a substantial number of new workers in these occupations.

The bottom-left quadrant corresponds to the 'Consistent decline' group, which experiences a *decline* in demand during *both* the scale-up and scale-down phase. The 13 occupations of this group are mainly employed in mining and extraction and fossil fuel operations. We find some of the largest reductions in demand for power plant workers, roof bolters, mining machine operators and mine shuttle operators. Note that our analysis focuses on the power sector only and thus does not include other fossil fuel uses, such as direct coal use in the steel sector or fossil-fuel powered vehicles. If the power sector transition is accompanied by a low-carbon transition in other sectors, the decline in these occupations and others in fossil fuel extraction industries will be even more dramatic.

The top-left quadrant of Fig. 3 corresponds to the 98 'temporary growth' occupations that have an increase in demand during the scale-up phase followed by a decline during the scale-down phase. The temporary growth occupations cover more than half of production, construction, and engineering occupations, as well as some installation and maintenance, management, business, and administrative occupations.

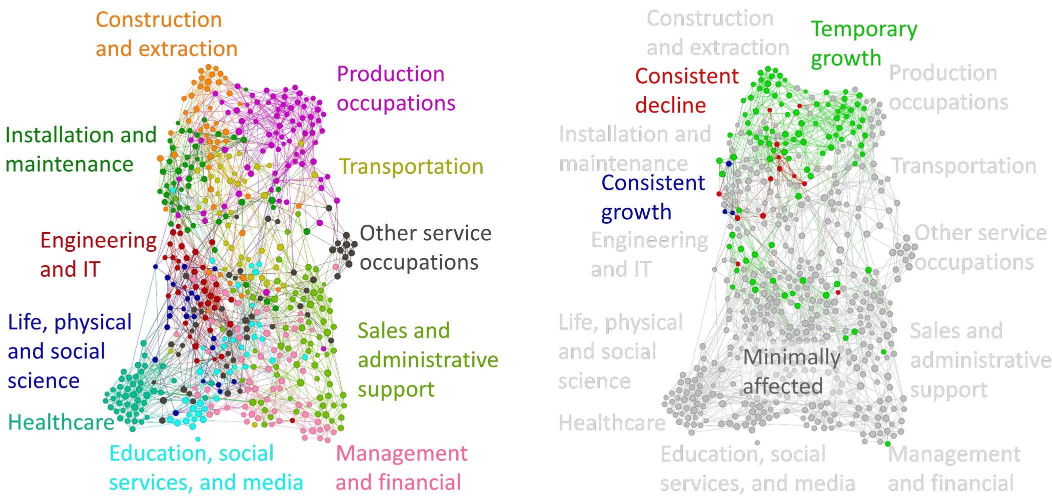
Finally, there are no 'late growth' occupations in the bottom-right quadrant; i.e., there are no occupations that experience a decrease in demand during the scale-up phase and an increase in demand during the scale-down phase.

Following the methodology developed by Consoli et al. (2016), we examine the skill content of these groups in SM Section D.2.2. We find that the occupations most adversely affected by the transition have higher manual and routine skills. This is particularly true for the 'Consistent decline' occupations. Consistent growth occupations score above average on non-routine interactive skills, and 'Consistent decline' occupations score below average. The other skills (analytical and cognitive) show fewer differences in aggregate. In SM Section D.2.1 we map the current location quotients by US state of the occupation typology, which highlights the current geographical differences between some of these occupations. In Section B.7, as part of our robustness check, we present an alternative definition of the transition groups.

As expected, 'Consistent decline' occupations mostly belong to brown occupations as defined by Vona et al. (2018), and 'Consistent growth' occupations mostly belong to 'Green new & emerging' occupations as defined by Dierdorff et al. (2009). Temporary growth occupations do not fit neatly into either category. This challenges the green vs brown dichotomy: the demand pattern of temporary growth occupations is similar to 'Consistent growth' occupations for the scale-up phase, but better reflects the pattern of 'Consistent decline' occupations during the scale-down phase. We find that temporary growth occupations are included in existing classifications of *both* green and brown occupations. See SM Section D.3 for more information.

Skills shortages and stranded labor

A key focus of this study is to identify skill mismatch frictions that may arise in the scale-up and scale-down phases of the transition. We follow previous work on skill mismatch using skill-relatedness networks (Bowen et al., 2018; Neffke et al., 2022; Mealy et al., 2018). We use a list of related occupations from O*NET that provide career switching options for each occupation and create an occupational mobility network where the nodes represent occupations. Links are drawn between two occupations if workers can switch between them, similar to the network used in Bowen et al. (2018) (see Methods and SM Sections A.4 and B.9). Figs. 4a and 4b show the network structure with the nodes (occupations) colored by eleven broad occupational categories (SM Section A.3.1) and our trajectory-based typology, respectively. Most affected occupations cluster in the upper side of the network, suggesting that the transition affects specific parts of the labor market much more. Because affected occupations are linked, skill mismatch frictions are likely to be present for some occupations.



(a) (b)

Figure 4: Network of occupations with connections between related occupations. The occupations are colored by a) broad occupational categories, and b) their temporal profile typology. Figure layout was created using a force-pull algorithm.

We use assortativity, a standard network science metric as a measure of skill mismatches in the labor market (see Methods). Assortativity in networks refers to the tendency of nodes to be connected to other nodes that are like (or unlike) them with respect to specific attributes. We use assortativity to find whether occupations that are connected in the network are often part of the same occupational typology and face a similar demand change during the scale-up and scale-down phase. An assortativity value of 1 means occupations only link with similarly impacted nodes. A value of 0 indicates random mixing.

Using our typology of 'Consistent growth', 'Consistent decline', and 'Temporary growth' occupations, we find positive and significant assortativity (Table 1). Thus, as suggested by Fig. 4, occupations tend to be connected with other occupations within the same group, rather than with occupations of other groups.

When we calculate the assortativity coefficient directly on the change in demand during the two transition phases, we find a lower level of assortativity, especially for the scale-up period. The positive but low assortativity for the initial period indicates that while frictions do exist in the scale-up phase, there are still career options available for workers moving out of shrinking occupations. This concretely means that workers in the 'Consistent decline' group have possibilities to move to occupations in the 'Temporary growth' or 'Consistent growth' groups. In contrast, assortativity in the scale-down phase is higher, indicating that career changes from 'Consistent decline' and 'Temporary growth' occupations to 'Consistent growth' occupations are likely to be less common. This means that skill mismatch frictions are of greater concern in the later stages of the transition. The results show that the network exacerbates the labor market impacts of the different phases of the transition but that these impacts are not static – they evolve.[8]

	Assortativity
Occupational typology (Consistent decline, Consistent growth, Temporary growth)	0.43***
2021–2034: Demand change during the scale-up phase	0.05***
2035–2038: Demand change during the scale-down phase	0.26***

Table 1: Assortativity of the shock relative to employment on different occupation networks. ***, **, * indicate results that are greater than the randomized case for 99.9%, 99%, or 95% of values respectively in a Monte Carlo simulation (see Methods for details).

Skill mismatch frictions can affect both the supply and demand side of the labor market. An increase in demand for an occupation as well as for its neighbors means employers will find vacancies

[8] In SM Section D.2.3 we show that our results are robust when we use an occupational network based on empirically observed occupational changes rather than O*NET's measure of relatedness. In SM Section D.4 we also explore how IO model assumptions affect the assortativity levels.

harder to fill. A decrease in demand for an occupation and its occupational mobility neighbors can make it harder for displaced workers to find new employment.

To highlight occupations most affected by skill-mismatch frictions during the first phase of the transition, in Fig. 5 we plot the demand change for the scale-up phase against the demand change for the pool of workers in related (neighboring) occupations. Frictions are strongest in the grey areas of this figure, where the demand change for individual occupations is similar to the demand change for its neighbors. On the left side of the $x = 0$ line, the darker shading indicates increased frictions for workers: that is, it becomes harder for displaced workers to find new employment. On the right side of the $x = 0$ line, the darker shading indicates increasing employer frictions: that is, it becomes harder for employers to fill vacancies. Along the identity line, occupational frictions are aligned assortatively, and an occupation is as affected as their neighboring pool of related occupations. In other words, for occupations along the identity line, labor market pressure caused by the transition cannot easily be alleviated by switching occupation or headhunting workers with compatible skills.

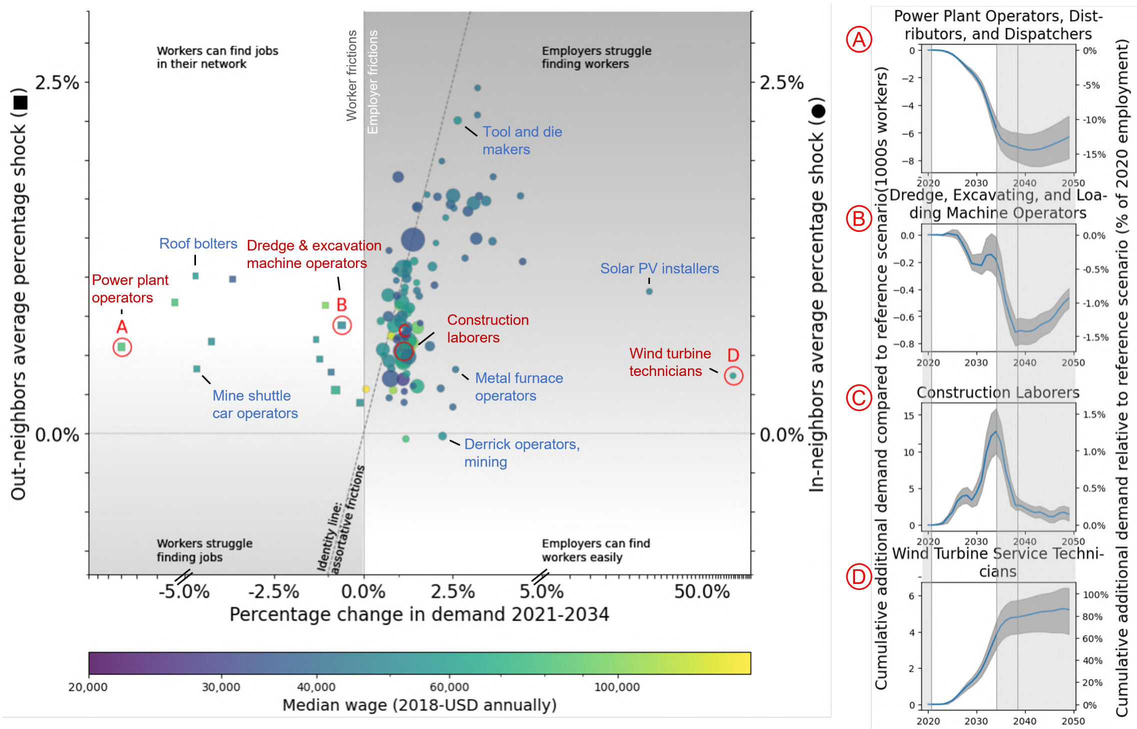


Figure 5: Scatter plot of demand change in the scale-up phase (2021-2034) per occupation (x-axis) and their neighbors (y-axis). The x-axis scale is linear until ±5%, and logarithmic beyond that. If the occupation has a positive (negative) demand change, we average the neighbor demand change over its in- (out-) neighbors. Out-neighbors of occupation α are related occupations that form potential career switching options for workers in α. Vice versa, in-neighbors of α are occupations for which α is a related occupation. The identity line is plotted, and selected occupations are highlighted. On the right, demand change profiles over time are plotted for occupations highlighted in red. The intensity of background shading corresponds to more occupational frictions: worker frictions for $x < 0$, employer frictions for $x > 0$. The grey scaling is a linear function of the neighborhood shock, when the sign of the demand change for individual occupations is the same as for its neighbors (i.e., top right and bottom left quadrants).

During the scale-up phase, most of the skill mismatch frictions affect employers struggling to find suitable workers, including for manufacturing occupations such as 'Tool and die makers', construction occupations such as 'Construction laborers', and renewable operations workers, such as 'Wind turbine service technicians'. 'Derrick, rotary drill and service unit operators, mining' see an increase in demand in this phase, but its neighbors, on average, see a very small decline, suggesting an availability of workers. Some occupations, such as 'Roof bolters' and 'Power plant operators', see their demand decrease, but experience a milder overall impact as job growth does occur in their pool of out-neighboring related occupations, meaning the network helps alleviate (part of) the direct negative impact.

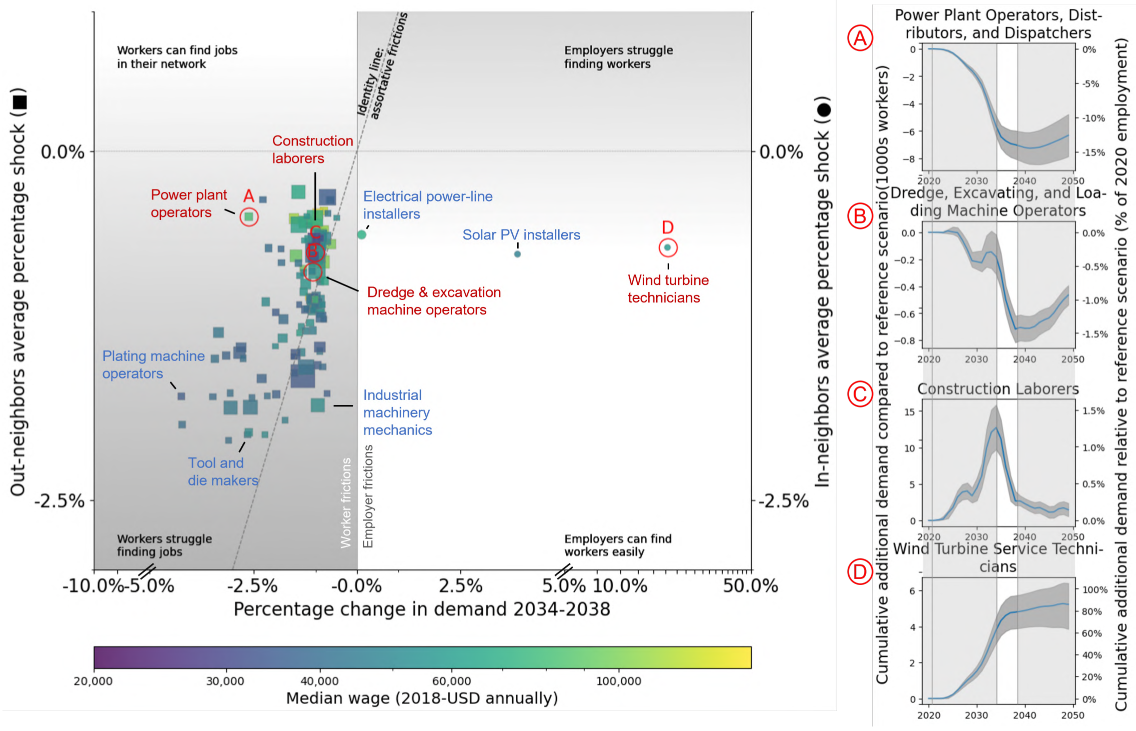


Figure 6: Scatter plot of demand change in the scale-down phase (2034-2038) per occupation (x-axis) and their neighbors (y-axis). The x-axis scale is linear until ±5%, and logarithmic beyond that. If the occupation has a positive (negative) demand change, we average the neighbor demand change over its in- (out-) neighbors. Out-neighbors of occupation α are related occupations of α. In-neighbors of α are occupations for which α is a related occupation. The identity line is plotted, and selected occupations are highlighted. On the right, demand change profiles over time are plotted for occupations highlighted in red. The grey intensity of shading corresponds to more occupational frictions: worker frictions for $x < 0$, employer frictions for $x > 0$.

In the scale-down phase, as shown in Fig. 6, the situation is reversed. In contrast to the scale-up phase, displaced workers in many occupations, excluding the minimally affected, will struggle to find compatible jobs in the scale-down phase. The construction and manufacturing occupations, as well as mining and fossil fuel workers, all see a decline in demand, as well as a decline in demand for occupations with similar skills (that they might be able to transition to).

We find that many of these occupations align along the identity line of assortative frictions, confirming the relatively large assortativity coefficient for the scale-down phase in Table 1. Solar PV installers and wind turbine service technicians still face larger demand increases than demand declines in their neighborhood, indicating potential challenges in filling vacancies in these occupations. This effect is less pronounced in the scale-up phase, but still present. Thus, successfully managing the power system decarbonization will involve policies aimed at supporting workers to switch from other occupations into 'Consistent growth' occupations.

The six occupations most closely related (in-neighbors) to *Wind turbine service technicians* are *Energy engineers*, *Solar PV Installers*, *Power Plant Operators, Distributors, and Dispatchers*, *Pipelayers, Plumbers, Pipefitters, and Steamfitters*, *Installation, Maintenance, and Repair Workers, All Other*, and *Industrial Production Managers*. Using these neighboring related occupations, we can see how Figs. 5 and 6 relate to Fig. 3 and 4. For example, in Fig. 3, wind turbine service technicians are in the 'Consistent growth' quadrant, and Power plant operators in the 'Consistent decline' quadrant. Wind turbine service technicians are part of *Installation, repair, and maintenance* occupations, and Power plant operators are part of *Production occupations* in Fig. 4a, but these two occupations are connected and are placed close together in the network in Fig. 4. Because wind turbine technician is an out-neighbor of power plant operators, and, vice versa, power plant operators is an in-neighbor of wind turbine technicians, they influence each others' y-axis value in Figs. 5 and 6. In particular, the connection between the two occupations increases the out-neighbors average shock to power plant operators, and lowers the in-neighbors average shock to wind turbine service technicians, lowering skill-mismatch frictions for both. Occupations most closely related to *solar PV Installers* are similar to those related to wind turbine service technicians, but, in addition, include *Electricians*, *Broadcast and Sound Engineering Technicians and Radio Operators*, *Construction and Building Inspectors*, and *First-Line Supervisors of Construction Trades and Extraction Workers*.

Beyond 2038, the demand for workers is above pre-transition levels and is relatively stable. Although demand is lower than at the peak of the scale-up phase, there is a net increase with respect to the reference scenario. This increase arises for two reasons. First, grid expansion is ongoing until at least 2050 (SM Fig. 9). Second, the scenario foresees an increase in both capacity and demand for electricity on top of the reference scenario, which increases the overall demand for labor.

In testing the sensitivity of our results to key sources of uncertainty, we find that the employment level in the decarbonized system can change for a number of reasons. Most notably, lower labor requirements in transmission and distribution (e.g., due to higher levels of innovation and automation) could lead to lower employment in the electricity supply chain, almost on par with the no-new-policies reference scenario. For more information, see SM Section D.4.

Discussion and conclusion

The transition to a world powered by renewable energy coupled with storage will involve a significant transformation of part of the labor market. In this work we couple a dynamic IO model with a network analysis of occupational mobility and show that such a transition has the potential to generate significant temporal labor market fluctuations and skill mismatches. In line with previous research, we find more jobs will be created than lost in the US during the initial part of the renewable electricity transition. However, a large fraction of these new jobs will only be required during the scale-up period of the fast transition. The labor market dynamics will change throughout the transition phase until the new stable decarbonized energy system is in place. These dynamics are missed if the scale-down phase and a new stable decarbonized energy mix phase are not included in the time horizon.

In addition to the direct effects on occupational labor demand, we show that there are important secondary effects as related occupations are affected in similar ways. This creates a substantial skill mismatch, especially in later stages of the transition. In the initial scale-up phase, we find the potential for skill shortages that could jeopardize the speed of the transition. In the later scale-down phase we anticipate that related occupations experience similar demand declines, negatively affecting workers' ability to find jobs. Temporal skill mismatches have received limited attention in previous literature, but are important when considering employment impacts of the transition.

Relative to historic fluctuations in the total US labor market, the impact of a fast transition in the electricity supply chain is modest. Our estimates are lower than those of others (e.g., Jacobson et al., 2015; Mayfield et al., 2021; Ram et al., 2022), mainly because our scope is limited to the power sector rather than the entire energy sector. Nonetheless, we conclude the changes might still create difficulties for employers, individuals, and local communities both in the scale-up and scale-down phases. Moreover, as already mentioned, we do not treat regional effects here, which could further exacerbate labor market frictions (Lim et al., 2023).

We identify a fourfold occupational typology based primarily on the scale-up and scale-down phases of the transition. Besides the large group of mostly unaffected occupations, a small number of occupations see a sustained growth in demand, more see a consistent decline, and a large group experiences a temporary rise in demand during the scale-up with an almost equal decrease in demand after the electricity sector reaches its decarbonization target.

The green and brown jobs dichotomy cannot fully capture the temporal dynamics of the electricity sector transition. We find that the occupations that experience only temporary growth do not fit neatly in either category, overlapping with both brown jobs from Bowen et al. (2018) and green jobs from Dierdorff et al. (2009). More specifically, the demand pattern of 'Temporary growth' occupations is similar to 'Consistent growth' occupations for the scale-up phase, but better reflects the pattern of 'Consistent decline' occupations during the scale-down phase. Workers in such occupations will be vital to ensuring the renewable electricity transition happens quickly, but additional care needs to be taken to manage their long-term career trajectories. For such 'Temporary growth' jobs, the initial inflow and especially the outflow of workers later on can cause labor market bottlenecks if not managed carefully.

The NREL rapid transition also involves a non-marginal increase in the demand for three key 'Consistent growth' occupations: solar PV installers, wind turbine service technicians and power line installers. Given that the skills needed for these occupations will be in high demand during the scale-up, it will be important to ramp up training in anticipation of such shortages to avoid bottlenecks slowing down the transition. To find how much the transition may be slowed by such skill shortages, the occupational bottlenecks would need to be coupled with, or incorporated endogenously in the energy-economy model that produces the transition scenario.

Our sensitivity analysis in the Methods and SM Section D.4 discusses the most important assumptions in our model. For example, the continuing cost declines of renewables is an important consideration. We take our projections from NREL's ATB, but recent research using empirically grounded technology learning curves suggests that we might see even more aggressive cost declines for renewables and storage in the future (Way et al., 2022; Creutzig et al., 2023). While cost curves for some technologies are well documented, estimating future cost and labor requirements for grid expansion is challenging due to limited available estimates in the literature. Cost curves affect our labor demand estimates because we assume a fixed ratio of workers per constant-dollar cost. This suggests a cost-breakdown neutral path of innovation where productivity is fixed in monetary units (USD output per worker) but can change in energy units (GW(h) output per worker). We provide here some empirical evidence for why we think this assumption can hold in SM Section C.7 and discuss further methodological assumptions in SM Section B.1.

We have demonstrated an approach that can provide valuable insights into the labor market frictions associated with a major transition, applied to the US power sector. This method is relatively simple, transparent and generic, yet can give granular results. Our approach naturally incorporates cost-reduction forecasts and can be easily extended with more data granularity. In light of the heterogeneous demand trajectory types that we have identified and the need for rapid decarbonization, we conclude that the transition requires enlightened management to minimize skill mismatch for displaced workers and skill shortages in filling vacancies. Our method is sufficiently simple that it can and should be applied regularly as new data and insights on labor market changes become available. Early identification of the potential causes of labor stranding and shortages can enable policymakers to effectively help workers and employers tackle these frictions, thereby making the green transition happen faster and more equitably, and ultimately reduce the levels of harmful greenhouse gases in the atmosphere that future generations must face.

Methods

Resource availability

Correspondence and requests for resources should be addressed to joris.bucker@seh.ox.ac.uk.

Materials availability

This study did not generate any new materials.

Methods approach

We followed a 4-step framework that couples a power transition scenario (step 1) with a dynamic input-output model to estimate upstream impacts (step 2), applying detailed occupational employment data (step 3) and an occupational mobility network (step 4) to assess labor market frictions. The approach is pictured stylistically in Fig. 7, and each of the steps are described in detail below.

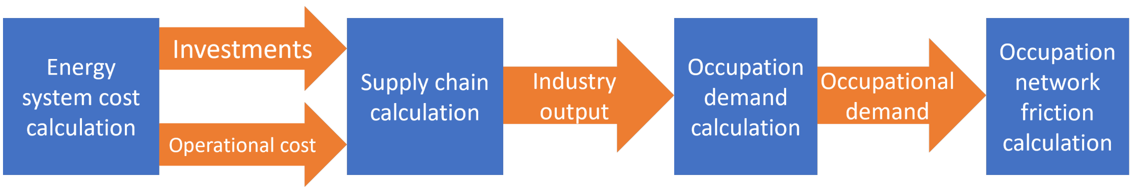


Figure 7: Methodology overview: Our methodology works in four steps. Firstly, we calculate the cost of the power sector decarbonization, both in terms of capacity changes (investments), and electricity production (operational costs) of different technologies. The IO model then calculates the direct and upstream supply chain changes in terms of industry output and, subsequently, demand changes for workers per occupation. Finally, we use occupational networks to calculate skill mismatch and skill shortage frictions.

Step 1: Energy and cost scenarios

The first step in our approach involves quantifying future technology-specific expenses at the industry and country level. We achieve this by incorporating scenarios of future capacity, generation, and unit costs for various detailed electricity technologies as exogenous inputs, which are then aggregated into sectors. For our analysis, presented in the main text, we utilize the exogenous deployment and cost trajectories from the fast decarbonization scenario (95% by 2035) outlined in

NREL's *2021 Standard Scenarios Report: A US Electricity Sector Outlook* (Cole et al., 2021). To focus specifically on the labor impacts of the low carbon transition all of our results are shown as relative to a no-new-policies reference scenario (which is translated into our framework using the same four-step procedure). In SM Section D.1, we present some of the results relative to the year 2020, rather than those relative to the no-new-policies scenario that are shown in the main text.

For each scenario, we map the deployment (capacity and generation) of 19 technologies and unit cost projections of 17 technologies onto 10 electricity generation and supporting sectors (coal, natural gas, biomass, geothermal, hydro, nuclear, solar, wind, battery storage, and transmission and distribution (T&D)), as explained in detail in the SM Section C.2. Since investments and operational expenses affect the input-output model differently (see Step 2 below), we consider disaggregated cost projections, which comprise capital expenditure (capex) and operational expenditure (opex, which consists of variable and fixed opex, and fuel cost). See SM Section B.4 for more details on why we make this cost component disaggregation.

More formally, let $c^j_{i,t}$ denote the unit cost projection of electricity generation technology i of a given cost category j for the year t. We obtain the total annual costs $C^j_{i,t}$ for each cost category as

$$C^{\text{fix opex}}_{i,t} = Y_{i,t} c^{\text{fix opex}}_{i,t}, \tag{1}$$

$$C^{\text{var opex}}_{i,t} = X_{i,t} c^{\text{var opex}}_{i,t}, \tag{2}$$

$$C^{\text{fuel}}_{i,t} = X_{i,t} c^{\text{fuel}}_{i,t}, \tag{3}$$

$$C^{\text{opex}}_{i,t} = C^{\text{fix opex}}_{i,t} + C^{\text{var opex}}_{i,t} + C^{\text{fuel}}_{i,t}, \tag{4}$$

$$C^{\text{capex}}_{i,t} = \max\left\{(Y_{i,t} - Y_{i,t-1} + R_{i,t-1}), 0\right\} c^{\text{capex}}_{i,t}, \tag{5}$$

where $Y_{i,t}$ is the installed capacity of technology i at t in MW, $R_{i,t}$ the retired capital stock in MW and $X_{i,t}$ the generated electricity in MWh. The maximum operator in Eq. (5) avoids negative investment values when total installed capacity declines.[9] Note that capex and fixed opex unit costs are measured in USD per MW, whereas variable opex and unit costs are given in USD per MWh.

Since scenarios generated by power system optimization models can lead to substantial year-on-year fluctuations in installed capacities, we avoid overly erratic job impacts by smoothing the total technology-specific cost estimates using 3-year moving averages. In SM Section D.4, we discuss the impact on our results of removing this smoothing or extending it to a 5-year moving window.

Step 2: Input-output model

In the second step, we feed the investment and cost estimates of the previous step into a demand-driven input-output (IO) framework to calculate the output changes throughout the electricity sector and its upstream supply chain. We consider a standard domestic demand-driven IO model where the total output $x_{i,t}$ of industry i at time t can be described as the weighted sum of final demand $f_{i,t}$ and the intermediate demand of other industries:

$$x_{i,t} = \sum_{j=1}^{n} a_{ij,t} x_{j,t} + f_{i,t}, \tag{6}$$

and in matrix notation:

$$x_t = A_t x_t + f_t. \tag{7}$$

The technical coefficient matrix (also called 'IO table') A with elements $a_{ij,t}$ stipulates the fixed amount of input i required to produce one unit of output j (Blair and Miller, 2009).[10] By defining the Leontief inverse $L_t = (\mathbb{I} - A_t)^{-1}$, and taking the time difference of Eq. (7), we can write

$$\Delta x_t = L_t f_t - L_{t-1} f_{t-1}, \tag{8}$$

which demonstrates that industrial gross output can change over time as a result of changes in final demand (Δf_t) or/and of changes in the IO network (ΔA_t). We model both components explicitly by mapping the investments and operational expenses computed in Step 1 onto the final demand f_t and the IO table A_t, respectively.[11]

[9] Due to data constraints, we calculate opex and capex for battery storage and T&D differently; see SM Sections B.3 and B.2 respectively.

[10] In our study, IO table A and final demand vector f refer to their *domestic* versions. See SM Section B.5 for how we calculate them using the official IO data.

[11] We note two important assumptions. One: the linear demand-driven relationship implies the assumptions of immutable production recipes without substitution and constant returns to scale (Blair and Miller, 2009). However,

Mapping electricity costs to the IO framework

Changes to electricity technology capex from Eq. (5) lead to changes in final demand in the IO framework. Changes to the electricity technology opex in Eq. (4) instead rewire the intermediate expenses. We require that every electricity generation technology is represented as a separate sector in the IO data. In SM Section B.6, we discuss how we disaggregate the energy sector for that purpose.

Capex. Let K_{ij}^{capex} be the the fraction of $C_{i,t}^{\text{capex}}$ (technology i's capex) that is spent on industry j, and let m_i be the fraction of capex that is imported from a foreign industry i.[12] The capex of technology i spent on the domestic industry j is then

$$\widehat{K}_{ij}^{\text{capex}} = (1 - m_j) K_{ij}^{\text{capex}}. \tag{9}$$

The total domestic final demand in industry i due to capex in technology j follows then as

$$f_{i,t}^{\text{capex},j} = C_{j,t}^{\text{capex}} \widehat{K}_{ji}^{\text{capex}}. \tag{10}$$

Summing over all technologies results into

$$f_{i,t}^{\text{capex}} = \sum_j C_{j,t}^{\text{capex}} \widehat{K}_{ji}^{\text{capex}}. \tag{11}$$

We assume all capex is created in the year it comes online, such that the impact on the industry output at time t is

$$\Delta x_t^{\text{capex}} = L_t f_{i,t}^{\text{capex}} - L_{t-1} f_{i,t-1}^{\text{capex}}. \tag{12}$$

Opex. We use the opex in year t to update the base year IO matrix A_{2018} to A_t (with elements $a_{ij,t}$) as follows: industry i's production requirement for electricity generated by technology j is

$$a_{ji,t} = a_{ji,2018} \frac{C_{j,t}^{\text{opex}}}{C_{j,2018}^{\text{opex}}}. \tag{13}$$

We perform a similar shift on the opex part of final demand f_t^{opex} at time t. Final demand at time t for the opex of electricity generation technology j is $f_{j,t}^{\text{opex}} = f_{j,t-1}^{\text{opex}} C_{j,t}^{\text{opex}} / C_{j,t-1}^{\text{opex}}$. We assume here that the final demand for electricity is proportional to the total operational cost, which assumes a fixed and constant markup. The change in output per industry between time $t-1$ and t becomes, following Eq. (8):

$$\Delta x_t^{\text{opex}} = L_t f_t^{\text{opex}} - L_{t-1} f_{t-1}^{\text{opex}}. \tag{14}$$

Total effect of opex and capex. To quantify the total change in sectoral output in a given year, we combine Eqs. (8), (12) and (14) to:

$$\Delta x_t = \Delta x_t^{\text{opex}} + \Delta x_t^{\text{capex}} = L_t \left(f_t^{\text{opex}} + f_t^{\text{capex}} \right) - L_{t-1} \left(f_{t-1}^{\text{opex}} + f_{t-1}^{\text{capex}} \right). \tag{15}$$

Step 3: Modelling occupational demand impacts

We assume that demand for workers per occupation changes proportionally to industry output, i.e. the number of jobs in a given occupation per constant-price USD output of an industry is fixed through time. This means that we allow for proportionally fewer jobs per MW(h) if innovation pushes real prices down. We show in SM Section C.7 some empirical evidence for this proportionality in the solar and wind cost breakdown. In Section D.4 we show how our results depend on the speed of such cost reductions.

Let M be the matrix of workers per output, where M_{ij} is the number of workers in occupation i working for industry j per constant-USD output. We calculate the total demand change Δo_t for workers per occupation between time $t-1$ and t with Eq. (15) as

$$\Delta o_t = M \Delta x_t \tag{16}$$

where $\Delta o_t = [\Delta o_{1,t}, \ldots, \Delta o_{m,t}]$ where each elements $\Delta o_{i,t}$ is the demand change for workers in occupation i between time $t-1$ and t.

as explained further below, we do allow the electricity sector to rewire over time. Two: because our model does not feed how labour wages are spent back into final demand, our analysis does not include the *induced* output effect, but only the output of sectors directly involved in the electricity supply chain. (In other words, it includes the supply side intermediate effects but not changes in consumption demand). See Section B.1 for more details on our scope.

[12] The calculation for m_i can be found in SM Section C.3.

Skills and location quotient We follow (Consoli et al., 2016) for our calculation of skill content per occupation (see SM Section D.2.2). In SM Section B.8 we explain how we calculate the location quotients of occupation-state pairs.

Step 4: Occupational network and frictions

We quantify occupational skill mismatch frictions using measures derived from network science. We will first define the occupation network, then define network-wide assortativity measures, and finally our local neighborhood-friction measure. We are concerned with frictions caused by reallocation of workers between occupations. Any frictions arising from job transitions between industries within the same occupation are not considered, but could be significant if a geographic relocation is required, or industry-specific knowledge is important (Lankhuizen et al., 2022).

Related occupation networks

The related occupation network is a directed network $G(V, E)$ where the nodes V are occupations and the edges E contain a link between occupations i and j if j is a related occupation of i. We construct this network using data on *related occupations* from O*NET (see SM Section A.4 for further details). The network is defined by the adjacency matrix R with items $R_{ij} = RelOcc_{ij} / \sum_j RelOcc_{ij}$, where $RelOcc_{ij} = 1$ if j is a related occupation of i according to O*NET, and 0 otherwise. O*NET determines relatedness between occupations by comparing the similarity in: tasks and work activities, knowledge importance, and job titles (Dahlke et al., 2022). Note that this network is not necessarily symmetric.

Assortativity

We formalize a measure of overall frictions using assortativity. In network science, assortative mixing refers to the inclination of nodes to be connected if they are similar with respect to specific characteristics. We study assortative mixing of the demand change for occupations during the scale-up and scale-down phase, and for the demand trajectory typology we identify in this study.

Assortativity is a network-wide property. We say that a network is assortative if a significant fraction of the edges in the network connect similar nodes, or nodes that are of the same type. In an unweighted network we can compute the assortativity coefficient (Newman, 2018), which is equivalent to a Pearson correlation between connected nodes' attributes. The attributes we are interested in are the demand change, a continuous variable, and our demand trajectory typology, a categorical variable. In our analysis we use weighted continuous assortativity and weighted categorical assortativity, which are extensions to the assortativity coefficient for weighted networks with continuous and categorical variables, respectively. We also define a local node assortativity metric that we use to highlight frictions for individual occupations.

Weighted continuous assortativity We use an extended version of this coefficient for weighted and directed networks; see also Yuan et al. (2021). This gives the following assortativity coefficient $\rho_{s,x}$ between the edge weights s and continuous node value x for a weighted and directed network G:

$$\rho_x = \frac{\sum_{ij}\left(R_{ij} - \frac{s_i^+ s_j^-}{W}\right) x_i x_j}{\sqrt{\sum_{ij}\left(s_i^+ \delta_{ij} - \frac{s_i^+ s_j^+}{W}\right) x_i x_j \sum_{ij}\left(s_i^- \delta_{ij} - \frac{s_i^- s_j^-}{W}\right) x_i x_j}}. \tag{17}$$

where $s_i^+ = \sum_j R_{ij}$ and $s_j^- = \sum_j R_{ji}$ denote the in and out strength (i.e. weighted degree) of nodes i and j respectively, R_{ij} is the weighted adjacency matrix, W the sum of edge strength, and δ_{ij} the Kronecker delta that is 1 if $i = j$ and 0 otherwise. For the unweighted and undirected case we have $s_i^+ = s_i^- = k_i$, the degree of node i, and we recover the standard assortativity coefficient from Newman (2018):

$$\rho'_x = \frac{\sum_{ij}\left(R_{ij} - \frac{k_i k_j}{W}\right) x_i x_j}{\sum_{ij}\left(k_i \delta_{ij} - \frac{k_i k_i}{W}\right) x_i x_j}. \tag{18}$$

Standard errors were obtained on each observation by reshuffling the demand for workers over occupations, while keeping the network structure intact. We reshuffle the shocks 100,000 times and compare our results with the random shocks, and report if the assortativity is larger than 95%, 99%, or 99.9% of the reshuffled values with one, two, or three starts, respectively.

For Table 1 we calculate $\rho_{\sum_{t=2021}^{2034} o_t}$ and $\rho_{\sum_{t=2035}^{2038} o_t}$ using Eq. (17).

Weighted categorical assortativity The categorical assortativity values in Table 1 are calculated with a weighted variety of Eq. 2 in Newman (2003). In Newman's notation, categorical assortativity is

$$r = \frac{\sum_i e_{ii} - \sum_i d_i b_i}{1 - \sum_i d_i b_i}, \tag{19}$$

with $d_i = \sum_j e_{ij}$ and $b_j = \sum_i e_{ij}$, and where e_{ij} is the fraction of all edges that connects a node of type i to a node of type j (Newman, 2003). In our application, with weighted networks, we use Eq. (19) to calculate r but define e_{ij} as the fraction of edge *weights* in the occupational network that connects a node of type i to one of type j, such that

$$e_{ij} = \frac{\sum_{k\in i, l\in j} R_{kl}}{\sum_{kl} R_{kl}}; \tag{20}$$

e_{ij} can be interpreted as the probability that any given occupational transition happened between occupation archetypes i and j. In our application, the types are the occupational groups Temporary growth, Consistent growth, Consistent decline, and all other occupations.

Randomization robustness We run Monte Carlo simulations with randomized shocks to understand the robustness of our estimates. For each value of assortativity we measure, we run 100,000 additional calculations where we keep the network fixed, and assign the attribute values to randomly picked nodes. We highlight results that are greater in absolute value than 99.9%, 99%, or 95% of Monte Carlo runs using three, two, or one star (***, **, *), respectively.

Node-specific frictions Assortativity is a network-wide measure, and might not be informative on individual occupations. For occupation i, it matters what happens in its direct neighbourhood $\mathcal{N}_i = \{j | R_{ij} > 0\}$. We call all jobs in the neighborhood occupations of i the pool of i.

Node-specific frictions arise when the pool of i and i itself are affected in the same way. This borrows from the logic of assortativity. The change in demand in the pool of i at time t is

$$\Delta o_{\mathcal{N}_i,t} = \sum_{j in \mathcal{N}_i} \Delta o_{j,t}. \tag{21}$$

The neighborhood friction $q_{i,t}$ of occupation i is then the weighted average of neighboring occupations demand change:

$$q_i = \frac{\Delta o_{\mathcal{N}_i,t}}{o_{\mathcal{N}_i,t}}. \tag{22}$$

We define two types of node-specific frictions: employer (labor demand) frictions and worker (labor supply) frictions. If both occupation i and its pool experience an increase in demand, it may be hard to find workers to fill all vacancies in i. We call this employer frictions, which can arise even if the pool of i increases but at a slower rate than demand for i decreases. Vice versa, if occupation i and its pool experience a fall in demand, it may be difficult for workers in i to find a new job. We call this worker frictions.

Sensitivity analysis and robustness of results

We do a sensitivity analysis on seven assumptions and data sources. For more details, see the sensitivity analysis results in SM Section D.4. For each sensitivity analysis, we reproduce Fig. 2b in Fig. 21. In Fig. 22a and 22b we plot the cumulative worker demand at the peak (2034) and in the new steady state (2045) respectively. In Fig. 23 we reproduce part of Table 1 and plot the assortativity in the scale-up and scale-down phase for the different assumptions. For each of the assumptions, we also reference which section of the SM discusses the default options.

We probe the following assumptions in our sensitivity analysis:

1. We have assumed (see SM Section B.5) that the input-output network structure does not change in time, i.e., $a_{ij,t} = a_{ij}$. Our sensitivity analysis shows that our results are highly robust with respect to changing this assumption.

2. The capex cost vectors translate how the capital expenditure per electricity technology from the scenario is spent on specific industries in the IO table (see Section C.4). We add noise to the capex cost vectors and find the results robust.

3. The opex literature weights translate how intermediate costs are spent on industries in the IO table. These are used to disaggregate the energy sector in the IO table (see Section C.4). We add noise to the opex cost vectors and find the results robust.

4. The transmission and distribution (T&D) grid line cost are calculated in Section B.2 following the methodology in Way et al. (2022). We test the sensitivity of some parameters and find that these parameters can have a large influence on the results.

5. To remove overly erratic results, we apply a 3-year smoothing window to the energy scenario costs. We also present results without smoothing and with a 5-year smoothing window.

6. We take the employment per occupation-industry pair from BLS and use it to calculate the labor requirements per industry and occupation (see Section A.3). BLS publishes error bars together with the point estimates that we use. We find that our results are robust against using values that are on the extremes of the error bars.

7. We assume unit costs for electricity technologies can change over time according to the ATB cost curves as mentioned in Section C.2. Our default assumption is to use the moderate cost development for each technology. We find that using advanced or conservative cost curves can have a significant impact on the results.

We also do a robustness check of the assortativity values in SM Section D.2.3 for different network types: the original relatedness network, a network of empirical occupational mobility between 2011 and 2019, and a combination of the two.

Data and code availability

We used data from a wide range of sources. Almost all were free and openly available on the internet, but some were accessed via standard university-wide subscription licenses held by the University of Oxford. For more details, see Supplementary Materials Section A. All data will be made available upon request following journal publication (unless legal restrictions exist).

Acknowledgements

This work was supported by funding from the Economics of Energy Innovation and System Transition project (EEIST), which is jointly funded through UK Aid by the UK Government Department for Business, Energy, and Industrial Strategy (BEIS) and the Children's Investment Fund Foundation (CIFF) (J.B., M.C.I., and J.D.F.); Baillie Gifford (J.D.F.); the James S. McDonnell Foundation (A.P. and R.M.dR.C); and the Institute of New Economic Thinking and the Post-Carbon Transitions programme (M.C.I.). The contents of this manuscript represent the views of the authors and should not be taken to represent the views of the UK government or CIFF. The authors gratefully acknowledge all these sources of financial support and, additionally, the Institute for New Economic Thinking at the Oxford Martin School for its continuing support.

Author contributions

Conceptualization, J.B.; methodology, J.B., A.P. and R.M.dR.C.; software, J.B., A.P., R.M.dR.C, and M.C.I.; investigation, J.B. and R.M.dR.C.; data curation, J.B., A.P. and R.M.dR.C.; formal analysis, J.B. and R.M.dR.C; writing—original draft, J.B. and M.C.I.; writing—review & editing, J.B., M.C.I., A.P., R.M.dR.C, and J.D.F.; visualization, J.B., R.M.dR.C, and A.P.; supervision, M.C.I. and J.D.F.; funding acquisition, M.C.I. and J.D.F.

Declaration of interests

The authors declare no competing interests.

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Supplementary Materials (SM)

Contents

A Data

This section discusses the datasets we use in this study. All datasets we use are publicly accessible. We begin with the data on power system scenarios, followed by the supply chain (input-output) data. We then discuss the occupational employment data and the occupational network data. This section is split according to the same four steps as the methods section in the main text.

A.1 Step 1: Energy and cost scenarios

For our analysis we use the NREL's Standard Scenarios[13] which is a widely used set of scenarios based on the US power system capacity expansion models ReEDS (Ho et al., 2021) and dGen (Sigrin et al., 2016). Broadly speaking, these models take the decarbonization pathway as given

[13] https://www.nrel.gov/analysis/standard-scenarios.html

and calculate the power capacities and generated electricity for each technology, obtained via cost minimization. In particular, we focus on two specific scenarios of the main national-level results of the 2021 Standard Scenarios Report (Cole et al., 2021): 1) *No New Policy* and 2) *95% by 2035*. The *No New Policy* scenario assumes no new carbon reduction policies beyond those in place as of June 2021. The *95% by 2035* scenario assumes a 95%-decrease in CO_2e emissions in 2035 compared to 2005, resulting in a reduction from 1750 Mt CO_2e in 2021 to less than 250 Mt CO_2e by 2035. We show the emission pathways in Fig. 8.

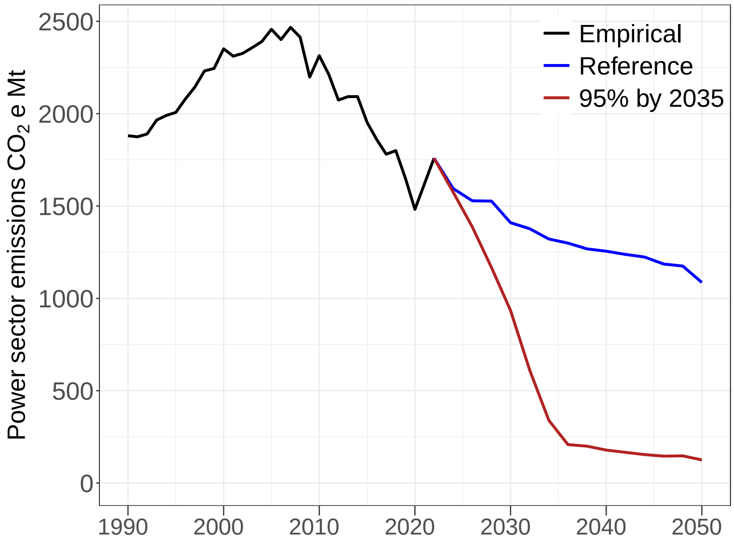

Figure 8: **Annual US power sector emissions in MT of CO_2e.** The black line shows historical power emissions (EPA, 2022), and the blue and red lines, estimated emissions based on the scenarios.

To fit with the rest of the analysis, we aggregate the generation and capacity data to eight electricity generation technologies, plus battery storage and transmission and distribution (T&D). The electricity capacity and generation mix scenarios are shown in the main text and the transmission lines capacity are depicted in Figure 9. In the fast decarbonization scenario, transmission lines are required to grow faster and to higher levels than in the reference scenario.

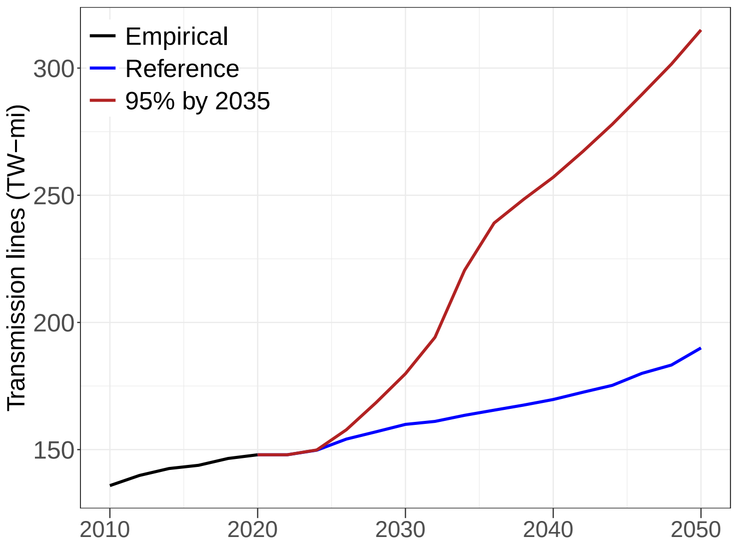

Figure 9: **Transmission lines in MW-mile through time.** Data until 2020 represents historical data; data after 2020 are scenario-specific.

The decarbonization pathways rely heavily on solar and wind. Nuclear and hydro are maintained roughly at their current levels. Coal is phased out, as well as a large portion of natural gas generation, although gas capacity remains fairly constant. Bioenergy and geothermal electricity generation remain small throughout. New generation capacity to deal with growing energy demand also comes from wind and solar, due to their lower cost. The decarbonization scenario manages the increased levels of renewable intermittency from renewables in three ways: increased (battery) storage, a relatively high level of natural gas capacity compared to natural gas electricity generation, and grid expansion.

In the No New Policy reference scenario coal electricity capacity and generation drop – albeit slowly – but natural gas grows over time. The share of renewables also grows, due to their lower cost.

Technology-specific cost projections and capacity factors are based on NREL's Annual Technology Database (ATB).[14] The cost data are broken down into capital expenditures (capex), fixed and variable operational expenditures and fuel costs (opex).[15] Data on unit costs, power capacities, generation and retirement, as well as the input-output data all use different technology aggregation levels. More details on how we harmonize these can be found in Section C.2. See Section D.4 for more information on the sensitivity analysis of the unit cost projections.

The scenarios we consider here are an interesting study case, as they are widely known and allow us to compare a business-as-usual scenario with an aggressive decarbonization scenario of the US power sector. However, it should be pointed out that many possible low-carbon energy mixes are feasible, possibly involving very different sets of technologies (e.g., see Pickering et al. (2022)). Different technology choices would lead to different labor market impacts. Thus, results presented in the main text should not be understood as covering the whole spectrum of labor market impacts of the power sector transition but rather are based on specific future scenarios. The scenarios considered here assume exogenous unit cost projections, although it has been pointed out that energy technology costs develop endogenously, depending on overall deployment (Way et al., 2022). We test the impact of such cost assumptions in Section D.4 but leave a more thorough examination of the effects of endogenous price mechanisms on the labor market for future research.

A.2 Step 2: Input-output model

To estimate the direct and upstream supply chain effects of the changes in electricity technology capex and opex, we use the 2018 US data published by the Bureau of Economic Analysis to construct domestic input-output (IO) tables (Bureau of Economic Analysis, 2022*b*). We remove any imports from the IO table, so that our results only point to US jobs. Vice versa, we assume exports are not affected by the scenarios and remain constant over time. We use the 2018 data to have an estimate of a relatively stable economic situation before the COVID pandemic.[16] See Section B.5 on how we calculate domestic IO tables. We show in Section D.4 that our results are highly robust when using IO tables from different years.

The relevant electricity generation technologies are not separate industries in the official IO tables but are bundled together in the *Utilities* sector. We manually disaggregate the *Utilities* sector into nine electricity generation sectors.[17] We do this partially using the 2012 detailed IO table and partially using literature estimates of the opex cost structure of different electricity technologies. We use additional literature estimates for translating capex changes to final demand shocks. See Section B.6 on our disaggregation approach, Section C.5 for the data used, and Section D.4 for a sensitivity analysis on the literature estimates. Electricity generation outside of the Utilities sector is out of scope, as discussed in Section C.6.

There are alternatives available to the national IO tables that already include several electricity generation technologies, such as the multi-regional IO tables (MRIOs) EXIOBASE and GTAP (Stadler et al., 2018; Aguiar et al., 2023). We chose to work with the national tables for two reasons: 1) the employment data we use from the Bureau of Labor Statistics (BLS) is a natural fit for the BEA data, and 2) The BEA tables are the standard for the US, forming the basis for the US tables of EXIOBASE and GTAP. Those MRIOs are designed for global supply chain analysis, and require further statistical fitting to make the countries' imports and exports aligns. MRIOs also require the additional effort of combining and disaggregating industries to create a uniform dataset.

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[14] https://atb.nrel.gov/

[15] The 2021 ATB gives cost in 2019-USD, which we further deflate to 2018-USD using BEA's GDP deflator (which was 1.8% for 2018-2019: https://www.bea.gov/data/prices-inflation/gdp-price-deflator). Coal and gas fuel cost were absent in the 2021 ATB, so we use the cost estimates from the 2020 ATB, which were already in 2018-USD.

[16] We use 2018 rather than 2019 to leverage the fact that BLS has not yet updated its occupational classification, allowing us a direct comparison with earlier years.

[17] This contains one *Other electricity generation* sector, which we assume to be zero in NREL's scenario.

A.3 Step 3: Modelling occupational demand impacts

We use data from the US Bureau of Labor Statistics (BLS) Occupational Employment and Wage Statistics (OEWS) database (Bureau of Labor Statistics, 2021) to create the industry-occupation matrix B where element B_{ij} is the number of workers of occupation i working in industry j, and $\sum_{ij} B_{ij} = 145$ million, the total size of the US employed labor force in 2018. This is also sometimes called the manpower matrix (e.g. Bezdek, 1973). BLS industry codes are slightly different from BEA industry codes. We manually impute industry-occupation data that is censored in the published tables. We harmonise the datasets using a crosswalk provided by the U.S. Environmental Protection Agency (EPA) (Environmental Protection Agency, 2022). See Section C.8 for more details on the imputation and data harmonization. We use BLS's standard errors on their estimates for a sensitivity analysis on matrix B in Section D.4

Combining B with industry output data x allows us to calculate M_{ij}, the number of workers from occupation i employed in industry j per dollar of output as

$$M_{ij} = \frac{B_{ij}}{x_j}, \tag{23}$$

where x_j is the total output of industry j in 2018-USD.

A.3.1 Occupations

We divide all workers into 539 occupations. We use 2010 SOC codes, which BLS uses for its annual OEWS surveys between 2010 and 2018. This data is available at four aggregation levels: major (22 occupations in the 2018 OEWS), minor (93), broad (455), and detailed (809). To generate the results shown in Fig. 4b we further define eleven high level occupational categories.[18]

Our list of occupations is a combination of broad and detailed occupation categories, generated using the most detailed one-to-one harmonization possible with *OCC* codes, which is a different classification used by the US Census bureau.

As a starting point, we take the list of occupations from a US Census bureau harmonization table of Census *OCC* codes with 2010 SOC codes.[19] We limit ourselves to the codes available in BLS (i.e., excluding military occupations). For more details on the exact mapping between the two datasets, see Section C.9.

A.3.2 Skill data

Data on occupational skills is taken from O*NET 25.0 Data Dictionary.[20] See Consoli et al. (2016) for details.

A.4 Step 4: Occupational network and frictions

We use two datasets on the relatedness between occupations: O*NET's data on related occupations,[21] and an empirical occupational mobility network based on US Census bureau data from IPUMS, following Vom Lehn et al. (2022). We only use the latter to impute missing data in the related occupation network, as explained below, and for robustness testing. For a further discussion on the different occupational networks, see Section B.9.

The Related Occupations network is created using O*NET data and a list of twenty most related other occupations, following Bowen et al. (2018). For each occupation, O*NET lists twenty

[18] The 11 occupational categories are based on the 22 major BLS occupations as follows: Healthcare contains *Healthcare Practitioners and Technical Occupations* and *Healthcare Support Occupations*; Engineering and IT contains *Computer and Mathematical Occupations* and *Architecture and Engineering Occupations*; Life, physical, and social science contains *Life, Physical, and Social Science Occupations*; Education, social services, and media contains *Arts, Design, Entertainment, Sports, and Media Occupations*, *Education, Training, and Library Occupations*, and *Community and Social Service Occupations*; Construction and extraction contains *Construction and Extraction Occupations* and *Farming, Fishing, and Forestry Occupations*; Transportation contains *Transportation and Material Moving Occupations*; Installation and maintenance contains *Installation, Maintenance, and Repair Occupations* and *Building and Grounds Cleaning and Maintenance Occupations*; Other service occupations contains *Personal Care and Service Occupations*, *Food Preparation and Serving Related Occupations*, and *Protective Service Occupations* ; Management and financial includes *Management Occupations*, *Business and Financial Operations Occupations*, and *Legal Occupations*, and Sales and administrative support contains *Office and Administrative Support Occupations* and *Sales and Related Occupations*

[19] https://www.census.gov/topics/employment/industry-occupation/guidance/code-lists.html

[20] https://www.onetcenter.org/dictionary/25.0/excel

[21] https://www.onetcenter.org/dictionary/26.3/excel/related_occupations.html

occupations it is related to. In previous versions of O*NET, this data was called the *career changers matrix*.

Not all occupations are covered by the related occupation network. Occupations whose name contains 'All other' (e.g., *Sales and Related Workers, All Other'*), or 'Miscellaneous' tags (e.g., *'Miscellaneous Financial Clerks'*), are often missing because they are deemed too general. Instead, we impute links for these occupations from the occupational mobility network of observed past mobility.

B SM methods

B.1 Improvement potential of proposed methodology

Our IO model has a few important limitations that are beyond the scope of our research to address. Our results are aggregated to 82 industries and 539 occupations but differences between firms in the same industry (e.g., Ishikawa, 2021) or variation within the same occupation (Saussay et al., 2022; Caunedo et al., 2023; Atalay et al., 2020) can be obfuscated by our level of aggregation. For example, we did not separate metal mining from coal mining.[22]

As mentioned before, changes in labour demand and their associated wages and how differently workers spend them do not feed back into final demand in our model specification. Our results therefore include direct and indirect upstream supply chain jobs, but not *induced* jobs. Induced jobs are created when increased employment or higher wages lead to more spending by workers, which in turn further increases economic demand, creating more jobs. Stavropoulos and Burger (2020) argue that studies that include induced jobs often report lower overall job growth for the energy transition.

Also out of scope for this research effort are the capital goods used in the electricity capex supply chains that are not part of the final electricity mix. For example: the operation of oil platforms, pipelines, and oil tankers is part of the analysis, but not the construction of these secondary capital goods. I.e., workers on the opex side of these operations (oil rig staff, pipeline controllers, and oil tanker sailors) are part of this analysis, but not the welders on the shipyards, or the ground clearance construction worker for a pipeline project. This is a consequence of the exclusion of capex in IO tables and national accounts data, and may underestimate the total job estimates in this study (Södersten and Lenzen, 2020).

Additionally, out of scope for this research are both opex and capex impacts from transition related projects outside the electricity sector, such as in automotive (e.g. batteries for electric vehicles), or heating (e.g. heat pump installation or other building climate control equipment).

As mentioned in the introduction, our study also disregards geographical effects. In previous studies, these have been taken into account by disaggregating Input-Output tables (Kahouli and Martin, 2018), or by using firm level supply chain data (Ishikawa, 2021; Kahouli and Martin, 2018). Our model also leaves out the effect of potential wage changes, including the *green premium* (for a discussion on the green wage premium, see, e.g., Antoni et al., 2015; Saussay et al., 2022), and changes beyond the power sector. We also assume an unchanged economic structure and policy landscape, where only the electricity mix changes. Changing effects and policies regarding manufacturing on-shoring, automation, and aging will undoubtedly impact the results of our analysis, either directly (e.g., more wind turbine components are manufactured domestically), or indirectly (e.g., aging will require more health care staff), which potentially changes the skill mismatch frictions in the labor market. Automation, in particular, could generate important changes to labour markets and the nature of work (see, e.g., Acemoglu and Restrepo, 2019; Atalay et al., 2020; Frey and Osborne, 2017). All such changes can exacerbate or reduce the direct and indirect impacts presented in this study. Further research into how all aspects of a fast green transition can best be managed while minimizing disruptions to the labor market might be worthwhile. The methods we have employed here are sufficiently general that they could be applied to such analyses or virtually any mix of labor transforming trends, in the US and elsewhere.

B.2 Transmission and Distribution cost calculation

NREL reports transmission line capacity T_t (in MW-mile) in year t, but not their associated capex or opex costs. We follow the methodology of Way et al. (2022) for transforming MW-mi into

[22]The mining industry will undergo an eventual decline during the transition due to lower fossil fuel use, but will receive a boost in our analysis from increased demand for the materials that are required for clean energy technologies sourced within the US.

capex, and assume opex scales linearly with the equipment capital new-value. Way et al. (2022) assume that additional electricity distribution requirements can partially be met by increasing the capacity of lines on existing grid infrastructure. As the grid requires more capacity, we assume old grid infrastructure is replaced with lines that carry three times the capacity of the old ones, for 1.37 times the capex of *standard* transmission line cost. That means that for every 100 MW-mi of grid expansion, 50 mile of existing grid is replaced with lines that are three times as powerful (see p. 44 supplementary information of Way et al., 2022). Unit costs used in our study are based on an NREL study showing average transmission line project costs of 1,384 USD (Jorgensen et al., 2017, Table 4) (1,433 2018-USD).[23]

We include changes to both the transmission and distribution grid (T&D), although NREL does not model the latter. We follow Way et al. (2022) by inferring from IEA data that between 2010–2019 about 69% of all US grid investments were on distribution grids, while 31% were on transmission grids (IEA, 2022). Since this 69/31-ratio remained fairly stable in the 2010s, we assume the same investment ratio for the future.

Thus, grid capex spending is given by:

$$C^{\text{capex}}_{\text{T\&D},t} = T_t/2 \times 1.37 \times 1433 \times (100/31), \tag{24}$$

where T_t is the amount of new transmission capacity in MW-mi, $T_t/2$ the number of miles of old transmission grid that are upgraded, $T_t/2 \times 1.37 \times 1433$ the cost of upgrading to three times as powerful lines in 2018-USD, and (100/31) the factor to account for the distribution grid too. As with the generation technologies, we smooth the capex spending using a 3-year rolling window.

Similarly, we assume opex scales with the new-cost of the transmission grid capital stock, in particular

$$C^{\text{opex}}_{\text{T\&D},t} = C^{\text{fix opex}}_{\text{T\&D},t} \propto 1.00 \times (T_0 - (T_t - T_0)/2) + 1.37 \times (T_t - T_0)/2, \tag{25}$$

where the first part relates to the old part of the grid, and the second to the new upgraded part. We assume T&D's variable costs to be zero: $C^{\text{var opex}}_{\text{T\&D},t} = 0$.

In Section D.4, we test the sensitivity of our results with respect to the unit cost assumption, as well as the 1.37 factors for capex and opex, and find that T&D cost uncertainties to be one of the largest sources of uncertainty in our analysis.

B.3 Battery cost

We cannot include battery storage as a technology in our IO table because it is not part of the electricity sector NAICS 2211. In fact, there is not a NAICS code (yet) for grid-scale battery storage facilities. We add battery storage opex workers to our results via *capex*, following the final demand approach as laid out in Blair and Miller (2009) (see Section B.4). We assume all battery storage opex is fixed and represents maintenance and replacement costs. We assume the spending breakdown of battery storage opex is the same as used for battery storage capex. We justify this on two battery cost breakdown analyses, which report that battery opex work is often mainly replacement maintenance that has a similar breakdown to newly manufactured and installed capex (Feldman et al., 2021; Black & Veatch, 2012). Instead of Eq. (5), we take

$$C^{\text{capex}}_{\text{battery},t} = C^{\text{pure capex}}_{\text{battery},t} + C^{\text{fix opex}}_{\text{battery},t}, \tag{26}$$

where $C^{\text{fix opex}}_{\text{battery},t}$ follows Eq. (1), and

$$C^{\text{pure capex}}_{\text{battery},t} = \max\left\{(Y_{\text{battery},t} - Y_{\text{battery},t-1} + R_{\text{battery},t-1}), 0\right\} c^{\text{capex}}_{\text{battery},t} \tag{27}$$

is similar to Eq. (5), and $C^{\text{var opex}}_{\text{battery},t} = C^{\text{fuel}}_{\text{battery},t} = 0$.

B.4 Differentiation between capex and opex

In our methodology we treat opex and capex costs separately, despite the overhead this creates. We do this for three reasons. Firstly, fossil fuel technologies and renewables have very different cost structures: renewables often require more capex and less opex. Secondly, the distinction between the two costs matters for workers. Opex employment is generally stable and required for the duration of electricity generation. Capex work is often only available before electricity generation can start (and later during capital goods replacement). Their occupational profiles are different too.

[23] We use the BEA price index for private fixed investment in power and communication structures (T50304).

Thirdly, input-output frameworks naturally treat opex and capex differently. Capex mutations can be modelled as a change in investment, a final consumption category. Opex mutations require a modification of the intermediate expenses matrix. Blair and Miller (2009) indicate two potential routes for dealing with new industries that are not yet encapsulated in the IO data: A complete inclusion in the technical coefficient matrix (p. 636), or the final-demand approach (p. 634). The final-demand approach has the advantage of requiring fewer data inputs. A disadvantage is that only backward upstream links are included, and no downstream effects. A further caveat is that most of the electricity generation sectors are not completely *new*, as these operational expenses (opex) are partly already included in the existing *Utilities* sector. For these reasons, we decided to follow the final-demand approach for capex, and for opex we split the utility sector in the IO table into several electricity generation technologies. The exception is battery storage opex, for which we follow the final demand approach, as was explained in Section B.3.

B.5 Domestic input-output tables

This section provides an explanation of how we calculated the domestic production network matrix A. Matrix A is calculated using US domestic make and use tables from BEA at the summary (71 industries/commodities) level. Elements $a_{ij}; i, j \leq n$, represent the value of goods from domestic industry i required to produce one dollar output for industry j.

We derive the domestic IO table A and domestic final demand vector f, which we use in Eq. (6), following the official BEA derivation calculations,[24] and proceed as follows:

Make and use tables The symmetric *use* matrix U has elements U_{ij}: the value in USD in 2018 used of commodity i in the production of industry j. The *make* matrix V has elements V_{ij}: the value in USD in 2018 created of commodity i by industry j. Let W be the part of U that is imported, with W_{ij} the value in USD of commodity i that is imported for the production of industry j. The vector g is the total industry output for the US (g_i is the 2018 USD output of industry i), and q the total commodity output. The total amount of imports used in industry j is $w_j = \sum_i W_{ij}$.

Scrap and noncomparable imports In addition to the commodities associated with its 71 industries, the BEA data contains two more commodities, *Scrap, sed, and secondhand products* h, and *Noncomparable imports and rest-of-the-world adjustment* i. For both we have three vectors (use, make and import per industry), respectively h^u, h^v and h^w, and i^u, i^v, and i^w. We add the noncompareable imports to the total amount of imports per industry $\tilde{w}$ with elements $\tilde{w}_j = w_j + (i^u_j - i^w_j)$.

Market share matrix The same commodity can be produced by different industries. The *market share* matrix $D = V\hat{q}^{-1}$ has elements D_{ij} that give the share of industry i in producing commodity j, where $\hat{q}$ indicated a diagonal matrix with the elements of vector q along the diagonal.

Next, we adjust the market share matrix for scrap. Let p be the industry scrap adjustment vector with elements $p_i = g_i/(g_i - h^v_i)$, which is larger than 1 if industry i produces scrap. The adjusted market share matrix $\tilde{D}$ leaves out scrap; each element $\tilde{D}_{ij}$ gives the market share of industry i in commodity j, excluding scrap production, as $\tilde{D}_{ij} = p_i D_{ij}$.

Domestic industry by industry spending and recipe matrices The domestic industry-by-industry matrix $\tilde{Z}$ can be found by multiplying the domestic use matrix $\tilde{U} = U - W$[25] with the market share matrix

$$\tilde{Z} = \tilde{D}\tilde{U}. \tag{28}$$

In the final step, we add a row with total imports to get the domestic production network including imports

$$Z = [\tilde{Z}; \tilde{w}]. \tag{29}$$

Thus, Finally, the domestic IO table is

$$A = Z\hat{g}^{-1}. \tag{30}$$

[24](See chapter 12 of the BEA IO manual https://www.bea.gov/sites/default/files/methodologies/IOmanual_092906.pdf) as well as the domestic requirements derivation as per https://apps.bea.gov/scb/pdf/2017/03%20March/0317_introducing_domestic_requirement_tables.pdf

[25]To maintain the same total amount of use in the absence of scrap, we inflate the columns of $\tilde{U}$ proportionally with the amount spent on scrap by each industry.

Domestic final demand The domestic final demand follows analogously. Let F_c be the final commodity demand matrix, with $F_{c,ij}$ the final demand in 2018-USD for commodity i by final demand category j. Different categories of final demand can include *household spending*, *government spending*, and *exports*. Let F_c^W be the final demand that is spent abroad, and $\tilde{F}_c = F_c - F_c^W$ the domestic final demand per commodity (including exports). The domestic final demand per industry F with F_{ij} the final demand in 2018-USD for goods from industry i by final demand category j is then

$$F = \tilde{D}\tilde{F}_c. \tag{31}$$

We can sum over the categories to find the total domestic final demand vector f with elements $f_i = \sum_c F_{ic}$ of domestic final demand for industry i.

B.6 Electricity sector disaggregation in the US IO tables

In order to model the power sector transition, we disaggregate the generic utility sector in the IO matrix A, as calculated in Eq. (30), into different electricity generation sectors and other utilities. This requires additional input from BEA's 2012 detailed (389 industries) US IO table and literature estimates on production inputs (see Section C.4). We also use BEA data on detailed industry output in 2018, which includes several electricity generation sectors. We do not include battery electricity storage as it has not been part of the BEA utility industry. We add it via the final demand approach as explained in Section B.3.

While we add different electricity generation sectors in our IO matrix, the IO table totals must remain internally consistent. We use a bi-proportional method-based technique to ensure this. Blair and Miller (2009, sect 7.4.7) discuss this method in the context of projecting IO tables forward in time when only aggregate data was available. Our problem can be dealt with in a similar fashion. But rather than an outdated matrix we use literature estimates of disaggregated sectors.

This section lays out the IO table disaggregation procedure, and Section C.5 then demonstrates how we apply it to the US utility sector.

B.6.1 IO industry disaggregation procedure

Recall the IO matrix A represents the production network. We call the i^{th} columns of A the production recipe of industry i. The j^{th} row of A shows the fraction of spending of other industries on industry i. We call these rows output recipes.

New industries Let A^* be the IO matrix with industry i disaggregated into m sub-industries $(i_1, \dots, i_m)$ with element $A^*_{i_k,j}$ the amount of industry i_k's goods required to produce one 2018-USD of output of industry j, with $k \leq m; j \leq n$. The output of sub-industry i_k as a fraction of i's total output w_k such that $\sum_k w_k = 1$.

Following Lindner et al. (2012),[26] the subsequent constraints need to be satisfied:

a) The sub-industries' production recipes should sum to the original production recipe:

$$\sum_{k=1}^{m} w_k a^*_{ji_k} = a_{ji} \quad \forall j \tag{32}$$

b) The output recipes of the sub-industries should sum to the output recipe of industry i:

$$\sum_{k=1}^{m} a^*_{i_k j} = a_{ij} \quad \forall j \tag{33}$$

c) Any intermediate flows between the sub-industries should sum to the self-link of the original industry:

$$\sum_{k=1}^{m} \sum_{k'=1}^{m} w_k a^*_{i_k i'_k} = a_{ii} \tag{34}$$

In addition, we require the following two regularization constraints to hold:

d) All items of A^* should be non-negative: $a^*_{ij} \geq 0$

[26] Equations 6-8

e) Total output should equal intermediate spending plus value added. The production recipes should sum to $\sum_j a^*_{i,j} = \alpha_i \leq 1$, where $\alpha_i + \beta_i = 1$ with $\beta_i = \frac{\text{value added}_i}{x_i}$ the fraction of value added of output of industry i.

Let us assume that we have an approximation of the production recipes D of the m sub-industries of industry i where element $d_{j,k}; k \leq m, j \leq n$ is the approximation of the value of goods required from industry j for one dollar of output of sub-industry k. While the approximate recipes could be imputed directly in A to create A^*, they are unlikely to satisfy the aforementioned constraints.

We use an iterative bi-proportional fitting method that fits the initial estimates in the larger table such that it respects the aforementioned constraints.

Iterative proportional fitting procedure We use bi-proportional fitting, also known as the 'RAS method', as a heuristic to find a matrix D^* which is closest to an initial matrix D but has the row and column total of a target matrix A (Blair and Miller, 2009; Stephan, 1942). Matrix D^* is then used as a proxy for A, whose interior is unknown. The fitted matrix is of the form $D^* = PDQ$ where P and Q are diagonal matrices.

Most algorithms to find D^* are iterative, adjusting P and Q successively until convergence, called iterative proportional fitting (IPF).

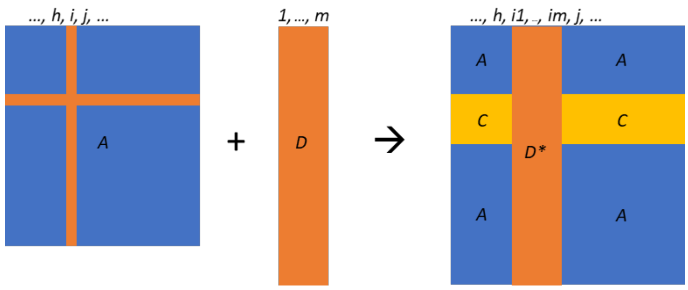


Figure 10: ipfp procedure, with production network matrix A on the left, the new recipes matrix D in the middle, and the new production network matrix A^* with industry i disaggregated into m sub-industries on the right

Our IO disaggregation procedure has the following steps (see also Fig. 10):

1. We identify the production recipes $1, \ldots, m$ that will take the place of the original production recipe i (matrix D in Fig. 10)

2. We insert a set of new output recipes $i_1, \ldots, i_m$ by splitting the original output recipe i; we split it proportional to the fraction of output attributed to each of the sub-industries $1, \ldots, m$. This refers to area C in Fig. 10 and satisfies constraints *b, d* and *e* above for the non-disaggregated industries. We assume that all industries are agnostic about the source of electricity, and consume electricity as per the average grid mix.

3. We apply IPF to fit the new recipes in D with two constraints: The columns sum to the fraction of output that we attribute to intermediate demand (constraint e above), while the rows sum to the original production recipe (constraint a above). We then replace production recipe i with these new values. This refers to area D^* in Fig. 10. The new production recipes of the disaggregated industries now satisfy constraints *a, d* and *e* above, and the self-links satisfy constraint *c*.

4. We combine the new production recipes, output recipes and self-links with the original input-output matrix to create the new input-output matrix.

B.7 Occupational typology

In this section, we formalize the definition of occupational typology, and present an alternative method for robustness checks. We classify occupations into four types according to their demand dynamics in the scale-up and scale-down phases (see Fig. 3).

Occupation i has a change of demand between 2020 and 2034 of $\dot{o}_i^{\text{up}} = (\sum_{t=2021}^{t=2034} \Delta o_t)/o_{i,2020}$, and, similarly, $\dot{o}_i^{\text{down}} = (\sum_{t=2035}^{t=2038} \Delta o_{i,t})/o_{i,2020}$. If $\sqrt{(\dot{o}_i^{\text{up}})^2 + (\dot{o}_i^{\text{down}})^2} < 0.01$ we conclude occupation i is not markedly affected. In all other cases, we assign the occupations to the three different types as follows:

$$i \in \text{Consistent growth if } (\dot{o}_i^{\text{up}} > 0) \wedge (\dot{o}_i^{\text{down}} > 0) \tag{35}$$

$$i \in \text{Temporary growth if } (\dot{o}_i^{\text{up}} > 0) \wedge (\dot{o}_i^{\text{down}} < 0) \tag{36}$$

$$i \in \text{Consistent decline if } (\dot{o}_i^{\text{up}} < 0) \wedge (\dot{o}_i^{\text{down}} < 0), \tag{37}$$

Alternative typology definition Our alternative definition is based on the idea that all occupations can be part of multiple 'occupation types' to a certain degree, depending on how the actual values of demand increase and decrease over all industries in which workers are employed in that occupation. We will say that a fraction of jobs in a particular occupation can be part of type α, and a second fraction to type β etc. Let us define the following quantities for occupation i, which calculate the total positive impact $o_{i,+}$ and total negative impact $o_{i,-}$ on demand for occupation i through the scenario between 2020 and 2050:

$$o_{i,+} = \sum_{t=2021}^{t=2050} M_{ij} \max(0, \Delta x_{t,j}), \tag{38}$$

and

$$o_{i,+} = -\sum_{t=2021}^{t=2050} M_{ij} \min(0, \Delta x_{t,j}), \tag{39}$$

where $\Delta x_{t,j}$ is the change in industry j's output in year t, and $M_i j$ the number of workers in occupation i per USD-2018 output of industry j.

The number of *Consistent Growth* jobs in occupation i is

$$o_{i,\text{perm}} = \max(0, o_{i,+} - o_{i,-}). \tag{40}$$

Jobs classified as *Consistent Decline* are jobs that are lost in shrinking industries that did not recover. The number of *Consistent Decline jobs* in occupation i is

$$o_{i,\text{decline}} = -\min(0, o_{i,+} - o_{i,-}). \tag{41}$$

Temporary growth jobs are jobs created by industries that are phased out after the transition reaches its zenith. The number of *Temporary growth* jobs in occupation i is

$$o_{i,\text{temp}} = o_{i,+} - o_{i,\text{perm}}. \tag{42}$$

The fraction of occupation i that is part of type α is then $f_i^\alpha = \frac{o_{i,\alpha}}{o_{i,2020}}$. Our alternative, three dimensional, type definition of occupation i is then given by $f_i = (f_i^{\text{perm}}, f_i^{\text{temp}}, f_i^{\text{decline}})$.

B.8 Occupational typology location quotients

The location quotient of occupation i in state β is the occupation i's share in state β's workforce relative to the US as a whole. Specifically, we define

$$\text{LQ}_{i,\beta} = \frac{o_{i,\beta} / \sum_{i \in \text{Occupations}} o_{i,\beta}}{\sum_{\beta \in \text{States}} o_{i,\beta} / \sum_{i \in \text{Occupations}} \sum_{\beta \in \text{States}} o_{i,\beta}} = \frac{o_{i,\beta}/o_\beta}{o_i/o}, \tag{43}$$

with $o_{i,\beta}$ is the total number of workers in occupation i in state β, and o_β the total number of workers in state β, o_i the total number of workers in occupation i, and o the total number of workers in the US. In Fig. 16 we plot the mean location quotient for all occupations per type.

B.9 Occupation network choice

The occupational network reflects the options workers have outside their current occupation. There are different reasons why workers would change their occupation, including wage and career progression considerations, preferences for specific job tasks, location and travel requirements, and perceived status (Nedelkoska et al., 2018; Hollywood, 2002; Schmutte, 2014; Neffke et al., 2022). We therefore considered multiple options for measuring relatedness between occupations. Besides O*NET's relatedness measure, there are empirically observed mobility networks, and networks based on tasks or skills. We will introduce each of these approaches and weigh the pros and cons of our chosen approach against the alternatives.

Relatedness network As explained in the Methodology section, the network we use for the main results is based on O*NET's classification of related occupations (previously known as the *career changers* matrix) and is defined by adjacency matrix R.

Empirical occupational mobility network Empirical occupational mobility networks infer the likelihood of transitioning between occupations from empirical job mobility data, such as census data or surveys. Del Rio-Chanona et al. (2021) construct an occupational mobility network from US census data to inform an agent-based labour market model. Vom Lehn et al. (2022) use data from the Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS) (Flood et al., 2021) that takes part every year in March. Participants are asked about their current occupation and their occupation the previous year. In this way, the ASEC supplement reduces errors in the estimation of occupational mobility due to misclassification (Cheng and Park, 2020).

Following Vom Lehn et al. (2022), we construct an occupational mobility network for 2010–2019 with adjacency matrix A^{OMN}. Edges in the occupational mobility network are weighted and directed – the weight of an edge from occupation i to j is the average number of workers per year that changed from occupation i to j between 2010 to 2019 (inclusive). We only include occupations that presented transitions between 2010 to 2019. This leads to a strongly connected network with 539 nodes.

Skill-based networks Links between nodes can also be informed by the skill difference between occupations, or other job characteristics, directly. For example, Anderson (2017) pulls skills data off an online work platform and shows which skills lead to higher wages for individual workers. Workers with diverse skills that are in high demand but short supply are especially valuable. Mealy et al. (2018) construct a network where occupations are more strongly connected if they perform the same tasks.

Combined network We define a combined network using both O*NET's Relatedness Occupation data and the empirical occupation transitions data following Vom Lehn et al. (2022). We define the mixed 50/50 network with the adjacency matrix

$$A^{\mathrm{mix50}} = \frac{R + A^{\mathrm{OMN}}}{2}, \tag{44}$$

where R and A^{OMN} are the adjacency matrices defined by O*NET's related occupation list and the empirical occupational mobility network, respectively.

Pros and cons of our approach vs alternatives We chose to present our main results using O*NET's relatedness network because it attempts to capture various reasons for relatedness in one metric, and it is intended to be forward-looking. A relatedness measure that is based on the skill or task difference between occupations captures an important factor that may induce or inhibit a worker from moving into a particular occupation but neglects other aspects of the decision. Mealy et al. (2018) find that task similarity is a significant exploratory variable for empirical occupational mobility, although with a lot of variation left unexplained. This type of relatedness measure may represent an upper limit of mobility: if workers are willing to relocate or take a pay cut in a disruptive situation, their skill set may still inhibit them from getting a job.

Empirical occupational mobility networks have the advantage that they combine all job-switching considerations by measuring occupational mobility directly. A downside is that economic factors of the period in which the data was gathered can influence the results. For example, if the financial sector saw a decline in activity, fewer workers would be observed moving into financial occupations, even if many more would take up such a job were the economic situation different.

A further, more practical, limitation of the empirical occupational mobility network is that some occupations that are relevant to the transition have not existed for very long, such as wind turbine technicians and solar panel installers. Indeed, we were only able to observe a handful of transitions in and out of those occupations, which leads to noisy results.

In Methods and Section A.4 we discuss the occupational network built using O*NET's list of *related* occupations. O*NET's Related Occupation list was constructed using different data sources, including expert opinions, and is meant as a forward looking measure. For this reason we decided to use this network for our main analysis. A downside is that it is an ad-hoc list that contains some arbitrariness and may not fully reflect reality; for example, each occupation that is included has 20 related occupations, but it is not clear why every occupation should have exactly 20 related occupations.

In the robustness test for assortativity in Section D.2.3, we show that our main results using the relatedness network hold when we use the empirical occupational mobility network or the 50/50 combined network instead.

C Supplementary data

C.1 Summary of data used in this study

The data relevant for our methodology can be visualised as a two-layer network of connected industries and occupations, as can be seen in Fig. 11. In total it includes 82 industry nodes and 539 occupation nodes and their connections. The full data set consists of a combination of this bipartite network of occupations and industries, the IO network of industries, and the occupational mobility networks described in the preceding sections.

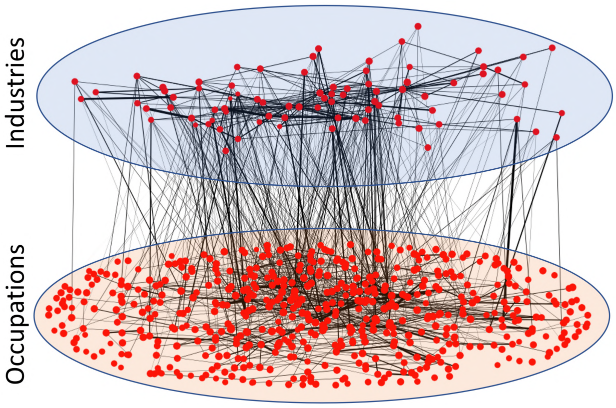


Figure 11: Two-layer network of US industries and occupations showing input-output relationships between the 82 industries of the BEA IO tables (top), occupational relatedness between 539 occupations as defined by O*NET (bottom), and connecting occupational employment by industries according to data from the BLS (inter-layer connections). Nodes are sized by the log of total industrial output or total employment; a link's width is determined by the strength of its connection. The layout is produced by a force-directed algorithm that tends to move connected industries and occupations close together, and then we manually split the industry and occupation nodes into two layers.

C.2 Matching of technologies and industries

In our analysis we combine several large datasets which comes with the challenge of aligning different definitions of technologies and industries across these datasets. We take the unit costs for various power technologies from NREL's 2021 Annual Technology Baseline (ATB) (NREL, 2021). Technology costs are further separated into capital expenditure, fixed and variable operational expenditure, and fuel costs. Since no fuel costs for gas and coal are reported in the 2021 ATB version, we have used the 2020 ATB costs for these cases. For all technologies we have used the *moderate* future cost pathways which are consistent with the power sector scenarios considered here.

As can be seen in Table 2, there is not always a clear one-to-one mapping between the ATB technologies and the capacity and generation technologies from NREL's Standard Scenarios from (Cole et al., 2021). The cost data tends to be much more granular for most technologies but does not include all technologies that are reported in the Cambium scenarios (e.g. Oil-Gas-Steam or Bioenergy with carbon capture).

Our results in the main text are based on input-output industries where we disaggregate 10 key energy technologies (see Section C.5). We thus have to further aggregate the more granular cost and power system scenario data. The mappings between the technology definitions of the various datasets are described in detail in Table 2. We also used annual capacity retirement data which we have obtained via personal correspondence with authors of the Cambium report.

The NREL scenarios include both utility and distributed electricity generation and capacity, but the other data sources (BLS and BEA) only include utility-scale establishments. Contrary to other generation technologies, distributed solar can be a significant contribution to solar electricity total production. We therefore add distributed solar to the solar IO industry as: $a_{\text{solar},i,t} = a_{\text{solar},i,2018} \times \frac{C^{\text{opex}}_{\text{solar util},t}}{C^{\text{opex}}_{\text{solar util},2018}} \times \frac{C^{\text{opex}}_{\text{solar util},t}+C^{\text{opex}}_{\text{solar dist},t}}{C^{\text{opex}}_{\text{solar util},t}}$, and equivalently for $f_{\text{solar},t} = f_{\text{solar},t-1} \times \frac{C^{\text{opex}}_{\text{solar util},t}}{C^{\text{opex}}_{\text{solar util},t-1}} \times \frac{C^{\text{opex}}_{\text{solar util},t}+C^{\text{opex}}_{\text{solar dist},t}}{C^{\text{opex}}_{\text{solar util},t}}$.

ATB Technology	ATB Technology Detail	Cambium technologies	IO
Utility-Scale Battery Storage	4Hr Battery Storage	battery	Batteries
Biopower	Dedicated	beccs	Bio
Biopower	Dedicated	biomass	Bio
Coal_FE	newAvgCF	coal	Coal
NaturalGas_FE	CCAvgCF	gas.cc	Gas
NaturalGas_FE	CCCCSAvgCF	gas.cc.ccs	Gas
NaturalGas_FE	CTAvgCF	gas.ct	Gas
NaturalGas_FE	CTAvgCF	o.g.s	Gas
Geothermal	HydroFlash	geothermal	Geo
Hydropower	NPD1	hydro	Hydro
Nuclear	Nuclear	nuclear	Nuclear
Pumped Storage Hydropower	Class 3	phs	Hydro
CSP	Class3	csp	Solar
ResPV	Class5	distpv	Solar
CommPV	Class5	distpv	Solar
UtilityPV	Class5	upv	Solar
LandbasedWind	Class4	wind.on	Wind
OffShoreWind	Class3	wind.ofs	Wind
-	-	Transmission grid	T&D

Table 2: **Matching technologies across different datasets.** The left column represents the ATB technologies which are further differentiated into **detailed** categories (second column). We refer to NREL (2021) for further details on these technologies. The third column gives the technological detail of the NREL Cambium Standard Scenarios as they can be downloaded from `https://scenarioviewer.nrel.gov/` (accessed: September 21, 2022). The fourth column shows the input-output energy categories. ATB cost estimates for transmission and distribution (T&D) are not available: see Section B.2 for details on how we deal with that.

C.3 Domestic capex spending

We only include the capex that is spent domestically. As mentioned before, we use the domestic IO tables to restrict our analysis to US domestic employment (including both direct and indirect jobs) for different electricity generation technologies. However, part of the capex cost can be spent abroad directly and thus never enter the domestic IO table. In Eq. (9) we defined m_i as the fraction of goods produced by industry i that are imported rather than sourced domestically. We calculate m_i using the 2018 BEA use and import table (Bureau of Economic Analysis, 2022*b*). Recall from Section B.5 that the use table U has elements U_{ij} that are the use of commodity i by industry j, and the import part of that is matrix W where W_{ij} is the value of commodity i that is imported by industry j. The market share matrix D has elements D_{ij} that give the share of industry i in producing commodity j.

The total industry-to-industry spending matrix is $Z^{\text{tot}} = DU$, of which the import part is $Z^{\text{imp}} = DW$. The total fraction m_i of spending on industry i that is imported is then

$$m_i = \frac{\sum_j Z^{\text{imp}}_{ij}}{\sum_j Z^{\text{tot}}_{ij}}. \tag{45}$$

How much is spent on the domestic industry differs per industry. Table 3 shows the top and bottom 3 industries by import percentage m in 2018 are shown. For example, 66% of goods acquired from the *Electrical equipment, appliances, and component* industry, and about half of those from the *Computer and electronics* industry were imported in 2018. We assume that these fractions remain constant at 2018 levels. However, recent policy discussions and policies, such as the Inflation Reduction Act and CHIPS and Science Act, indicate that the US is keen to produce more of its own demand domestically (The White House, 2022).

Industry	Imports for use in other industries, as percentage of total intermediate demand
Apparel and leather and allied products	69
Electrical equipment, appliances, and components	56
Computer and electronic products	49
...	...
Construction	0
Wholesale trade	0
Management of companies and enterprises	0

Table 3: Most and least three imported from industries by domestic production of intermediate use in 2018

C.4 Cost vectors for opex and capex

The link between the energy technologies and IO industries are the cost vectors K in Eqs. (9) and (11). K_j^{capex} is a vector of industries that embeds knowledge of the capital expenditure process of electricity generation technology j, with elements K_{ji}^{capex}: the fraction of capex cost for technology j that is spent on industry i, and $\sum_i K_{ji}^{\text{capex}} = 1$. For example, wind turbines consist of metal products (e.g. for the tower), machinery (e.g. for the nacelle), and electrical equipment (e.g. for the grid connection). Finally, construction work is required to prepare the turbine foundations and installation. Thus, the wind energy capex cost vector $K_{\text{wind}}^{\text{capex}}$ will have non-zero entries for metal industries ($K_{\text{wind,fabricated metal products}}^{\text{capex}} > 0$), certain manufacturing industries, and construction, and all must sum to unity with $\sum_i K_{\text{wind},i}^{\text{capex}} = 1$. Similarly, we require cost vectors of operational (e.g. fuel and maintenance) expenses $K_{\text{j}}^{\text{opex}}$ for disaggregation of the utility sector.

We construct cost vectors for the eight electricity generation technologies by taking the average of previous estimates available in the literature, most of which are based on technical reports by engineering firms or (inter)national agencies, such as IRENA and NREL. Specifically, for wind, solar, geothermal, and biomass both opex and capex we use the mean of values taken from Dell'Anna (2021) and Pollin et al. (2014). NACE industry codes from Dell'Anna (2021) were transformed to NAICS using a crosswalk from Eurostat (Remond-Tiedrez and Defense-Palojarv, 2014). We also use the three different solar and wind vectors and one geothermal cost vector from Garrett-Peltier (2017), which represent 'total cost' according to the authors. However, because the cost items can solely be attributed to materials and construction, we reinterpret these as capex. We further include the cost vectors for coal and natural gas electricity generation by Garrett-Peltier (2017) and Pollin et al. (2014) respectively as opex cost estimates.[27] For gas capex costs, we use the estimates for new oil and natural gas capacity from Pollin et al. (2014). We did not construct any capex cost vectors for coal electricity technologies, as our scenarios assume no new coal electricity generation capacity will be added in the US, nor has any been added since 2014 (EIA, 2021). Similarly, we assume nuclear capacity remains stable and thus leave it out of the analysis. This also implicitly assumes that nuclear capex unit costs will not decline, which is in line with technological trend assessments provided in the literature (e.g. Way et al., 2022).

In addition to electricity generation technologies, we construct capex cost vectors for battery storage from two reports (Feldman et al., 2021; Black & Veatch, 2012). We manually assign the cost items to industries in our IO table, taking the simple mean of the two technical reports. Finally, we take transmission and distribution grid capex vectors from Schreiner and Madlener (2021).[28,29]

Table 4 shows the capex cost vectors used for this study. Note that while we take the cost breakdown per USD spent from the (grey) literature and assume it remains constant over time, we allow the total cost in 2018-USD per MW(h) to vary according to data from NREL's ATB.[30] See

[27] We note that Garrett-Peltier (2017)'s coal and natural gas cost vectors are sparse and only represent fuel costs, which is the main supply chain cost component for fossil fuel electricity but not the only one. Our matrix inclusion method can account for opex costs beyond fuel costs.

[28] We assume US transmission lines are mostly DC overhead lines (their Table D.2).

[29] Schreiner and Madlener (2021) uses commodity group categories (CPAs), which we translate to IO industries as follows: we match *Services of architecture, engineering and technical and physical investigation* on *Miscellaneous professional, scientific, and technical services*; *Metal products* on *Fabricated Metal Product Manufacturing*; *Ceramics, processed stones and soils* on *Nonmetallic Mineral Product Manufacturing*; both *Electrical gears* and *Electric current, services in electricity, heating and cooling* on *Electrical Equipment, Appliance, and Component Manufacturing*; and finally both *Civil engineering works (Tiefbauarbeiten)* and *Preparation of construction sites, construction installation and other finishing work* on *Construction*.

[30] Except for T&D cost which we calculate separately, as discussed in Section A.1.

Industries	**Codes**	Wind	Solar	Nat. gas	Coal	Biomass	Geo thermal	Hydro	Battery storage	T&D
Farms	**111CA**	0.	0.	0.	0.	0.	0.	0.	0.	0.
Forestry, fishing, and related activities	**113FF**	0.	0.	0.	0.	0.	0.	0.	0.	0.
Oil and gas extraction	**211**	0.	0.	0.	0.	0.	0.	0.	0.	0.
Mining, except oil and gas	**212**	0.	0.	0.	0.	0.	0.03	0.	0.	0.
Support activities for mining	**213**	0.	0.	0.	0.	0.	0.23	0.	0.	0.
Utilities	**22**	0.	0.	0.	0.	0.	0.	0.	0.	0.
Construction	**23**	0.25	0.2	0.07	0.	0.35	0.15	0.39	0.09	0.09
Petroleum and coal products	**324**	0.	0.	0.	0.	0.	0.	0.	0.	0.
Chemical products	**325**	0.	0.	0.	0.	0.	0.	0.	0.	0.
Plastic and rubber products	**326**	0.05	0.	0.	0.	0.	0.	0.	0.	0.
Nonmetallic mineral products	**327**	0.04	0.03	0.	0.	0.	0.	0.	0.	0.05
Fabricated metal products	**332**	0.18	0.23	0.	0.	0.11	0.1	0.1	0.	0.58
Machinery	**333**	0.22	0.13	0.79	0.	0.47	0.38	0.15	0.	0.
computer and electronic products,	**334**	0.01	0.13	0.14	0.	0.03	0.01	0.01	0.	0.
electrical equipment, appliances, and components	**335**	0.17	0.15	0.	0.	0.03	0.04	0.08	0.82	0.22
Wholesale trade	**42**	0.	0.	0.	0.	0.	0.	0.	0.	0.
Rail transportation	**482**	0.	0.	0.	0.	0.	0.	0.	0.	0.
Truck transportation	**484**	0.01	0.	0.	0.	0.	0.	0.	0.	0.
Pipeline transportation	**486**	0.	0.	0.	0.	0.	0.	0.	0.	0.
Real estate	**ORE**	0.01	0.	0.	0.	0.02	0.02	0.04	0.	0.
Federal Reserve banks, credit intermediation, and related activities	**521CI**	0.	0.	0.	0.	0.	0.01	0.01	0.	0.
Insurance carriers and related activities	**524**	0.01	0.	0.	0.	0.	0.	0.	0.	0.
Miscellaneous professional, scientific, and technical services	**5412OP**	0.04	0.1	0.	0.	0.	0.02	0.22	0.05	0.06
Management of companies and enterprises	**55**	0.01	0.02	0.	0.	0.	0.02	0.	0.04	0.
Accommodation	**721**	0.0005	0.	0.	0.	0.	0.	0.	0.	0.
Food services and drinking places	**722**	0.0005	0.	0.	0.	0.	0.	0.	0.	0.
Administrative and support services	**561**	0.	0.	0.	0.	0.	0.	0.	0.	0.
Other transportation and support activities	**487OS**	0.	0.	0.	0.	0.	0.	0.	0.	0.
Legal services	**5411**	0.	0.	0.	0.	0.	0.	0.	0.	0.
Sum		1.0	1.0	1.0	0.0	1.0	1.0	1.0	1.0	1.0

Table 4: Capex cost vectors of electricity generation technologies for the 71 industry US input-output table. The estimates we use are the mean of values taken from the literature with some manual adjustments. Coal and Nuclear capex is zero as we assume no new coal electricity generation capacity will be built and nuclear capacity will remain constant. T&D is Transmission and Distribution grid.

Section C.7 for some empirical evidence on the stability of the solar and wind cost breakdown.

In Section D.4 we test the sensitivity of our literature estimates by adding noise to all values of K.

C.5 US electricity sector disaggregation

We apply the opex cost vectors to the procedure of Section B.6 to disaggregate the IO tables.

In practice, we perform the procedure twice. We will first discuss how we disaggregate the Utility sector into three more detailed utility sectors, one of which concerns electricity generation and distribution. Following this we will discuss how we further disaggregate the electricity sector into detailed generation and transmission sectors.

Utilities split in electricity, natural gas direct distribution, and water and sewage systems We disaggregate the Utility sector (NAICS code 22) into its three more detailed components: Electric power generation, transmission and distribution (NAICS code 2211), Natural gas distribution (2212), and Water, sewage, and other systems (2213). The 2018 IO table only contains the aggregate Utility sector, but the (latest) 2012 detailed IO table contains the three more detailed sectors. For the three more detailed utility sectors we do have 2018 data on their total output (Bureau of Economic Analysis, 2022*a*). We first isolate both the production and output recipes of the 2012 utility sectors. We crosswalk all non-utility sectors to match the 70 other industries available in 2018, and thus end up with three output- and production recipes associated with 73 sectors.

We perform the disaggregation procedure of Section B.6.1 to update the 2012 production and output recipes to fit the 2018 table. This created a new 2018 IO table with 73 industries.[31]

Electricity sector split in eleven sub-industries The new IO table with 73 industries contains one electricity generation and distribution sector, which we further split in eleven sectors consisting of eight specific electricity generation technologies, one 'other' electricity generation technology, and two sectors for electricity transmission and distribution respectively:

1. Hydroelectric Power Generation (NAICS 221111) (short name: Hydro)
2. Gas Electric Power Generation (221112[32]) (Gas)

[31]Because we update the 2012 IO table with 2018 data, this method is equivalent to the biproportional fitting method for projecting tables into the future mentioned before in Blair and Miller (2009).

Electricity generation	2018 output in million (2018-USD)
Hydroelectric power generation	3,045
Fossil fuel electric power generation	100,489
Nuclear electric power generation	35,737
Solar electric power generation	779
Wind electric power generation	6,458
Geothermal electric power generation	1,376
Biomass electric power generation	1,066
Other electric power generation	230
Electric bulk power transmission and control	12,403
Electric power distribution	240,901

Table 5: Total output of the electricity sector (Source: Bureau of Economic Analysis, 2022*a*). In our analysis we split the fossil fuel electric power generation output in coal (43%) and gas (57%), using the relative numbers in GWh electricity generation output for the US in 2018 from the EIA.

3. Coal Fuel Electric Power Generation (221112[32]) (Coal)
4. Nuclear Electric Power Generation (221113) (Nuclear)
5. Solar Electric Power Generation (221114) (Solar)
6. Wind Electric Power Generation (221115) (Wind)
7. Geothermal Electric Power Generation (221116) (Geothermal)
8. Biomass Electric Power Generation (221117) (Biomass)
9. Other Electric Power Generation (221118) (Other)
10. Electricity transmission and control (221121) (Trans)
11. Electric power distribution (221122) (Dist)

In this disaggregation we follow BEA's industry classification at the sixth digit level, with the added benefit that for all these sectors we have 2018 total output data from BEA (see Table 5).[32] In the main text, we combine the final two industries (Trans and Dist) together into one Transmission and Distribution (T&D) sector.

As mentioned in Section B.3, battery storage is not part of the Utility industry, and we model that separately via a final demand inclusion as explained in Section C.4.

We use the literature opex cost vectors discussed in Section C.4 and shown in Table 6 as initial estimates of the production recipes. We did not prepare opex cost vectors for Trans, Dist, Nuclear, and Other. We initialize these instead with the same production recipe as the higher level industry (*Electricity generation and distribution and transmission* (2211)), excluding any obvious fuel costs (mining, extraction, refineries, agriculture and pipeline transportation). For Nuclear (221113), we make an extra manual modification and assume it requires nuclear fuel from the *Chemical industry* (325), as explained in the paragraph below.

We make three further modifications in order for the disaggregation procedure to work. First, the literature estimates are often not exhaustive and only highlight the most relevant parts of the production recipes. For example, the fossil fuel production recipes do not include spending on the utility industry that provides electricity, water, and gas, which is a cost they would incur. We therefore add 2% spending on *Utilities* for *Fossil fuel electricity generation*. For all other industries that are not mentioned in the literature Table 6, we assume relative spending by all electricity generation sectors equal to the aggregated *Electricity generation and transmission sector* (2211).

Second, zero-valued entries can lead to matrix inversion problems. We set any zero-valued entry to the equivalent of 2018-USD 1,000. Then we use the disaggregation procedure from Section B.6 to fit according to the constraints as detailed above. After fitting, the biomass fuel component fall

[32] BEA does not distinguish between fossil fuel technologies. Gas and Coal electric power generation are both part of the same Fossil Fuel Electric Power Generation industry (NAICS 221112). We use additional data by the US Energy Information Administration (EIA) on total GWh electricity production to be able to distinguish between Coal and Natural gas powered electricity plants (Bureau of Economic Analysis, 2022*a*).

away completely as agriculture is not an input to the utility sector in the official IO table. We make the decision to manually add agricultural inputs for biomass.

Third, we assume the value-added components are the same across electricity sectors, except for spending on employee compensation, which we assume scales with total wages paid in that sector. We calculate total wage spending by multiplying the number of workers in each electricity sector with their mean wage as reported by BLS (Bureau of Labor Statistics, 2021). We scale the employee compensation part of value added with the total wage that is spent in that sector. The other components (taxes, subsidies, and gross margin) we assume to be constant across the *Electricity generation and transmission sectors* (2211xx). For the Solar electricity generation sector, scaling value added with employee compensation results in a value added that is larger than total output, which should not be possible. We lower it proportionally so that value added represents 98% of total output, and 2% intermediate spending.

See Table 7 for the top 25 industries in the production recipes of the electricity sectors, and their values.

Nuclear fuel Nuclear fuel is an important input for the Nuclear electricity generation sector. From the US Energy Information Administration (EIA, 2022*b*) we learn that about 1/5th (11 million ton) of nuclear fuel was produced domestically in 2018, and that the total costs of this was about 480 million 2018-USD, about 1.3% of total nuclear electricity output.

We use the IO data to find the right source of nuclear fuel. Three candidates are: *Uranium mining*, *Uranium refining*, and/or the *Chemical industry*. In the 2018 IO data *Uranium Mines* are grouped together with all other mines under a generic mining sector (NAICS 212), and it is unclear whether any uranium is used this way, or if all items relate to coal, a ubiquitous mining good in electricity generation. The more detailed 2012 tables can help here. Uranium mines are classified under NAICS 212291 (grouped with gold and miscellaneous metals as 2122A0), and uranium smelting and refining grouped under all non-ferrous metal smelting and refining (331410), and/or rolling, drawing, alloying of nonferrous metals (331490). The combined use by the *Electricity generation and transmission sector* of products from all three sectors (2122A0, 331410 and 331490) in 2012 was 1 million 2012-USD ($< 0.001\%$ of total electricity output), not enough to account for nuclear fuel costs.

Enriched nuclear fuel can also be an output of *Other Basic Inorganic Chemicals Manufacturing* (NAICS 325180). In 2012 the use by *Electricity generation and transmission sector* (221100) of products from NAICS 325180 was about 166 million 2012-USD (182 million 2018-USD), domestic and imported. In 2018, the *Utility* sector (220000) in total used products from the more aggregate *Chemical manufacturing* (NAICS 325) as a whole for about 2 billion 2018-USD in 2018, enough to cover the uranium input. We thus decided to assign the full 1.3% of Nuclear fuel cost to sector 325.

Industry	Code	wind		PV		Hydro		Geothermal		Biomass		Gas	Coal
Farms	111CA	0	0	0	0	0	0	0	0	0	0.29	0	0
Forestry, fishing, and related activities	113FF	0	0	0	0	0	0	0	0	0	0.29	0	0
Oil and gas extraction	211	0	0	0	0	0	0	0	0	0	0.14	0.5	0
Mining, except oil and gas	212	0	0	0	0	0	0	0	0	0	0	0	0.5
Utilities	22	0	0.25	0	0.25	0	0.8	0	0.1	0	0.08	0	0
Construction	23	0.02	0.25	0	0.25	0	0	0	0.5	0	0.02	0	0
Petroleum and coal products	324	0	0	0	0	0	0	0	0	0	0.07	0.25	0.5
Plastic and rubber products	326	0.05	0	0	0	0	0	0	0	0	0	0	0
Machinery	333	0.3	0.25	0.15	0	0.35	0.1	0.35	0	0.15	0	0	0
computer and electronic products	334	0.075	0	0.075	0.125	0.075	0	0.075	0	0.025	0	0	0
electrical equipment, apliances, and components	335	0.075	0	0.075	0.125	0.075	0	0.075	0	0.025	0	0	0
Wholesale trade	42	0	0	0	0	0	0	0	0	0.3	0	0	0
Rail transportation	482	0.005	0	0	0	0	0	0	0	0.2	0.02	0	0
Truck transportation	484	0.005	0	0	0	0	0	0	0	0.2	0.05	0	0
Pipeline transportation	486	0	0	0	0	0	0	0	0	0	0	0.25	0
Real estate	ORE	0.3	0	0.2	0	0.3	0	0.3	0	0	0	0	0
Federal Reserve banks, credit intermediation, and related activities	521CI	0.17	0	0.5	0	0.2	0	0.2	0	0.1	0	0	0
Miscellaneous professional, scientific, and technical services	5412OP	0	0.25	0	0.25	0	0.1	0	0.4	0	0.04	0	0
Source		Dell'Anna 2021	Pollin 2014	Dell'Anna 2021	Pollin 2014	Dell'Anna 2021	Pollin 2014	Dell'Anna 2021	Pollin 2014	Dell'Anna 2021	Pollin 2014	Garret-Peltier 2017 Pollin	Garret-Peltier 2017 Pollin

Table 6: Literature operational expenses (opex) cost vectors

	Total	Hydro	Nuclear	Solar	Wind	Geo thermal	Biomass	Coal	Gas	Other	Trans	Dist
221100	**3.9%**	6.0%	4.3%	0.2%	3.4%	1.4%	0.6%	3.3%	5.4%	5.4%	0.1%	0.1%
imports	**3.7%**	2.1%	3.8%	0.2%	3.8%	3.9%	2.0%	2.9%	4.8%	4.8%	0.9%	0.8%
561	**3.1%**	1.8%	3.3%	0.1%	3.3%	3.3%	1.7%	2.5%	4.1%	4.1%	0.8%	0.7%
211	**2.9%**	0.0%	0.0%	0.0%	0.0%	0.0%	7.6%	0.0%	0.0%	0.0%	0.0%	20.1%
324	**2.6%**	0.0%	0.0%	0.0%	0.0%	0.0%	2.5%	0.0%	0.0%	0.0%	15.4%	6.6%
GSLE	**2.2%**	1.3%	2.3%	0.1%	2.3%	2.3%	1.2%	1.7%	2.9%	2.9%	0.5%	0.5%
212	**2.1%**	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	19.2%	0.0%
23	**1.7%**	0.0%	1.9%	0.2%	4.2%	7.8%	0.2%	1.4%	2.4%	2.4%	0.0%	0.0%
5412OP	**1.6%**	0.9%	1.8%	0.2%	3.8%	6.2%	0.3%	1.3%	2.2%	2.2%	0.0%	0.0%
487OS	**1.6%**	0.9%	1.7%	0.1%	1.7%	1.7%	0.9%	1.3%	2.1%	2.1%	0.4%	0.3%
42	**1.4%**	0.0%	1.6%	0.0%	0.0%	0.0%	2.5%	1.2%	2.0%	2.0%	0.0%	0.0%
521CI	**1.2%**	1.7%	1.3%	0.3%	2.6%	3.1%	0.8%	1.0%	1.6%	1.6%	0.0%	0.0%
486	**1.2%**	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	8.4%
482	**1.0%**	0.0%	1.1%	0.0%	0.1%	0.0%	1.9%	0.8%	1.4%	1.4%	0.0%	0.0%
484	**0.9%**	0.0%	1.0%	0.0%	0.1%	0.0%	2.1%	0.8%	1.3%	1.3%	0.0%	0.0%
5411	**0.7%**	0.4%	0.8%	0.0%	0.8%	0.8%	0.4%	0.6%	1.0%	1.0%	0.2%	0.2%
ORE	**0.6%**	2.3%	0.6%	0.1%	4.1%	4.2%	0.0%	0.5%	0.8%	0.8%	0.0%	0.0%
221300	**0.6%**	0.9%	0.6%	0.0%	0.5%	0.2%	0.1%	0.5%	0.8%	0.8%	0.0%	0.0%
4A0	**0.5%**	0.3%	0.5%	0.0%	0.5%	0.5%	0.3%	0.4%	0.6%	0.6%	0.1%	0.1%
514	**0.4%**	0.3%	0.5%	0.0%	0.5%	0.5%	0.2%	0.4%	0.6%	0.6%	0.1%	0.1%
513	**0.4%**	0.2%	0.4%	0.0%	0.4%	0.5%	0.2%	0.3%	0.6%	0.6%	0.1%	0.1%
325	**0.4%**	0.2%	1.1%	0.0%	0.4%	0.4%	0.2%	0.3%	0.5%	0.5%	0.1%	0.1%
722	**0.4%**	0.2%	0.4%	0.0%	0.4%	0.4%	0.2%	0.3%	0.5%	0.5%	0.1%	0.1%
5415	**0.2%**	0.1%	0.2%	0.0%	0.2%	0.2%	0.1%	0.1%	0.2%	0.2%	0.0%	0.0%
721	**0.2%**	0.1%	0.2%	0.0%	0.2%	0.2%	0.1%	0.1%	0.2%	0.2%	0.0%	0.0%
532RL	**0.2%**	0.1%	0.2%	0.0%	0.2%	0.2%	0.1%	0.1%	0.2%	0.2%	0.0%	0.0%
333	**0.2%**	1.8%	0.1%	0.0%	4.0%	2.5%	0.6%	0.1%	0.1%	0.1%	0.0%	0.0%

Table 7: Final production recipes imputed. This table only shows the top 26 industries on which the aggregated *Electricity generation and transmission* sector spends more than 0.2% of total output (left-most column). The full columns, including all industries plus value added, sum up to 100% of output.

C.6 Electricity generation outside the BEA utilities sector not in scope

We only model electricity generation that happens in NAICS industry 221100, plus commercial and rooftop solar, battery storage, and T&D in NAICS industries 22121 and 22122. This leaves out electricity production that may happen in other sectors, such as government enterprises and waste incinerators.

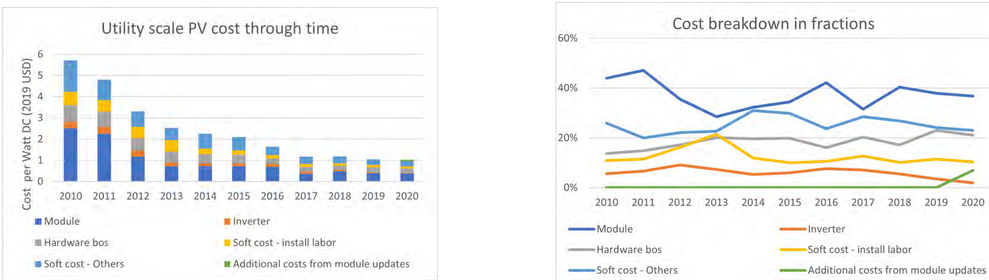
Government enterprises that might also produce electricity are out of scope (specifically industry codes S00101 and S00202 in the detailed classification for federal and state/local electric utilities respectively, which are aggregated in GFE and GSLE in the 2018 BEA respectively). These might comprise about 15% of total electricity sector output (Bureau of Economic Analysis, 2022*a*). We took this decision as the available data is often mixed with other data on government branches. Government utilities are not a separate industry in the latest BEA IO tables, nor an employment industry in the BLS data. Manually disaggregating the government industries for IO and occupational inclusion would add more noise to our analysis.

We also do not consider electricity generated by the *Solid Waste Combustors and Incinerators* industry (NAICS 562213, which is part of the *Waste management and remediation services* [NAICS code 562] in the IO table).

C.7 Cost breakdown through time

Throughout our analysis, we assume that the spending breakdown per energy technology is constant. We assume cost-factor neutral technical change, meaning that we allow for unit cost per technology to change, but not how each dollar is spent (c.f. hicks-neutral technical change). We think this assumption is reasonable based on two empirical sources for solar and wind cost breakdown over time: NREL's ATB solar cost data, and Elia et al. (2020)'s analysis of wind power data.

From NREL's ATB data over time, we find that while the cost for utility-scale solar PV installations declined almost five-fold in the years 2010–2020, the breakdown of these costs into several cost buckets has remained remarkably stable (Fig. 12). While there are fluctuations, no clear pattern can be discerned over the entire period. We use this as evidence to assume that although costs are likely to decline in the future according to technology learning curves, the relative breakdown of cost elements will remain constant over time.



(a) Cost per Watt DC

(b) Cost fraction of total

Figure 12: Utility-scale PV cost through time. In a) the breakdown per year in constant 2019-USD per Watt DC output. In b) the fraction of each of the cost components through time. Data from NREL (Feldman et al., 2021).

Further evidence for the case of wind turbines comes from Fig. 8 of Elia et al. (2020), which looks at the US wind turbine price per kW breakdown for the period 2005-2017. Labor costs are responsible for a 15% to 23% share of the turbine price, with the former estimates most prevalent for the 2005-2008 period. While there are clear fluctuations in different price components, there is no clear trend visible in labor cost as percentage of the wind turbine price, especially after 2009.

C.8 BEA to BLS industry and occupations crosswalk

The Bureau of Labor Statistics (BLS) publishes employment data for industries and occupations at various levels of detail. We use the level of industry detail that matches with that of the BEA industries.[33] A correspondence table from the EPA is used to connect the two classifications, which gives mostly one-to-one or one-BEA-to-many-BLS matches (Environmental Protection Agency, 2022). This allows us to directly link the number of workers per occupation to the BEA industries, or the sum of several BLS industries linked to one BEA industry.[34] Extra care was given to distinguish between government-run and private education services, which are part of government services in the BEA data, and education services for BLS. The same is true for government-run and private hospitals. We exploit the BLS information on ownership to get the distinction right.

Two sets of industries had many-to-one relationships. While BLS distinguishes governments by regional level (local, state, federal), BEA distinguishes between level (federal and state/local) and function (general government and government enterprises). We sum all BLS government codes and assign them to the BEA government codes (except local/state government enterprises and *GFGD*, the defense part of the federal general government), with fractions based on BEA spending on employee compensation. We thus assume the relative occupational make-up of government services is the same on the state and federal level. 28% of government employees work on the federal level. The aforementioned government-run hospital and education services were matched on the remaining local/state government enterprise sector.

The second many-to-one relation concerns the real estate sector. BEA distinguishes between Housing (HS) and Other real estate (ORE) sectors, which both map on BLS's more general 531000 (Real Estate) sector. We assume HS and ORE sectors have the same occupational make-up as the BLS's 531000 sector, with the absolute number split according to the relative difference in employee benefits spending by HS and ORE respectively. This results in our estimate that 17% of Real Estate workers work in the HS sector, and 83% in the ORE sector.

Agricultural and government defense industries are not included in the BLS data, and we leave them out of this analysis.

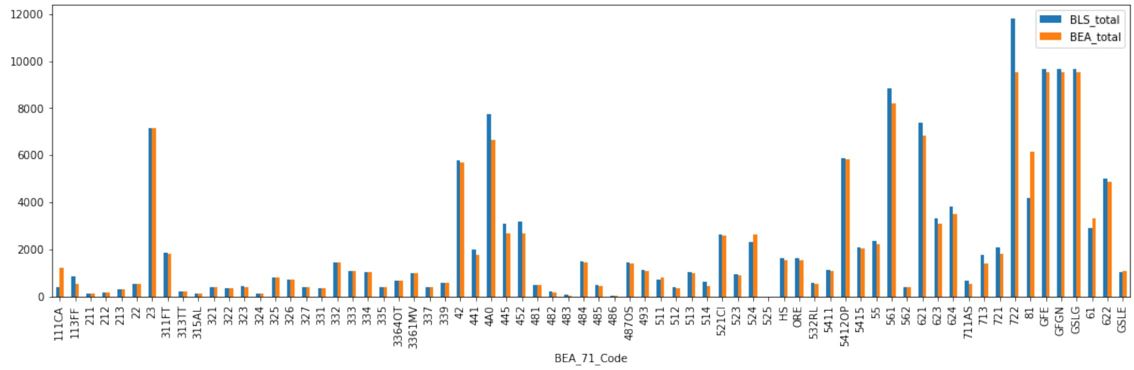
In Fig. 13 we compare the two datasets as a sanity check of our harmonization. BEA also publishes numbers of total full-time equivalent workers per industry. We find a good agreement with BLS's total employment in Fig. 13a, with the largest difference for Other services (81), which has more workers according to BEA than to BLS. This might be due to the eclectic nature of this industry, or measurement differences on either side.

We also compare total employee compensation as published by BEA with total wage spending according to BLS. Employee compensation includes everything the employer pays for its workers, including additional taxes and bonuses that are not reflected in average wages. It is almost always higher than the wage a worker receives, but can also be lower due to subsidies. the difference is

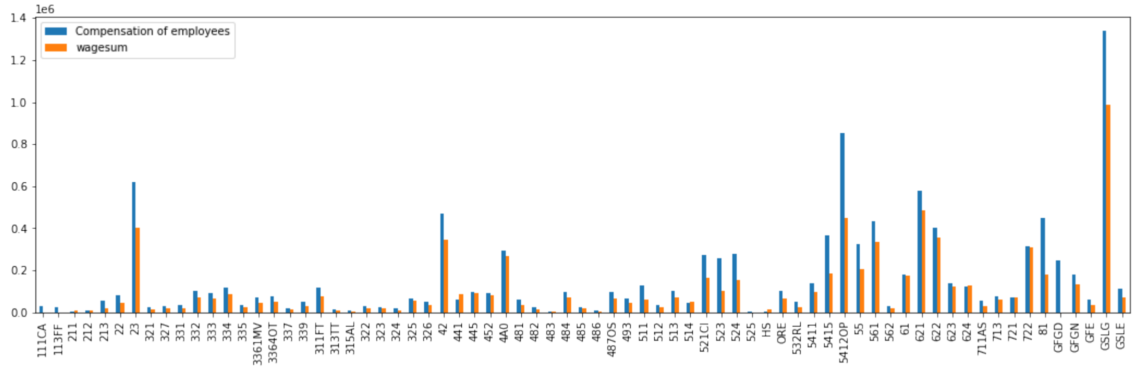
[33] Except for the disaggregated Utility sector: see paragraph below.

[34] e.g. BEA industry 315AL (Apparel and leather and allied manufacturing) consists of BLS industries 351500 (Apparel manufacturing) and 351600 (Leather and allied product manufacturing).

often larger for high-paid workers. We conclude that Fig. 13b reflects this to a large extent, and that our harmonization can be used.



(a)



(b)

Figure 13: Comparison of BLS and BEA industry data. In a) thousands of workers in the BLS dataset vs the thousands of full time equivalent workers in BEA, and in b) the compensation of employees according to 2018 IO tables published by BEA, and the sum of wages of all employees working in the industries in 2018 according to data from BLS, both in millions of 2018-USD. Note that we do not have wage data for military (GFGD) or agricultural (111CA and 113FF) workers.

Electricity sector industries and workers. As explained in Section C.5 we split the utilities sector into 13 industries including eight electricity generation technologies. Since 2015 BLS reports on the number of workers and their occupation per electricity generation technology, we incorporate their data for 2018 in our analysis. Following on from Table 2, we show which BLS and BEA industries match on the IO classifications for industries in Table 8.

Four things should be noted. First, *Battery storage* is not present as a separate electricity technology in either BEA or BLS. As explained further in Section B.3, we add battery storage opex workers manually, with a similar occupational makeup as its capex workers. Second, as mentioned before, neither BEA nor BLS split fossil fuel electricity generation into gas or coal. We use EIA electricity production data for that split,[35] both for the BEA and BLS data. Third, we combine transmission and distribution (T&D) in our IO analysis, which are separated in the BEA data. We simply sum them together. BLS does not report any data on electricity transmission and distribution but does report figures on the NAICS 2211 level (*Electric power generation, transmission and distribution*). We assume any workers in NAICS 2211 that are not accounted for by the other sub-industries work in T&D. Last, while we do not report on *Other electric power generation*, it is included in our IO table. As we assume all electricity generation comes from the technologies identified in Table 2, the 'Other' sector output was set to always be zero.

The Utilities sector employed over half a million workers in 2018, almost 400,000 of which were working in electricity generation, transmission and distribution. Just over 150,000 workers were directly involved with electricity generation facilities, the majority in fossil fuel (89,000), followed by nuclear (44,000). Total employment in renewables (hydro, wind, solar, biomass, and geothermal) stood at about 17,000 in 2018, with about a third of that for wind and another third for hydro.

Because the electricity generation sectors are small compared to the more aggregated sectors

[35] https://www.eia.gov/energyexplained/us-energy-facts/

IO industry	NAICS code	BLS industry	BEA industry
Battery	-	-	-
Bio	221117	Biomass electric power generation	Biomass Electric Power Generation
Coal Gas	221112	Fossil fuel electric power generation	Fossil Fuel Electric Power Generation
Geo	221116	Geothermal Electric Power Generation	Geothermal electric power generation
Hydro	221111	Hydroelectric Power Generation	Hydroelectric power generation
Nuclear	221113	Nuclear Electric Power Generation	Nuclear electric power generation
Solar	221114	Solar Electric Power Generation	Solar electric power generation
Wind	221115	Wind Electric Power Generation	Wind electric power generation
Other	221118	Other Electric Power Generation	Other electric power generation
T&D	221121	-	Electric bulk power transm. and control
	221122	-	Electric power distribution
Gas dist	221200	Natural Gas Distribution	Natural gas distribution
Water and sewage	221300	Water, Sewage and Other Systems	Water, sewage and other systems

Table 8: IO, BLS, and BEA industry matching for the disaggregated Utility sector

this data is not as detailed and more error prone than the utilities sector data as a whole. This is also highlighted by the larger relative standard error reported by BLS. BLS gives both the total number of workers per industry and an occupational breakdown for most workers. We first matched the occupational breakdown to our occupational list. Some of these have censored values. In the OEWS files, these occupations have two stars (**) instead of an estimated number of workers for that occupation-industry pair. We infer from more aggregated occupation levels how many workers there should roughly be. We impute those values with those in Table 9. Additionally, the utility industries report total employment figures that are larger than the sum of their detailed occupation list. We take two approaches. First, for the high-level utilities industries (first 221000 (Utilities), then 221100 (Electric Power Generation, Transmission and Distribution), 221200 (Natural Gas Distribution), and 221300 (Water, Sewage and Other Systems)), we assign missing workers to their existing occupations proportional to employment.

Secondly, the proportion of missing workers is larger for smaller sectors. For example, 900 of 2,560 Solar electricity generation workers did not have detailed occupations assigned in the BLS data. This means that those industries often also report on a smaller number of occupations. Potentially there are unreported occupations. We call these *missing* occupations. We know how many there are as BLS also reports the total number of workers per industry regardless of their occupation. We assign these workers to occupations as follows:

1. We sum all workers to the *minor* occupation level (often 3-digit level). If that value is larger than OEWS reports at that minor level, we add workers to all occupations in that minor level, including those that are not in the OEWS data.

2. We next sum all workers to the *major* occupation level (often 2 digits). These occupation categories group together dozens of more detailed occupations. If they sum to a total number of workers that is lower than OEWS reports, we add workers only to those occupations that BLS reports on or to those occupations we had added in the previous step.

3. We remove any *tiny* occupations (i.e. those industry-occupations pairs with less than 30 workers or 0.2% of industry total, and add those workers proportionally to all other occupations in that industry.

OEWS does not report an occupational breakdown for Electric power Transmission and Distribution industry (NAICS code 221120). We assume that all workers in 221100 (Electric Power Generation, Transmission and Distribution) that do not work in Electricity generation (NAICS 22111) work for Electric Power Transmission and Distribution.

Finally, we split fossil fuel electricity generation in two, one dedicated to coal and the other to natural gas based electricity generation. The occupational profiles are kept identical, but the total number of workers is split according to the electricity output as reported by EIA (2022*a*).

In Section D.4 we perform a sensitivity analysis on the number of workers per occupation per industry, using the standard errors reported by BLS. That analysis shows that the impact on the results is larger for small but fast-growing occupations such as Wind Turbine Service Technicians.

BLS NAICS code	BLS OCC code	Total employment imputation
221000	17-1010	50
221000	17-1020	980
221000	21-1090	0
221000	41-9040	120
221000	47-4070	250
221000	47-5020	210
221000	53-6030	80
221000	53-6090	80
221100	17-3010	2340
221100	19-4040	80
221100	21-1090	0
221100	41-3030	160
221100	49-2020	440
221100	49-9052	1660
221100	51-8090	1100
221100	53-2010	0
221100	53-6090	90
221200	17-1020	460
221200	41-9040	120
221200	41-9099	60
221200	43-4190	100
221200	43-5070	30
221200	43-9050	70
221200	49-9051	2650
221200	51-8010	830
221200	51-8020	710
221200	53-6030	80
221300	17-3010	80
221300	33-9030	0
221300	47-3010	170
221300	47-4070	270
221300	49-9051	120
221300	51-8010	165
221300	51-8090	165
221300	51-9199	160
221300	53-7030	40
221111	13-1070	75
221111	13-1080	75
221111	51-8090	70
221111	51-9060	110
221111	51-9198	100
221112	53-2010	0
221115	49-9041	430
221115	15-1120	50
221115	51-1010	80
221118	51-8010	390

Table 9: All employment imputations in the industry-occupation matrix B_{2018}

C.9 Occupation crosswalk Census - BLS

The crosswalk includes occupations that are grouped together. We perform a manual operation to split them. For example, we split 25-90XX (Other Education, Training, and Library Occupations) into four occupations that BLS reports on within that group: 25-9010 Audio-Visual and Multimedia Collections Specialists; 25-9020 Farm and Home Management Advisors; 25-9030 Instructional Coordinators; 25-9090 Miscellaneous Education, Training, and Library Workers). Table 10 shows the full list of imputed alterations that we performed.

We drop two census occupations that are not in BLS: 6100 (*Fishers and related fishing workers*; soc code 45-3011), and 6110 (*Hunters and trappers*; soc code 45-3021).

The final list of BLS occupations has 539 entries on the BLS side, and 529 census occupations. Our set of BLS occupations comprises 138 6-digit occupations, 497 5-digit occupations and 3 4-digit occupations.

C.10 Occupational typology

We list all ‘Consistent growth’ occupations in Table 11, all ‘Consistent decline’ occupations in Table 12, and all ‘Temporary growth’ occupations in Table 13.

2010 SOC Code	Imputed
15-113X	15-1132
15-113X	15-1133
25-90XX	25-9010
25-90XX	25-9020
25-90XX	25-9030
25-90XX	25-9090
31-909X	31-9093
31-909X	31-9099
33-909X	33-9092
33-909X	33-9099
37-201X	37-2011
37-201X	37-2019
39-40XX	39-4000
47-50XX	47-5050
47-50XX	47-5090
49-209X	49-2094
49-209X	49-2095
49-904X	49-9041
49-904X	49-9045
49-909X	49-9093
49-909X	49-9099
53-40XX	53-4040
53-40XX	53-4090
53-60XX	53-6040
53-60XX	53-6090

Table 10: SOC crosswalk imputation of missing values

O*NET-SOC Code	Occupation title	Mean annual wage (2018)
47-2230	Solar Photovoltaic Installers	46,010
49-9051	Electrical Power-Line Installers and Repairers	70,240
49-9080	Wind Turbine Service Technicians	58,000

Table 11: Consistent growth occupations. All occupations that are affected more than 1% of total pre-transition employment and see a demand increase in both the scale-up and scale-down phase.

O*NET-SOC Code	Occupation title	Mean annual wage (2018)
17-2150	Mining and Geological Engineers, Including Mining Safety Engineers	98,420
47-5040	Mining Machine Operators	53,090
47-5050	Rock Splitters, Quarry	35,760
47-5060	Roof Bolters, Mining	59,090
47-5090	Miscellaneous Extraction Workers	54,300
49-2095	Electrical and Electronics Repairers, Powerhouse, Substation, and Relay	80,040
51-8010	Power Plant Operators, Distributors, and Dispatchers	81,760
51-8090	Miscellaneous Plant and System Operators	66,430
53-7030	Dredge, Excavating, and Loading Machine Operators	48,790
53-7040	Hoist and Winch Operators	56,390
53-7070	Pumping Station Operators	52,510
53-7110	Mine Shuttle Car Operators	56,150
53-7120	Tank Car, Truck, and Ship Loaders	42,330

Table 12: Consistent decline occupations. All occupations that are affected more than 1% of total pre-transition employment and see a demand decrease in both the scale-up and scale-down phase.

O*NET-SOC Code	Occupation title	Mean annual wage (2018)
11-3050	Industrial Production Managers	113,370
11-3060	Purchasing Managers	125,630
11-9020	Construction Managers	103,110
11-9040	Architectural and Engineering Managers	148,970
13-1020	Buyers and Purchasing Agents	67,530
13-1050	Cost Estimators	69,710
13-2082	Tax Preparers	46,860
17-2070	Electrical and Electronics Engineers	104,250
17-2110	Industrial Engineers, Including Health and Safety	91,800
17-2130	Materials Engineers	96,930
17-2140	Mechanical Engineers	92,800

Continued on next page

Table 13 – continued from previous page

O*NET-SOC Code	Occupation title	Mean annual wage (2018)
17-2170	Petroleum Engineers	156,370
17-2199	Engineers, All Other	99,410
17-3010	Drafters	58,180
17-3020	Engineering Technicians, Except Drafters	61,380
19-4040	Geological and Petroleum Technicians	62,890
41-9030	Sales Engineers	108,610
43-5060	Production, Planning, and Expediting Clerks	50,020
43-5070	Shipping, Receiving, and Traffic Clerks	34,980
47-1010	First-Line Supervisors of Construction Trades and Extraction Workers	70,540
47-2010	Boilermakers	63,240
47-2020	Brickmasons, Blockmasons, and Stonemasons	52,810
47-2030	Carpenters	51,120
47-2040	Carpet, Floor, and Tile Installers and Finishers	45,330
47-2050	Cement Masons, Concrete Finishers, and Terrazzo Workers	47,340
47-2060	Construction Laborers	40,350
47-2071	Paving, Surfacing, and Tamping Equipment Operators	44,360
47-2072	Pile-Driver Operators	64,360
47-2073	Operating Engineers and Other Construction Equipment Operators	53,030
47-2080	Drywall Installers, Ceiling Tile Installers, and Tapers	50,420
47-2110	Electricians	59,190
47-2120	Glaziers	48,620
47-2130	Insulation Workers	46,910
47-2141	Painters, Construction and Maintenance	43,050
47-2142	Paperhangers	40,840
47-2150	Pipelayers, Plumbers, Pipefitters, and Steamfitters	56,980
47-2160	Plasterers and Stucco Masons	47,610
47-2170	Reinforcing Iron and Rebar Workers	54,670
47-2180	Roofers	43,870
47-2210	Sheet Metal Workers	52,710
47-2220	Structural Iron and Steel Workers	58,170
47-3010	Helpers, Construction Trades	32,900
47-4020	Elevator Installers and Repairers	79,370
47-4030	Fence Erectors	37,650
47-4090	Miscellaneous Construction and Related Workers	43,000
47-5010	Derrick, Rotary Drill, and Service Unit Operators, Oil, Gas, and Mining	52,950
47-5020	Earth Drillers, Except Oil and Gas	47,570
47-5070	Roustabouts, Oil and Gas	40,220
47-5080	Helpers–Extraction Workers	37,660
49-2094	Electrical and Electronics Repairers, Commercial and Industrial Equipment	59,210
49-9020	Heating, Air Conditioning, and Refrigeration Mechanics and Installers	50,160
49-9041	Industrial Machinery Mechanics	54,000
49-9043	Maintenance Workers, Machinery	48,720
49-9044	Millwrights	56,250
49-9045	Refractory Materials Repairers, Except Brickmasons	52,510
49-9096	Riggers	51,330
51-1010	First-Line Supervisors of Production and Operating Workers	64,340
51-2020	Electrical, Electronics, and Electromechanical Assemblers	35,910
51-2030	Engine and Other Machine Assemblers	45,330
51-2040	Structural Metal Fabricators and Fitters	41,640
51-2090	Miscellaneous Assemblers and Fabricators	34,300
51-4010	Computer Control Programmers and Operators	43,940
51-4021	Extruding and Drawing Machine Setters, Operators, and Tenders, Metal and Plastic	36,620
51-4022	Forging Machine Setters, Operators, and Tenders, Metal and Plastic	40,770
51-4023	Rolling Machine Setters, Operators, and Tenders, Metal and Plastic	40,790
51-4031	Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic	36,180
51-4032	Drilling and Boring Machine Tool Setters, Operators, and Tenders, Metal and Plastic	41,490
51-4033	Grinding, Lapping, Polishing, and Buffing Machine Tool Setters, Operators, and Tenders, Metal and Plastic	36,690
51-4034	Lathe and Turning Machine Tool Setters, Operators, and Tenders, Metal and Plastic	41,090
51-4035	Milling and Planing Machine Setters, Operators, and Tenders, Metal and Plastic	44,490
51-4040	Machinists	45,250
51-4050	Metal Furnace Operators, Tenders, Pourers, and Casters	41,160
51-4060	Model Makers and Patternmakers, Metal and Plastic	53,430
51-4070	Molders and Molding Machine Setters, Operators, and Tenders, Metal and Plastic	34,200

Continued on next page

Table 13 – continued from previous page

O*NET-SOC Code	Occupation title	Mean annual wage (2018)
51-4080	Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic	37,510
51-4110	Tool and Die Makers	53,650
51-4120	Welding, Soldering, and Brazing Workers	43,930
51-4191	Heat Treating Equipment Setters, Operators, and Tenders, Metal and Plastic	39,050
51-4192	Layout Workers, Metal and Plastic	47,380
51-4193	Plating and Coating Machine Setters, Operators, and Tenders, Metal and Plastic	34,830
51-4194	Tool Grinders, Filers, and Sharpeners	40,890
51-4199	Metal Workers and Plastic Workers, All Other	38,140
51-6091	Extruding and Forming Machine Setters, Operators, and Tenders, Synthetic and Glass Fibers	35,500
51-9020	Crushing, Grinding, Polishing, Mixing, and Blending Workers	37,960
51-9030	Cutting Workers	35,090
51-9040	Extruding, Forming, Pressing, and Compacting Machine Setters, Operators, and Tenders	36,800
51-9050	Furnace, Kiln, Oven, Drier, and Kettle Operators and Tenders	40,610
51-9060	Inspectors, Testers, Sorters, Samplers, and Weighers	42,010
51-9120	Painting Workers	39,850
51-9140	Semiconductor Processors	39,810
51-9192	Cleaning, Washing, and Metal Pickling Equipment Operators and Tenders	33,090
51-9194	Etchers and Engravers	34,550
51-9195	Molders, Shapers, and Casters, Except Metal and Plastic	35,190
51-9197	Tire Builders	45,530
51-9198	Helpers–Production Workers	29,380
51-9199	Production Workers, All Other	34,490
53-7020	Crane and Tower Operators	58,160
53-7063	Machine Feeders and Offbearers	31,710

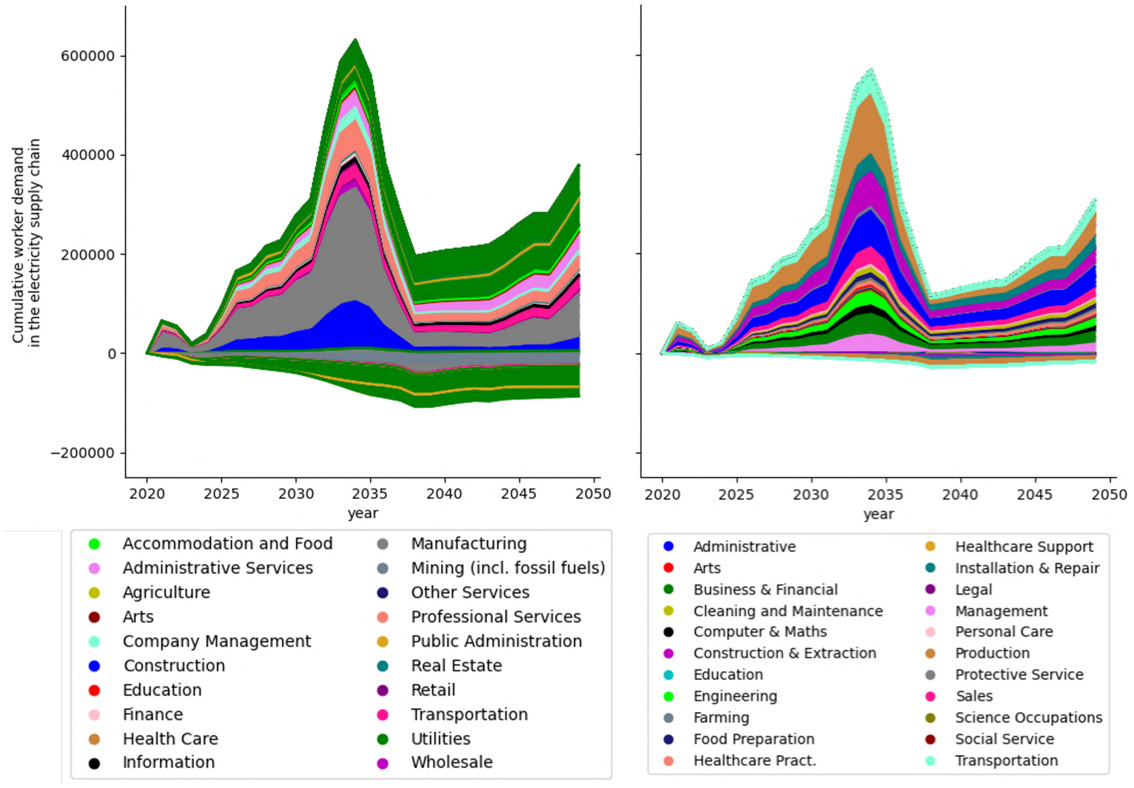
Table 13: Temporary growth occupations. All occupations that are affected more than 1% of total pre-transition employment and see a demand increase in the scale-up phase and a demand decrease in the scale-down phase.

D SM Results

D.1 Results not relative to the reference scenario

The results presented in the main text are shown as relative to NREL's No New Policies reference scenario. Because of the cost declines in renewables, this reference scenario does include some decarbonization driven by cost optimization rather than climate policy. See the left columns of Fig. 1 for the capacity and generation mix in the reference case.

In Fig. 14 we plot the aggregate demand change from 2020 (net per industry (left) and occupation (right) through time for the 95% decarbonization by 2035 scenario. Compared to Fig. 2, we find the same scale-up and scale-down phases, but the steady state phase is less visible. While there appears to be a steady state for the period 2038-2043, employment rises again in subsequent years. This is likely due to the gradual increase in the use of electricity and the end-of-life replacements that are included in the reference scenario.



(a) Industries (b) Industries

Figure 14: Cumulative new job demand since 2020 a) per industry, and b) occupation. Compare to Fig. 2. Industries and occupations are plotted at the detailed level (82 industries and 530 occupations respectively) but colored by their aggregated categories.

Fig. 15 shows some trajectories for selected occupations through time (relative to the reference scenario in Fig. 20). We find the main differences in the last decade 2040-2050. As the reference scenario also decarbonizes (but slowly), the difference between the two scenarios becomes smaller in the late 2040s. This causes some occupational trajectories, such as Mining Machine Operators and Solar PV Installers, to trend towards the $x = 0$ line in the 2040s relative to the baseline in Fig. 20 but not in Fig. 15.

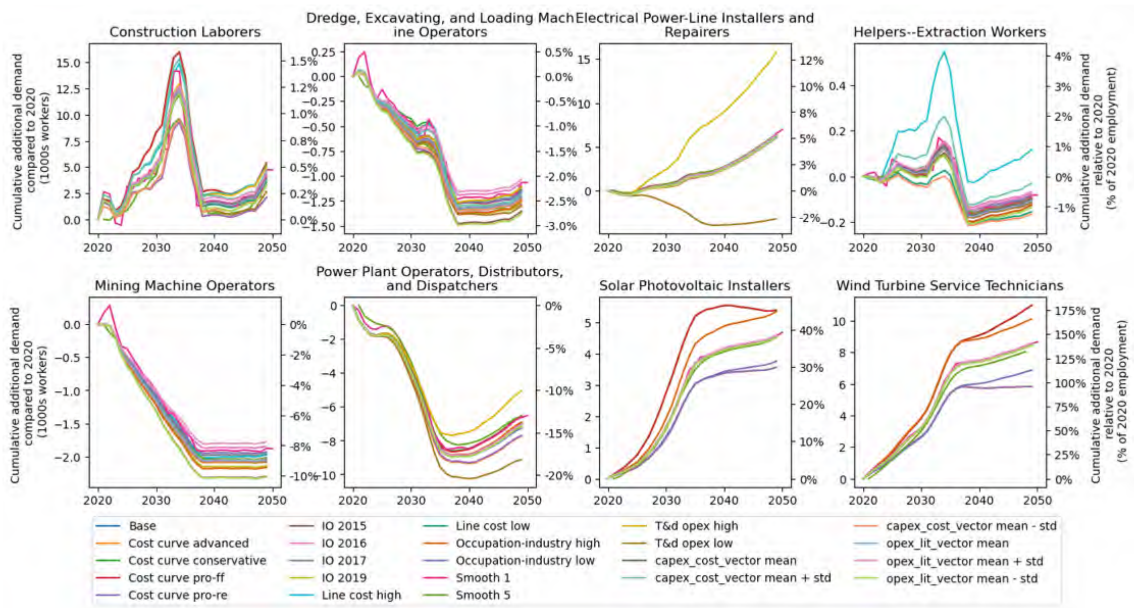


Figure 15

D.2 Location, skills, and frictions

In this section, we shows the current geographical spread and skill content of the occupational typology presented in the main text.

D.2.1 Geographical spread

Our main results are for the US as a whole, but such national aggregation may obfuscate local differences, as mentioned in the main text. In Fig. 16 we show the 2018 average location quotients for different occupational types. Because we do not disaggregate our forward-looking results, we can not confidently predict the places where future jobs will be located. *Consistent growth* occupations were located in 2018 where the US is generating most of its renewable energy: in the south-west, where most utility-scale solar electricity is generated, and the central Great Plains states that see the highest on-shore wind resource and economic potential (McCabe et al., 2022). Temporary growth occupations are less concentrated but more prevalent in traditional manufacturing states in the Northeast and Midwest. Phase out occupations display the highest level of concentration, and are mostly located in a few coal and gas-rich states. See Appendix B.8 for more details on how we calculate the location quotients.

While the location quotients of the phase out occupations might be a good indicator of where job losses are concentrated, this is not necessarily true for occupations with growing demand. Newer generations of wind turbines, for example, are taller, and wind potential at higher altitudes can be different (McCabe et al., 2022), opening up new places for competitive wind energy generation. And local regulations can change. The best wind turbine locations for the future may thus not be where most wind turbines are located right now. Additionally, the current US government domestic manufacturing agenda may well benefit places beyond the traditional rust belt states (The White House, 2022).

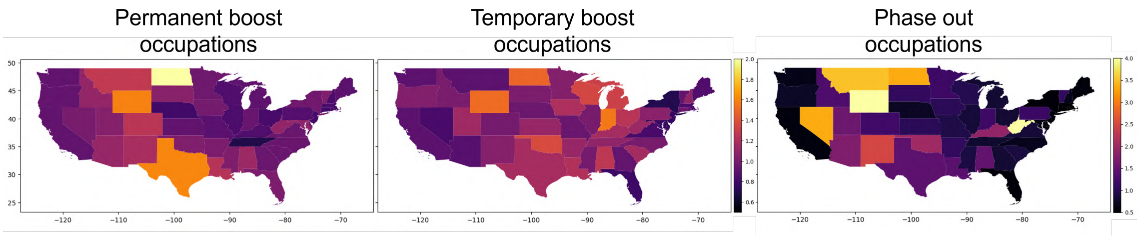


Figure 16: Average location quotient in 2018 of selected occupations in the three occupation types as defined in the main text. These may not be the states where future jobs are located. The location quotient of occupation a in state β is $\frac{x_{a,\beta}/x_{\beta}}{x_a/x}$, with $x_{a,\beta}$ is the number of workers in occupation a in state β, and any subscripts that are left out are summed over (e.g. $x_\beta = \sum_i x_{i,\beta}$). Permanent and Temporary growth occupations share the same colormap; phase out occupations has their own.

D.2.2 Skill content

Skill differences between occupations has been identified in the literature as one of the main factors influencing the ease of transition between occupations (Consoli et al., 2016; Bowen et al., 2018; Saussay et al., 2022). In this section, we highlight the skill content of the occupation typology. We follow Consoli et al. (2016) who quantify the skill categories of Autor et al. (2003) for green jobs. These skill categories are Non-routine analytical (NRA), Non-routine interactive (NRI), Routine cognitive (RC), Routine manual (RM), Non-routine manual (NRM), and the Routine index (RTI index).

In Fig. 17 we find that compared to all other jobs, occupations in the three affected groups in our typology have higher manual and routine (NRM, RTI, RM) skills. The other skills show less differences across occupation types on aggregate.

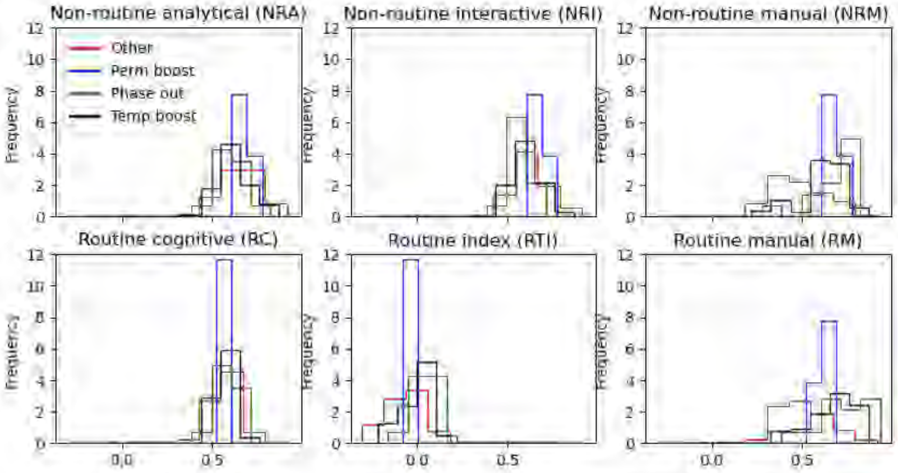


Figure 17: Average skill content per affected job in the electricity supply chain, split into occupations that see a 'Temporary Growth' (black), 'Consistent Growth' (blue), or 'Consistent decline' (green). Average skill content of all other occupations is plotted in red.

In Fig. 18 we plot the same skill distribution using the alternative typology definition (see Section B.7). We compute the average skill content of all occupations, weighted by the fraction of workers in an occupation that are part of each type. Fig. 18 show that for non-routine analytical (NRA), non-routine interactive (NRI), and routine cognitive (RC), the differences between transition workers and all workers distribution are small. However, all affected types of occupations score score higher on routine manual (RM) and non-routine manual (NRM) indicators on average.

Figs. 17 and 18 are similar in that all three affected occupation types exhibit higher manual and routine skill levels (NRM, RTI, RM) than the average job.

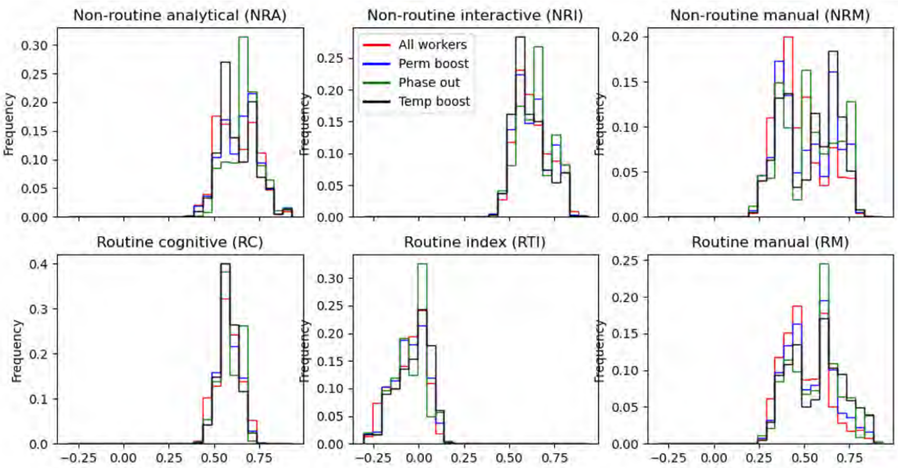


Figure 18: Average skill content per affected job in the electricity supply chain, split into those that see a *Temporary growth* (black), *Consistent growth* (blue), or *Consistent decline* (green), using the alternative typology definition. Average skill content of all workers is also plotted in red.

D.2.3 Occupation network frictions and alternative networks

This section expands the assortativity analysis of Table 1 in the main text by incorporating alternative occupational network definitions and the alternative typology. We also discuss the Monte Carlo simulation approach and results that give the confidence intervals for Table 1.

We will first expand the analysis of categorical assortativity, and after that the analysis of continuous attribute assortativity. We use three networks for our analysis: in addition to the related occupation network, we use an occupational mobility network constructed from census data and a combination of both. For more details on the two networks, see Section A.4.

Categorical assortativity results Table 14 shows the assortativity between the occupational types. All of these results use the categorical assortativity method of Eq. (19). The *Categorical* result on the related network (RN) is the same as in Table 1. The assortativity results of the three individual types are calculated by only including two categories in Eq. (19): that particular type, and an *other* group containing all other occupations.

We find that the categorical results are robust over the networks, if somewhat smaller in magnitude than for the related network. For the individual occupational types, we find that in particular the *Temporary Growth* has high assortativity in both networks but in particular the related occupation network. This indicates that it may be difficult to find a lot of workers to fill vacancies for all the *Temporary growth* jobs simultaneously. Interestingly, the assortativity for *Consistent growth* and *Consistent decline* occupations are much lower and less significant, indicating that the affected occupations are more spread out in the network. On the occupational mobility network, the *Consistent growth* shock has a slightly negative assortativity, meaning that very few transitions have been observed between them in the past.

	OMN	RN	mixed 50/50
Categorical	0.29***	0.43***	0.39***
Consistent growth	-0.00	0.05**	0.01
Temporary growth	0.28***	0.45***	0.39***
Consistent decline	0.18**	0.13***	0.17***

Table 14: Network assortativity of the occupational typology of the power sector transition. OMN = occupational mobility network, RN = related network. ***, **, * indicate results that are greater than 99.9%, 99%, or 95% of values respectively in a Monte Carlo simulation.

In Table 15 we randomise the impact per occupation while keeping the network intact. The standard errors are computed across 100,000 randomizations, which we also use to get confidence intervals for the assortativity results in Table 14. That is, a value in Table 14 gets three (***), two (**), or one (*) star if it is larger in absolute value than 99.9%, 99%, or 95% of randomised runs respectively.

	OMN	RN	mixed 50/50
Categorical	-0.002 (0.02)	-0.002 (0.01)	-0.002 (0.01)
Consistent growth	-0.002 (0.02)	-0.002 (0.01)	-0.002 (0.01)
Temporary growth	-0.002 (0.02)	-0.002 (0.01)	-0.002 (0.02)
Consistent decline	-0.002 (0.02)	-0.002 (0.01)	-0.002 (0.02)

Table 15: Average network assortativity coefficient of occupational typology; average of 100,000 randomised runs. OMN = occupational mobility network, CCN = related network. Standard deviation in brackets.

Continuous assortativity The alternative occupational typology is a continuous variable, so we use the weighted continuous assortativity measure of Eq. (17). The results for the scale-up and scale-down results on the related network are the same as in Table 1. These are robust over the different networks, if slightly higher for the scale-up phase in the empirical occupational mobility network, and lower for the scale-down phase.

The results for the 'Consistent growth' and 'Temporary growth' occupations is very similar to the categorical assortativity in Table 14. For 'Consistent decline' occupations the sign is the same, but assortativity on the binary type classification is higher and more significant, indicating that the most impacted occupations cluster together more than the impact more broadly.

	OMN	RN	mixed 50/50
2020-2034 (scale-up)	0.08**	0.05***	0.05**
2035-2038 (scale-down)	0.16***	0.26***	0.23***
Consistent growth (alternative)	-0.02**	0.04**	0.02*
Temporary growth (alternative)	0.32***	0.51***	0.46***
Consistent decline (alternative)	0.07*	0.06**	0.06**

Table 16: Assortativity of the shock relative to employment on different occupation networks. OMN = occupational mobility network, RN = related network. ***, **, * indicate results that are greater than 99.9%, 99%, or 95% of values respectively, which were obtained from a Monte Carlo simulation.

Table 17 shows the average results over 100,000 randomizations of the results in Table 16.

	OMN	RN	mixed 50/50
2020-2034	-0.002 (0.02)	-0.002 (0.01)	-0.002 (0.01)
2034-2038	-0.002 (0.02)	-0.002 (0.01)	-0.002 (0.01)
Consistent growth (alternative)	-0.002 (0.01)	-0.002 (0.00)	-0.002 (0.01)
Temporary growth (alternative)	-0.002 (0.02)	-0.002 (0.01)	-0.002 (0.02)
Consistent decline (alternative)	-0.002 (0.02)	-0.002 (0.01)	-0.002 (0.01))

Table 17: Average assortativity of the randomised shock relative to employment on different occupation networks. OMN = occupational mobility network. OMN = occupational mobility network, RN = related network. Standard deviations obtained from monte carlo simulation in brackets.

D.3 Beyond Green and Brown occupations

Our measure of dividing the occupational demand patterns into 'Consistent growth', 'Temporary growth', and 'Consistent decline' is related to the *green jobs* literature, which aims to classify which occupations or jobs more generally can be deemed green or brown. Some studies have attempted to define green and brown occupations with respect to the green transitions (e.g., Bowen et al., 2018; Dierdorff et al., 2009; Vona et al., 2018; Peters, 2014). Their measures lead to a distinction between green and brown jobs, sometimes with sub-classifications of green jobs. Green occupations are generally regarded as those that will see a growth in demand due to the green transition, while brown occupations will see a decrease in demand due to the phase out of fossil fuels. For example, Dierdorff et al. (2009) classify occupations into three green classes: *Green increased demand* for occupations whose demand increase when pursuing green policies, *Green new & emerging* occupations, and *Green enhanced skills* occupations that may require significant modifications to their tasks and skill requirements due to greening the economy.

In total, Vona et al. (2021) indicate five ways to classify green occupations. Besides the binary approach (e.g., the aforementioned Dierdorff et al. (2009)) and the task approach from Vona et al. (2018), one can use green job vacancies, information on green technologies and productions, and the pollution content of jobs to define green occupations.

In Table 18 we compare our trajectory-based occupational classification with both O*NET's green occupational typology, and Vona et al. (2018)'s classification of *Brown* occupations. We find that *Consistent growth* occupations correlate with *Green new & emerging* occupations, and that *Consistent decline* occupations correlate with *Brown* occupations. Interestingly, *Temporary growth* occupations correlates both with *Green increased demand* occupations and *Brown* occupations.

	Consist. decline	Consist. growth	Temp. growth	Green enhanced skills	Green new & emerging	Green increased demand	Brown
Consistent decline	1.0***	-0.0	-0.1	0.0	0.0	-0.0	0.3***
Consistent growth	-0.0	1.0***	-0.0	-0.0	0.2***	0.1	0.0
Temporary growth	-0.1	-0.0	1.0***	0.1	0.0	0.3***	0.3***
Green Enhanced Skills	0.0	-0.0	0.1	1.0***	-0.1	-0.1*	-0.0
Green New & Emerging	0.0	0.2***	0.0	-0.1	1.0***	-0.1	-0.1
Green Increased Demand	-0.0	0.1	0.3***	-0.1*	-0.1	1.0***	0.0
Brown	0.3***	0.0	0.3***	-0.0	-0.1	0.0	1.0***

Table 18: Pearson correlation coefficient between different occupational classifications, namely our trajectory-based occupational typology, the occupational classification of different types of green jobs by O*NET (Dierdorff et al., 2009), and the classification of brown jobs by Vona et al. (2018).

D.4 Sensitivity Analysis

We test the sensitivity of our results to seven specific data inputs and modeling choices: 1) The 'supply and use' table base years used in Section B.5; 2) the capex cost vectors of Section C.4; 3) the opex literature weights of Section C.4; 4) the T&D cost in Section B.2; 5) the number of years over which we perform the cost smoothing as explained in the Methods; 6) the employment per occupation-industry pair of Section A.3; and 7) the ATB cost curves per technology as mentioned in Section C.2. We explain each of the separate items in more detail below, and Table 19 gives an overview of each item, the relevant methodology section, and the sensitivity analysis approach and values.

	First relevant equations or sections	Sensitivity analysis approach	Default	Values in sensitivity analysis
Base year supply and use tables	Eq. (7)	Alternative years	2018	2015 2016 2017 2019
Capex cost vectors	Eq. (11)	Add noise	No noise	30 runs with all values multiplied by random normal noise, and re-normalised to sum to unity
Opex literature weights	Section B.6	Add noise	No noise	30 runs with all values multiplied by random normal noise, and re-normalised to sum to unity
T&D cost per MW-mile	Eq. (24)	Min / max literature value	1,433 (2018-USD)	932 (2018-USD) (min) 3,624 (2018-USD) (max)
T&D cost factor for three times more powerful lines	Eq. (24)	plus-minus 25%	1.37	1.0275 1.7125
Number of years of cost smoothing	Methods	Alternative values	3	1 (no smoothing) 5
Employment per occupation-industry pair	Eq. (16)	Standard deviation	Point estimate	Point estimate + standard deviation Point estimate - standard deviation
Technology cost curves	Eqs. 1-5	Alternative projections from NREL's ATB	Moderate	Advanced Conservative Pro-fossil fuel (pro-ff) Pro-renewables (pro-re)
T&D Opex	Eq. (25)	plus-minus 25%	1.37	1.0275 1.7125

Table 19: Sensitivity analysis approach

Base year supply and use tables The A matrix in Eq. (7) and beyond is the domestic input output table, the basis of which are the 2018 'supply and use' tables provided by BEA as explained in Section B.5. In our sensitivity analysis we also use the 'supply and use' tables from 2015, 2016, 2017, and 2019. Fig. 19 shows the different in technical coefficients of the domestic IO table after performing the electricity sector disaggregation procedure of Section B.6.1. There is some diffusion visible, but we find that a different choice of IO base year has only limited impact on our results.

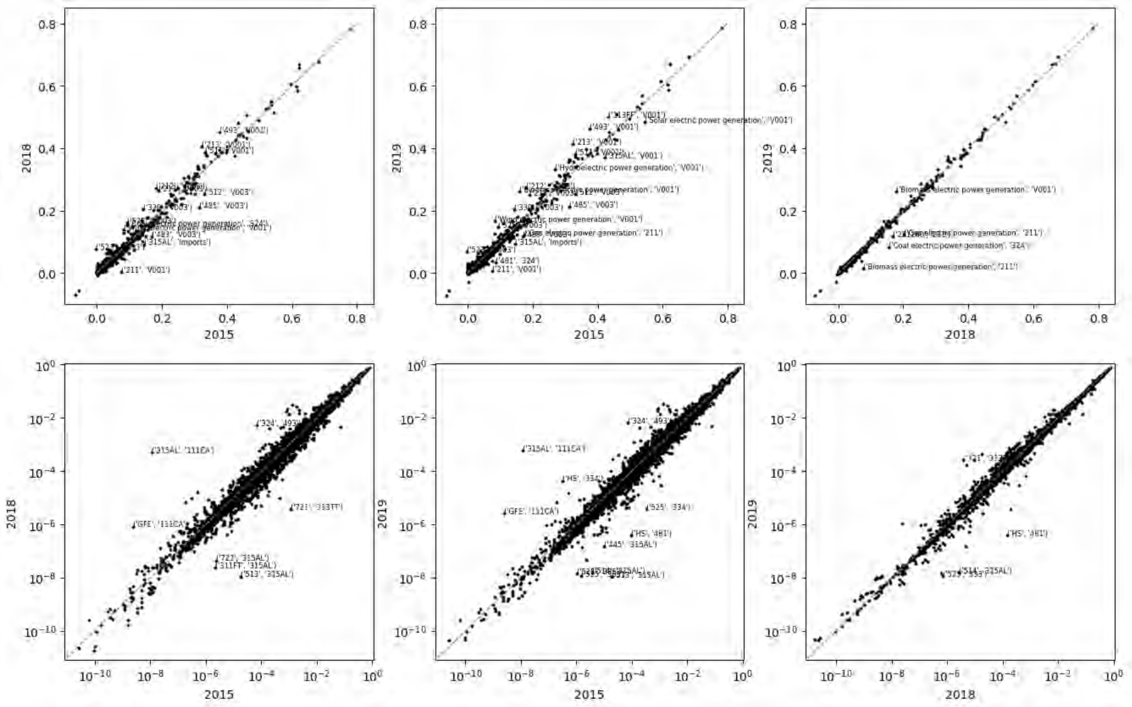


Figure 19: Scatter plot of technical coefficients for different IO base years, from left to right: 2015 vs 2018, 2015 vs 2019, and 2018 vs 2019. Bottom row log-log plots correspond to the linear plots from the top row. Any changes of more than 5 percentage points (top) or 50x (bottom) are labeled.

Capex cost vectors We translate capex cost per technology into spending on final demand per industry in Eq. (11). The translation from technology i to the IO industries is done using capex cost vector K_i^{capex}, where each element K_{ij}^{capex} is the the fraction of technology i capex that is spent on industry j. We initialize the K_{ij}^{capex} using previous literature estimates. The cost vectors we use in our main analysis are shown in Table 4.

For our sensitivity analysis we use random noise to generate alternative cost vectors around the estimates used to produce the main results

$$K_{ij}^{\text{SAcapex}} = \max(0, 1 + \epsilon_{ij}^{K}) K_{ij}^{\text{capex}} \beta_i, \tag{46}$$

where $\beta_i = \frac{1}{\sum_j \max(0, 1+\epsilon_{ij}^{K}) K_{ij}^{\text{capex}}}$ is the normalization constant such that $\sum_j K_{ij}^{\text{SAcapex}} = 1$, and the maximum operator makes sure no value is negative. We draw $\epsilon_{ij}^{K} \sim \mathcal{N}(\mu, \sigma^2)$ from a normal distribution with $\sigma = 0.5$. We do this 30 times, which we show in Fig. 22, and take the mean and standard deviation of all 30 runs to show the results in Figs. 20 and 21.

Opex cost vectors In Section B.6 we discuss how we disaggregate the IO table using literature estimates of their production recipes.

Analogously to the capex cost vectors, we apply Eq. (46) to the electricity sector opex cost vectors B from the literature of Table 6 to create additional opex cost vectors

$$B_{ij}^{\text{SA}} = \max(0, 1 + \epsilon_{ij}^{B}) B_{ij} \beta_i, \tag{47}$$

where $\beta_i = \frac{1}{\sum_j \max(0, 1+\epsilon_{ij}^{B}) B_{ij}}$ is the normalization constant such that still $\sum_j B_{ij}^{\text{SA}} = 1$. We draw $\epsilon_{ij}^{B} \sim \mathcal{N}(\mu, \sigma^2)$ from a normal distribution with $\sigma = 0.5$.

T&D cost In Eq. (24) we assume transmission grid costs 1,433 2018-USD / MW-mile. A different publication, Brinkman et al. (2021) puts the cost between 900 (932 2018-USD) and 3,500 USD (3,624 2018-USD) per MW-mile. We use those two numbers as a lower and upper bound on T&D line cost. Secondly, In Eq. (24) we assume three times more powerful lines can be installed for 1.37 times the cost. In the sensitivity analysis, we change this value by 25% to 1.0275 and 1.7125.

T&D opex In Eq. (25) we use a factor of 1.37 to calculate the opex needs to maintain 3 times as powerful lines, analogous to the capex calculation. In the sensitivity analysis, we increase and decrease this value by 25%, i.e. 1.0275 and 1.7125.

This parameter has a small effect on most occupations and the peak value in 2034, but a large effect on specialised occupations such as Electrical power-line installers and repairers, and the steady-state level of employment post-2038.

Number of years of cost smoothing To make the investment flows less erratic, we smooth them using a 3-year moving window. We change this using a 5-year moving window, or by applying no smoothing. More smoothing results in a less peaky and erratic trajectory, as can be seen in Fig. 21.

Employment per occupation-industry pair In Eq. (16) we use M_{ij}, the number of workers in occupation i in industry j per million output. We calculate M_{ij} in Eq. (23) using B_{ij}, the total number of workers in occupation i employed in industry j in 2018. This data is from BLS. BLS also provides Percent relative standard error (PRSE) per B_{ij}. We construct two additional versions $B_{ij}^{+\sigma} = B_{ij} + \sigma_{ij}^{B}$ and $B_{ij}^{-\sigma} = B_{ij} - \sigma_{ij}^{B}$ to test our results sensitivity to this data input. This affects some smaller occupation-industry pairs that are important to the transition most, such as wind turbine service technicians.

ATB cost curves Our baseline scenarios use the *moderate* ATB unit cost curves per technology as provided by NREL. These unit costs are used in Eqs. (1)-(5) to translate electricity capacity and generation to capex and opex.

We will test our model for sensitivity by employing NREL's other unit cost trajectories: the *conservative* and *advances* scenario. In addition, we add a pro-fossil fuel (pro-ff) and pro-renewables (pro-re) cost curves, which are combinations of the conservative and advanced cost curves. In the pro-ff (pro-re), we take the advanced (conservative) estimate for fossil fuel technologies, and the conservative (advanced) estimates for all renewable technologies and battery storage.

D.4.1 Impact of sensitivity analysis on temporal profiles

Fig. 20 shows the impact of the parameter sensitivity on trajectories of individual occupations. What item has the most impact differs per occupation. Electrical Power-Line Installers and Repairers are impacted mostly by T&D opex changes. Solar PV installers and Win Turbine Technicians have different trajectories that depend mostly on the assumption of energy cost reductions over time, as well as measurement errors by BLS, as these occupations are still relatively new and small.

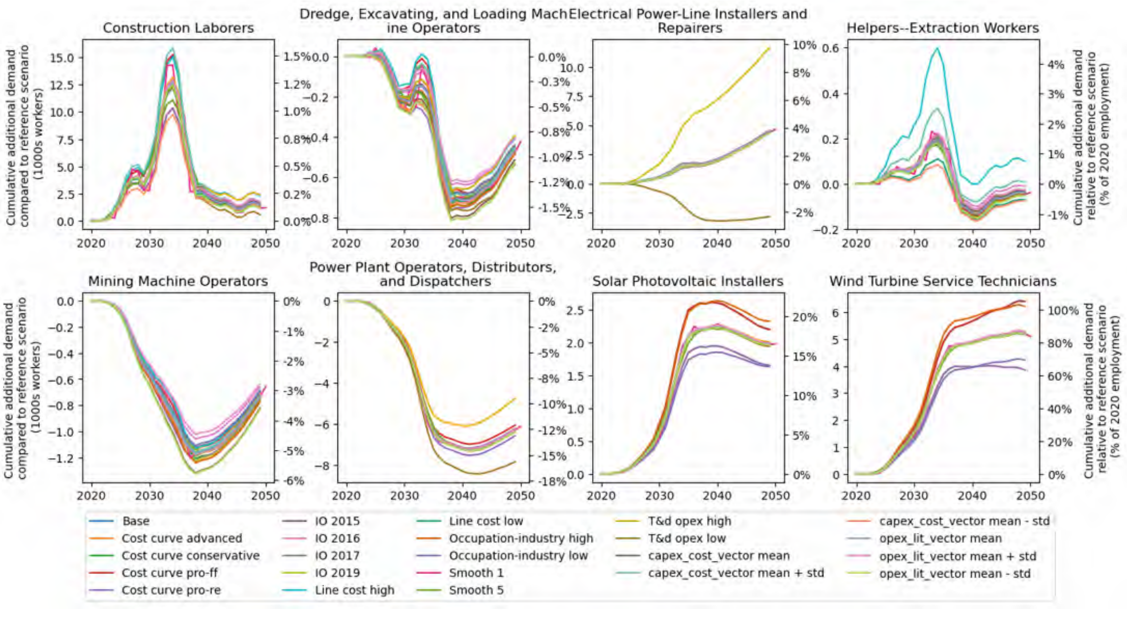


Figure 20: Sensitivity of occupation trajectories over time of selected occupations.

Fig. 21 shows the aggregated demand for workers of all occupations in a stacked bar plot. The top left sub-figure reproduces the right-hand side figure of Fig. 2a. While their overall figure is very similar, with a peak at 2034, and a relatively steady state after 2038, the size of the peak and steady-state employment can differ. Fig. 22 shows the net employment demand changes relative to the reference scenario for the peak in 2034, and the steady state phase in 2045.

Higher line costs lead to much higher net labor demand in 2034, as do more conservative cost curves and not using a smoothing window. The latter also leads to much more erratic occupational demand profiles. The largest impact on steady-state employment are opex T&D employment factors and transmission line costs.

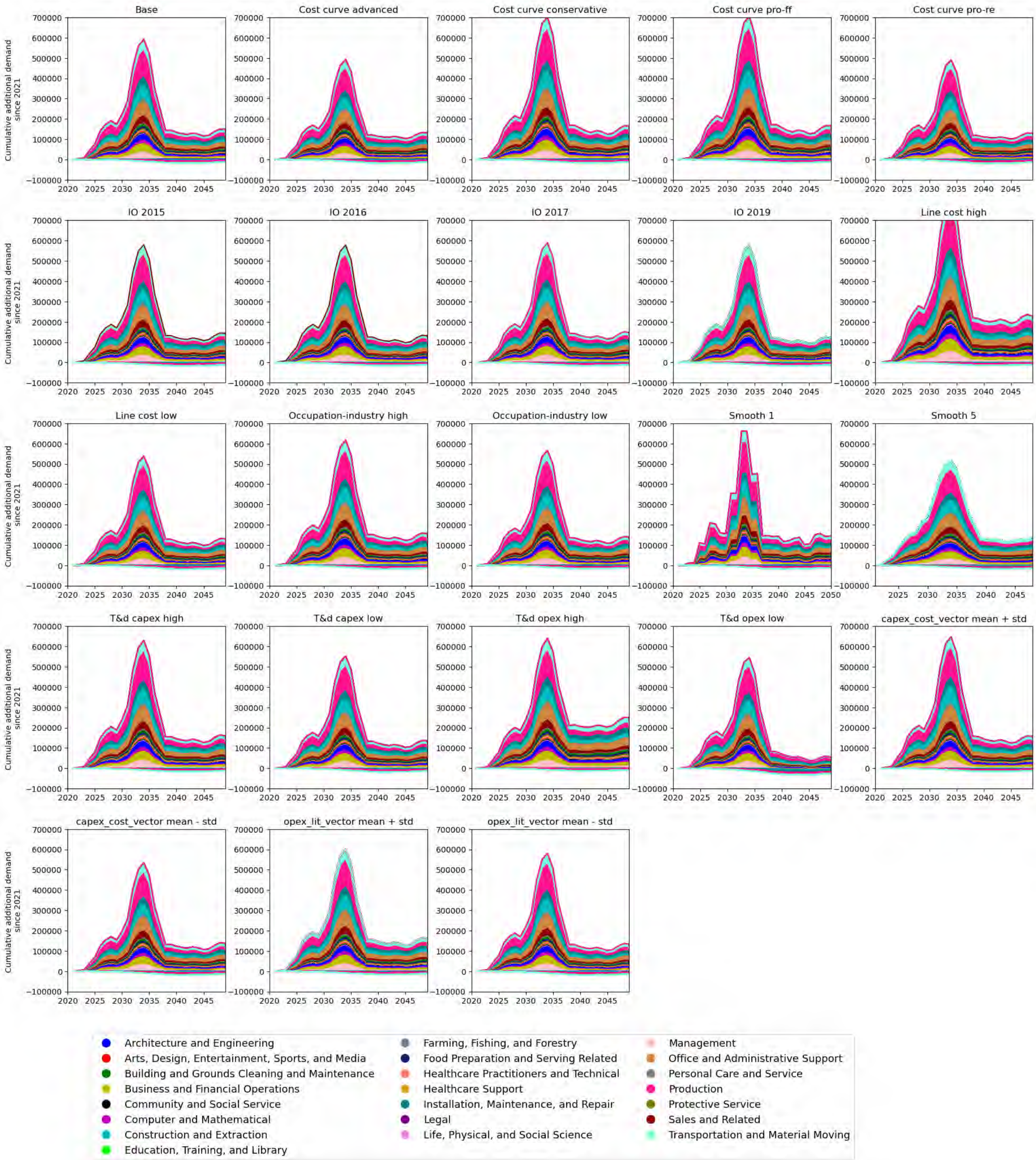
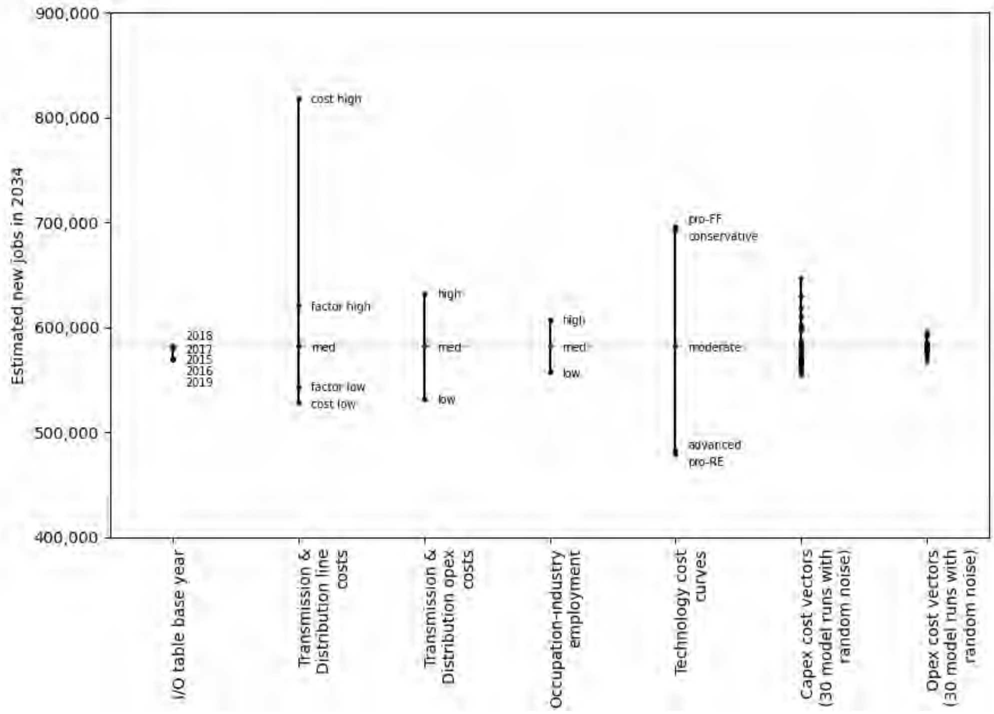
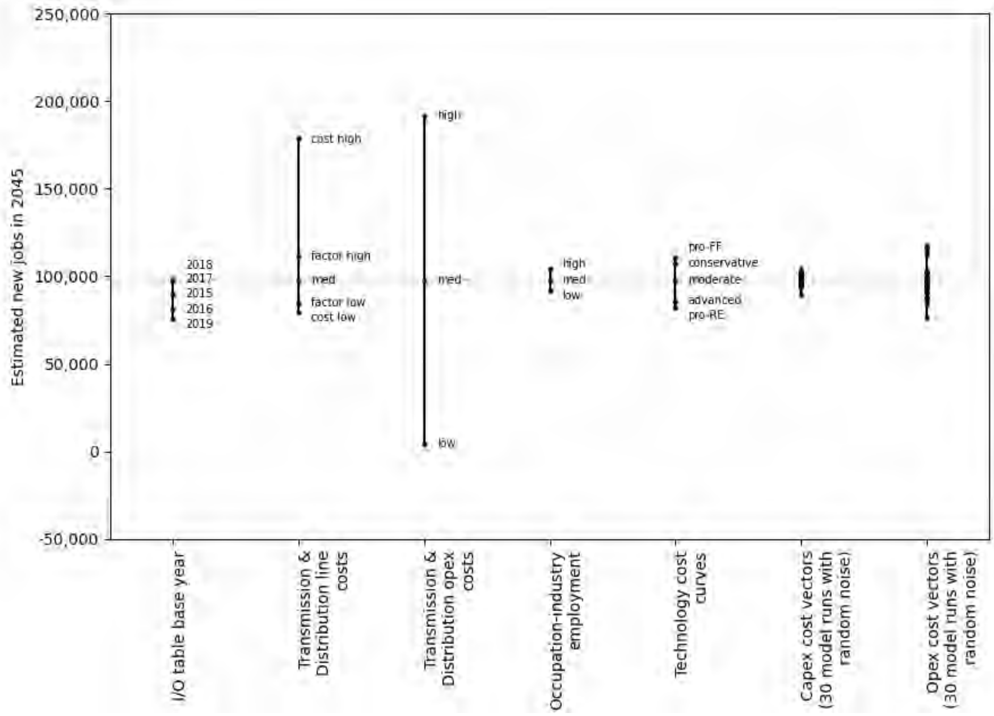


Figure 21: Cumulative sum of net occupational demand changes over time. Each plot changes one parameter of the sensitivity analysis. Top left figure reproduces the right-hand side figure of Fig. 2a.



(a)



(b)

Figure 22: Results from a sensitivity analysis on estimated net additional jobs from changes to key variables and components used in the modelling for a) 2034 during the peak, and b) 2045 during the steady state phase

D.4.2 Assortativity analysis

For each of the sensitivity analysis items, Fig. 23 shows the assortativity of shocks relative to employment on the combined network before and after the peak during the transition, as a further robustness check on Table 1. We also included the assortativity calculation of the base assumptions using the empirical occupational mobility network (OMN) and the mixed network (as defined in Section B.9). For more results on the assortativity levels of the different networks, see Section D.2.3.

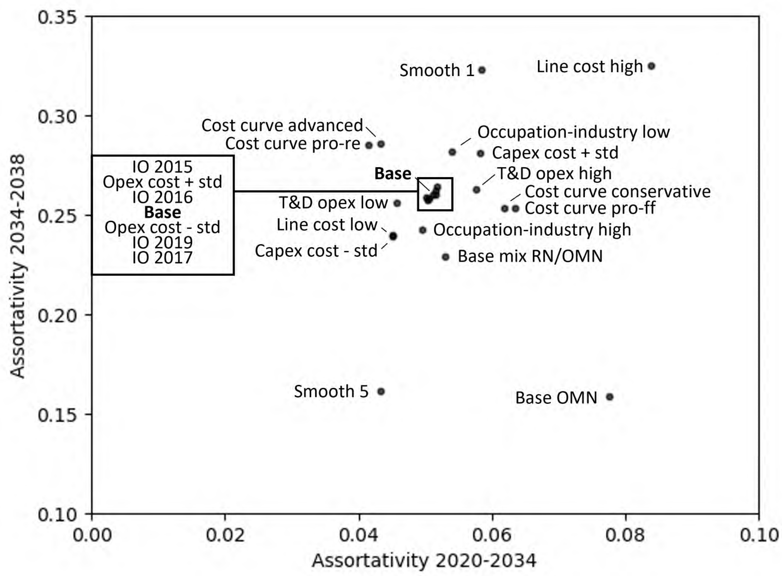


Figure 23: Sensitivity analysis of assortativity analysis of scale-up (x axis) and scale-down (y-axis) phases. The value for Base corresponds to the scale-up and scale-down values in Table 1. RN = related network. The mix RN/OMN = 50/50 mix of related network and empirical occupational mobility network (see Section B.9)

We can see that the assortativity levels for the 2034-2038 period all deviate by less than 25% from the Base estimate, except for 5-year smoothing and the assortativity using the occupational mobility network (OMN), which moves the assortativity to almost 40% lower than the base estimate. For the 2020–2034 period we find that the assortativity values for OMN and high line cost are more than 25% removed from the base estimate, respectively 40% and 55% higher.

Most of the assumptions move assortativity up or down for both time periods, but two do not. Using more ambitious (*advanced* learning rates on cost curves leads to lower assortativity in the scale-up phase (2020–2034) but higher assortativity in the scale-down phase (2034–2038). The occupational mobility network, vice versa, has higher assortativity for the scale-up phase and lower for the scale-down phase.

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