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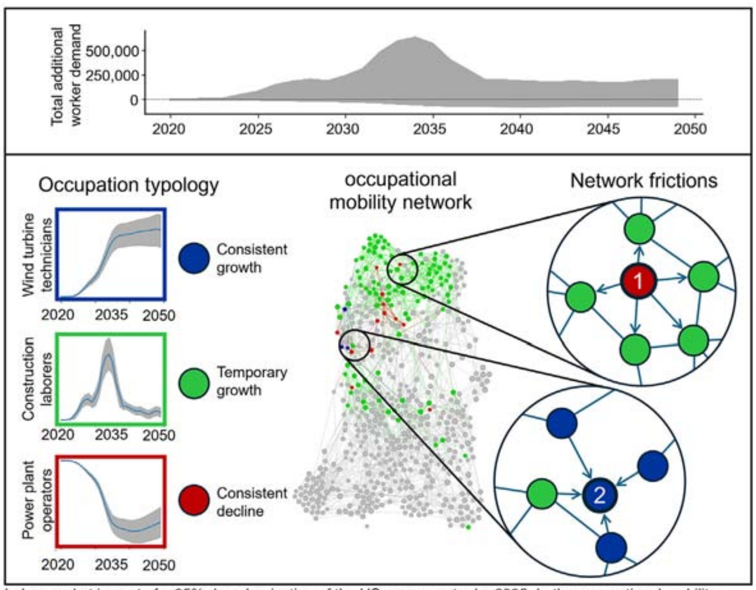
# Employment dynamics in a rapid decarbonization of the US power sector

## Graphical abstract




Labor market impact of a 95% decarbonization of the US power sector by 2035. In the occupational mobility network, each node is an occupation. Occupations are connected to other occupations that are related to them. In the zoom circles, the frictions for displaced workers from occupation **1** are both alleviated and amplified at different points during the transition. Vice versa, occupation **2** faces skill shortages throughout the transition.

## Highlights

- Employment demand in the energy transition follows nonlinear dynamics
- Diverse occupational impacts challenge the classic green vs. brown jobs framework
- Occupational mobility networks reveal skill mismatches and labor frictions

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## In brief

The transition to a world powered by clean energy will involve transforming part of the labor market. We show that this transition has the potential to generate temporal labor market fluctuations and skill mismatches. Compared with the size and fluctuations of the US labor market, the impact of this transition is modest. However, heterogeneous impacts across occupations and over time, without proper planning, can make specific industries struggle to find skilled labor and displaced workers have difficulty finding jobs.

Bücker et al., 2025, Joule *9*, 1–18
February 19, 2025 
https://doi.org/10.1016/j.joule.2024.12.004

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Please cite this article in press as: Bücker et al., Employment dynamics in a rapid decarbonization of the US power sector, Joule (2024), https://doi.org/10.1016/j.joule.2024.12.004

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# Employment dynamics in a rapid decarbonization of the US power sector

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https://doi.org/10.1016/j.joule.2024.12.004

**CONTEXT & SCALE** The urgency of the transition to a low-carbon world requires a fast decarbonization of the electricity generation system. Such a transition will change the demand for skills in the energy sector, which can generate labor market frictions: skill shortages arise if employers cannot find enough skilled workers and, vice versa, if displaced workers find it hard to get new work. This paper identifies occupation- and time-specific skill mismatch frictions during a fast transition scenario of the US power sector. We use methods from complex network theory to identify potential skill frictions for workers in these occupations, adding nuance to the green jobs debate in the literature. The changes in demand that we find are small compared with the total US labor market and can be influenced by changes to US competitiveness of energy-related products.

## SUMMARY

We analyze the employment dynamics of a rapid decarbonization of the US power sector, reducing emissions by 95% before 2035. We couple an input-output model with an occupational mobility network and identify three labor market phases: “scale-up,” “scale-down,” and a long-term, low-carbon, “steady state.” During the scale-up (2023–2034), for every job lost in an industry, 12 new jobs are created elsewhere. However, few occupations see sustained growth throughout the transition. We predict that skill mismatches will create frictions during the transition, especially in the scale-down phase. Compared with the size and fluctuations of the US labor market, the impact of this transition is modest, particularly if the US increases exports of clean energy technologies to counteract the domestic scale-down phase. However, without proper planning, rapidly growing industries will struggle to find skilled labor during the scale-up phase, while displaced workers might struggle finding jobs during the scale-down phase.

## INTRODUCTION

An immediate and accelerated decarbonization of the global economy is required to limit global warming to below 2°C above pre-industrial levels.[1,2] Since the majority of greenhouse gas emissions (more than 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.[3] While a fast transition to a net-zero energy system could end up being economically beneficial by itself,[4,5] 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 underscore the importance of managing such transitions and finding ways to alleviate the negative impacts of stranded labor on displaced workers and communities.[6–10]

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,[11] as it currently is in many places in Europe and North America.[12] A shortage of workers with the right skills could slow down the energy transition.

Previous literature is broadly aligned in concluding that there will be a net gain of jobs in the US during a clean energy transition. For example, Jacobson et al.[13] find almost 2 million net jobs created in the US (6 million gained, 4 million lost), while the International Labor Organization (ILO)[14] finds a 0.45% economy-wide net increase in employment for the Americas as a whole, representing around 700,000 jobs[15] for the US if we assume it follows the regional average. Mayfield et al.[16] estimate that the fraction of the US workforce in the energy supply chain will grow from 1.5% in 2020 to 2.5%–5% in 2050, representing, approximately, a 1.5–6 million increase in workers. Ram et al.[17] find a roughly 4 million net increase in energy-related jobs between 2020 and 2050 for the US in a 100% renewable energy scenario. Xie et al.[18] 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,[19] Lehr et al.,[20] and Černý et al.[21] Only a few studies find a negative impact on job creation; for an overview, see, e.g., Stavropoulos and Burger.[22]

Most of these studies only focus on aggregate job numbers in the initial transition phase and do not address the heterogeneity of impacts across workers and over time. Workers' occupations, skills, experience, geographic location, available alternative employment options, and perceived socio-economic status can affect their employment prospects.[23–27] Workers are more likely to transition to jobs in industries and occupations related to their previous job.[28–30] 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.[31]

The net-zero transition has the potential to generate skill mismatches, which can evolve over time. To assess the employment implications of the net-zero transition, it is important to consider the heterogeneous effects across all occupations and over time. Traditional global integrated assessment models rarely analyze the evolving labor structure or categorize households by occupation, lacking information on employment shifts linked to specific mitigation scenarios.[32] Although some macroeconomic models have begun to explore labor market impacts at a detailed level and consider different skills and occupations, e.g., ILO[14] and Mayfield et al.,[16] most of these studies overlook potential skill mismatches that result from correlated displacement shocks across occupations and over time.

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.[33] apply an industry and geography mobility model to the Netherlands, and Berryman et al.[34] 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.[18] look at the distributional effects for workers of a US power sector decarbonization, disaggregated by skill level and gender across states.

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. For example, O*NET classifies occupations as "green new and emerging" if they are likely to see a demand increase when shifting to a "greener" economy.[35] Vona et al.[36] analyze 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.[37–39] Nevertheless, more transitions from brown to green jobs can be expected as the availability of green jobs increases.[40]

In this study, we argue that temporal effects 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 may decline, particularly in construction and manufacturing. 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 occupation-specific skill mismatches as they evolve during the clean energy transition. In our framework, 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 frictions, so that they can make targeted interventions to mitigate skill-mismatch frictions.

We follow a four-step procedure (see methods; Figure 7). First, we translate the different cost components (capital expenditure, operational expenditure, and fuel cost) of power sector decarbonization scenarios into annual demand shocks and intermediate consumption changes.

Second, we use a simple demand-driven input-output (IO) model to estimate direct and upstream industry output changes 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 in tandem with the energy mix (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 breakdown per constant-dollar output—this also means that wages are kept constant in real terms. 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.

Finally, by linking occupational demand trajectories to an occupational mobility network, we quantify potential skill-mismatch

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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 (see supplemental methods section D.6).

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.[3] 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. All the results in the main text concern the implications of the "95% by 2035" scenario relative to NREL's "no-new-policy" scenario, which we take as the "reference" scenario.

Recently announced policies, such as those included in the Inflation Reduction Act (IRA), also make a fast transition in the power sector more likely. The current US President Biden's stated goal is to deliver 100% clean electricity by 2035.[41] The IRA moves the US much closer to that trajectory, although Bistline et al.[42] show that IRA-compliant power sector scenarios could still fall short of this target. A fast decarbonization might also be accelerated further by economic forces if it becomes financially beneficial.[4,5]

NREL is a US Department of Energy sponsored research center that produces scenarios that are closely examined by US policymakers, with high credibility in the research community. NREL's fast transition scenario also 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 temporal implications of the transition.

NREL does not make assumptions about whether clean technologies are imported or produced domestically, so we need to specify that ourselves. However, it is important to bear in mind that a substantial fraction of the demand for labor from the clean energy transition is domestic, independent of imports and exports. This is because almost all of the operational expenses are for domestic labor, and many categories of capital expenses are for domestic industries such as construction. Thus, while what happens in terms of imports and exports is important, we find our basic conclusions hold across a range of plausible import and export scenarios, as shown in Figures S18–S21 in supplemental methods section D.6. Our main assumptions represent a form of "business as usual": keeping the relative share of import sf capital goods constant at 2018 levels, while keeping exports fixed in absolute terms. The logic for our approach and a description of the alternate scenarios, and how they affect the results, is given in the section titled "robustness of results."

Our model works with national-level data and thus neglects sub-national differences. The total flux of workers that the NREL scenario causes in our model is small, especially for large industries such as construction and manufacturing that are engaged in many activities beyond renewable energy. However, local impact can be more problematic. Green jobs are likely to arise in different locations than fossil-fuel jobs,[43] 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 supplemental methods 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 are assumed to have already been included in the NREL energy scenarios that we apply.

We make three contributions to the wider debate on the labor market impact of the green transition. First, we show that the aggregate demand for jobs does not follow a linear pattern but rather three distinct phases—scale-up, scale-down, and the low-carbon power system. Second, we challenge the commonly used green vs. brown jobs dichotomy of occupations, providing a more accurate and meaningful list of demand trajectory typologies for occupations—temporary growth, consistent growth, consistent decline, and late growth. Third, we use methods from network science to quantify the frictions faced both by employers seeking qualified labor and workers looking for jobs in each phase of the transition.

While it is beyond the scope of this work, the extent and timing of further electrification and prospective efficiency drives will be important factors. 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-policy 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.

The remainder of this paper is organized as follows. In section "temporal heterogeneity in labor demand during the transition," we present the transition scenarios and estimations of labor demand dynamics. This is followed by "temporal typology of occupational demand change," where we introduce our suggested classification of occupations according to the demand dynamics. In "skills shortages and stranded labor," we use network tools to identify potential skill mismatches and frictions. We discuss the results of several robustness check in section "robustness of results." We conclude with a discussion on this paper's contributions and implications. Our methodological approach, based on coupling power transition scenarios with a dynamic IO model to assess labor demand and occupational mobility, is detailed in "methods."

## RESULTS

### Temporal heterogeneity in labor demand during the transition

The two NREL scenarios we use are shown in Figure 1. The left panels display the capacity and generation profile of the reference scenario that we use, which assumes no new carbon reduction policies beyond those in place as of June 2021 (without, e.g., the more recent IRA). The right panels depict the fast transition scenario, where the model is required to reach a 95% decarbonized system from 2035 onward. Both models

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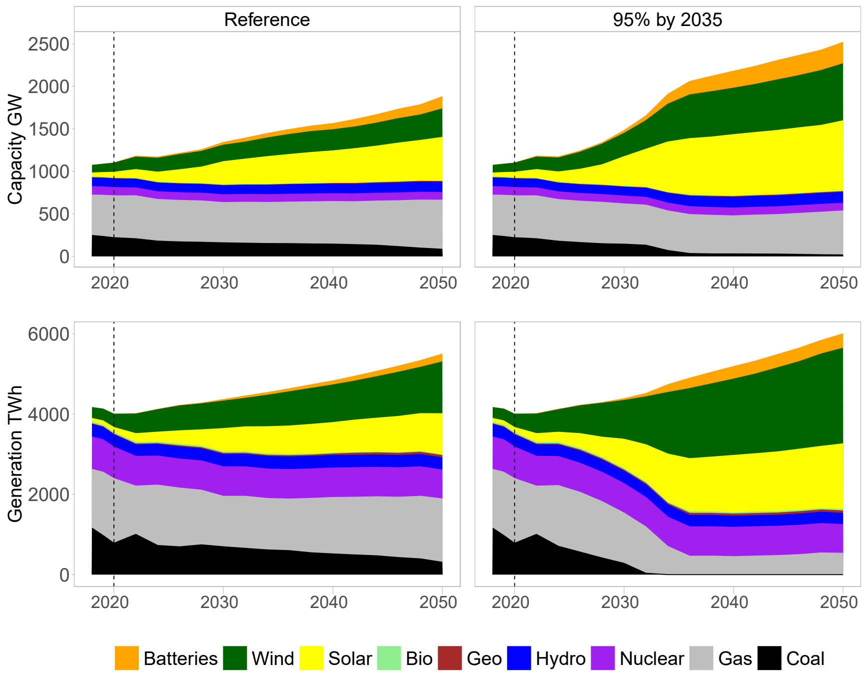


**Figure 1. The US power sector scenarios we use in this study**

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-policy reference scenario that we use as the counterfactual and on the right NREL's fast 95% by 2035 scenario. Source: NREL,[44] with technological categories aggregated according to Table S1: gas electricity also includes gas with carbon capture and storage (CCS) technology. Up to 2020, the figures show historical data from the Electric Power Annual 2020.[45]

are the result of a cost-optimized energy model with fixed and inelastic electricity demand. The increase in renewables in the reference scenario, for example, shows the cost effectiveness of including renewables with policies as of June 2021. For more details on the modeling assumptions used in the NREL scenarios, see Cole et al.[44] The corresponding emission pathways are shown in the supplemental methods Figure S1. 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. Note that we model natural gas with carbon capture technology as a separate variety included in the natural gas part of our study (see Table S1 in supplemental methods section C.1).

The fast transition scenario we consider here is an interesting study case, but it should be pointed out that other low-carbon energy mixes are feasible, possibly involving very different sets of technologies (e.g., see, Bistline et al.[42] and Pickering et al.[46]). Different technology choices would lead to different labor market impacts. Thus, the results presented should not be understood as covering the whole spectrum of labor market impacts of the power sector transition but, rather, model the potential impacts of specific future scenarios.

In supplemental methods section D.1 and accompanying Figure S7, we show how the scenarios translate to operating expenses (opex) and capital expenses (capex), taking replacement and newly built capacity into account. In the 95% by 2035 scenario, we find a large increase in investment in renewable technologies (solar, wind, and batteries) and the transmission and distribution (T&D) network until 2035 and a decline afterward in the 95% by 2035 scenario. On the opex side, renewable technologies require a larger share of total cost over time in the 95% by 2035 scenario, while the main change in the reference scenario is a switch from coal to natural gas opex. As explained further in the methods section, we use an IO model to estimate the direct and indirect—supply chain—effect on worker demand.

## Transition scenario and labor market impact

In Figure 2, we present our model's estimates of the labor demand relative to the reference scenario for industries and occupations between 2020 and 2050. For visualization purposes, the labels indicate 2-digit NAICS (North American Industry Classification System) 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. These industries and occupations represent all nonfarm US firms and workers—with the exception of the US government defense sector. See supplemental methods section E for the full list of industries and occupations. When we refer to "jobs" gained (lost) or worker demand that increased (decreased) in this study, we refer to the net increase (decrease) in demand within industries or occupations relative to the reference scenario. See methods for more information.

Across all industries with labor demand growth, we predict an increase in demand of about 633,000 workers by 2034 compared with the reference scenario. In the same time period, 52,000 jobs are lost in industries with a decrease in demand, giving a net growth of around 580,000 workers by 2034. In testing the sensitivity of our analysis against some of the key uncertainties in the modeling (see supplemental methods section D.6), 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 580,000 being our base case.

To put our estimates in perspective, a total change of 685,000 jobs (633,000 growth plus 52,000 decline) accounts for just 0.4% of the current US employment and roughly 0.15% of the estimated US labor market flux within 15 years.[48] Not all job transitions are occupational transitions: Vom Lehn et al.[49] calculates that approximately 5.9% of US workers switched occupations per year between 2000 and 2018, although in recent times, occupational switching appears to have slowed down. While a change of 685,000 workers may seem small with respect to total employment and labor flows, job changes caused by the energy transition could be highly geographically concentrated.[43]

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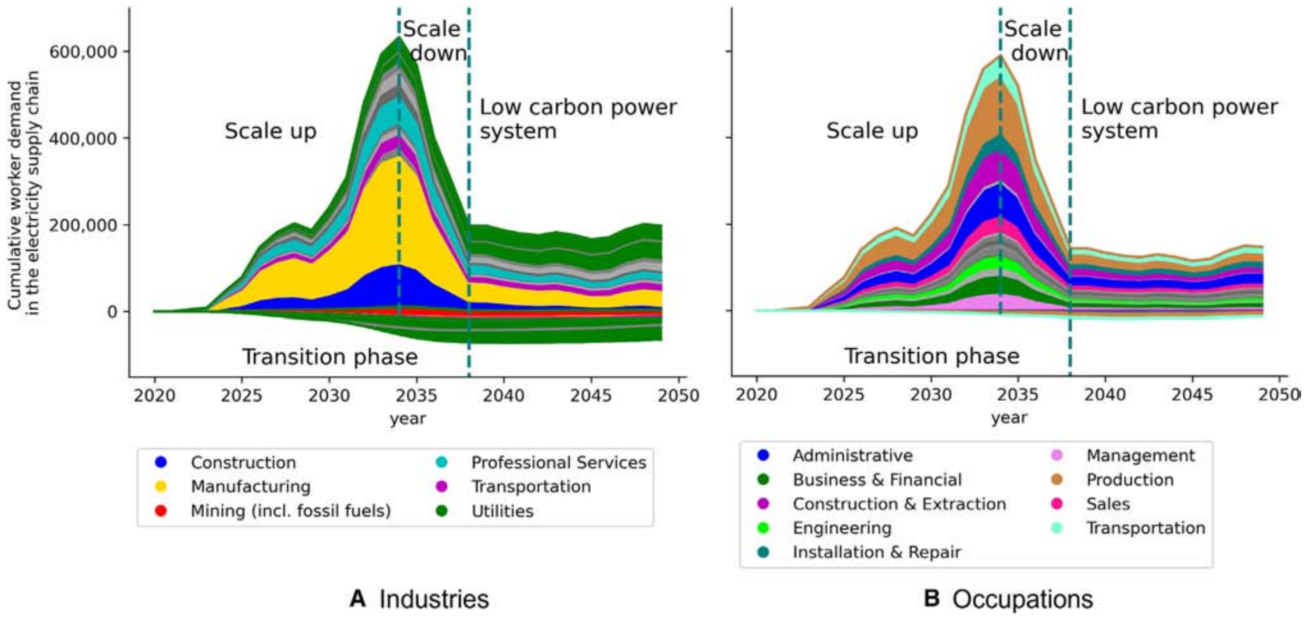


**Figure 2. Total additional demand change for workers in the 95% decarbonization by 2035 scenario**

(A) Per aggregated industry and (B) per occupation category. The demand change is net of 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 (14 of 20 categories are minimally affected and shown in gray scale[14]). Occupations are plotted at the detailed level used in the analysis (539 occupations) and colored by their 2-digit level aggregation (13 of 22 occupation groups are minimally affected and shown in gray scale[47]). Different phases of the transition are demarcated with dotted vertical lines and labeled.

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.[50] Furthermore, the US labor market is still relatively tight with low unemployment and high number of vacancies,[51] which can make additional skill shortages harder to absorb.

An important contribution of this study is the temporal dimension of labor demand and skill mismatch, both during the electricity sector transition and beyond. We focus on the heterogeneity of temporal trajectories for demand of detailed industries and occupations.

## Temporal phases of labor demand

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, in which the work is done to reach the goal of a 95% decarbonized electricity generation 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, characterized by decreasing overall labor demand as 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 are 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 1860.[52] 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.[53]

After the transition phase begins 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 with a no-new-policy reference scenario (see supplemental methods section D.6 for a sensitivity analysis on this estimate).

When we dive deeper into the industry profile details (Figure 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 deploying 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. Such losses could be lessened depending on global demand for US exports, such as possible increases in demand for US natural gas.[54,55] (See also supplemental methods section D.6 for more details on import and export scenarios). Vice versa, 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. Figure 2B shows the labor requirement dynamics per aggregate

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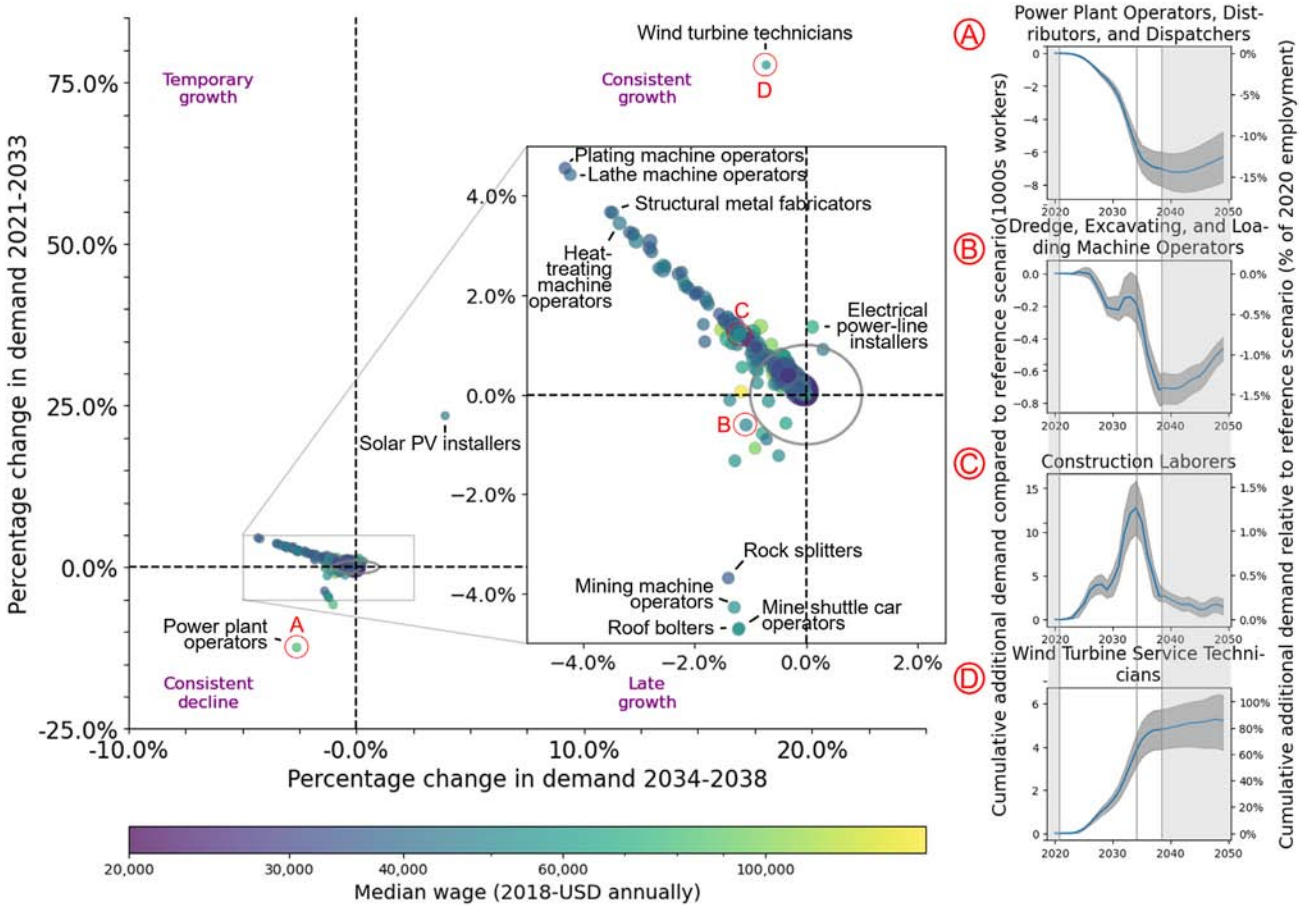


**Figure 3. Occupation demand change relative to employment in the 95% by 2035 scenario**

On the vertical axis, the net demand change between 2021 and 2034 (scale-up phase), and on the horizontal axis, the change between 2034 and 2048 (scale-down phase). The demand change is relative to the no-new-policy reference scenario. Three occupations (wind turbine technicians, power plant operators, and solar PV installers) that lie outside of the rectangular zoom-in box are labeled. The zoom-in box does not cover any data point in the main plotting area. Occupations within the gray circle shown in the zoom-in box experience less than 1% demand change are considered minimally affected; all other occupations are categorized by the labor transition typology that is formed by the four quadrants, which are labeled in purple. Occupations are colored according to their mean wage. The occupational profiles on the right show the full temporal dynamics for four selected occupations. Gray error bars are constructed via the sensitivity analysis on the trajectory calculation (see supplemental methods section D.6).

occupation category. This represents an unconstrained estimate without considering elasticity of demand or substitution between physical capital and labor. We will discuss potential frictions this causes in the later section skills shortages and stranded labor.

We highlight two results on Figure 2B: 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 more detailed occupation level.

## Temporal typology of occupational demand change

To better understand skill mismatches, we study the temporal dynamics of different occupations. In Figure 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.[56] We classify occupations that lie within the gray 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.[57] 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.

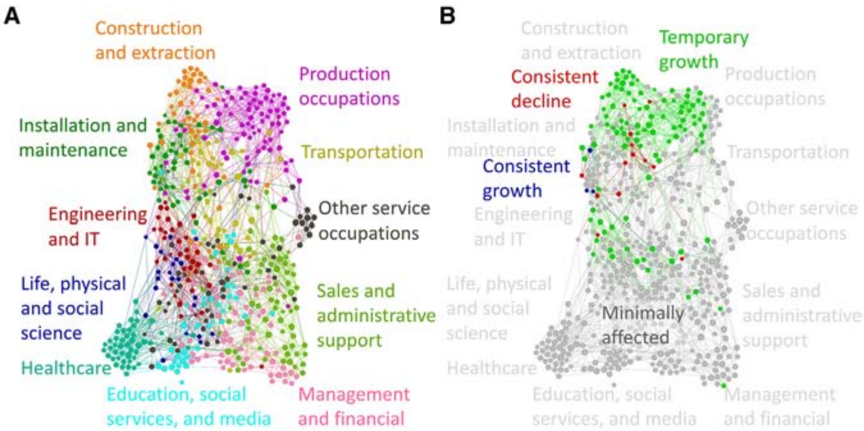


**Figure 4. Network of related occupations**

Nodes represent occupations, and two occupations are connected if workers can switch between them, as defined by the list of related occupations from O*NET. The layout of both networks is the same and is obtained using a force-pull algorithm. In (A), the network is colored by broad occupational categories, and in (B) by their temporal profile typology.

The remaining occupations are classified based on the quadrants in Figure 3. 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 photovoltaic (PV) installers, wind turbine service technicians, and power line installers. Relative to the no-new-policy 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 to increase by 80%. To achieve the fast transition scenario, a substantial number of new workers in these occupations needs to be trained.

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. On the other hand, some of these losses might be reduced if global demand for US fossil-fuel exports, such US natural gas, increases, as some have predicted.[54,55] (See also supplemental methods section D.6 for more details on import and export scenarios).

The top-left quadrant of Figure 3 corresponds to the 97 "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.

## Skill content and overlap with green jobs classifications

Following the methodology developed by Consoli et al.,[58] we examine the skill content of these groups in supplemental methods section D.4.2. 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 on aggregate. We find a slightly negative correlation coefficient of $-0.06$ between mean annual wage and "temporary growth occupations." The correlation coefficients between wage and consistent growth or consistent decline are less than 0.01.

In Figure S13 in supplemental methods section D.4.1, we map the current location quotients by US state of the occupation typology, which highlights the current geographical differences between some of these occupations. For example, both Wyoming and West Virginia see a strong permanent decline profile, but Wyoming has more permanent growth occupations because it has more installed wind power capacity relative to its population. However, we want to stress that this refers to 2018 data and does not include potential future renewable capacity locations.

As expected, consistent decline occupations mostly belong to brown occupations as defined by Vona et al.,[36] and consistent growth occupations mostly belong to "green new and emerging" occupations as defined by Dierdorff et al.[35] 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 supplemental methods section D.5 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.[27,28,38] 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

**Table 1. Assortativity of labor demand during the transition**

| Assortative attribute | Assortativity |
|---|---|
| Occupational typology (consistent decline, consistent growth, temporary growth) | 0.43[a] |
| 2021–2034: demand change during the scale-up phase | 0.05[a] |
| 2035–2038: demand change during the scale-down phase | 0.26[a] |

[a]Indicates results that are greater than for a randomized shock in 99.9% of simulations in a Monte Carlo simulation (see methods for details).

represent occupations. Links are drawn between two occupations if workers can switch between them, similar to the network used in Bowen et al.[38] (see methods and supplemental methods sections A.4 and B.9).

Figures 4A and 4B show the network structure with the nodes (occupations) colored by eleven broad occupational categories (supplemental methods 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.

## Overall presence of skill-mismatch frictions

We confirm our visual analysis using assortativity, a standard network science metric (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. Assortativity is a network-wide measure. An assortativity value of 1 means all occupations only link with similarly impacted nodes; a value of 0 indicates random mixing. Thus, a high assortativity value indicates that occupations are only connected to other occupations that face a similar shock, and overall skill-mismatch frictions are high.

Using our typology of consistent growth, consistent decline, and temporary growth occupations, we find positive and significant assortativity (Table 1). Thus, as suggested by Figure 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 scale-up phase, we find a positive but relatively low level of assortativity. This 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.

By 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.[59]

## Skill-mismatch consequences for individual occupations

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 related occupations (neighbors) means employers will find vacancies harder to fill. Conversely, a decrease in demand for an occupation and its related occupations can make it harder for displaced workers to find new employment. We therefore look at both frictions in moving away from one's occupation to other occupations (its out-neighbors) and frictions in attracting workers to an occupation from other occupations (its in-neighbors). For occupations that see a decline in demand, out-neighbors are important. Vice versa, in-neighbors are important when considering occupations that experience demand growth.

To highlight occupations most affected by skill-mismatch frictions during the first phase of the transition, in Figure 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 gray areas of this figure, where the demand change for individual occupations is similar to the demand change for its neighbors.

The figure is split along the $x = 0$ line. 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. We thus compare the average shock to occupations with their out-neighbors on the y axis. These data points are shown as squares in Figure 5. For a given occupation $\alpha$, out-neighbors are related occupations: they form potential career switching options for workers in $\alpha$.

Vice versa, 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. Here, we compare the shock to occupations with the average shock to their in-neighbors. These data points are shown as circles. Again, for a given occupation $\alpha$, in-neighbors are occupations for which $\alpha$ is a related occupation: workers in those occupations see $\alpha$ as a potential career switching option. In- and out-neighbors can overlap but are not necessarily the same.

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 occupations or headhunting workers with compatible skills. Farther away from the $x = 0$ line, shocks to individual occupations can be partially alleviated by switching between occupations.

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, and mining" see an increase in demand in this phase, but its neighbors, on average, see a very small decline, suggesting an availability of workers to fill vacancies.

Some occupations, such as "roof bolters" and "power plant operators," see their demand decrease but experience a milder

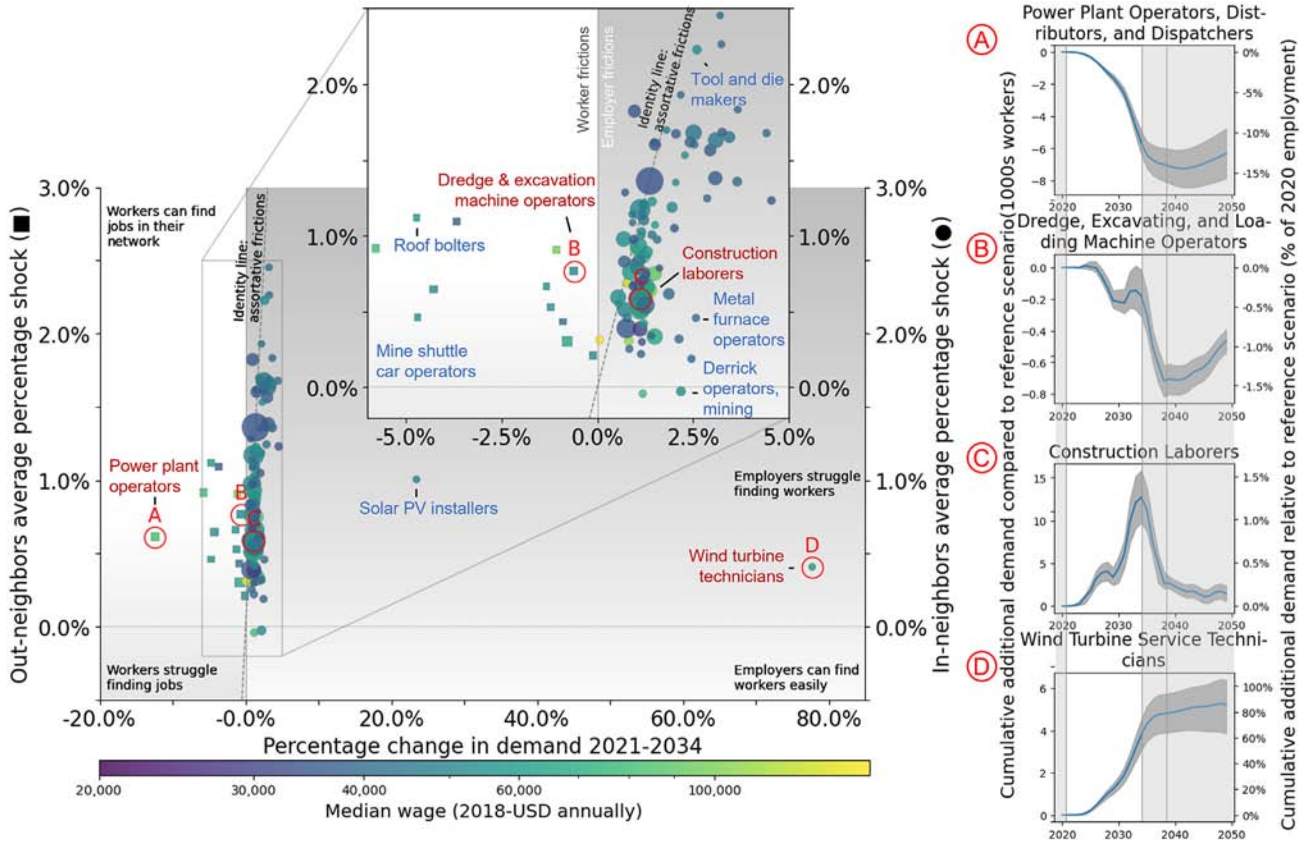


**Figure 5. Skill mismatch during scale-up phase**

Scatterplot of demand change in the scale-up phase (2021–2034) per occupation (x axis) and their neighbors (y axis) in the 95% by 2035 scenario, relative to the no-new-policy reference scenario. If the occupation has a positive (negative) demand change, we average the neighbor demand change over its in- (out-) neighbors. Out-neighbors of occupation $\alpha$ are related occupations: they form potential career switching options for workers in $\alpha$. Data points using out-neighbors are shown with squares. Vice versa, in-neighbors of $\alpha$ are occupations for which $\alpha$ is a related occupation: workers in those occupations see $\alpha$ as a potential career switching option. Data points using in-neighbors are shown with circles. In- and out-neighbors are not necessarily the same. The identity line is shown with a dashed line, and selected occupations are highlighted. Three occupations (wind turbine technicians, power plant operators, and solar PV installers) that lie outside of the rectangular zoom-in box are labeled. The zoom-in box does not cover any data point in the main plotting area. The intensity of background shading corresponds to more occupational frictions: worker frictions for $x < 0$, employer frictions for $x > 0$. The gray 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). On the right of the main plot, demand change profiles over time are shown for occupations highlighted in red. The four quadrants are labeled by the main effect of the occupational network faced by each occupation.

overall impact as demand increases in their pool of out-neighboring related occupations, meaning the network helps alleviate (part of) the direct negative impact.

In the scale-down phase, as shown in Figure 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 large demand increases but see some of the hiring difficulties alleviated because demand declines in their neighborhood, albeit to a limited extent. Thus, successfully managing the power system decarbonization will involve policies aimed at supporting workers to switch from temporary growth and consistent decline occupations into consistent growth or minimally affected occupations.

We find no relationship (Pearson correlation coefficients are smaller than 0.05) between mean annual wages and an increase or decrease in demand in the scale-up or scale-down phases. This means that, while specific occupations with low or high wage may be impacted, the temporal dynamics of the transition may have limited effects on the overall mean wage.

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;

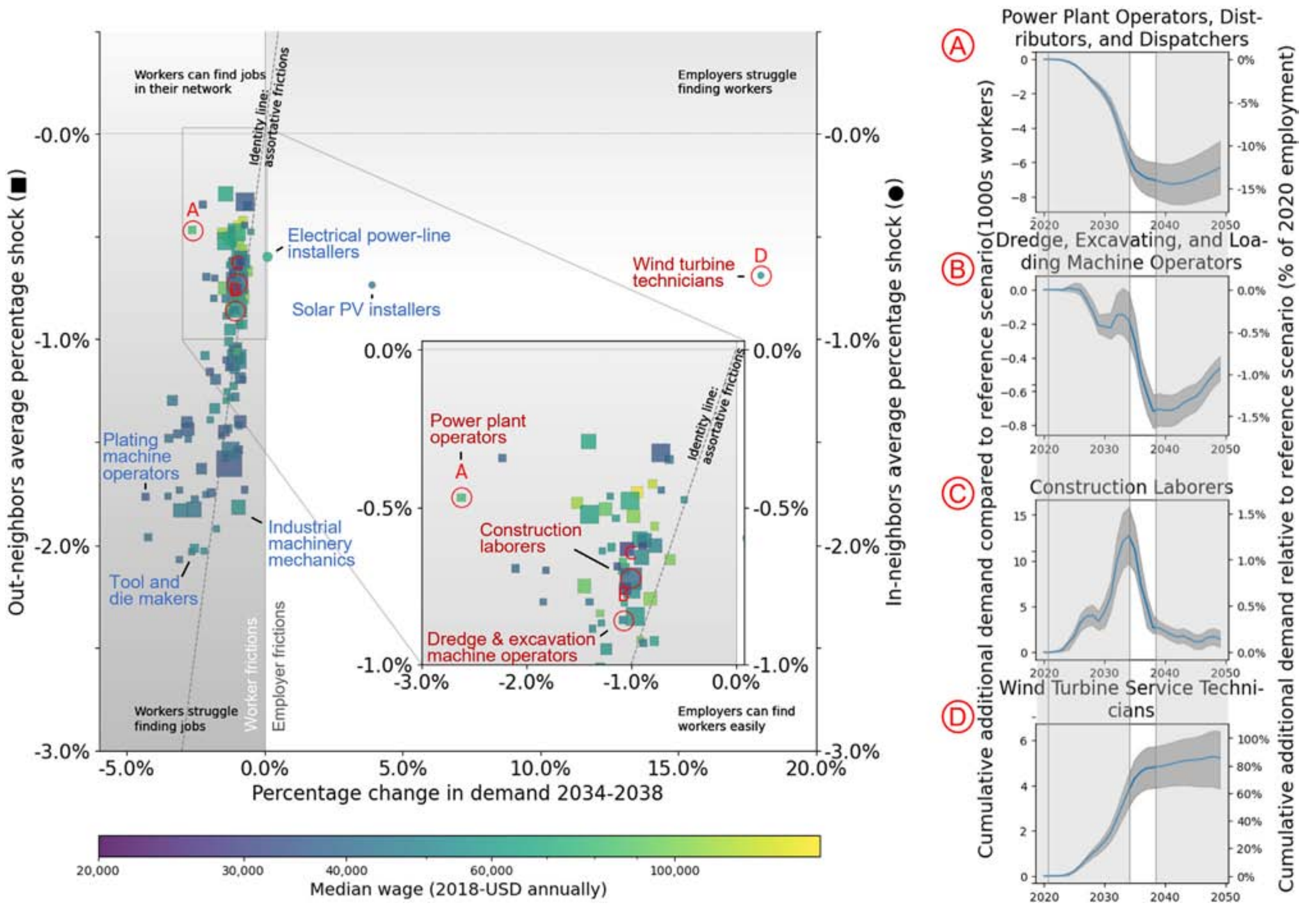


**Figure 6. Skill mismatch during scale-down phase**

Scatterplot of demand change in the scale-down phase (2034–2038) per occupation (x axis) and their neighbors (y axis) in the 95% by 2035 scenario, relative to the no-new-policy reference scenario. If the occupation has a positive (negative) demand change, we average the neighbor demand change over its in- (out-) neighbors. Out-neighbors of occupation $\alpha$ are related occupations of $\alpha$: they form potential career switching options for workers in $\alpha$. Data points using out-neighbors are shown with squares. Vice versa, in-neighbors of $\alpha$ are occupations for which $\alpha$ is a related occupation: workers in those occupations see $\alpha$ as a potential career switching option. Data points using in-neighbors are shown with circles. In- and out-neighbors are not necessarily the same. The identity line is shown with a dashed line, and selected occupations are highlighted. The zoom-in box does not cover any data point in the main plotting area. The intensity of background shading corresponds to more occupational frictions: worker frictions for $x < 0$, employer frictions for $x > 0$. The gray 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). On the right of the main plot, demand change profiles over time are shown for occupations highlighted in red. The four quadrants are labeled by the main effect of the occupational network faced by each occupation.

installation, maintenance, and repair workers, all other; and industrial production managers. Using these neighboring related occupations, we can see how Figures 5 and 6 relate to Figures 3 and 4. For example, in Figure 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 Figure 4A, but these two occupations are connected and are placed close together in the network in Figure 4B. 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 other's y axis value in Figures 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 remains higher than the reference scenario and is relatively stable, although demand is much lower than at the peak of the scale-up phase. This increase in demand for workers arises for two reasons. First, grid expansion is ongoing until at least 2050 (Figure S2). Second, the scenario foresees an increase in both capacity and demand for electricity relative to the reference scenario, which increases the overall demand for labor.

## Robustness of results

As we show in detail in the methods and supplemental methods section D.6, we have extensively tested the sensitivity of our model and found that our results are robust with respect to a number of important assumptions (fixed IO coefficients and cost vectors, industry-occupation composition, etc.) We have also identified two key sources of uncertainty in our analysis.

First, lower labor requirements from T&D investments (e.g., due to higher levels of innovation and automation) could lead to lower employment in the electricity supply chain, bringing them almost on par with the no-new-policy reference scenario. This would affect occupations related to T&D most strongly, such as electrical power line installers.

Second, the fraction of imports and exports can change during the transition, which impacts the demand for labor. As mentioned in the introduction, our main scenarios reference everything to 2018 levels, keeping the relative share of imports fixed and absolute size of exports fixed. The underlying logic for the inconsistent treatment of imports and exports is motivated by two facts: first, NREL's 95% by 2035 scenario concerns the transition in the US only. If the US shifts from the reference scenario path to the 95% by 2035 scenario, but the rest of the world does not change course, and import and export shares remain constant, the US will import more in absolute terms but exports will remain the same. Second, our results are presented relative to a no-new-policies reference scenario. Potential imports and export changes that affect both the reference scenario and the US 95% by 2035 scenario equally cancel each other out in our results. If, however, the US changing course to the 95% by 2035 scenario induces the rest of the world to also increase the pace of the power sector transition, our assumptions about imports still correspond to "all else being equal," but our assumptions about US exports might be pessimistic because US exports would become smaller in proportional terms, corresponding to a situation where US manufacturing becomes less competitive, relatively speaking, than it is now.

To deal with these uncertainties, we investigate four alternative scenarios. In broad outlines, in order of most pessimistic about changes to US competitiveness to most optimistic, these are:

(1) The share of US imports increases by 50% while exports remain constant.
(2) The share of US imports decreases by 50% while exports remain constant.
(3) The share of US imports remains constant while the exports, compared with 2022 levels, double to triple in 2030 and increase 4- to 9-fold in dollar-terms by 2040, depending on how 2022 export data are interpreted (this is also consistent with a scenario in which the global market for renewables increases by a factor of four to nine and the US share of this market remains constant).
(4) The share of US imports decreases by 50% while exports increase as in scenario (3) above.

These are stylized scenarios, but we have chosen the magnitude of import share changes in the alternate scenarios to be roughly in line with the historical behavior, as seen in Figure S4 in supplemental methods section C.2. To put this in perspective, between 1997 and 2014, the import share of computer and electronic product manufacturing went from 33% to 54% in 2014 and then declined to 44% in 2018. It is conceivable that the results of the IRA, which has the ambition to increase US domestic manufacturing,[60] or other legislation will increase US production beyond any of our scenarios here. Regardless of whether such a rise in US exports occur, our qualitative conclusions remain robust in the four alternative scenarios that we tested, as shown in Figure S20 in supplemental methods section D.6: relative to the reference scenario, the variation in the total number of jobs in our model between the most pessimistic and most optimistic scenarios ranges from about 560,000 to 630,000 in 2034, and ranges from about 40,000 to 270,000 in 2045.

# DISCUSSION

The transition to a world powered by renewable energy will involve a 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 temporal labor market fluctuations and skill mismatches.

We make three contributions to the wider debate on the labor market impact of the green transition. First, we find that more jobs will be created than lost in the US during the initial part of the renewable electricity transition—which is in line with previous research—but we also find that 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.

Second, in addition to the direct effects on occupational labor demand, we show that there are important secondary effects if related occupations are affected in similar ways. This creates a skill mismatches, 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 the employment impact of the transition.

Third, we identify a 4-fold 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, a larger group sees a consistent decline, and most occupations that are affected experience a temporary rise in demand during the scale-up and 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 Vona et al.[36] and green jobs from Dierdorff et al.[35]

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.

Compared with the estimates in previous literature, as spelled out in the introduction, our results are in line with Xie et al.[18]'s estimate of US employment changes due to power sector decarbonization (439,000 net jobs) and the ILO's estimate for the Americas as a whole of an IEA scenario to keep warming below 2°C[14] (~700,000 net US jobs). Conversely, our estimates are roughly an order of magnitude lower than those reported by Jacobson et al.[13] (~2 million), Mayfield et al.[16] (~1.5–6 million), or Ram et al.[17] (~4 million). 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 do not report results relative to a reference scenario, which in our case already contains substantial decarbonization, or have their headline results aggregated over a longer time period. Thus, while we look at a subset of changes, the effects we uncover may be amplified when considering the entire energy sector or longer time periods.

Our results are derived specifically for the US. Other countries have a different economic structures and, hence, results should not be extrapolated. For example, in ILO,[14] the change in labor demand ranges from +0.45% of the workforce (Americas) to −0.48% (Middle EAST) for a scenario consistent with limiting warming to 2°C. Likewise, Jacobson et al.[61] report global net job growth for a scenario with 100% renewable energy by 2050 but also find that net job losses are possible for some fuel producing countries. Furthermore, the scope and pathway of emission reduction will differ per country. For example, while energy is the major source of emissions in most countries, in Brazil, it is deforestation and agriculture, as its energy sector is already highly decarbonized.[34]

The rapid transition scenario considered here involves a non-marginal increase over the reference scenario 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 supplemental methods section D.6 tests and discusses the most important assumptions in our model, including changes to import and export assumptions and T&D cost calculation. In our main scenarios, we keep import fractions at the industry-level constant and exports constant in absolute value. However, if the US's international competitiveness in green technologies could be improved by a fast transition, this could alleviate some of the difficulties for workers in the domestic scale-down phase. Similarly, growing natural gas exports could limit the negative impact on some fossil-fuel workers.[54,55] The continuing cost declines of renewables is another important consideration. We take our projections from NREL's annual technology baseline (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,[4,5] especially with additional policies such as the IRA. In our sensitivity analysis, more advanced cost curves lead to lower demand growth for labor in the power sector supply chain. 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 directly because we assume a fixed ratio of workers per constant-dollar of 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 some empirical evidence on this assumption in supplemental methods section C.6 and discuss further methodological assumptions in supplemental methods 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 it 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. For example, targeted retraining programs can make additional transition options become feasible and alleviate pressure on certain occupations.

Monitoring how workers make career decisions during the transitions can help validate our skill-mismatch results. Empirical transition data from national surveys and CV repositories have been used to show that occupational similarity translates into how workers move between them.[28,62] Future work could employ a similar approach to validate the frictions identified in this work with future empirical data.

Our method is sufficiently simple that it can and should be applied regularly as new data and insights on labor market changes become available. Likewise, the convergence of different perspectives regarding future technological selections will enhance scenario refinement and subsequently improve the results. 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 global warming that future generations must face.

## METHODS

### Methods approach

We followed a four-step framework that couples a power transition scenario (step 1) with a dynamic IO model to estimate

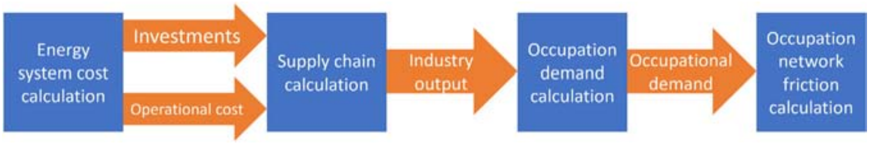


**Figure 7. Overview of our four-step methodology**

First, 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.

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 Figure 7, and each of the steps are described in detail below. To focus specifically on the labor impacts of the low-carbon transition, all of our results are shown as relative to a no-new-policy reference scenario (which is translated into our framework using the same four-step procedure). In supplemental methods section D.3, we present some of the results relative to the year 2020, rather than those relative to the no-new-policy reference scenario that are shown in the main text. Additionally, in supplemental methods section D.2, we show implications for the more gradual 95% by 2050 scenario.

## Step 1: Energy and cost scenarios

The first step in our approach involves quantifying future technology-specific expenses for electricity generation sectors. We achieve this by combining the scenarios of future electricity capacity and generation with exogenous projections of unit costs for various detailed electricity technologies. 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*.[44]

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 T&D), as explained in detail in the supplemental methods section C.1. Since investments and operational expenses affect the IO model differently (see step 2 below), we consider capital expenditure (capex) and operational expenditure (opex, which consists of variable and fixed opex, and fuel cost) separately. See supplemental methods 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 $j$ as

$$C^{\text{fix opex}}_{i,t} = Y_{i,t}c^{\text{fix opex}}_{i,t}, \qquad \text{(Equation 1)}$$

$$C^{\text{var opex}}_{i,t} = X_{i,t}c^{\text{var opex}}_{i,t}, \qquad \text{(Equation 2)}$$

$$C^{\text{fuel}}_{i,t} = X_{i,t}c^{\text{fuel}}_{i,t}, \qquad \text{(Equation 3)}$$

$$C^{\text{opex}}_{i,t} = C^{\text{fix opex}}_{i,t} + C^{\text{var opex}}_{i,t} + C^{\text{fuel}}_{i,t}, \qquad \text{(Equation 4)}$$

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

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 Equation 5 avoids negative investment values when total installed capacity declines.[63] 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 supplemental methods section D.6, we discuss the impact on our results of removing this smoothing or extending it to a 5-year moving window.

## Step 2: IO model

In the second step, we feed the capex and opex estimates of the previous step into a demand-driven 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:

$$x_{i,t} = \sum_{j=1}^{n} a_{ij,t}x_{j,t} + f_{i,t}, \qquad \text{(Equation 6)}$$

and in matrix notation:

$$x_t = A_t x_t + f_t. \qquad \text{(Equation 7)}$$

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 $j$.[64,65] By defining the Leontief inverse $L_t = (\mathbb{I} - A_t)^{-1}$, and taking the time difference of Equation 7, we can write

$$\Delta x_t = L_t f_t - L_{t-1} f_{t-1}, \qquad \text{(Equation 8)}$$

which demonstrates that industrial gross output can change over time as a result of changes in final demand $(\Delta f_t)$ or/and of changes in the IO network $(\Delta A_t)$. We model both components explicitly by mapping capex and opex, computed in step 1, onto the final demand $f_t$ and the IO table $A_t$, respectively. Note that this approach explicitly calculates the alteration in input structure within the electricity sector as different electricity technologies replace each other, while maintaining constant input coefficients for other sectors. We do not directly account for Keynesian income and consumption effects stemming from shifts in wages or electricity prices. Consequently, our model focuses on direct and indirect effects while disregarding induced impacts.

### *Mapping electricity costs to the IO framework*

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

*Capex*. Let $K_{ij}^{\text{capex}}$ be the fraction of $C_{i,t}^{\text{capex}}$ (technology $i$'s capex) that is spent on industry $j$,[66] and let $m_i$ be the fraction of capex that is imported from a foreign industry $i$.[67] The capex of technology $i$ spent on the domestic industry $j$ is then

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

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

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

Summing over all technologies results into

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

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

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

*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

$$a_{ji,t} = a_{ji,2018}\frac{C_{j,t}^{\text{opex}}}{C_{j,2018}^{\text{opex}}}. \qquad \text{(Equation 13)}$$

We perform a similar shift on the opex part of final demand $f_t^{\text{opex}}$ 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 Equation 8:

$$\Delta x_t^{\text{opex}} = L_t f_t^{\text{opex}} - L_{t-1} f_{t-1}^{\text{opex}}. \qquad \text{(Equation 14)}$$

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

$$\begin{aligned}\Delta x_t &= \Delta x_t^{\text{opex}} + \Delta x_t^{\text{capex}} \\ &= L_t\left(f_t^{\text{opex}} + f_t^{\text{capex}}\right) - L_{t-1}\left(f_{t-1}^{\text{opex}} + f_{t-1}^{\text{capex}}\right).\end{aligned} \qquad \text{(Equation 15)}$$

## Step 3: Modeling 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 supplemental methods section C.6 some empirical evidence for this proportionality in the solar and wind cost breakdown. In supplemental methods section D.6, 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 $\Delta o_t$ for workers per occupation between time $t-1$ and $t$ with Equation 15 as

$$\Delta o_t = M\Delta x_t \qquad \text{(Equation 16)}$$

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

### *Skills and location quotient*

We follow Consoli et al.[58] for our calculation of skill content per occupation (see supplemental methods section D.4.2). In supplemental methods 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.[33]

### *Network of related occupations*

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 supplemental methods section A.4 for further details). The network is defined by the adjacency matrix $R$ with items $R_{ij} = RelOcc_{ij} / \sum RelOcc_{ij}$, where $RelOcc_{ij} = 1$ if $j$ is a related occupation of $i^j$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.[68] 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 connects similar nodes, or nodes that are of the same type. In an unweighted network, we can compute the assortativity coefficient,[69] 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.[70] 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 $G$:

$$\rho_x = \frac{\sum_{ij}\left(R_{ij} - \frac{S_i^+ S_j^-}{W}\right)x_i x_j}{\sqrt{\sum_{ij}\left(S_i^+\delta_{ij} - \frac{S_i^+ S_j^-}{W}\right)x_i x_j \sum_{ij}\left(S_i^-\delta_{ij} - \frac{S_i^- S_j^-}{W}\right)x_i x_j}} \quad \text{(Equation 17)}$$

where $s_i^+ = \sum_j R_{ij}$ and $s_j^- = \sum_i R_{ji}$ 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 $\delta_{ij}$ 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[69]:

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

For Table 1, we calculate $\rho_{\sum_{t=2021}^{2034} O_t}$ and $\rho_{\sum_{t=2035}^{2038} O_t}$ using Equation 17.

*Weighted categorical assortativity*. The categorical assortativity values in Table 1 are calculated with a weighted variety of Eq. 2 in Newman.[71] In Newman's notation, categorical assortativity is

$$r = \frac{\sum_i e_{ii} - \sum_i d_i b_i}{1 - \sum_i d_i b_i} \quad \text{(Equation 19)}$$

with $d_i = \sum_j e_{ij}$ and $b_j = \sum_i e_{ij}$, where $e_{ij}$ is the fraction of all edges that connects a node of type $i$ to a node of type $j$.[71] In our application, with weighted networks, we use Equation 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

$$e_{ij} = \frac{\sum_{k\epsilon i, l\epsilon j} R_{kl}}{\sum_{kl} R_{kl}} \quad \text{(Equation 20)}$$

$e_{ij}$ 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 nodes and edges fixed but randomize the demand shocks over the nodes. We highlight results that are greater in absolute value than in 99.9% of randomized runs in Table 1 and identify, in supplemental methods section D.4.3, with one, two, or three stars if the assortativity value is larger than in 95%, 99%, or 99.9% of randomized runs, 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 neighborhood $\mathcal{N}_i = \{j | R_{ij} > 0\}$. 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

$$\Delta o_{\mathcal{N}_i,t} = \sum_{j in \mathcal{N}_i} \Delta o_{j,t}. \quad \text{(Equation 21)}$$

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

$$q_i = \frac{\Delta o_{\mathcal{N}_i,t}}{o_{\mathcal{N}_i,t}}. \quad \text{(Equation 22)}$$

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 perform a sensitivity analysis on nine assumptions and data sources. For more details, see the sensitivity analysis results in

Please cite this article in press as: Bücker et al., Employment dynamics in a rapid decarbonization of the US power sector, Joule (2024), https://doi.org/10.1016/j.joule.2024.12.004



supplemental methods section D.6. For each sensitivity analysis, we reproduce Figure 2B in Figure S19. In Figures S20A and S20B, we plot the cumulative worker demand at the peak (2034) and in the new steady state (2045), respectively. In Figure S21, 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 supplemental methods discusses the default options.

We probe the following assumptions in our sensitivity analysis:

(1) We have assumed (see supplemental methods section B.5) that the IO 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 supplemental methods section C.3). 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 supplemental methods section C.3). We add noise to the opex cost vectors and find the results robust.
(4) The T&D grid line cost are calculated in supplemental methods section B.2 following the methodology in Way et al.[4]. 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 supplemental methods 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 supplemental methods section C.1. 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.
(8) We assume that exports per sector remain constant over time and that the direct import fraction ($m_j$ in Equation 9) is fixed. We test the sensitivity of these assumptions by using other, stylized, projections for direct imports and exports of solar and wind electricity generation products. Specifically, we include 4 additional scenarios: decreasing direct imports, increasing direct imports, increasing exports, and combined decreasing direct imports and increasing exports. We find that these changes to our trade and competitiveness assumptions can have a strong impact on the results, especially the net worker demand in the decarbonized steady-state phase.
(9) We test the sensitivity of the construction sector granularity by using more detailed data on power and communication line and related structures construction for the construction part of T&D capex in the $B$ matrix of Equation 23. Our results are robust to this modification.

We also do a robustness check of the assortativity values in supplemental methods section D.4.3 for different network types: the original relatedness network, a network of empirical occupational mobility between 2011 and 2019, and a combination of the two. Figure S21 shows the assortativity coefficient values for the scale-up and scale-down phase for all tested scenarios in the sensitivity analysis.

## RESOURCE AVAILABILITY

### Lead contact

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.

### 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 personal correspondence with data providers. For more details, see supplemental methods section A. All data will be made available upon request (unless legal restrictions exist).

## ACKNOWLEDGMENTS

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) (to J.B., M.C.I., and J.D.F.); Baillie Gifford (to J.D.F.); the James S. McDonnell Foundation (to A.P. and R.M.d.R.-C.); and the Institute for New Economic Thinking and the Post-Carbon Transitions programme (to 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, as well as its members for their feedback. We thank Christian vom Lehn for clarifying measures of occupational mobility obtained from the US Census and Pieter Gagnon for help on the NREL scenarios. We also thank employees at BEA for additional insights into the energy sector in BEA's input-output tables.

## AUTHOR CONTRIBUTIONS

Conceptualization, J.B.; methodology, J.B., A.P., and R.M.d.R.-C.; software, J.B., A.P., R.M.d.-R.C., and M.C.I.; investigation, J.B. and R.M.d.R.-C.; data curation, J.B., A.P., and R.M.d.R.-C.; formal analysis, J.B. and R.M.d.R.-C.; writing – original draft, J.B. and M.C.I.; writing – review and editing, J.B., M.C.I., A.P., R.M.d.R.-C., and J.D.F.; visualization, J.B., R.M.d.R.-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.

## SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.joule.2024.12.004.

Received: November 20, 2023
Revised: September 15, 2024
Accepted: December 10, 2024
Published: January 17, 2025

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