Understanding and Preparing for the Labor Impacts of Decarbonizing the U.S. Economy: A Proposed Research Agenda

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ABSTRACT. To avoid worst-case scenarios of climate change hazards, the U.S. economy must rapidly decarbonize. Policymakers and citizens alike, however, share concerns about the disruptive effects of decarbonizing on employment. This concern is justified for sectors directly related to the extraction and use of fossil fuels, such as coal mining. But these represent a tiny fraction of the U.S. workforce. How might other industries be affected? Each industry is defined by a distinct composition of labor occupations, which in turn consist of a portfolio of skills embodied by workers. The central issue is whether decarbonizing the economy will render skills obsolete or create opportunities to combine existing skills with new technologies to generate value. Consider that when the U.S. entered World War II it transformed its economy virtually overnight which required new tasks, but which mostly utilized existing worker skills. Might decarbonizing the economy be similar – applying existing skills to new tasks rather than creating a massive need for new skills? Nearly all workers experience small and periodic transitions in day-to-day routines which require new knowledge – new software used by programmers, new tax laws that alter accounting procedures, new environmental regulations that change purchasing rules. An economic transition almost by definition will reconfigure the worker tasks, but depending on the magnitude of that task reconfiguration, it may or may *not* also require new worker skills. We propose a research agenda to assess the impact of decarbonization on workers by disentangling the need for new skills versus new tasks, identifying occupations most susceptible to disruption, and critically contrasting a decarbonizing transition with historical transitions. Results can inform the design and priorities of worker retraining programs as well as curricula at community colleges and universities equipping students with skills needed to facilitate the transition to a decarbonized economy.

1. Introduction

The technological changes required to transition away from using fossil fuels (decarbonizing the economy), adopting sustainability-enhancing production methods and responding (adapting) to the effects of climate change—hereby referred to as "greening" the economy—and imply a transformation of employment patterns and of occupational structures. These potential changes to existing employment structures, occupational staffing patterns, and the skills needed to perform key jobs generate concerns about losers and winners. These concerns are echoed and highlighted in three recent reports published by the U.S. National Academies of Sciences [1-3]. The possible negative employment consequences of leaving fossil assets on the ground have become major obstacles to transitioning away from fossil fuels, and they are compounded by the concerns about the employment impact of generative AI.

To alleviate those fears, and thus an obstacle to a smoother clean energy transition, workers and policy makers need empirically robust arguments about what jobs will be affected, and to what degree, by the transition towards non-fossil fuels. This includes not only the destruction of existing jobs and the creation of new jobs but, just as crucially, the transition of existing occupations into a decarbonized economy. We propose a research effort on the effects of decarbonizing the nation's energy system on employment to complement research efforts on how "net zero" energy system affects other components of the economy. One of the principal benefits of the research into transitioning to "net zero energy systems" has been to highlight which economic sectors can most easily decarbonize, which ones will require the use of fossil fuels into the foreseeable future and which economic activities will be largely unaffected [4-7]. Similalrly, we propose to move beyond the dichotomous view that decarbonation will render some jobs unnecessary while creating many more new jobs and also inquire as to which existing jobs, occupations and economic activities can be easily reconfigured so as to be part of a decarbonized economy.

Reconfiguration of economic activities is central to the process of economic development, understood as changes in the type of products and services that an economy can produce. What an economy does is crucial to its development: as economies develop, different industries and products are born [8-10]. What goods and services an economy provides, and how well it provides them, is largely determined by the technologies, skills, and tacit knowledge integrated in the process of value creation. The ease with which an economy can shift to new activities is in turn constrained and facilitated by its current portfolio of technologies and skills. The interconnections among these technologies and skills form an economic structure—a network—enabling some developmental pathways while foreclosing others. Recent work shows that such a network helps to explain economic development at the national level: the technologies and skills prevalent in the economy of a country, embodied in the goods it produces and services it provides, place that economy in a specific region of a global ''product space'' and constrain the ease with which that economy can transform its production structure [11, 12].

A network view of development posits that there that there are links connecting some products or economic activities and not others; links through which knowledge, inputs, and workers can. Movement from one node to another might be possible by transversing a few links or via a lengthy path, while some activities are not connected at all. The occupations that constitute an economy can be linked in an "occupational network": the extent to which occupations share skills and tasks is reflected in the links directly or indirectly connecting occupations [13-17]. A new product can more easily be developed if it uses labor skills similar to those used in making existing products.

The effects of decarbonization on existing and future jobs depends on what *skills* and *occupations* decarbonization renders unnecessary, which existing skills and occupations can transition to new "green" activities and which new skills and occupations will be engendered. Recent advances on economic modeling and economic history, the use of concepts and tools from network mathematics and the availability of data on the skills embodied in the economy's occupations make it possible to describe different pathways for how decarbonizing the economy will affect employment. While it is inherently difficult to predict what new jobs a decarbonized and AI-reliant economy will create, it is empirically feasible to identify jobs which decarbonization will not directly affect or which can continue to be performed even under a reconfigured economy. It is possible to study the mobility of labor between industries as workers try to adjust to changes in the demand for their skills. Thus, we outline key research questions, as well as potential measurement approaches, relevant data sources, and promising methodological frameworks. Our agenda consists of four overarching questions to be addressed:

- Which workers will be negatively affected and in which industries?
- What will be the occupation and industry-specific magnitude of those negative effects?
- How can those negative effects best be mitigated?
- What emerging methods, such as occupation space, can help anticipate economic changes and map transition pathways?
- How will decarbonization and the AI-facilitated automation interact to render existing skills and occupation unnecessary or necessary?

2. Transitions and the U.S. Economy

The effects of technological change on employment have long been a subject of interest in the social sciences [18-22]. Adam Smith, David Ricardo, Karl Marx, and John Maynard Keynes were among the many influential writers who had a concern about the effect of technological change on employment. The automation of activities which the Industrial Revolution, which historian Peter Sterns characterizes as the single most important development in human history over the past three centuries [23], and its effect on employment has been the subject of much examination. The introduction of machines in manufacturing allowed low-skilled workers to engage in the production of goods that previously required specific expertise in artisanal shops. Technology thus substituted high-skilled labor and complemented low-skilled labor. Combined with political, social, and cultural changes, which resulted in increased demand for mass produced goods, including foodstuffs produced from a mechanized and fertilized agricultural sector, the Industrial Revolution everywhere generated many more jobs to compensate for those which were made obsolete [24, 25].

The effects of subsequent waves of technological change on employment, and the specifically the interplay between education, skills, work experience and technology—substitution, complementarities, augmentation—received renewed attention as ICT and computer-based technologies diffused throughout the economy [26-30]. Concerns about the polarization of labor-market opportunities (between high- and low- skilled jobs) and the effects of AI on jobs considered highly skill has focused attention on the disruptive effects of accelerated automation on labor markets [31-34].

Historically, technological change was often considered factor-neutral, meaning it affected all types of labor equally. In his pioneering work Jan Tinbergen explored the impact of technological change on labor markets by noting that certain types of technology require specific skills for their implementation [34]. Technology can therefore be factor-augmenting, complementing either high or low skill workers. To satisfactorily examine the ways in which technological change can affect existing employment—complementary, augmenting, displacing—Acemoglu and Autor [35] distinguish between "skills" and "tasks". A *task* is a unit of work activity that produces output (goods and services). A *skill* is a worker's endowment of capabilities for performing various tasks. Workers apply their skill endowments to tasks in exchange for wages, and skills applied to tasks produce output. The distinction between skills and tasks becomes particularly relevant when workers of a given skill level can perform a variety of tasks and change the set of tasks that they perform in response to changes in labor market conditions and technology. Performing tasks requires problem-solving and facilitates learning, thereby generating knowledge. We have understood since the work of Kenneth Arrow that "learning by doing" is a major deriver of productivity increases and incremental improvements in the efficacy of technologies [36, 37].

To describe how an economy-wide energy system transition will impact the economy, and labor in particular, we begin with a simple model that echoes the distinction made by Acemoglu and Autor [35]. A canonical firm is an entity that takes in several factors or inputs, processes those inputs, and then delivers finished goods and services for use by consumers or as inputs into other firms (Figure 1). Any major economic transition, including a transition to a decarbonized energy system, will likely impact each of component in Figure 1 differently. Some will be seemingly unaffected while others may experience significant disruption. The degree of these impacts will of course depend on the nature of the firm and the products or services it produces. In this report we focus on the input factor of *Labor*.

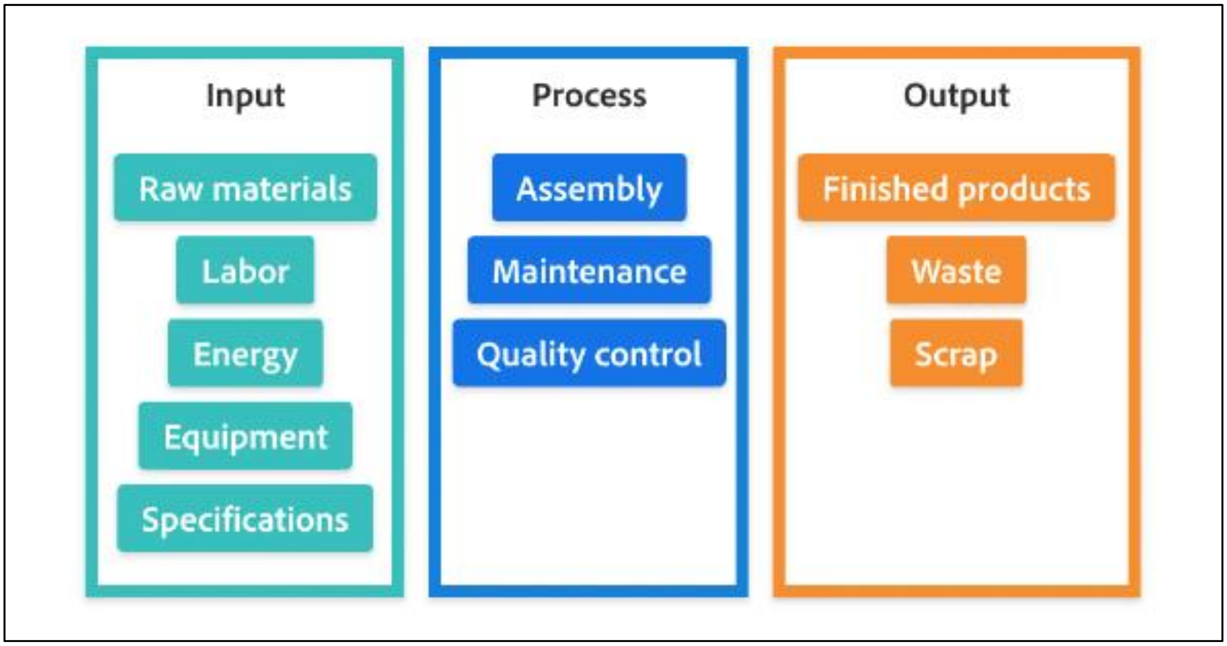

Figure 1. A simple model of a firm. Each of a firm's economic factors and functions will be impacted by a clean-energy transition. Some outputs will disappear, and new ones will be added, while processes of transformation and recombination will change in ways that minimize CO2 byproducts. These changes will almost certainly affect labor, which beg the questions: how will labor be affected and to what degree?

The integrative role played by firms represented in Figure 1 is that they bring together a bundle of skills, embodied in occupations, and match it to a bundle of tasks, embodied in a final product or services. The process of producing an output effectively aligned worker skills with tasks during the production process. Those tasks are directly impacted by an economic transition. The manner in which tasks are abandoned, supplanted, or repurposed determines the degree to which a bundle of skills must be adjusted to maintain a match between skills and tasks. The tasks associated with every industry and product will be affected differently by decarbonization and it is central to the proposed research agenda to identify and quantify those differences.

Small changes in tasks are routine for workers. We all face situations in our daily work lives that we have not encountered before, but which are so similar to past situations that we are able to apply our bundle of skills to accomplish a slightly different albeit novel task. However, as the magnitude of changes to a bundle of tasks increases, adjustments to skills may be needed. For instance, if workers are asked to use a new software platform, a short training session may be required to familiarize themselves with its nuances. If a new appliance or automobile model is introduced, maintenance professionals may need time to become acquainted with the specifications of the new product. Still larger changes in tasks may require extended skill upgrading or schooling, such as when the creation of blueprints moved from handheld drafting tools to computer aided drafting. Finally, tasks may change so radically that a new bundle of skills, embodied in a different occupation, is required to complete the production process.

The proposed research effort will elucidate the effects on employment of economy-wide decarbonization by distinguishing the extent to which a transition will require a reconfiguration of *tasks* versus a reconfiguration of *skills.* Firms produce/provide *goods* and *services* and this production/generation requires performing a set of coordinated *tasks*. The tasks are performed by orkers drawing on *skills*, bundled skills constitute *occupations*, and an *economic activity* is the matching of skills to tasks (Figure 2). Thus, an economic transition almost by definition reconfigures the tasks required of a firm. But depending on the magnitude of that task reconfiguration, it may or *may not* also require the reconfiguration/addition of new skills. The central question of our proposed agenda is to determine the magnitude of change in each economic task that will take place during a transition to a decarbonized economy.

2.1. How does a net-zero transition compare and contrast with past transitions?

To better understand the context and potential employment outcomes of an energy transition, a component of the research agenda should include a revisiting of recent employment transitions in the U.S. economy. Past transitions should be examined through a critical historical lens and assessed for generalizable properties of large-scale economic transitions. Regarding past transitions, consider that when the U.S. was thrust into World War II, it was forced to rapidly shift national production to supply equipment for war. However, this did not generally require a "retooling" of labor. Instead, it required a retooling of firms. The skills required of labor – working with sheet metal, assembling moving vehicles, building engines – changed little. Instead, workers applied their skills to new products, and thus auto factories shifted to manufacturing airplanes and tanks instead of cars, while sheet metal plants churned out artillery casings and ammunition clips instead of auto panels. In other words, the bundle of tasks embodied in war products did not differ so much from their peace-time counterparts that workers had to significantly change the bundle of skills they offered. The transition in manufacturing in the 1970s led to a permanent decrease in manufacturing jobs. To what extent did the service sectors which became the dominant areas of economic activity draw on previous skills and new skills on their path towards predominance? Addressing such historical questions and critically analyzing past transitions can help the U.S. prepare for and guide an imminent clean-energy transition.

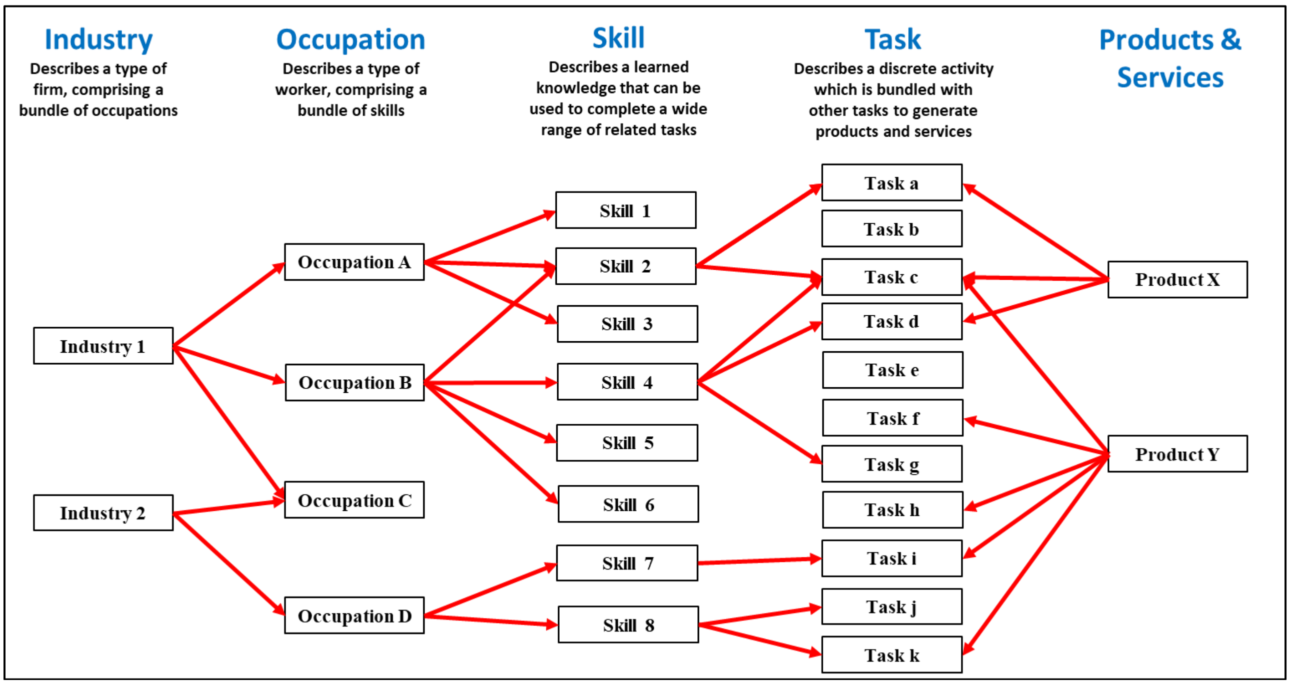

Figure 2. The labor components of the U.S. economy. In this hierarchical representation, products and services result when a firm coordinates and facilitates the completion of a set of tasks by workers with required skills.

2.2. Sustainability Enhancing Economic Activities

In 2022 the European Union published a comprehensive taxonomy of sustainable industrial activities [38] to guide and stimulate financial investments by firms, institutions, or individuals in environmentally sustainable activities. The taxonomy is meant to enable investors to assess the sustainability of potential investments. Interestingly, 96% of the activities identified in the taxonomy were mapped to existing industries, meaning that only 4% of sustainable economic activities would require new industries, likely composed of novel technologies and worker skills. Here we take the taxonomy's sustainable activities as a proxy for the types of economic activities that would be prevalent in a low-carbon economy.

In a preliminary study we linked the EU taxonomy of sustainable activities to the industry codes of three industrialized countries to assess the extent to which these countries already have capabilities to undertake sustainable activities [39]. When aggregating employment in those linked industries we found that approximately 1/3 of all workers in The United States, Canada, and Germany are already employed industries mapped to sustainable activities. This proportion varies considerably across space and industries within each country and thus, a key component of our research agenda is refining this assessment of impact.

One interpretation of this preliminary study is that most existing firms may need to reconfigure the tasks they undertake but will otherwise continue with business as usual. Indeed, long-lived firms evolve over time in response to markets and technology and so in this sense a clean-energy transition may be nothing unordinary. On the other hand, existing firms may only be able to undertake new sustainable activities after considerable reconfiguration of labor and capital, such as replacing workers in one occupation with workers of a different occupation. Finally, the impact may be somewhere in between, with workers requiring novel skills to undertake new tasks associated with sustainable activities.

Thus, there is a continuum of possible impacts on workers, from simply changing the routine tasks a worker performs to becoming obsolete. Understanding where workers will fall along this continuum in response to a low-carbon energy transition – and how to address that impact – is the core of the proposed research agenda. In the following sections we expand each of these questions into a detailed agenda for future research.

3. How will workers be affected by decarbonization?

The answer to this question must be more than simply which occupations will go away. Workers are identified not only by the occupation they hold but also by the industry they work in, by the credentials they hold or must acquire, by their educational attainment and formal training, and also by where they work. Their ability to change is further determined by demographic factors such as age, cultural background, etc. All of these aspects must be considered when determining which workers are affected and to what extent. Below we list specific questions to be addressed.

Q3.1. How will employment impacts of decarbonization differ by industry sector?

Some industries will be affected by nothing more than a change in the source of their energy, while others will feel significant impacts, including possible obsolescence (e.g., coal mining). Quantified impacts should be developed using North American Industry Classification System (NAICS) codes. Research should seek to understand and quantify the employment impact by industry sector at the most detailed level of industry that is practicable and relevant to policy making.

Q3.2. How will employment impacts of decarbonization differ by occupation?

Like industries, the impact of an energy transition will vary greatly by occupation. It is generally accepted that some occupations will become obsolete. However, there is no agreement on how many will become obsolete or on how many new occupations might arise due to a transition. Researchers should assess the impact of a transition on the lowest level of our labor framework in Figure 2, tasks. That impact can then be aggregated to higher levels, including occupation, to determine which occupations are likely so altered that they will become obsolete. Assessing the impact on each of nearly 20,000 tasks is non-trivial and we suggest that the application of generative AI (i.e., Large Language Models) will greatly help in this endeavor. With a quantified impact of a transition assigned to each of those thousands of tasks, impact can be aggregated to the level of skills, occupations and industries and the impact on individual occupations may be assessed. Those impacts will range across a continuum from almost no noticeable difference to obsolescence of certain occupation (Figure 3). Policy interventions may then be matched to occupations along different ranges of that occupational impact continuum.

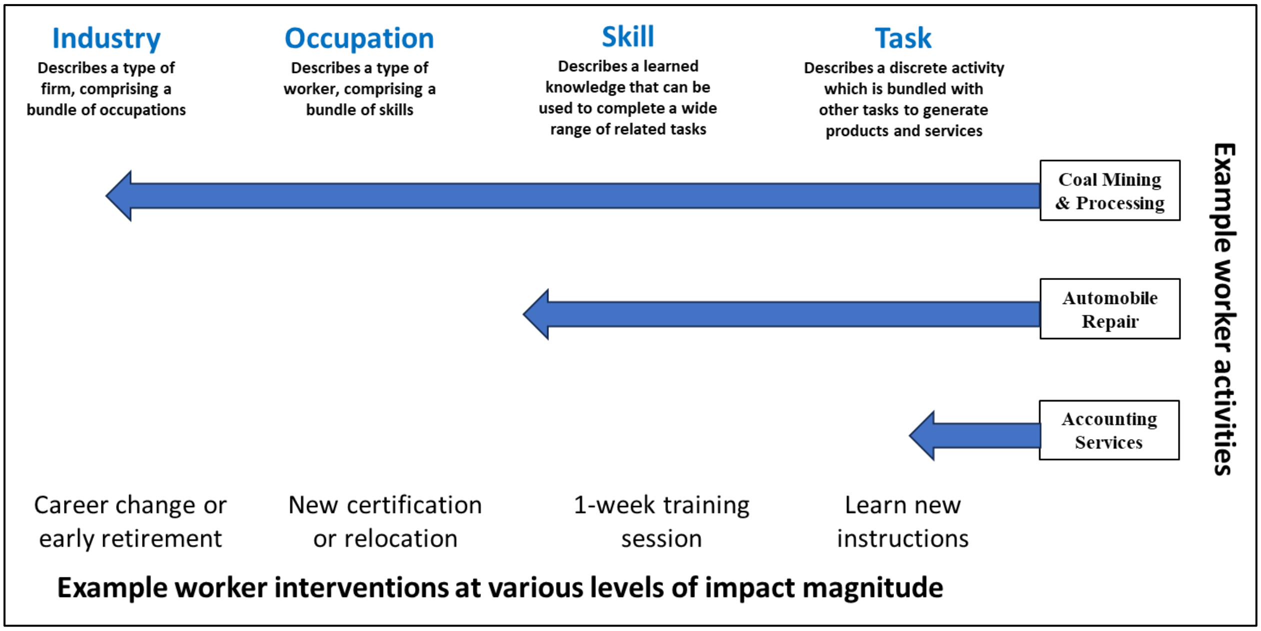

Figure 3. Application of our labor framework to examples of affected occupations. Note that some worker activities will be so affected that entire industry sectors may become obsolete, while other workers may notice little or no difference in their daily tasks. Researchers should assess and quantify the differential impacts of an energy transition on each occupation and industry so that the magnitude of impact can be mapped to potential policies designed to mitigate negative employment impacts. Examples of possible policies are shown in relation to the severity of impacts.

Q3.3. How will decarbonization impact various products and services?

While above we propose aggregating tasks to skills and then to occupations, an alternative approach would be to determine the impact of decarbonization on individual products and services, which are comprised of multiple tasks. For instance, identifying products that will be non-viable in a decarbonized economy means that the tasks embodied in those products will be less viable. The impacts of those product level determinations may then be linked to tasks which are again aggregated to skills and ultimately occupations.

Q3.4. How will employment impacts of decarbonization differ by geography?

The U.S. is increasingly turning to place-based policy solutions for economic development, adopting a practice that has been embraced in Europe for several years. To guide those policies, it is important not only to know which industries and occupations will be most affected by a clean-energy transition, but also to understand how those changes will manifest geospatially. Thus, researchers should answer the previous two questions also in the context of geography.

Because of worker mobility, labor phenomena in the U.S. are generally examined at the scale of labor markets. Nearly 85% of U.S. workers are captured in spatial units known as Core-Based Statistical Areas (CBSA), which include both the larger Metropolitan Statistical Areas and smaller Micropolitan Statistical Areas [40]. We recommend researchers follow this convention, assessing labor impacts at the level of CBSAs where applicable and at the level of county for areas outside of CBSAs.

4. How can policy makers minimize the disruption to workers and firms of a clean-energy transition

The role of social science should not only be to identify how workers will be affected by decarbonization but to offer innovative approaches to mitigating those disruptions. It is likely that such questions will be addressed in collaboration with policy makers and thus the U.S. National Science Foundation's framework for so-called "Convergence Research" will likely be instrumental in addressing these questions [41].

Q4.1. What are low-resistance pathways for workers to move between legacy occupations and industries to new occupations and industries?

Having identified occupations and industries that are most impacted by a transition, researchers should seek to identify other occupations to which workers can move with the least retraining or disruption. When possible, it is preferable to quantify the ease of transition so that alternatives can be compared. are "closest" to affected ones in skills space and occupation space? In this endeavor, the emerging methodology of viewing economies as networks offers a promising framework for evaluating and quantifying alternatives for worker retraining [42].

Q4.2. How much will decarbonization require worker relocation as opposed to skills upgrade?

Options to mitigate worker disruption will likely include not only augmentation of existing skills but the need to relocate to places where those skills are in demand. Thus, researchers should assess the degree to which each occupation/industry disrupted by a transition may be amenable to relocation options. Furthermore, research should assess the likelihood that relocation is a viable option depending on the demographic and cultural attributes of workers for which relocation is an option. For instance, workers with young children and/or a working spouse may have limited ability to relocate as an option to remain unemployed. Knowing the degree to which relocation is not an option will allow policy makers to prioritize alternative strategies that do not include relocation.

Q4.3. How does worker age and experience affect the likely success of different disruption mitigation strategies?

Even in the case that a mitigation strategy is developed specific to an occupation, industry, and place, it is still likely that the applicability of that strategy will depend on the demographics of the worker, especially age. A strategy that involves significant retraining and/or relocation will likely have a different likelihood of success with a worker that has recently entered the labor force compared to one that is near retirement. Researchers should assess the develop a method of assessing the applicability of various disruption mitigation strategies as a function of worker age.

Q4.4. How can the resilience of the future workforce be increased?

As with any disruption, a transition is also an opportunity – an opportunity to build back better. If it is a certainty that the U.S. labor force will undergo significant alterations, then it is also a chance to enhance the resilience of the future workforce. But that will require a deeper understanding of *resilience* in social-economic systems than now exists. Too often invocation of resilience when discussing the economy relies on a crude analogy from biology. Thus, a component of a comprehensive research agenda should focus on increasing understanding of what socioeconomic resilience is, what its drivers are, and what policy options might facilitate higher resilience.

While climate change mitigation, by way of decarbonization, remains an important societal goal, adapting to the effects of climate change has become an urgent task, with the urgency expected to worsen in the next two decades. The question is no longer if we can halt global warming at 1.5°C but how large the overshoot will be and for how long we will be in an overshoot phase [43]. Climate change will affect different parts of the United States differently: rising sea levels, increasing temperatures, more frequent flooding, drought, forest fires, to name just a few [44]. Climate change adaptation will disrupt the economy while adaptation will require significant allocation of resources and the building of infrastructure (for example, to protect coastal settlements from rising sea levels [45]. How will climate change affect labor markets? How will adaptation to climate change affect labor markets?

5. Data and Methods

5.1. Employment data

Reliable, high-quality employment data is critical to anticipating the labor impact of economic transitions. This includes employment by occupation, by industry, by location, and with relevant demographics such as age and educational attainment level. Currently the U.S. Bureau of Labor Statistics is the primary provider of publicly available data sets related to employment. These include:

- **Quarterly Census of Employment and Wages** (QCEW) – published quarterly, these data tabulate employment by detailed industry by county along with aggregate wages and other relevant data [46].
- **Occupational Employment and Wage Statistics** (OEWS) – published annually, these data tabulate employment by detailed occupation by state and metropolitan statistical area, along with average annual wages and other relevant data [47]. Note that these data are not available for spatial units smaller than MSAs, such as micropolitan statistical areas or counties.

- **National Employment Matrix** (NEM) – published annually, these data project national employment by occupation-industry pairs and compares them to current values [48]. The BLS has also begun to experiment with state level projections and counts as granular as county-level projections are available from state government agencies on a state-by-state basis.
- **Current Population Survey** (CPS) – published monthly, this small survey of U.S. households is a joint endeavor of the BLS and the U.S. Census Bureau, and includes employment by occupation, by industry, and by several demographic categories such as age and ethnicity.

Other employment datasets are also available from the BLS which are relevant to the proposed research agenda, including the Current Employment Statistics (CES) and National Longitudinal Surveys (NLS).

High quality data related to employment is also available from the U.S. Census Bureau (CB), including:

- **Public Use Microdata Sample** (PUMS) – published annually, these data are an anonymized sample of individual-level data taken from the American Community Survey, a comprehensive panel of nearly 400 questions collected from 1% of the U.S. population [49]. Topics covered include employment by occupation and by industry, college degree area, location, and several household and demographic characteristics. However, given the small sample size compared to BLS data, PUMS data is best used as complementary to BLS employment data instead of an alternative.
- **County Business Patterns** (CBP) – published annually, this dataset is an alternative to BLS Quarterly Census of Employment and Wages. Providing essentially the same measures of employment by detailed industry by county, the methodology and sampling of the two datasets is nevertheless different enough that both should be considered when designing research plans under this agenda [50].

Finally, comparable data is also published annually by the U.S. Bureau of Economic Analysis (BEA) including employment by detailed industry by county. BEA data are modified versions of the BLS QCEW data, incorporating additional data sources to restate BLS estimates so that they best meet the needs of BEA objectives. Thus, the BEA employment data offers a third set comparable to the QCEW and CBP described above.

Each of the publicly available data sets described above has limitations that may limit the ability of researchers to best inform policy makers of the impacts of a clean-energy transition. These limitations are primarily due to finite resources of the statistical agencies involved and statutory limitations on the release of private information. In the latter case, several datasets have repressed data which are simply left blank in the publicly available datasets. Therefore, researchers should assess the utility of proprietary datasets available for purchase from firms now specializing in data aggregation and estimation. These include firms specialized in estimating high quality labor data at granularity not available from U.S. federal agencies, such as Lightcast (https://lightcast.io/) or LinkedIn's Workforce Data (https://economicgraph.linkedin.com/workforce-data).

Another data type frequently used to study labor markets is establishment-level data. An establishment represents a single physical location where a predominant activity takes place and establishment-level data is collected and analyzed at this level. Establishment-level data has become the predominant type of data to measure and study workplace productivity. The detailed data on the workers employed by establishments can be used to match skills with technology and output types. The Longitudinal Business Database (LBD), published by the U.S. Census Bureau, a restricted-use microdata accessible only to qualified researchers for approved projects in secure Federal Statistical Research Data Centers [51]. The LBD provides insights about business formation and growth, labor market dynamics, and the sources of productivity growth. The LBD is a census of business establishments and firms in the U.S. with paid employees comprised of survey and administrative records. The LBD covers all industries and all U.S. States. An alternative to the LBD is the National Establishment Time-Series Database© (NETS), an establishment-level database privately produced using data compiled by the firm Dun & Bradstreet [52].

5.2. Worker skills data

To assess the labor impact of an energy transition, industry and occupational employment data should be integrated with skills data. This role is typically filled by a data set known as O*NET [53]. Originally funded by the U.S. Burean of Labor Statistics, this data set is now maintained by a stand-alone entity that maintains the data with annual major releases and minor releases throughout a year. O*NET decomposes each U.S. occupation into several hundred quantified "elements" which are grouped into skills, abilities, interests, work contexts, knowledge, education, work activities, work styles, and work values. Those elements falling into the category "work activities" are further decomposed into nearly 20,000 detailed tasks performed by workers in the US. A schematic with examples of the O*NET data is shown in Figure 4. Thus, individual tasks can be aggregated to skills, then to occupations, and finally to industries and the impact of a clean-energy transition can be assessed at each level of aggregation and for each code at a particular level.

A comparable though more obscure dataset is the Occupational Requirements Survey (ORS) published periodically by the U.S. Bureau of Labor Statistics [54]. Like O*Net, the ORS decomposes occupations into several attributes similar.

Yet a shortcoming of both the O*NET and ORS data is that neither is contextual to place or industry. For example, the same skills are assigned to the occupation "accountant" whether that accountant works in a small town of 10,000 people or in New York City, and whether that accountant works in a small restaurant or in a major international accounting firm. Thus, an extension of the proposed research agenda may be an effort to improve upon this dataset.

Q5.1. How do worker skills for a given occupation systematically vary across industry and city size?

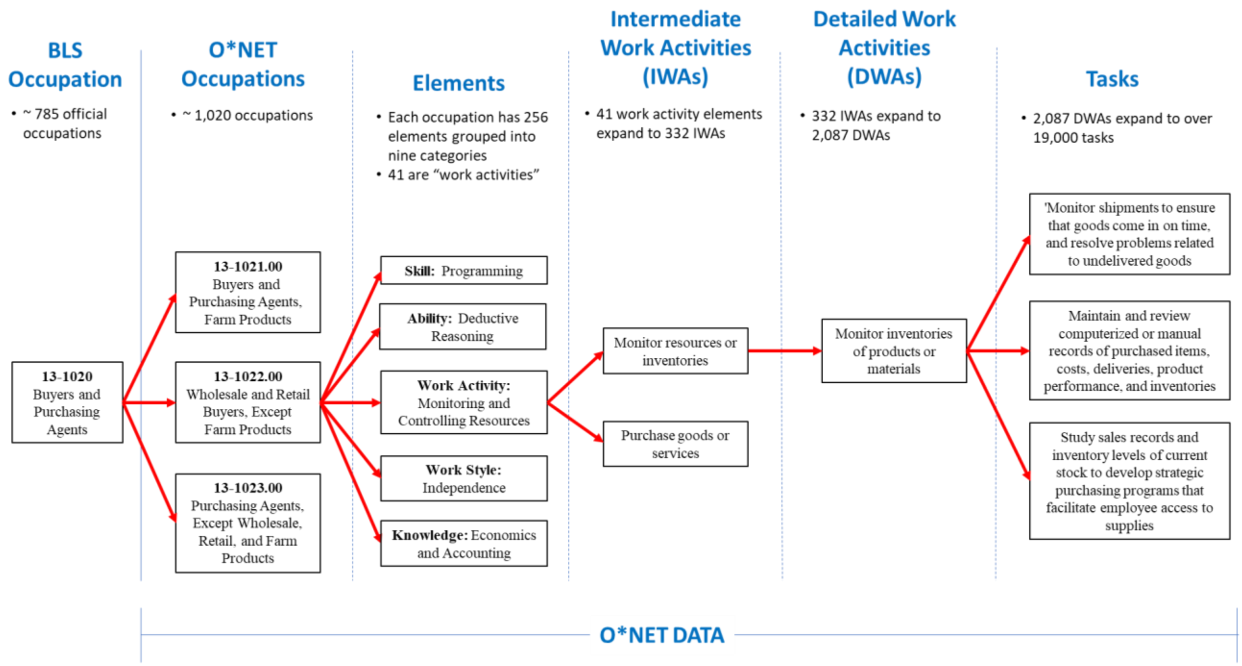

Figure 4. Partial schematic of the O*NET data set structure. The O*NET data set decomposes U.S. occupations into a set of skills, activities, and knowledge. It further decomposes work activities into a detailed list of over 20,000 tasks, which are executed to create products and services. The O*NET data are publicly available and updated at least annually.

To aid in addressing this question, several efforts have been undertaken to produce a superior skills taxonomy, some of which are publicly available. One of these efforts, the ESCO Taxonomy (Classification of European Skills, Competencies, Qualifications and Occupations) was recently published by the European Union [55]. Unlike the many hundreds of elements in the O*NET dataset, the ESCO dataset contains over 10,000 workers skills and should be investigated as a new alternative to O*NET. Efforts have also been undertaken in the private sector with offerings such as the OpenSkills API (https://lightcast.io/open-skills) available from the firm Lightcast. A free version of this taxonomy is available which includes over 30,000 labor skills with enhanced versions available for purchase. Again, researchers should explore this and similar dataset to assess whether can better answer questions about the impact of a clean-energy transition.

5.3. CO2 emissions data

Essential for this research agenda is a dataset that links industry sectors to carbon emissions and to greenhouse gas (GHG) emissions more generally. This interface between industry and emissions is mapped at high spatial and temporal resolution in the Vulcan Data, a project of Northern Arizona University funded jointly by NASA, NIST, NOAA, and the Department of Energy [56]. The purpose is to aid in quantification of the North American carbon budget, to support inverse estimation of carbon sources and sinks, and to support the demands posed by higher resolution FFCO2 observations (in situ and remotely sensed). The Vulcan dataset published estimated emissions by economic activity at a 1-km x 1-km resolution and at temporal scales as small as hour for the entire U.S. Researchers should seek to enhance the utility of this dataset by detailed mapping to not only high-level industry sectors but also to more detailed industry codes.

By linking GHG emissions to individual products, and then linking those products to worker tasks, researchers can directly link products that are likely to be phased out in a decarbonized economy to specific occupations.

Q5.2. What GHG emissions are linked to individual product codes and how do those product codes link to individual worker tasks?

5.4. "Green" jobs, industries, and activities

The terms "green jobs" and "green skills" are becoming ubiquitous in popular media and in copious literature from both governmental and non-governmental organizations. Early efforts to classify to classify a subset of occupations as "green jobs" include those by the U.S. BLS [57] and the International Labor Organization [58]. Yet what does it mean for an occupation to be "green"? The BLS taxonomy classified occupations such as "CEO" as a green occupation – after all, a green firm will require a leader. While the intention was novel and admirable, we believe such taxonomies have been plagued with difficulties because the designation was applied to the wrong level of the hierarchy in Figure 2. Other than a tiny fraction of arguably valid examples, such as coal mining, industries and occupations are not green or non-green.

It is even debatable whether individual skills are green or non-green – essentially the same bundle of skills is used by an auto mechanic to repair both a gasoline-burning vehicle, and hydrogen-burning vehicle, or an electric vehicle. Thus, attempts to classify skills as green or non-green may be more of an obstacle than a help to the proposed research agenda. Instead, we believe it is the individual tasks that should be examined for their contribution or not to a low-carbon energy system. The European Union's taxonomy of sustainable activities described above is a positive step in this direction. However, that endeavor resulted in approximately 100 activities that are mapped to high-level industry sectors. Instead, researchers should endeavor to classify the tasks presented in Figure 2 for their contribution to a low-carbon energy system. That contribution can be quantified and then aggregated to higher levels such as skill, occupation, and industry. Thus, the key dataset of green labor remains to be created and should be an integral goal of the proposed overall research agenda.

5.5. Methods

The *product, occupation,* and *tasks spaces* are modeling frameworks and analytical constructs, build using the data previously described with which to examine the connections economic sectors, activities, occupations and tasks and the ease with which existing occupations, tasks and skills can be reconfigured and repurposed. The frameworks all share a methodology of representing an economy as a complex network in which specific occupations, industries, etc. can be "located". The distance between locations can indicate the difficulty of moving between entities, such as occupations. Thus, this framework has relevant applications such as quantifying the difficulty of transitioning from one occupation to another or mapping a preferable transition pathway from one industry to another.

As this framework is relatively novel, there exist no generally agreed upon methodological details, such as specific formulae. Therefore, a portion of this research agenda should focus on fundamental aspects of this new methodology. What is the best measurement of proximity between nodes in skill/occupation space? While there is no consensus on the best measurement of proximity, proximity is generally derived from patterns of co-location of various economic units. For instance, what is the pattern of co-location of industries across U.S. cities? There remain lingering questions on how to translate those patterns of co-location into meaningful quantities that then inform weights of a complex network. How should those patterns be quantified?

Integrated assessment models (IAMs) are computational tools developed by engineers, earth and natural scientists, and economists to provide projections of interconnected human and natural systems under various conditions. The term assessment refers to focus on generating useful information for decision-making, even in case of large uncertainties. IAMs have become a standard approach in the research community seeking to understand the effects of climate change on ecological and socioeconomic systems and aiming to policy-relevant insights into global environmental change and sustainable development issues by providing a quantitative description of key processes in the human and earth systems and their interactions. The Intergovernmental Panel on Climate Change (IPCC) has relied on process-based integrated assessment models to quantify mitigation scenarios [59]. The experience and expertise of the Integrated Assessment Consortium (IAMC)—an organization of scientific research institutions that pursues scientific understanding of issues associated with integrated assessment modeling and analysis www.iamconsortium.org—could be leveraged to develop different scenarios for different pathways for labor market transformation brought about by different greening policies.

6. Conclusion

We have endeavored to outline a series of questions related to decarbonizing the U.S. economy and its impacts on employment. Addressing these questions requires a wide variety of social sciences and interdisciplinary approaches. Yet our questions represent some of the most obstinate obstacles to initiating and navigating a transition to a decarbonized economy. Central to our questions is the determination of which tasks performed by workers will need to change for the economy to decarbonize. With that knowledge we can then further answer questions about changes in skills, occupations, and industries and best guide policies that will mitigate the disruptions that are likely to come with decarbonization.

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