Workers and the Green-Energy Transition: Evidence from 300 Million Job Transitions

E. Mark Curtis
Wake Forest University

Layla O'Kane
Lightcast

R. Jisung Park
University of Pennsylvania, IZA

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ABSTRACT

Using micro-data representing over 130 million online work profiles, we explore transitions into and out of jobs most likely to be affected by a transition away from carbon-intensive production technologies. Exploiting detailed textual data on job title, firm name, occupation, and industry to focus on workers employed in carbon-intensive ("dirty") and non-carbon-intensive ("green") jobs, we find that the rate of transition from dirty to green jobs is rising rapidly, increasing ten-fold over the period 2005-2021 including a significant uptick in EV-related jobs in recent years. Overall however, fewer than 1 percent of all workers who leave a dirty job appear to transition to a green job. We find that the persistence of employment within dirty industries varies enormously across local labor markets; in some states, over half of all transitions out of dirty jobs are into other dirty jobs. Older workers and those without a college education appear less likely to make transitions to green jobs, and more likely to transition to other dirty jobs, other jobs, or non-employment. When accounting for the fact that green jobs tend to have later start dates, it appears that green and dirty jobs have roughly comparable job durations.

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Introduction

What are the consequences of transitioning away from fossil fuels for workers? The answer depends in part on the outside options that are available to potentially displaced workers, including in cleaner industries as well as in other local industries for which current carbon-intensive workers' skills provide a good match. This paper explores the potential labor market implications of the clean-energy transition, focusing on employment flows observed in data from roughly 130 million online employment profiles, representing approximately 300 million job-to-job transitions.

Climate mitigation policy can be thought of as a form of directed technical change away from carbon-intensive production processes.[1] Under perfectly competitive markets, the associated reallocation of labor (and capital) inputs have minimal efficiency costs, as workers frictionlessly and instantaneously adjust to new optimal input mixes by switching jobs and moving to areas with greater labor demand. In practice, search frictions, human capital acquisition costs, or ties to particular geographies may give rise to significant transition costs for workers (Manning, 2021).

Understanding the distributional consequences of the clean energy transition may be especially important in light of recent trends in labor market inequality, where workers with and without access to higher education have seen increasing "polarization" in wage and non-wage outcomes across many OECD countries (Hamermesh, 1999; Goos, Manning, and Salomons, 2009; Autor, 2014; Katz and Krueger, 2017). Transitioning away from fossil fuels may have distributional implications if some workers are better able to respond to changes in labor demand induced by changes in policy. Employment dislocations associated with labor demand shocks such as globalization and skill-biased technical change have been shown to be highly localized, scarring, and concentrated among non-college workers (Autor, Levy, and Murnane, 2003; Autor, Dorn, and Hanson, 2013).[2]

The magnitude of the shifts in product and labor demand arising from fully correcting the climate externality are likely to be large. Recent estimates of the social cost of carbon (Rennert et al., 2022; Carleton and Greenstone, 2022) suggest that the present value of

[1]Terms including "Green-energy transition", "Clean-energy transition" have been used to describe a wide range of phenomena, including the transition away from fossil fuels, improvements in air, soil, and water quality, and changes in sustainable management practices. We focus specifically on the expected shift in labor demand arising from correcting the carbon externality, which, while taking many possible forms (carbon tax, cap-and-trade, renewable portfolio standards, etc), will likely have the effect of reducing labor demand in carbon-intensive industries. As discussed below, this informs our arguably conservative definition of "green" and "dirty" jobs and transitions between them.

[2]For instance, Autor, Dorn, and Hanson (2013, 2019, 2021) find that trade liberalization and China's ascension to the WTO resulted in adverse wage and employment impacts for US commuting zones most exposed to import competition, particularly for less-educated workers, and that such trade shocks had significant adverse impacts on a range of non-market outcomes, including family formation, the number of children raised in poverty, and mortality from drug and alcohol abuse.

marginal damages created by greenhouse gases in a given year may be on the order of several trillion dollars globally.[3] Available estimates suggest that the US Inflation Reduction Act (IRA), passed in 2022, may cost up to $900 billion over the following ten years (Bistline, Mehrotra, and Wolfram, 2023). Both facts suggest that the labor-market impacts of shifts in policy-induced investment flows could have non-trivial welfare consequences.

In this paper, we use detailed job-to-job transition data to provide new descriptive evidence on this question. We develop novel, text-based measures of carbon-intensive "dirty" and non-carbon-intensive "green" jobs, which are generated on the basis of worker-job-level information on job title, firm name, industry, and occupation. This allows us to construct a broader measure of relevant jobs, particularly in emerging "green" sectors like electric vehicles, than many previous analyses. It also allows us to measure the rate of transition out of and into dirty and green jobs in a way that permits an exploration of heterogeneity across geographies, educational attainment, and age.

We find that the rate of transition from dirty to green jobs is growing rapidly, increasing nearly ten-fold over the period 2005 to 2021. A growing share of these transitions appear to be driven in particular by EV-related jobs. At the same time, the vast majority of workers in carbon-intensive jobs have not historically found work in green jobs. In 2021, 0.7 percent of workers who transitioned out of a dirty job transitioned into a green job. Conversely, the vast majority of workers obtaining green jobs do not come from carbon-intensive industries, but from a wide range of other industries and occupations (e.g. Sales Managers, Software Developers, Marketing Managers). Approximately a quarter (26.7 percent) of green jobs appear to be taken by first-time job-holders, and over 20,000 workers are observed entering green jobs from from overseas.

Some workers appear to be far better able to make – and some local economies much more likely to benefit from – these transitions than others. Overall, workers without a bachelor's degree are significantly less likely to transition into green jobs, as are older workers (e.g. workers in their 40's and 50's). In some local labor markets, such transitions appear exceedingly rare, despite a large number of workers in dirty jobs, who may increasingly face declining labor market prospects due to climate mitigation policies. Whereas some states, like California, feature relatively high rates of transition from dirty to green jobs, others, like West Virginia, appear to have low rates of dirty-to-green transitions despite a high density of existing dirty jobs.

Given the relatively low share of dirty workers who appear able to transition to green jobs, this begs an important question of where such workers might find alternative employment

[3]For instance, if one assumes a social cost of carbon estimate of $190 per ton at a 2 percent discount rate (Rennert et al., 2022), and that annual global emissions flows of approximately 3.5 gigatons add only marginally to the stock of total greenhouse gas emissions, the implied discounted present value of global damages associated with annual emissions may be on the order of $6 trillion.

as labor demand in fossil fuel-intensive industries declines. Our data allows us to assess the likelihood that workers who previously held dirty jobs are likely to transition into other dirty jobs, both within and outside of local labor markets. We find that, on average, approximately 20 percent of transitions out of dirty jobs are into other dirty jobs, including transitions within and out of local labor markets. The sector to which dirty workers are most likely to transition is manufacturing, which accounts for over 25 percent of all transitions out of dirty jobs.

The degree of persistence of employment within carbon-intensive sectors (dirty-to-dirty job transitions) varies considerably across educational attainment, age, and geography. The proportion of dirty-to-dirty transitions is 44 percent (8 percentage points) higher for workers with only a high school degree or less compared to those with at least an Associates degree. Older workers are also significantly more likely to remain in a dirty job; workers aged 55 to 64 are 25 percent (5 percentage points) more likely to transition into another dirty job compared to workers aged 18 to 34. In some cities, the share of dirty-to-dirty transitions can be as high as 90 percent, suggesting that nearly all workers in carbon-intensive sectors stay within such sectors, with limited attractive options in non-carbon-intensive industries.

One way to assess the potential welfare implications of a sustained transition away from fossil fuels is to look at how outside option wage values for dirty workers vary as other dirty jobs become more limited in a local labor market. We provide novel estimates of empirically observed outside option wage values for fossil fuel-intensive workers by geography, educational attainment, and age, following methods pioneered by Schubert, Stansbury, and Taska (2021). Our data suggest that non-BA workers are likely to experience a much larger decline in local outside options as fossil fuel-intensive jobs become more limited. The drop-off is far more pronounced in places where alternative jobs outside of fossil fuel-intensive industries appear to be more limited (e.g. Wilmington, DE, Oklahoma City, OK).

Research increasingly shows that workers place significant value on non-wage aspects of work (Maestas et al., 2018), including job stability (Hyatt and Spletzer, 2016). An important unanswered question pertains to the relative duration of dirty versus green jobs, regarding which our data provides novel evidence. For instance, an oft-cited concern has been that, even if wind and solar jobs are numerically plentiful, they may be relatively short-lived. We find that, while many green jobs appear to have shorter durations than dirty jobs in the cross-section, controlling for job-specific start and end dates erases much of the difference. In other words, controlling for the fact that green jobs will tend to be mechanically shorter in the cross-section due to their relatively recent emergence, we find relatively small duration differences between green and dirty jobs. Solar jobs appear to last 0.26 fewer years than dirty jobs, wind jobs do not appear to be significantly different in length than dirty jobs (which on average last 4.6 years in the cross-section), and EV jobs appear to be commensurate in length to the average dirty job.

Our findings contribute to a growing literature on the "green jobs" and the labor market consequences of environmental policies. Recent evidence suggests that the wage and employment implications of environmental regulation can vary by industry and region. For instance, Greenstone (2002) estimates that the U.S. Clean Air Act resulted in over 590,000 lost jobs in counties and industries that were historically heavily polluting. Curtis (2018) finds that overall employment in energy-intensive industries fell by up to 4.8% in the wake of the NOx trading program. Conversely, some analyses suggest that future "green jobs" could be plentiful and well-paying, resulting in net positive employment impacts (Lehr, Lutz, and Edler, 2012), and that well-designed labor market policies may help transition workers out of historically "brown" or "dirty" sectors.

One important knowledge gap pertains to the extent to which the skills demanded by, and geographic availability of, new "green" jobs overlap (or not) with those in traditionally "dirty" industries. Consider the following statement by former national climate adviser Gina McCarthy: "Take the U.S. manufacturing sector... It has relied on a carbon-based system for nearly 200 years, so *reshaping the system means ensuring that these industrial workers get the training and resources to build the clean energy economy* (emphasis added)."

Whether the workers who are currently employed in carbon-intensive jobs can be effectively matched to the jobs that will be demanded in a clean-energy economy is not immediately obvious. Our approach is to use observed job transitions to inform this question empirically. The papers closest in spirit to ours are Vona et al. (2018) and Curtis and Marinescu (2022), who explore potential wage and skill mismatches between brown and green workers, and the number and geographic distribution of new green jobs respectively. Our analysis features novel data that allows for a more detailed categorization of relevant jobs - including, for instance, the inclusion of new jobs in electric vehicle production and associated industries - as well as estimates of empirically observed job-to-job transitions between dirty and green jobs, as opposed to simulations based on measures of skill-similarity. Our paper also provides novel measures of job length across green and dirty jobs.

The rest of the paper is organized as follows. Section 2 discusses the empirical approach and the data. Section 3 presents our descriptive analysis of transitions into green jobs. Section 4 presents a discussion of transitions out of dirty jobs. Section 5 discusses average job length of green and dirty jobs. Section 6 discusses potential policy implications and concludes.

Data and Empirical Approach

Understanding the labor market implications of the clean-energy transition requires, among other things, knowledge of realistic outside options: in particular, of the outside options typically on offer to workers of varying skill-levels within exposed (carbon-intensive) industries. An electrical engineer employed in the fossil fuel industry may be able to find work in similar occupations in a renewable energy firm. Could the same be said for oil derrick operators? To what extent might such transitions also be constrained by geography? And how might the transition prospects of either occupational group depend on the worker's age or educational attainment?

Answering these questions requires detailed employer-employee data, the ability to observe job transitions, the characteristics of the workers that make them and detailed data on the jobs/firms they are transitioning to and from. Even Census' Longitudinal Employer-Household Dynamics program does not contain the detailed job information required to ascertain whether workers are in green jobs.

Lightcast Job Profile Data

A major contribution of this paper is to apply social profile data from Lightcast, which contains data on 130 million workers and their longitudinal job history, to questions pertaining to the labor market implications of environmental policy.[4] The data contain a unique identifier for each individual, their job title, education level, gender, occupation and industry of their company. Start dates are reported for each job and end dates are reported for previous jobs reported on the profile. We infer workers' age based on their education level and the start of their first job. The worker's city and state are also reported. While our sample consists of all workers who are currently in the United States or whose most recent job was in the United States, because we observe their full work history we can view transitions that have been made from other countries.

To identify job transitions we first order each worker's jobs according to their start dates. We define a job transition as having occurred when the start date of a worker's next job occurs simultaneously or after the end date of their previous job. Because changes in job title are also reported, we require the company name to change as well.[5]

Importantly, the data includes information on a worker's job title, employer name, indus-

[4]Lightcast has continuously updated worker profile data and newly created profiles. Because workers can report their full employment and educational history, the data go back to the earliest reported jobs, some of which go back before 1970. The data we use was most recently updated at the end of 2022.

[5]The timeline of most profiles lists jobs chronologically with the start of one job occurring simultaneous with or immediately after the end date of the next. However, by defining transitions this way we are not capturing new jobs acquired by multiple job holders. Also, this definition of a transition does not require the new job to have started immediately after the end of the previous job.

try (up to 6-digit NAICS codes), detailed occupation (SOC codes), as well as, for a subset of the data, the location of each job (city, state, and country). For the vast majority of observations, the data includes information on the start and end month and year for each job.

As discussed in greater detail below, one of the advantages of working with this data is that it allows us to construct job-to-job transitions, into and out of green and dirty jobs. By combining information on job titles, employer names, industries and occupations, we are also able to generate an arguably more comprehensive measure of green and dirty jobs than existing analyses. One of the disadvantages of using this data pertains to its representativeness of the population of interest. While our sample spans all fifty US states, most major occupation groups, and most industries, it appears to over-represent more educated workers, particularly in managerial and technical occupations. As shown in appendix tables A1 and A2, which compare the relative share of jobs in our data by occupation and industry group to data from the BLS, our worker profiles data over-represent some industries – including "Educational Services", "Finance and Insurance" and "Wholesale Trade" – as well as certain occupational groups: notably "Management Occupations" and "Architecture and Engineering Occupations". However, as shown in tables A1 and A2, our data includes jobs across all major industry and occupation categories, including in such industries as Manufacturing, Mining, Utilities, and Administrative Support and Waste Management and Remediation Services, as well as such occupation categories as Construction and Extraction, Production, and Sales. If anything, our data appears to slightly over-represent Mining, Utilities and Construction workers relative to the US population.

Another disadvantage of our data is that it is difficult to infer whether the observed transitions reflect voluntary movements up the job ladder or involuntary separations. It is unclear how such unobserved selection affects our interpretation of observed transitions. To the extent that one is interested in understanding the wage and employment consequences of adverse shocks to local labor demand, it is important to note that our measures of transition density or outside option wage values include a mix of "push" and "pull-"related factors.

Marklines Automobile Manufacturers Data

Marklines is a private company that collects detailed information on automobile and auto supplier sales and production data. Their data includes a list of all automobile plants in the United States and the models they produce. It also contains all EV battery plants in the United States. We use information on firm-specific automobile plant characteristics to identify jobs that are associated with EV production: for instance, jobs based in manufacturing plants owned and operated by EV manufacturers (e.g. Tesla), or in EV-specific plants owned by general automobile manufacturers (e.g. Toyota).

Bureau of Labor Statistics (BLS) Data

While Lightcast data provide considerable information on both firms and workers, it does not contain a direct measure of a worker's salary or earnings. To obtain a measure of worker pay, we use data from BLS' Occupational and Employment Wage Statistics (OEWS) program. The OEWS reports average earnings for every state by 6-digit SOC pairing. When calculating outside earnings option, we therefore assign workers to have the average earnings of the state by 6-digit SOC pairing to which they belong.

Categorizing "Dirty" and "Green" Jobs

Our conceptual object of interest is a continuous measure of the carbon-intensity of the marginal revenue of labor product associated with any given job. Such a measure would allow the researcher to array all existing jobs along a spectrum of potential adverse (or beneficial) labor demand effects associated with policies that provide incentives for less carbon-intensive production as a means of internalizing the negative externality associated with carbon pollution.

In practice, such a measure is not readily available, nor are existing standardized industry or occupation codes designed in a way that neatly partitions the labor market along these dimensions. Our categorization of jobs into carbon-intensive ("dirty"), non-carbon-intensive ("green"), and an omitted "all other" classification reflects the notion that, in order to understand the relevant labor market dynamics, starting with the extremes may be most instructive. As described below, we utilize information on job title, firm name, occupation and industry, as well as, in some instances, a combination of firm name and location to provide a robust definition.

We define jobs as "dirty" if they are associated with industries and occupations very clearly related to fossil fuel extraction and fossil energy production, as well as on the basis of text matching on job title and company name. For instance, workers are categorized as "dirty" if their jobs are in extraction occupations (SOC code 47-5000, extraction Workers) and in such industries as coal (NAICS 212), mining (213), oil and natural gas (211), and petroleum refining (324). We also include workers in the top 5 most energy-intensive manufacturing industries: namely cement and non-metallic (327), primary metals (331), paper and pulp (322) and chemicals, excluding cosmetics and pharmaceuticals (325), and textiles (313). In addition, we use keywords such as "coal", "petroleum", "fossil fuel", "shale", or "petrol" to match by job title.[6]

[6] We decided not to define dirty jobs on the basis of company names because there are companies, such as British Petroleum, which historically had petroleum in the company name but likely included a mix of dirty and green workers.

We define jobs as "green" similarly, using information on job title, occupation, company name, and industry, focusing in particular on jobs that are clearly associated with the production of renewable energy (solar, wind, etc.) or the production of electric vehicles.[7]

To identify jobs in renewable energy, we include job titles that feature text such as "solar", "photovoltaic", "wind turbine", or "wind energy", and occupation titles that are defined by O*NET as solar and wind jobs (five 8-digit SOC codes for solar, four 8-digit SOC codes for wind)[8] We also include worker-jobs employed in the top 5 wind and top 5 solar companies in terms of revenues and market capitalization respectively.[9] These include such solar companies as Avangrid, First Solar, Sunpower, and such wind companies as Vestas Wind Systems and Brookfield Renewables. Importantly, we exclude from our green jobs definition jobs based in companies like Siemens or General electric, which engage in renewable energy generation but also engage in a wide range of other activities. Despite the availability of industry codes specific to renewable power generation, we decided to exclude "Solar Electric Power Generation" and "Wind Electric Power Generation" (NAICS 221114 and 221115) on the basis of visual inspection which suggested that a non-trivial fraction of underlying data had 6-digit NAICS codes that were misclassified.

An important industry that has been missing from many previous analyses of green jobs are jobs associated with the production of electric vehicles (EVs), which have historically been difficult to classify. This difficulty stems in part from the strong overlap between existing internal combustion engine (ICE) automobile manufacturing firms and those engaging in EV production, as well as the lack of specific occupation codes associated with EV-production. We use data from Marklines to identify automobile plants and companies in the US that are exclusively engaging in EV production, as well as those firms that are engaged in the production of EV batteries. For instance, we categorize a job as a (green) EV-job if it is based in EV battery producing firms such as Ultium, Proterra, or SK Battery, or EV producing firms such as Tesla or Rivian. We also include jobs in such companies as Toyota or Mercedes if they are based in cities where EV plants of those firms are known to exist.

[7] Our measure of green jobs is likely a conservative one compared to some existing definitions. For instance, the International Labour Organization defines green jobs as follows. "Green jobs are decent jobs in any economic sector (e.g. agriculture, industry, services, administration) which contribute to preserving, restoring and enhancing environmental quality. Green jobs reduce the environmental impact of enterprises and economic sectors by improving the efficiency of energy, raw materials and water; de-carbonizing the economy and bringing down emissions of greenhouse gases; minimizing or avoiding all forms of waste and pollution; protecting or restoring ecosystems and biodiversity; and supporting adaptation to the effects of climate change." We focus primarily on jobs that directly benefit from an implicit or explicit price on carbon, as opposed to a wider set of environmental externality-correcting policies (e.g. water or soil quality enhancement).

[8] For instance, Solar Energy Systems Engineers (17-2199.11) and Wind Energy Operations Managers (11-9199.09).

[9] We take company names from the following sources. For solar: https://www.zippia.com/advice/largest-solar-companies/. For wind: https://www.fool.com/investing/stock-market/market-sectors/energy/wind-energy-stocks/.

Including these jobs expands our definition of green jobs significantly. Based on these classifications, we estimate that approximately 32.4 percent of green jobs are in solar, 13.5 percent are in wind, and 37.5 percent are associated with the production of electric vehicles and EV batteries. However, the total number of green jobs may be higher than our definition suggests. We do not capture workers in various up- or down-stream industries whose labor demand may increase, such as chip manufacturers or EV sales and maintenance jobs. Additionally, we do not capture EV jobs created by many established automobile manufactures whose plants are currently transitioning to EV production.

Transitions into Green Jobs

What proportion of workers successfully transition from dirty to green jobs? And who are these workers?

Figure 1 shows the evolution of dirty-to-green transition share over time. It plots the share of workers who ever held a dirty job and transitioned to a new job (which could be another dirty job, a green job, or something else) whose destination job was classified as green. It suggests that the rate of successful transition has been rising steadily since the early 2000's, from less than 0.1 percent in prior to 2005 and reaching nearly 0.7 percent of all transitions out of dirty jobs by 2021. It also suggests however that, as an overall share of transitions out of dirty jobs, such dirty-to-green transitions are exceedingly rare.

Figure 2 reproduces panel a of Figure 1, but reporting the share of transitions out of dirty jobs into green jobs by job category. We report jobs into EV, wind, solar, and renewables, as defined above. EV jobs stand out as having experienced notably rapid growth in recent years, having occupied a miniscule share prior to 2010 but undergone a significant increase particularly since around 2015.

Workers seeking to transition out of declining dirty industries may not be able to find a green job immediately. Therefore, it may be important to account for the possibility that workers may hold intermediate positions – including in other jobs – before transitioning into a green job. Figure 3 shows the probability that a worker separating from a dirty job is employed in a green job as a function of the number of quarters since dirty job separation, plotted separately by cohort, where a cohort is defined according to the year in which initial dirty job separation occurred. For instance, across all workers who left a dirty job in 2018, 0.2 percent of them had started a green job within 2 quarters of initial separation, roughly 0.4 percent had done so within 8 quarters (2 years), and more than 0.6 percent within 3 years. Consistent with the growing availability of green jobs, the slope of each cohort's transition rate appears to be growing steeper over time, with the exception of the 2022 cohort, for which we have limited data.[10]

The rate of dirty-to-green transition varies substantially by educational attainment. Workers without a BA are significantly less likely to successfully transition from dirty jobs to green ones compared to workers with at least a BA in our data. Figure 4 shows the transition shares across educational attainment categories. Workers with doctoral degrees appear to be 44 percent (0.15 percentage points) more likely to successfully transition from a carbon-intensive job to a green job than workers with a high school education or less, though only 4 percent (0.02 percentage points) more likely than those with associates degrees.

Figure 4 also shows the breakdown by age group. It suggests that older workers are significantly less likely to make a dirty-to-green transition than younger workers. Workers between the ages of 55 and 64 appear to be 38 percent (0.16 percentage points) less likely to make the transition than workers aged 25 to 34. Workers aged 65 and above are 60 percent (0.25 percentage points) less likely to do so than workers aged 25 to 34. Because young workers are far more likely to change jobs, the total number of dirty-to-green transitions we observe for young workers far exceeds the number we observe for older workers. Between 2020 and 2022, 30 times as many 25-34 year olds transition to green jobs as 55-64 year olds.

Consistent with previous work which finds job growth in green industries to be highly geographically concentrated, we find that the rate of dirty-to-green transition varies enormously across local labor markets. Figure 5 shows the top state and cities by share of workers who transitioned out of dirty jobs into green jobs. States like California, Oregon, and Arizona appear to have experienced higher rates of dirty-to-green transition, compared to states like South Carolina, Louisiana, or West Virginia.

Who are the workers most likely to transition into green jobs? Table 4 reports the most common occupations transitioning into each of the four green job categories we define. Table A3 reports the occupations of non-college workers most likely to transition into these categories. For example, column shows the top twenty occupation groups by thickness of transition share into wind jobs, limiting to non-college workers. Many of these workers previously worked as Maintenance and Repair Workers, General and Operations Managers, or Computer Support Specialists. Tables A4 show similar information for college workers entering wind jobs and both non-college and college workers entering solar jobs.

A non-trivial fraction of transitions into green jobs appear to come from abroad. In our data, 4.9 percent of transitions into green jobs are by workers whose previous jobs were located in other countries, including Denmark, the United Kingdom, Spain, Germany and India. Table A5 reports the top 10 countries sending workers to green jobs in the

[10] While we report data from 2022 in all results, it is likely that not all workers had reported 2022 job changes when our data was scraped. As such, we generally refrain from comparing results in 2022 to the years immediately preceding it.

United States. We are careful to note that our data does not include information on the worker's nationality, and that the nature of selection into our data may overstate the share coming from overseas, given relative over-representation of more highly educated workers and managerial, technical, and professional occupations. Nevertheless, it is notable that at least 14,066 green jobs during our study period were taken by individuals whose previous jobs were located overseas.

In summary, while some workers indeed appear to be able to transition from working in a carbon-intensive job to a less carbon-intensive one, the data clearly show that the majority of green jobs are not being filled by former dirty workers, at least not historically.

Transitions out of Dirty Jobs

If such a small fraction of workers who leave a dirty job enter a green one (fewer than 1 percent in our data), where do they go? From a welfare perspective, it is important to understand whether workers facing diminishing labor demand in one sector are able to transition out of that sector, including to jobs not obviously related to green technologies. In this section, we present descriptive evidence on where workers in carbon-intensive jobs have tended to transition to, and how the rate of successful transition out of declining dirty industries varies by educational attainment, geography, and age.

Tables 1 and 2 show the top 30 destination occupations for workers leaving dirty jobs, broken up by workers without a college degree (BA) and workers with at least a BA. Non-BA workers formerly employed in carbon-intensive jobs appear to transition to a wide range of occupations – including General and Operations Managers, Sales Managers, Computer User Support Specialists, Customer Service Representatives, Heavy and Tractor-Trailer Truck Drivers, and Mechanical Engineers – highlighting the breadth of outside options potentially available to formerly carbon-intensive workers. At the same time, many of the occupational categories listed may, depending on the degree of industrial concentration in a local labor market, be directly or indirectly dependent on carbon-intensive industries. This suggests that it may be important to understand the rate of transition within carbon-intensive jobs.

As shown in Table 3, which reports the most common industries that college and non-college workers in dirty jobs enter when they leave their dirty job, a large fraction of those leaving dirty jobs enter (or remain in) the manufacturing sector. For non-college workers, 24.5 percent of all transitions away from dirty jobs are to jobs in manufacturing industries.

We therefore estimate the share of workers who ever held and eventually leave a dirty job who transition to other dirty jobs. Specifically, we define the dirty-to-dirty transition share as the conditional probability of transitioning to a dirty job, conditional on having ever held a dirty job and moved to a new job at some point in our sample.[11] In our data, approximately 22 percent of workers who transition out of a dirty job transition into another dirty job.

This share is higher for workers without a bachelor's degree, at 27 percent, versus 19 percent for workers with at least a bachelor's degree. Workers with a high school diploma or less are 44 percent (8 percentage points) more likely than workers with at least an associates degree to remain in a dirty job when transitioning out of a dirty job. Interestingly, for workers with at least an associates degree, there do not appear to be large differences in dirty-to-dirty transition shares for workers of different levels of educational attainment.

The likelihood of remaining within carbon-intensive sectors appears to be significantly higher for older workers. Workers aged 55 to 64 are approximately 25 percent (5 percentage points) more likely to transition into another dirty job compared to workers aged 18 to 34. For prime-aged workers (ages 18 to 64), there appears to be a monotonically rising relationship between age and probability of remaining anchored to dirty jobs.

Consistent with previous work on the geographic concentration of fossil-fuel related jobs (Jacobsen and Parker, 2016; Raimi, 2021; Hanson, 2023), we find that the share of dirty-to-dirty transitions varies significantly across geographies. Table 5 shows the average dirty-to-dirty transition shares for the top 15 cities and states. States like Delaware, Oklahoma, Wyoming, Texas, Colorado and Louisiana appear to feature high degrees of persistence of employment within dirty industries. In some cities, like Oklahoma City, OK, Denver, CO, or Wilmington DE, nearly two-thirds of transitions out of a dirty job are into another dirty job. As seen in Figure 5, workers in states like Kansas and Alaska appear to be less likely to remain in dirty jobs, despite relatively low population density. This suggests that simply discerning whether labor markets are geographically isolated (or not) or feature many existing carbon-intensive jobs (or not) may be of limited value in identifying the workers most likely to experience adverse labor market shocks due to climate policy.

One way to measure the potential labor market impacts of transitioning away from fossil fuels would be to estimate the change in the set of outside options associated with ensuing reductions in labor demand. The extent to which the clean energy transition affects a worker's labor market prospects will depend in part on how labor demand in other jobs that she might be likely to transition to is affected. An informative hypothetical therefore would be to assess, for dirty workers in different local labor markets, how the menu of available job options changes in a world with dramatically reduced labor demand in other carbon-intensive sectors, and to do so in a way that accounts for local differences in the degree of thickness in historical job-to-job transition flows.

[11] Workers who took a dirty job and kept it for their entire careers to date are therefore not included in the denominator.

Our data allows something close to this, as we can empirically estimate the relevant outside options by job type and location (e.g. city, state), and do so separately for workers with higher and lower levels of human capital. We follow Schubert, Stansbury, and Taska (2021) to estimate outside option wages for each occupational category in our data, with modifications to allow for different occupation-to-occupation transition shares by industry and state.[12]

Figure 6 shows how the set of outside options changes in a hypothetical world in which other local dirty jobs are no longer available. For illustrative purposes, we make the admittedly extreme assumption that the wages associated with all other local dirty jobs goes to zero in this scenario. For both workers with and without a college degree, we can see that there are reductions in the set of available jobs across the wage distribution. This provides visual evidence regarding the extent to which such reductions in outside options may prove problematic for workers in different local labor markets. As shown in Figure 7, some states, including Texas, Louisiana, Oklahoma, and West Virginia appear to experience a much greater reduction in the total wage bill associated with remaining local outside options for dirty workers, compared to states like Washington, Massachusetts, Oregon, Illinois, and Florida.

We note that, in our data, it is not possible to systematically distinguish between transitions that arise from moving up the job ladder or moving to firms that provide better match quality ("pull" factors) and those that are due to involuntary dislocations ("push" factors). We therefore interpret these findings with the understanding that there may be selection effects that limit the applicability to the study of acute reductions in labor demand. Moreover, to the extent that dramatic reductions in labor demand in fossil-intensive industries may generate spillover effects in other adjacent industries, our assessment of potential changes in outside wage options may be biased in unknown directions. As such, we caution against interpreting the absolute magnitude of decline.

Job Duration

Even if a high fraction of workers in dirty jobs successfully transition to green ones, it may be important to know how stable or transitory such employment spells are. Such possibilities are part of a broader set of concerns around the relative quality of jobs that may prevail in an economy that transitions away from fossil fuels, including relative wages (Vona et al., 2018; Curtis and Marinescu, 2022).

One important feature of job transition for which there remains limited empirical evidence

[12] For example, this allows Oil and Gas Derrick Operators in Houston to have thicker or thinner transition shares into non-dirty jobs than other Oil and Gas Derrick Operators in the rest of Texas, where the concentration of jobs in the oil industry may be relatively lower on average.

pertains to the stability of resulting employment. For instance, a recent OECD report notes that “the duration of jobs is crucial when assessing the economic and societal impacts of green policies ... Replacing permanent mining jobs by temporary wind farm construction jobs, results in an overall loss of long-term employment.”[13] However, many occupation and industry classifications historically did not include designations for many newer green jobs. Even in instances when new classification schemes have become available over time, the ability to backward-cast new classifications to previous jobs has tended to be limited, particularly for data sets that provide a longitudinal picture of job-to-job transitions. As such, there are to our knowledge few measures of job length that allow for meaningful comparisons between dirty and green jobs.

Figure A1 shows average job lengths across job categories for both green and dirty jobs. It suggests that, in the naive cross-section, green jobs appear to be significantly shorter in duration than dirty ones. The average solar job lasts between 2.2 and 2.6 years (depending on whether one includes jobs that do not have an end date and are listed as “current” in our data). The average electric vehicle job lasts approximately 1.9 to 2.4 years. In contrast, the average dirty job has a duration of between 4.6 and 6.3 years.

However, such measures do not account for the fact that many green jobs are likely to have started relatively recently, and may be held by younger workers who tend to have shorter jobs on average (Hyatt and Spletzer, 2016). Indeed, controlling for start year changes the relative job lengths considerably. Table 6 presents the results of a series of analyses that regress job length in years on indicator variables for categories of green jobs, with the reference category being dirty jobs. As shown in column 2 of Table 6, adding fixed effects for starting year reduces the job length differences between green and dirty jobs considerably. Whereas solar, wind, and EV jobs appear 2.48, 1.30, and 2.89 years shorter than dirty jobs in the cross-section (column 1), adjusting for start date reduces the differences dramatically, such that solar jobs appear to last 0.26 fewer years than dirty jobs, wind jobs do not appear to be significantly different in length than dirty jobs, and EV jobs actually appear to be 0.24 years longer than dirty jobs. These are novel descriptive facts that may have important implications for how policymakers weigh the costs and benefits of transitioning away from carbon-intensive production.

Including additional controls for the number of prior jobs by the worker (column 3); worker-level demographic controls, including gender, age, education, and state (column 4); and broad occupation category in the form of 2-digit SOC fixed effects (column 5) does not change the qualitative finding that green jobs do not appear to be dramatically shorter in duration than dirty jobs that they may replace, though solar and wind jobs do appear

[13] https://www.oecd.org/environment/Employment-Implications-of-Green-Growth-OECD-Report-G7-Environment-Ministers.pdf

to be statistically significantly shorter in duration, by approximately 3 months (column 5: 0.28 years and 0.24 years respectively). If anything, EV jobs appear to last slightly longer (column 5: 0.046 years) than the average dirty job. Column 6 adds company fixed effects, which focuses on variation in job length across green and dirty jobs within the same firm. Our identifying variation in this instance shrinks considerably, as variation across companies is absorbed by the fixed effects, making the coefficient on solar and EV jobs no longer significant. Nevertheless, it is instructive that, adjusting for start date, the differences in job duration between green and dirty jobs do not appear be smaller than suggested in the cross-section.

How externally valid are our measures of job length? One concern with these findings pertains to possible selection into our worker profile database. According to BLS data, median employee tenure in 2022 was 4.3 years for men and 3.8 years for women. We hesitate to make direct comparisons of absolute job tenure given the selection into our sample.[14] It is worth noting that a significant fraction of observations in our data may have been missing information on the month of the year in which a job started, leading to what appears to be bunching in January. To the extent that this is the result of mechanically assigning January as a start date to some fraction of jobs which actually began in later months in the same calendar year, this would lead our measures of job tenure to be shorter across the board. To the extent that our sample under-represents certain "blue collar" occupations (e.g. construction), the external validity of these findings may be limited for some sub-groups for whom shorter job duration may be especially problematic. We note also that emerging work on alternative work arrangements and the "gig-economy" suggest that shorter jobs may play an important role in the labor market, either as sources of supplementary income or in providing flexible work arrangements that are valued in themselves, and so caution against interpreting relative job duration as an indicator of job quality or welfare.

Discussion and Conclusion

This paper explores the potential labor market implications of transitioning away from fossil fuels and towards less carbon-intensive energy sources. Previous research suggests that policy-induced shifts in labor demand can have highly localized and unequal labor market consequences: for instance, in the context of trade liberalization and import competition from China (Autor, Dorn, and Hanson, 2013, 2021).

In this paper, we provide novel descriptive evidence regarding how the shift away from carbon-intensive industries might affect workers. Our findings highlight the importance of understanding the outside options available to workers, including in cleaner industries and

[14] From BLS 2022: https://www.bls.gov/news.release/pdf/tenure.pdf

other local industries where their skills may be a good match.

We provide evidence that while the number of workers transitioning from carbon-intensive "dirty" jobs to non-carbon-intensive "green" jobs is still relatively small, the rate of dirty-to-green transition appears to be rising rapidly. The observed increase in this rate corresponds with the increase in the number of available green jobs. If this continues then we will expect to see a sizable number of workers currently employed in dirty jobs to transition to green jobs. Moreover, green jobs appear to offer similar opportunities for longer-term employment as many existing dirty jobs, as evidenced by roughly similar average job lengths.

At the same time, our data suggest that, if past trends continue, the clean energy transition may have important distributional consequences that could exacerbate underlying trends in labor market inequality. We find that workers without a college degree and older workers are significantly less likely to transition into green jobs, and more likely to remain in carbon-intensive jobs. The high rate of employment persistence within dirty jobs in some localities suggests that there may be limits to the extent to which local labor markets are able to absorb the workers who will be displaced by the move away from fossil fuels.

References

Autor, D H. 2014. "Skills, education, and the rise of earnings inequality among the "other 99 percent"." *Science* 344 (6186):843–851.

Autor, David, David Dorn, and Gordon Hanson. 2019. "When work disappears: Manufacturing decline and the falling marriage market value of young men." *American Economic Review: Insights* 1 (2):161–178.

Autor, David, David Dorn, and Gordon H Hanson. 2021. "On the persistence of the china shock." Tech. rep., National Bureau of Economic Research.

Autor, David H., David Dorn, and Gordon H. Hanson. 2013. "The China Syndrome: Local Labor Market Effects of Import Competition in the United States." *American Economic Review* 103 (6):2121–68. URL `https://www.aeaweb.org/articles?id=10.1257/aer.103.6.2121`.

Autor, David H., Frank Levy, and Richard J. Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration*." *The Quarterly Journal of Economics* 118 (4):1279–1333. URL `https://doi.org/10.1162/003355303322552801`.

Bistline, John, Neil Mehrotra, and Catherine Wolfram. 2023. "Economic Implications of the Climate Provisions of the Inflation Reduction Act." Tech. rep., National Bureau of Economic Research.

Carleton, Tamma and Michael Greenstone. 2022. "A guide to updating the US Government's social cost of carbon." *Review of Environmental Economics and Policy* 16 (2):196–218.

Curtis, E. Mark. 2018. "Who Loses under Cap-and-Trade Programs? The Labor Market Effects of the NOx Budget Trading Program." *The Review of Economics and Statistics* 100 (1):151–166. URL `https://doi.org/10.1162/REST_a_00680`.

Curtis, E. Mark and Ioana Marinescu. 2022. "Green Energy Jobs in the US: What Are They, and Where Are They?" Working Paper 30332, National Bureau of Economic Research. URL `http://www.nber.org/papers/w30332`.

Goos, Maarten, Alan Manning, and Anna Salomons. 2009. "Job polarization in Europe." *American economic review* 99 (2):58–63.

Greenstone, Michael. 2002. "The Impacts of Environmental Regulations on Industrial Activity: Evidence from the 1970 and 1977 Clean Air Act Amendments and the Census of Manufactures." *Journal of Political Economy* 110 (6):1175–1219. URL `https://www.journals.uchicago.edu/doi/full/10.1086/342808`.

Hamermesh, Daniel S. 1999. "Changing inequality in markets for workplace amenities." *The Quarterly Journal of Economics* 114 (4):1085–1123.

Hanson, Gordon H. 2023. "Local Labor Market Impacts of the Energy Transition: Prospects and Policies." Tech. rep., National Bureau of Economic Research.

Hyatt, Henry R. and James R. Spletzer. 2016. "The shifting job tenure distribution." *Labour Economics* 41:363–377. URL https://www.sciencedirect.com/science/article/pii/S0927537116300227. SOLE/EALE conference issue 2015.

Jacobsen, Grant D and Dominic P Parker. 2016. "The economic aftermath of resource booms: evidence from boomtowns in the American West." *The Economic Journal* 126 (593):1092–1128.

Katz, Lawrence F and Alan B Krueger. 2017. "Documenting decline in US economic mobility." *Science* 356 (6336):382–383.

Lehr, Ulrike, Christian Lutz, and Dietmar Edler. 2012. "Green jobs? Economic impacts of renewable energy in Germany." *Energy Policy* 47:358–364. URL https://www.sciencedirect.com/science/article/pii/S0301421512003928.

Maestas, Nicole, Kathleen J Mullen, David Powell, Till Von Wachter, and Jeffrey B Wenger. 2018. "The Value of Working Conditions in the United States and Implications for the Structure of Wages." Tech. rep., National Bureau of Economic Research.

Manning, Alan. 2021. "Monopsony in Labor Markets: A Review." *ILR Review* 74 (1):3–26. URL https://doi.org/10.1177/0019793920922499.

Raimi, Daniel. 2021. "Mapping County-Level Exposure and Vulnerability to the US Energy Transition." *Resources for the Future Working Paper* :21–36.

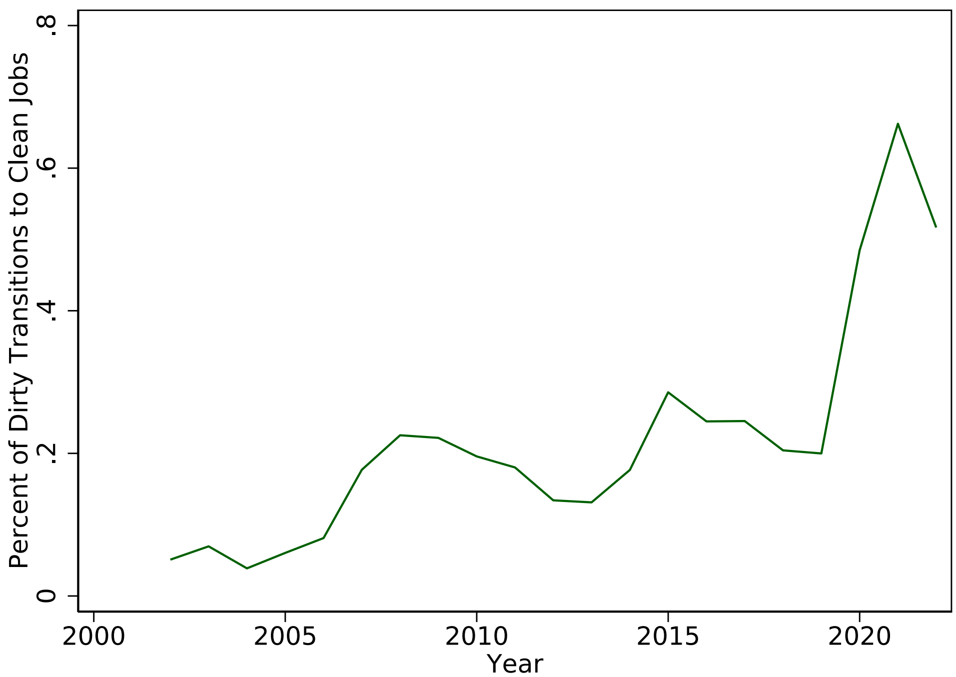
Rennert, Kevin, Brian C Prest, William A Pizer, Richard G Newell, David Anthoff, Cora Kingdon, Lisa Rennels, Roger Cooke, Adrian E Raftery, Hana Ševčíková et al. 2022. "The social cost of carbon: advances in long-term probabilistic projections of population, GDP, emissions, and discount rates." *Brookings Papers on Economic Activity* 2021 (2):223–305.

Schubert, Gregor, Anna Stansbury, and Bledi Taska. 2021. "Employer Concentration and Outside Options." Working Paper. URL http://www.ecineq.org/wp-content/uploads/papers_EcineqLSE/EcineqLSE-351.pdf.

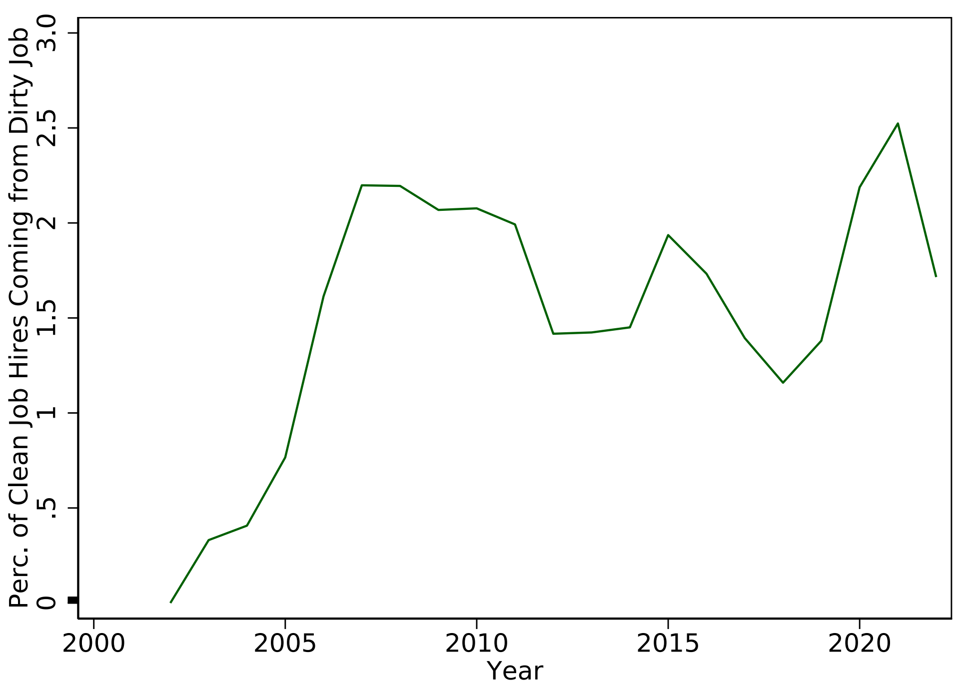
Vona, Francesco, Giovanni Marin, Davide Consoli, and David Popp. 2018. "Environmental Regulation and Green Skills: An Empirical Exploration." *Journal of the Association of Environmental and Resource Economists* 5 (4):713–753. URL https://www.journals.uchicago.edu/doi/full/10.1086/698859. Publisher: The University of Chicago Press.

Figure 1: Dirty-to-Green Transition Rates

(a) Dirty-to-Green Transitions as a percent of all Dirty Transitions

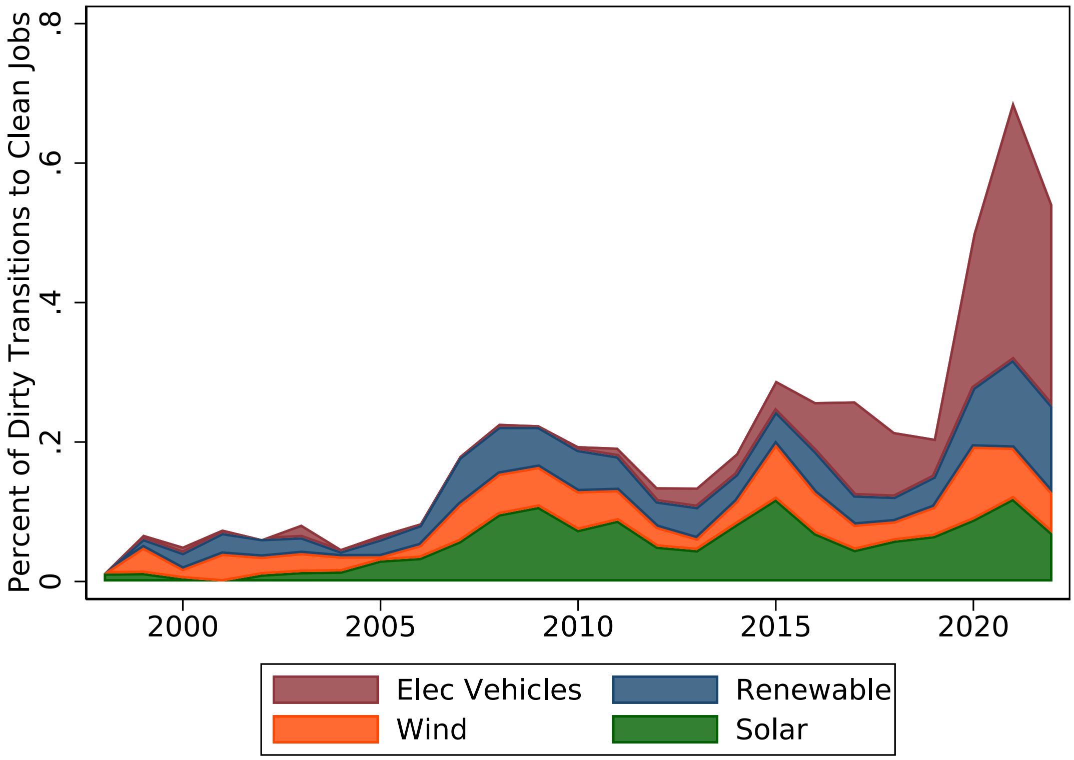


(b) Percent of New Green Hires Coming from Dirty Job



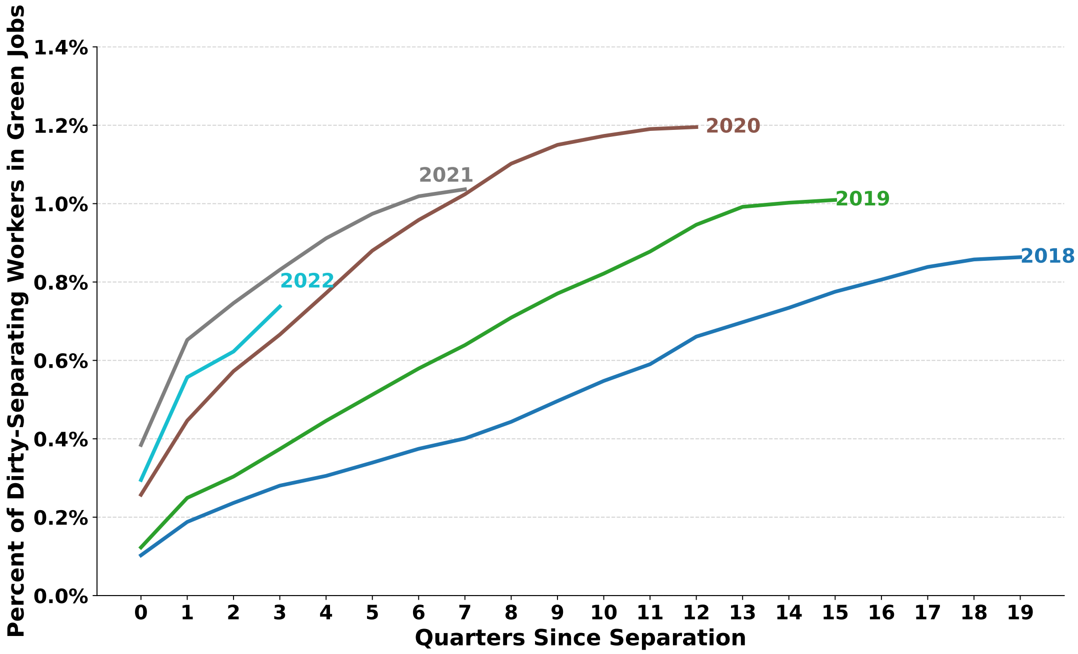
Notes: Panel a of Figure 1 shows a time-series plot of Dirty-to-Green transitions as a percent of all transitions out of Dirty jobs. Panel b shows a time-series plot of the percent of hires in clean jobs that come from dirty jobs. A transition is defined as occurring if a worker leaves their company and joins another company. *Source:* Worker profile data from Lightcast.

Figure 2: Dirty-to-Green Transition Probability by Job Category



Notes: Figure 2 reports the probability of a dirty worker transitioning to a clean job by green job category. *Source:* Worker profile data from Lightcast.

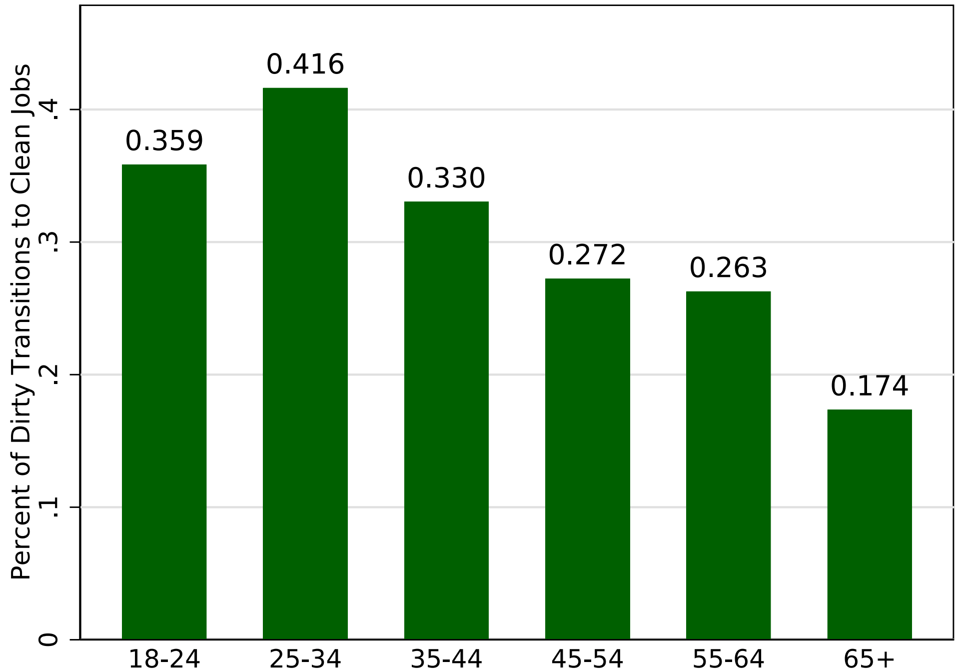
Figure 3: Probability of Green Employment by Year of Dirty Job Separation



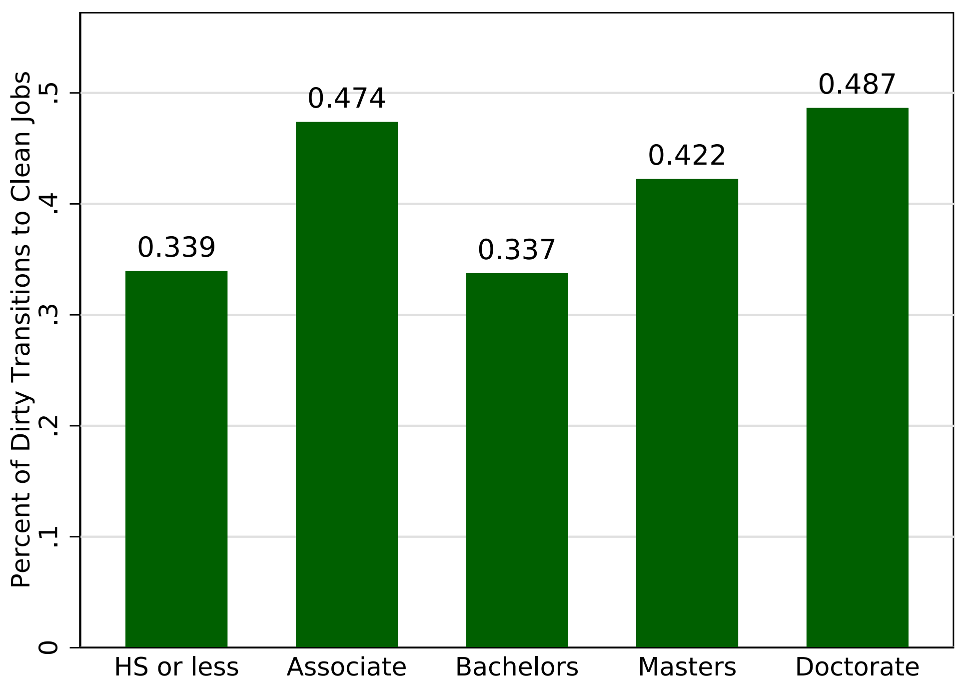
Notes: Figure 3 plots out the probability that a worker separating from a dirty job is employed in a green job as a function of the number of quarters since the dirty job separation. For example, 1.2% of worker leaving a dirty job in 2020 were employed in a green job 12 quarters after their separation. The figure tracks this out separately for workers separating in 2018, 2019, 2020, 2021 and 2022. *Source:* Worker profile data from Lightcast.

Figure 4: Probability of Dirty-to-Green Transition

(a) By Age Category



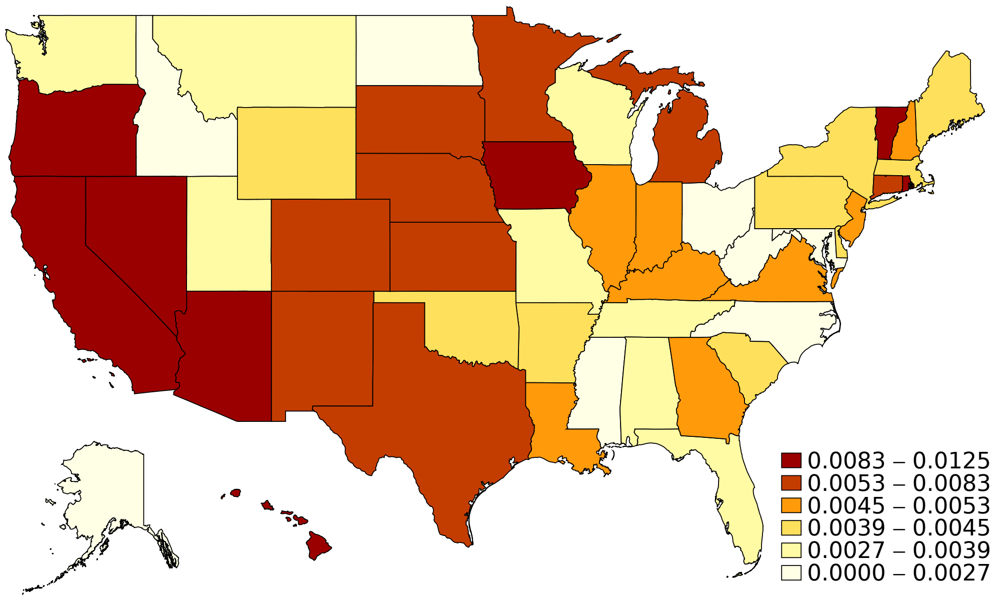
(b) By Education Level



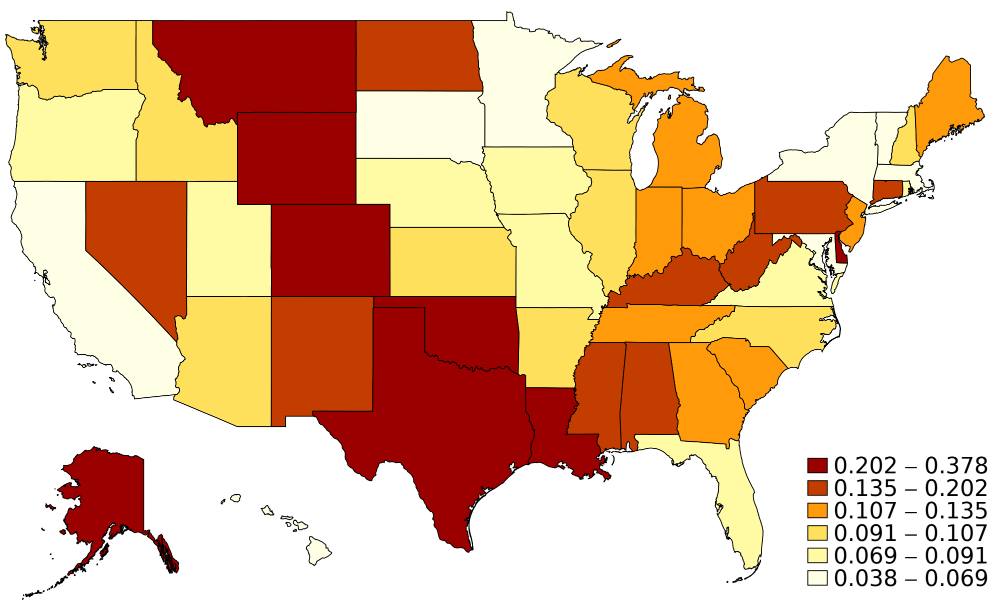
Notes: Figure 4 shows the probability that a worker leaving a dirty job enters a green job for workers of different ages and levels of education. For reference, the percentage of workers in our sample leaving a dirty job and entering a green job with a high school degree or less 28.1, and for Associates degrees is 7.1 percent. For Bachelors, Masters, and Doctorate degrees, the shares are 34, 25.2 and 5.5 respectively.
Source: Worker profile data from Lightcast.

Figure 5: Dirty-to-Green and Dirty-to-Dirty Transition Rates 2020-2022

(a) Dirty-to-Green Transition Rate 2020-2022



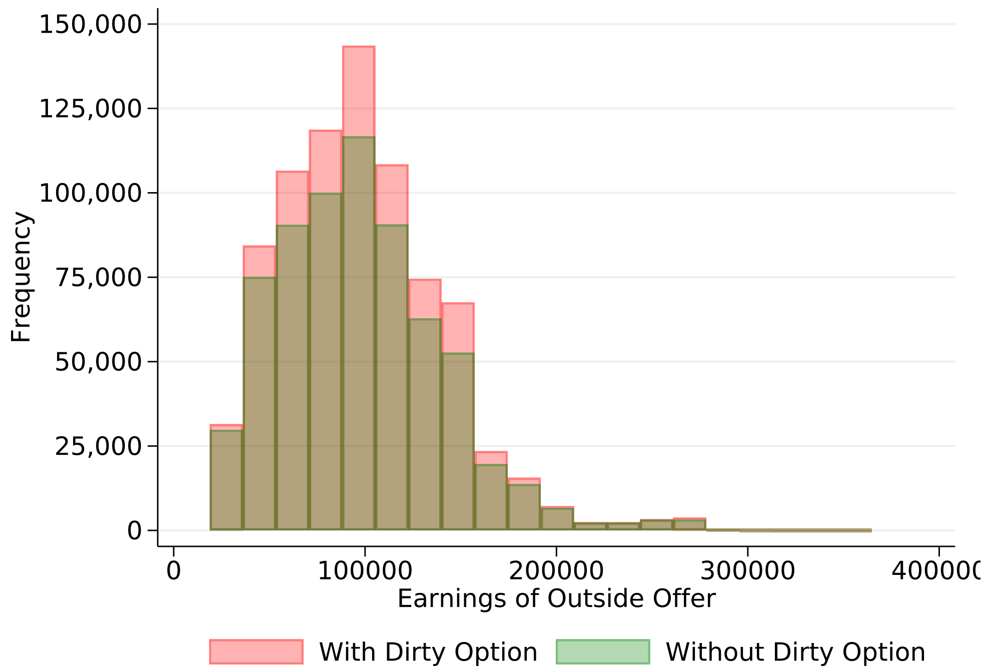
(b) Dirty-to-Dirty Transition Rate 2020-2022



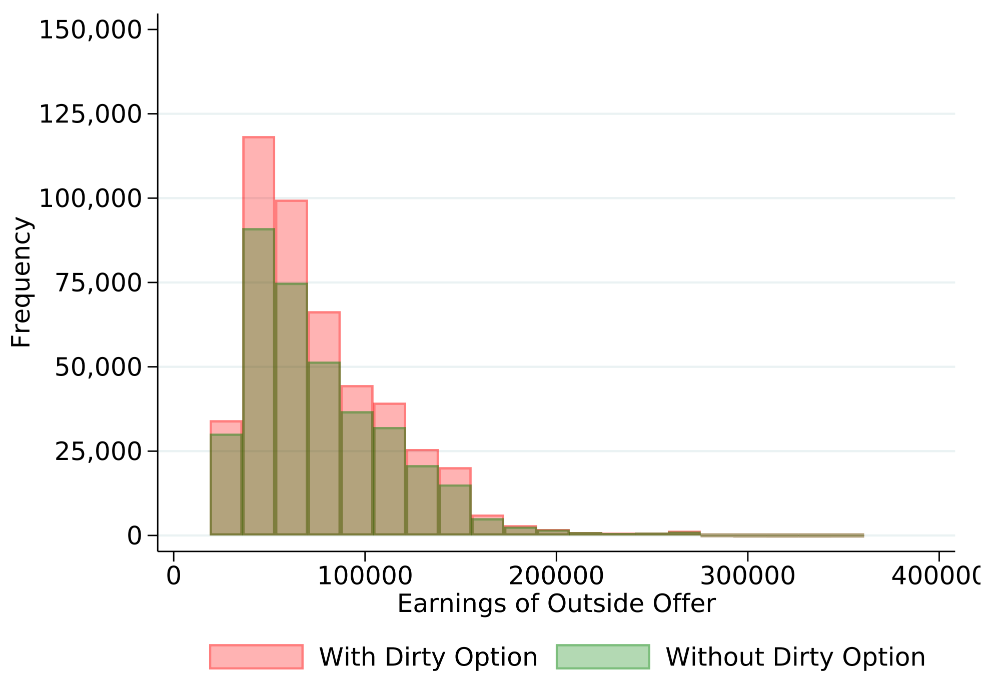
Notes: Figure 5a shows the probability that a worker leaving a dirty job enters a green job. Since 2020, over 1% of workers leaving a dirty job in California, Iowa, Nevada and Arizona have transitioned to a green job. Figure 5b shows the probability that a worker leaving a dirty job transitions to another dirty job. Delaware, Louisiana, Texas, Oklahoma and Wyoming are the highest Dirty-to-Dirty states. *Source:* Worker profile data from Lightcast.

Figure 6: Outside Transition Option With and Without Dirty Option

(a) Workers with a College Degree

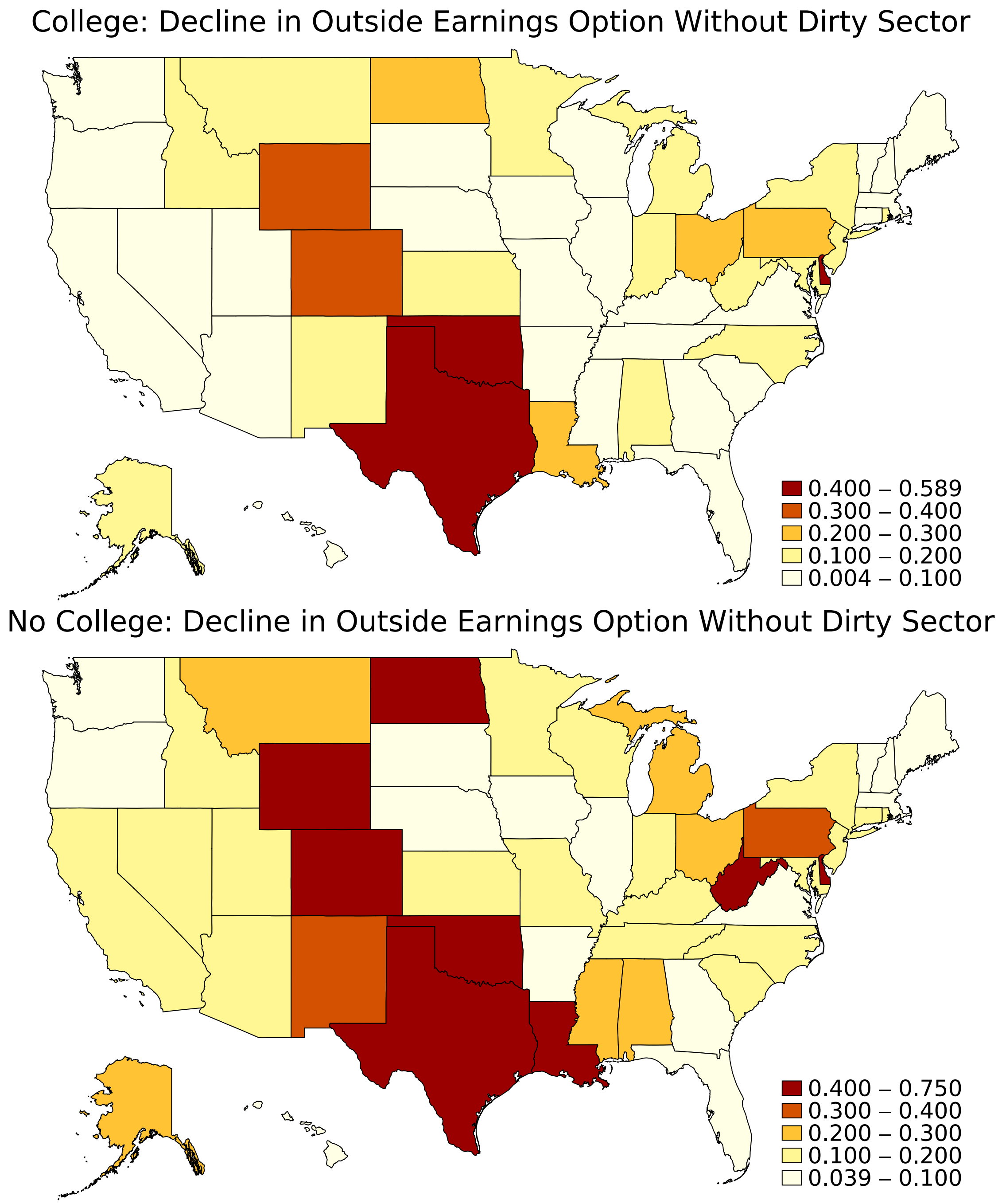


(b) Workers without a College Degree



Notes: Figure 6 shows the difference in our measure of outside earnings option for workers in dirty industries / occupations when they are not allowed to transition to another dirty industry. *Source:* Worker profile data from Lightcast.

Figure 7: Outside Earnings Difference w/out Dirty Option



Notes: Figure 7 shows the difference in our measure of outside earnings option for workers in dirty industries / occupations when they are not allowed to transition to another dirty industry. *Source:* Worker profile data from Lightcast.

Table 1: Top 30 Receiving Occupations from Dirty Jobs: Less than College

Occupation	SOC	# Transitions	Percent Transitions
General and Operations Managers	11-1021	24,384	3.6
Chief Executives	11-1011	24,110	3.6
Supervisors of Office and Admin	43-1011	20,290	3.0
Supervisors of Prod. & Operating Work	51-1011	18,983	2.8
Sales Managers	11-2022	18,289	2.7
Managers, All Other	11-9199	17,830	2.7
Computer User Support Specialists	15-1232	14,819	2.2
Supervisors of Construction & Extract.	47-1011	13,645	2.0
Customer Service Representatives	43-4051	12,548	1.9
Supervisors of Mechanics, Inst, Repair	49-1011	11,555	1.7
Sales Reps, Wholesale and Mftg	41-4012	11,157	1.7
Secretaries and Admin Assistant	43-6014	10,910	1.6
Maintenance and Repair Workers, General	49-9071	10,640	1.6
Heavy and Tractor-Trailer Truck Drivers	53-3032	10,292	1.5
Business Oper. Specialists, All Other	13-1199	8,686	1.3
Marketing Managers	11-2021	8,020	1.2
Bookkeeping, Accounting, and Auditing	43-3031	7,681	1.1
Industrial Engineers	17-2112	7,623	1.1
Network and Computer Systems Admin	15-1244	7,566	1.1
Mechanical Engineers	17-2141	6,818	1.0
Software Developers	15-1252	6,809	1.0
Inspectors, Testers, Sorters, Samplers	51-9061	6,776	1.0
Petroleum Engineers	17-2171	6,467	1.0
Financial Managers	11-3031	6,456	1.0
Service Unit Operators, Oil and Gas	47-5013	6,354	1.0
Executive Secretaries and Exec Admin	43-6011	6,285	0.9
Accountants and Auditors	13-2011	6,156	0.9
Retail Salespersons	41-2031	5,965	0.9
Industrial Production Managers	11-3051	5,735	0.9
Project Management Specialists	13-1082	5,726	0.9

Notes: Table 1 reports the most common occupations that non-college workers in dirty jobs enter when they leave their dirty job. The first row shows that 3.6% of all transitions away from Dirty are to General and Operations Managers. *Source:* Worker profile data from Lightcast.

Table 2: Top 30 Receiving Occupations from Dirty Jobs: College Grads

Occupation	SOC	# Transitions	Percent Transitions
Industrial Engineers	17-2112	42,499	4.0
Chief Executives	11-1011	41,439	3.9
General and Operations Managers	11-1021	37,534	3.5
Sales Managers	11-2022	35,443	3.3
Marketing Managers	11-2021	34,501	3.2
Financial Managers	11-3031	32,034	3.0
Accountants and Auditors	13-2011	31,241	2.9
Software Developers	15-1252	25,688	2.4
Managers, All Other	11-9199	24,217	2.3
Management Analysts	13-1111	22,003	2.1
Mechanical Engineers	17-2141	19,616	1.8
Supervisors of Office and Admin	43-1011	18,259	1.7
Computer Systems Analysts	15-1211	18,248	1.7
Human Resources Managers	11-3121	18,107	1.7
Architectural and Engineering Managers	11-9041	16,967	1.6
Computer User Support Specialists	15-1232	15,107	1.4
Computer Occupations, All Other	15-1299	14,638	1.4
Business Operations Specialists	13-1199	14,087	1.3
Supervisors of Production and Op Workers	51-1011	13,773	1.3
Computer and Information Systems Manager	11-3021	13,329	1.3
Geoscientists	19-2042	13,248	1.2
Sales Reps, Wholesale and Mftg	41-4012	13,123	1.2
Project Management Specialists	13-1082	13,018	1.2
Customer Service Representatives	43-4051	12,729	1.2
Engineers, All Other	17-2199	11,917	1.1
Market Research Analysts	13-1161	11,898	1.1
Industrial Production Managers	11-3051	11,498	1.1
Postsecondary Teachers	25-1099	11,357	1.1
Petroleum Engineers	17-2171	10,875	1.0
Life, Physical, and Social Science Tech.	19-4099	9,887	0.9

Notes: Table 2 reports the most common occupations that college workers in dirty jobs enter when they leave their dirty job. The first row shows that 4.0% of all transitions away from Dirty are to Industrial Engineering occupations. *Source:* Worker profile data from Lightcast.

Table 3: Receiving Industries from Dirty Jobs

(a) Less than College

Sector	**Sector Code**	**Total Trans**	**Percent (%)**
Manufacturing	31-33	141,180	24.5
Oil & Gas Extraction, Mining	21	81,416	14.2
Prof., Sci., and Tech. Serv.	54	51,387	8.9
Construction	23	43,872	7.6
Retail Trade	44-45	39,317	6.8
Wholesale Trade	42	37,596	6.5
Admin. and Support and Waste Mgmt.	56	23,308	4.1
Transportation and Warehousing	48-49	19,710	3.4
Finance and Insurance	52	18,329	3.2
Other Services (except Public Admin.)	81	15,264	2.7
Health Care and Social Assistance	62	14,761	2.6
Information	51	12,663	2.2
Accommodation and Food Services	72	12,552	2.2
Real Estate and Rental and Leasing	53	12,518	2.2
Public Administration	92	12,414	2.2

(b) College Grads

Sector	**Sector Code**	**Total Trans**	**Percent (%)**
Manufacturing	31-33	289,329	29.5
Prof., Sci., and Tech. Serv.	54	129,995	13.2
Oil & Gas Extraction, Mining	21	75,452	7.7
Educational Services	61	64,740	6.6
Wholesale Trade	42	63,116	6.4
Retail Trade	44-45	55,922	5.7
Finance and Insurance	52	43,923	4.5
Construction	23	38,247	3.9
Information	51	28,779	2.9
Health Care and Social Assistance	62	28,476	2.9
Admin. and Support and Waste Mgmt.	56	27,365	2.8
Other Services (except Public Admin.)	81	22,183	2.3
Public Administration	92	19,835	2.0
Utilities	22	18,111	1.8
Transportation and Warehousing	48-49	17,473	1.8

Notes: Table 3a reports the most common industries that non-college workers in dirty jobs enter when they leave their dirty job. The first row shows that 24.5% of all transitions away from Dirty are to the Manufacturing sector. Table 3b reports the same for college workers. *Source:* Worker profile data from Lightcast.

Table 4: Top Green Entering Occupations

Top Occs to Solar	Top Occs to Wind	Top Occs to EV	Top Occs to Renew
Sales Managers	Chief Executives	Industrial Engineers	Chief Executives
Chief Executives	General and Operations Managers	Software Developers	General and Operations Managers
General and Operations Managers	Sales Managers	Mechanical Engineers	Managers, All Other
Marketing Managers	Managers, All Other	General and Operations Managers	Marketing Managers
Managers, All Other	Marketing Managers	Chief Executives	Financial Managers
Sales Representatives, Wholesale and	Financial Managers	Marketing Managers	Sales Managers
First-Line Supervisors of Office and	Industrial Engineers	Sales Managers	Architectural and Engineering Manage
Industrial Engineers	Architectural and Engineering Manage	Managers, All Other	Management Analysts
Financial Managers	Mechanical Engineers	First-Line Supervisors of Office and	Accountants and Auditors
Customer Service Representatives	Computer User Support Specialists	Computer User Support Specialists	Project Management Specialists
Software Developers	First-Line Supervisors of Production	First-Line Supervisors of Production	Life, Physical, and Social Science T
Computer User Support Specialists	First-Line Supervisors of Office and	Human Resources Specialists	First-Line Supervisors of Office and
Project Management Specialists	Software Developers	Architectural and Engineering Manage	Electrical Engineers
Architectural and Engineering Manage	First-Line Supervisors of Mechanics,	Customer Service Representatives	Industrial Engineers
Electrical Engineers	Maintenance and Repair Workers, Gene	Financial Managers	Software Developers
Retail Salespersons	Project Management Specialists	Electrical Engineers	Engineers, All Other
Management Analysts	Management Analysts	Management Analysts	Business Operations Specialists, All
Mechanical Engineers	Human Resources Managers	Human Resources Managers	Market Research Analysts and Marketi
Business Operations Specialists, All	Computer and Information Systems Man	Computer Occupations, All Other	Mechanical Engineers
Engineers, All Other	Engineers, All Other	Business Operations Specialists, All	Postsecondary Teachers

Notes: Table 4 lists the top sending occupations for each of the four green job categories. Workers in these occupations are most likely to enter green jobs. *Source:* Worker profile data from Lightcast.

Table 5: Top Dirty-to-Dirty Cities and States

Top Cities	Dirty Trans Rate	Top States	Dirty Trans Rate
San Ramon	0.920	Delaware	0.552
Sugar Land	0.845	Oklahoma	0.533
The Woodlands	0.691	Wyoming	0.406
Oklahoma City	0.681	Texas	0.398
Midland	0.635	Colorado	0.369
Denver	0.598	Louisiana	0.335
Wilmington	0.594	North Dakota	0.299
Irving	0.482	Pennsylvania	0.242
Houston	0.443	West Virginia	0.235
Cleveland	0.416	South Carolina	0.205
Memphis	0.410	Ohio	0.192
Tulsa	0.399	New Mexico	0.185
Pittsburgh	0.394	Tennessee	0.180
San Antonio	0.368	Alaska	0.176
Philadelphia	0.342	Kansas	0.171

Notes: Table 5 provides the 15 cities and states with the highest Dirty-to-Dirty transition rates. These numbers are from all transitions in our sample. The maps in Figure 5 report results only for years 2020-2022. Cities are only included if there are more than 50,000 dirty jobs reported over the entirety of our sample. City definitions are self-reported in the data. Many "cities" in our data, such as Sugar Land and The Woodlands are suburbs located inside of large metropolitan areas like Houston. *Source:* Worker profile data from Lightcast.

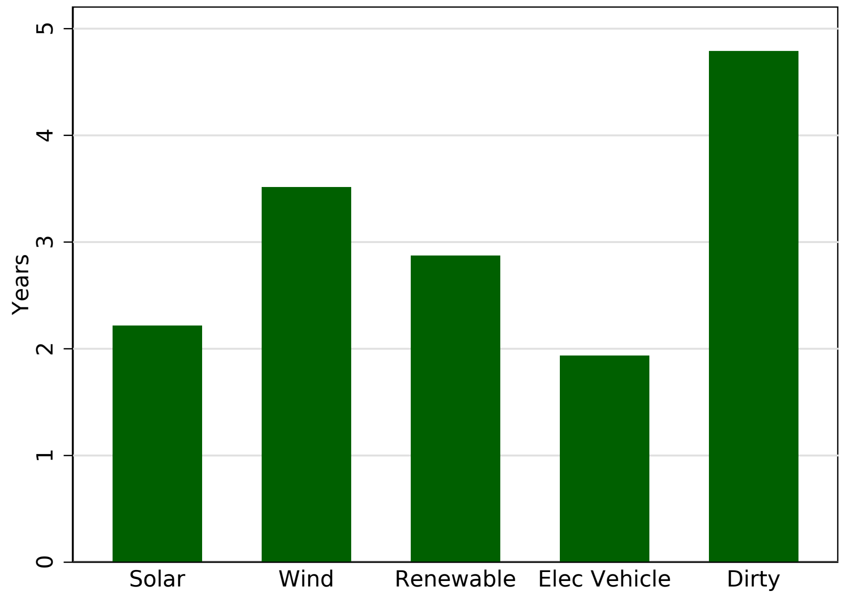
Table 6: Job Duration: Are Green Jobs Short-lived?

	(1) Job Length	(2) Job Length	(3) Job Length	(4) Job Length	(5) Job Length	(6) Job Length
Solar Job	-2.476***	-0.256***	-0.228***	-0.307***	-0.280***	-0.051
	(0.028)	(0.022)	(0.022)	(0.023)	(0.023)	(0.058)
Wind Job	-1.300***	0.018	0.023	-0.052	-0.240***	-0.263***
	(0.048)	(0.038)	(0.038)	(0.038)	(0.038)	(0.069)
EV Job	-2.891***	0.238***	0.266***	0.047*	0.046*	0.472
	(0.031)	(0.025)	(0.025)	(0.028)	(0.028)	(0.635)
Renewable Job	-1.749***	-0.131***	-0.080***	0.032	0.037	0.329***
	(0.037)	(0.029)	(0.029)	(0.029)	(0.029)	(0.075)
Job Start Date FE's	N	Y	Y	Y	Y	Y
Job Number FE's	N	N	Y	Y	Y	Y
Age, Educ, Gender, State FE's	N	N	N	Y	Y	Y
2-Digit SOC FE's	N	N	N	N	Y	Y
Company FE's	N	N	N	N	N	Y
Observations	1,960,074	1,960,074	1,960,074	1,960,074	1,960,074	1,960,074

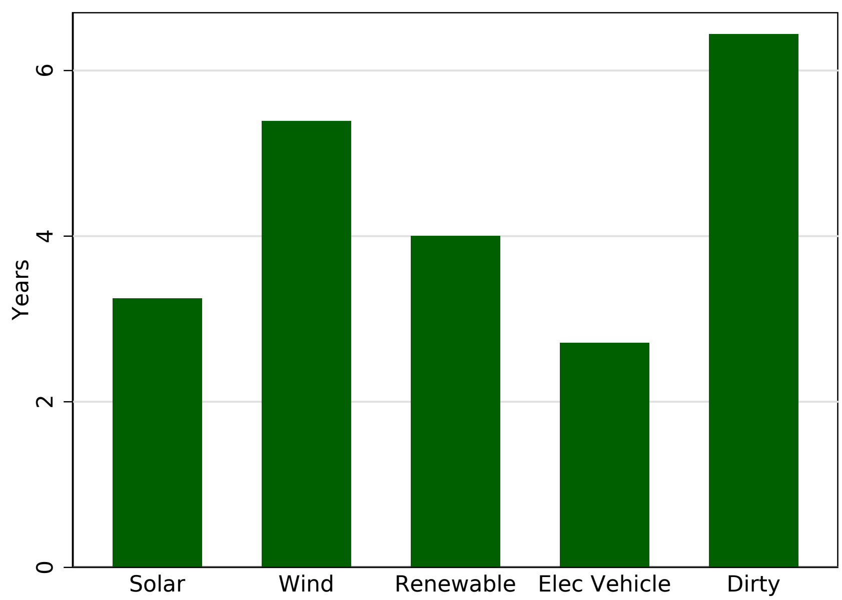
Notes: Table 6 regresses job length in years on indicator variables for categories of green jobs. The excluded category is dirty jobs Column. The sample consists of only Dirty and green categories and jobs that have both a start and end date. Table A6 reports results when including current jobs in the sample and setting 2023 as the end date. Column 1 is a naive specification which mirrors the results in Figure A1. Column 2 includes only a set of starting year fixed effects. Controlling for the year the job began dramatically changes the green job coefficients. Column 3 additionally controls for the number of prior jobs held by a worker. Column 4 controls for worker demographics (age, education, gender, state). Column 5 controls for the broad occupation category of the worker by including 2-digit SOC fixed effect. Column 5 is our preferred specification. We additionally report results that include company fixed effects in Column 6. By including company fixed effects we are absorbing much of the variation used to identify the differences in job length, nonetheless these inform of the within company differences in job length for those companies where this variation is present. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ *Source:* Worker profile data from Lightcast.

Figure A1: Naive Estimates of Average Job Length by Dirty/Green

(a) Jobs with End Date

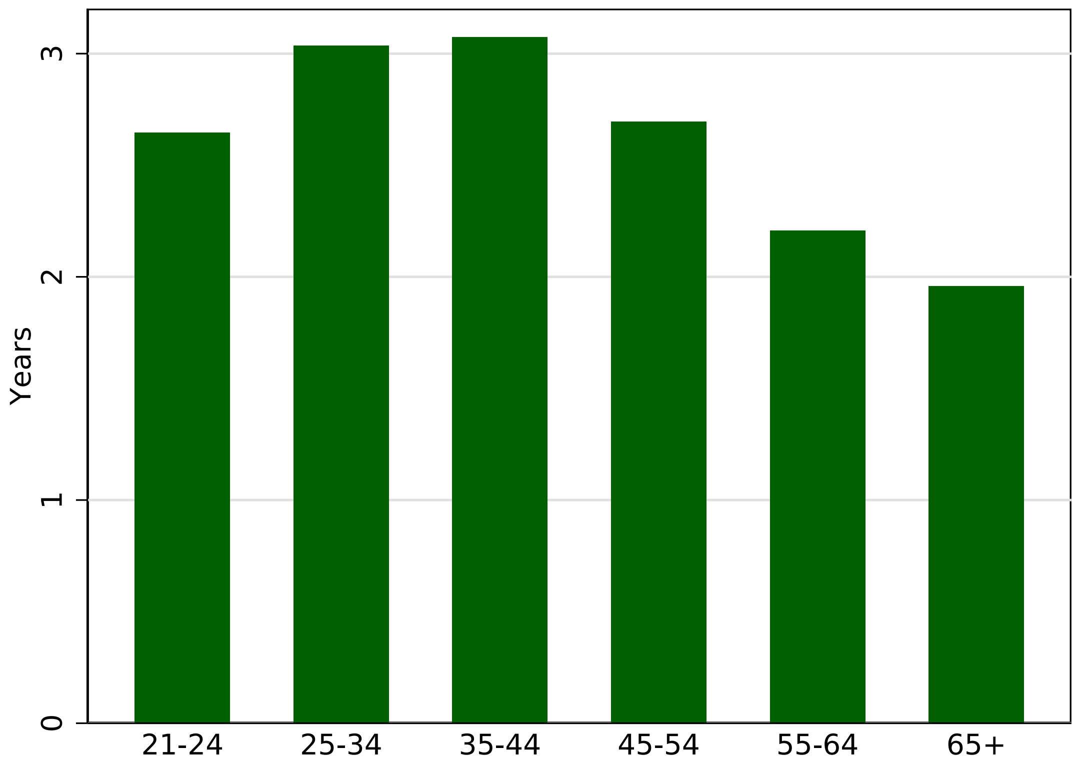


(b) Including Current Jobs



Notes: Figure A1 shows the average length of different brown/green job categories. Green jobs, which did largely did not exist 20 years ago, will by construction have a shorter job length than dirty jobs which have been prominent for decades. Table 6 reports regressions which control for the job start date as well as worker demographics. Those regressions show that the difference in job length shrink considerably or disappear after controlling for these differences. *Source:* Worker profile data from Lightcast.

Figure A2: Expected Job Length by Worker Age at Start of Job



Notes: Figure A2 reports the expected job length by Worker Age at the age of the start of the job.
Source: Worker profile data from Lightcast.

Table A1: Job Profile vs. BLS Industry Profile

	NAICS 2	BLS %	Profile %
Agriculture, Forestry, Fishing and Hunting	11	.13	.42
Mining, Quarrying, and Oil and Gas Extraction	21	.37	.65
Utilities	22	.49	.79
Construction	23	5.52	3.57
Manufacturing	31	9.08	12.3
Wholesale Trade	42	4.63	4.05
Retail Trade	44	12.15	9.06
Transportation and Warehousing	48	4.45	2.67
Information	51	2.67	5.16
Finance and Insurance	52	5.26	8.18
Real Estate and Rental and Leasing	53	1.71	2.51
Professional, Scientific, and Technical Services	54	7.37	12.2
Management of Companies and Enterprises	55	2.73	.47
Administrative and Support and Waste Management and Remediation Services	56	9.73	3.54
Educational Services	61	2.72	11.55
Health Care and Social Assistance	62	16.13	9.45
Arts, Entertainment, and Recreation	71	1.45	1.6
Accommodation and Food Services	72	9.43	4.23
Other Services (except Public Administration)	81	3.98	3.4
Industries not classified			4.2

Notes: Table A1 compares the industry distribution of the worker profile data to BLS. *Source:* Worker profile data from Lightcast.

Table A2: Job Profile vs. BLS Occupation Profile

	SOC 2	BLS %	Profile %
Management occupations	11-0000	7.39	23.55
Business and financial operations occupations	13-0000	6.32	8.88
Computer and mathematical occupations	15-0000	3.13	7.71
Architecture and engineering occupations	17-0000	1.62	3.04
Life, physical, and social science occupations	19-0000	.91	1.78
Community and social service occupations	21-0000	1.8	2.48
Legal occupations	23-0000	.87	1.18
Educational instruction and library occupations	25-0000	5.79	5.22
Arts, design, entertainment, sports, and media occupations	27-0000	1.76	4.74
Healthcare practitioners and technical occupations	29-0000	5.84	4.02
Healthcare support occupations	31-0000	4.44	1.14
Protective service occupations	33-0000	2.2	1.18
Food preparation and serving related occupations	35-0000	7.44	1.87
Building and grounds cleaning and maintenance occupations	37-0000	3.42	.39
Personal care and service occupations	39-0000	2.45	1.16
Sales and related occupations	41-0000	9.31	6.59
Office and administrative support occupations	43-0000	12.39	9.64
Farming, fishing, and forestry occupations	45-0000	.68	.08
Construction and extraction occupations	47-0000	4.44	.87
Installation, maintenance, and repair occupations	49-0000	3.82	1.34
Production occupations	51-0000	5.56	1.95
Transportation and material moving occupations	53-0000	8.44	1.82
Other			9.22

Notes: Table A2 compares the occupation distribution of the worker profile data to BLS. *Source:* Worker profile data from Lightcast.

Table A3: Top Green Entering Occupations: Non-College

Top Occs to Solar	**Top Occs to Wind**	**Top Occs to EV**	**Top Occs to Renew**
Sales Managers	Chief Executives	General and Operations Managers	Chief Executives
General and Operations Managers	General and Operations Managers	First-Line Supervisors of Office and	General and Operations Managers
Chief Executives	Computer User Support Specialists	Computer User Support Specialists	Managers, All Other
Sales Representatives, Wholesale and	Maintenance and Repair Workers, Gene	First-Line Supervisors of Production	Sales Managers
Managers, All Other	First-Line Supervisors of Mechanics,	Customer Service Representatives	First-Line Supervisors of Office and
First-Line Supervisors of Office and	First-Line Supervisors of Production	Automotive Service Technicians and M	Computer User Support Specialists
Customer Service Representatives	First-Line Supervisors of Office and	Managers, All Other	First-Line Supervisors of Mechanics,
Computer User Support Specialists	Managers, All Other	Chief Executives	First-Line Supervisors of Production
Retail Salespersons	Sales Managers	Sales Managers	Marketing Managers
First-Line Supervisors of Mechanics,	Customer Service Representatives	Industrial Engineers	First-Line Supervisors of Constructi
Marketing Managers	Automotive Service Technicians and M	Software Developers	Construction Managers
Electricians	Electricians	First-Line Supervisors of Mechanics,	Wind Turbine Service Technicians
First-Line Supervisors of Production	First-Line Supervisors of Constructi	Maintenance and Repair Workers, Gene	Project Management Specialists
First-Line Supervisors of Constructi	Industrial Engineers	Mechanical Engineers	Customer Service Representatives
Sales Representatives of Services, E	Marketing Managers	Retail Salespersons	Secretaries and Administrative Assis
Maintenance and Repair Workers, Gene	Mechanical Engineers	Sales Representatives, Wholesale and	Financial Managers
Project Management Specialists	Project Management Specialists	Human Resources Specialists	Software Developers
Construction Managers	Electrical and Electronic Engineerin	Marketing Managers	Business Operations Specialists, All
Business Operations Specialists, All	Financial Managers	Business Operations Specialists, All	Network and Computer Systems Adminis
Financial Managers	Software Developers	Network and Computer Systems Admin	Maintenance and Repair Workers

Notes: Table A3 lists the top sending occupations for each of the four green job categories for workers without a college degree. *Source:* Worker profile data from Lightcast.

Table A4: Top Green Entering Occupations: College

Top Occs to Solar	**Top Occs to Wind**	**Top Occs to EV**	**Top Occs to Renew**
Sales Managers	Chief Executives	Industrial Engineers	Chief Executives
Chief Executives	General and Operations Managers	Software Developers	General and Operations Managers
Marketing Managers	Marketing Managers	Mechanical Engineers	Financial Managers
General and Operations Managers	Sales Managers	General and Operations Managers	Marketing Managers
Managers, All Other	Financial Managers	Marketing Managers	Managers, All Other
Industrial Engineers	Industrial Engineers	Chief Executives	Sales Managers
Financial Managers	Architectural and Engineering Manage	Sales Managers	Architectural and Engineering Manage
Software Developers	Managers, All Other	Managers, All Other	Management Analysts
Architectural and Engineering Manage	Mechanical Engineers	Architectural and Engineering Manage	Life, Physical, and Social Science T
Electrical Engineers	Software Developers	Human Resources Specialists	Accountants and Auditors
Management Analysts	Management Analysts	Financial Managers	Electrical Engineers
Mechanical Engineers	Engineers, All Other	Electrical Engineers	Engineers, All Other
First-Line Supervisors of Office and	Human Resources Managers	First-Line Supervisors of Office and	Project Management Specialists
Project Management Specialists	Project Management Specialists	Management Analysts	Industrial Engineers
Engineers, All Other	Computer and Information Systems Man	Human Resources Managers	Market Research Analysts and Marketi
Accountants and Auditors	Accountants and Auditors	Computer Occupations, All Other	Software Developers
Sales Representatives, Wholesale and	First-Line Supervisors of Office and	Computer User Support Specialists	Postsecondary Teachers
Market Research Analysts and Marketi	Postsecondary Teachers	First-Line Supervisors of Production	Mechanical Engineers
Customer Service Representatives	First-Line Supervisors of Production	Accountants and Auditors	Business Operations Specialists, All
Business Operations Specialists, All	Electrical Engineers	Engineers, All Other	Teaching Assistants, Postsecondary

Notes: Table A4 lists the top sending occupations for each of the four green job categories for workers with a college degree. *Source:* Worker profile data from Lightcast.

Table A5: Countries Sending Most Green Workers to US

Country	Green Transitions
Denmark	7,803
United Kingdom	2,604
Spain	2,325
Canada	1,794
Italy	1,326
Germany	1,163
France	1,142
India	768
South Korea	763
Netherlands	528

Notes: Table A5 lists the countries sending the highest number of workers to US green jobs. Denmark is a world leader in wind energy. *Source:* Worker profile data from Lightcast.

Table A6: Job Duration: Are Green Jobs Short-lived?
Including Current Jobs

	(1) Job Length	(2) Job Length	(3) Job Length	(4) Job Length	(5) Job Length	(6) Job Length
Solar Job	-3.007***	-0.611***	-0.523***	-0.605***	-0.539***	-0.227***
	(0.030)	(0.026)	(0.025)	(0.026)	(0.026)	(0.063)
Wind Job	-1.164***	0.271***	0.252***	0.041	-0.114***	-0.191***
	(0.050)	(0.042)	(0.041)	(0.040)	(0.041)	(0.072)
EV Job	-3.764***	0.084***	0.187***	0.019	0.060**	0.893
	(0.031)	(0.026)	(0.026)	(0.029)	(0.029)	(0.723)
Renewable Job	-2.213***	-0.359***	-0.171***	0.119***	0.102***	0.216***
	(0.039)	(0.032)	(0.032)	(0.032)	(0.032)	(0.080)
Job Start Date FE's	N	Y	Y	Y	Y	Y
Job Number FE's	N	N	Y	Y	Y	Y
Age, Educ, Gender, State FE's	N	N	N	Y	Y	Y
2-Digit SOC FE's	N	N	N	N	Y	Y
Company FE's	N	N	N	N	N	Y
Observations	2,505,967	2,505,967	2,505,967	2,505,967	2,505,967	2,505,967

Notes: Table A6 mirrors the regression results in Table 6 but includes current jobs in the sample. Current jobs are assumed to have an end date of January 1, 2023. Column 1 is a naive specification which mirrors the results in Figure A1. Column 2 includes only a set of starting year fixed effects. Controlling for the year the job began dramatically changes the green job coefficients. Column 3 additionally controls for the number of prior jobs held by a worker. Column 4 controls for worker demographics (age, education, gender, state). Column 5 controls for the broad occupation category of the worker by including 2-digit SOC fixed effect. Column 5 is our preferred specification. We additionally report results that include company fixed effects in Column 6. By including company fixed effects we are absorbing much of the variation used to identify the differences in job length, nonetheless these inform of the within company differences in job length for those companies where this variation is present. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ *Source:* Worker profile data from Lightcast.