Upward mobility in the green sector for frontline fossil fuel workers

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Abstract

The green sector is often viewed as a source of new jobs for frontline fossil fuel (FFF) workers, yet concerns persist about uncompetitive salaries. This emphasis on short-run, horizontal moves into similar green jobs overlooks the sector's potential to enable long-run career mobility. As an emerging industry, the green sector may offer greater opportunities for advancement into management and engineering roles than mature fossil fuel sectors. Wage comparisons, therefore, should account for differences in upward mobility. Using résumé data on 190,648 U.S. FFF workers, we trace job switches over the career after each worker's first fossil fuel job and find that those who transition into the green sector earn about 10% higher average cumulative wages than those who remain in fossil-fuel employment. This advantage is partly driven by greater upward mobility: transitions into the green sector are associated with about two times higher likelihood of holding managerial jobs and 2.5 times higher likelihood of holding science and engineering (SE) jobs than transitions within the fossil fuel sector. For managerial and SE occupations, a given worker earns about 16% and 18% more, respectively, in the green sector relative to FFF jobs. Access to these roles is associated with distinct reskilling patterns: skill diversification is linked to managerial advancement, whereas deepening engineering-relevant skills increases the odds of entering SE occupations. These findings inform reskilling policies that promote both upward mobility and horizontal flexibility for FFF workers.

1 Introduction

Using data from the Bureau of Labor Statistics, we estimate that approximately 1.4 million people in the United States are employed in "frontline fossil fuel" (FFF) occupations, including extraction, construction, maintenance, production, and transportation workers directly tied to the fossil fuel sector.[1] Many face the risks of job loss if fossil fuel extraction is phased out[22,38]. This socioeconomic disruption motivates political opposition to the energy transition[1,15,20,30]. Supporters point to the potential for FFF workers to move into the green sector to mitigate this shock[11,27,29]. As a result, policymakers have attempted to facilitate job transitions between the two. Programs funded by the Economic Development Assistance, the Infrastructure Investment and Jobs Act (IIJA), the Inflation Reduction Act (IRA), and the CHIPS and Science Act[12,37,43] try to facilitate "horizontal" transitions from FFF jobs to similar trade occupations in the green sector. Such occupations require similar skills[29] and thus less retraining[24,45]. Unfortunately, these transitions might not provide wage increases to offset short-run job transition costs[16,18,39,41] and thus raise doubt over the capacity of green sector jobs to offer a desirable alternative for fossil fuel workers.

However, focusing on short-term outcomes misses important long-term benefits to workers. Rather than comparing the wages of green versus fossil fuel jobs holding the status of the occupation constant, a more holistic assessment would additionally consider potential gains over workers' careers (e.g., from promotions). For example, does the green sector provide opportunities for FFF workers to ascend the occupational ladder and thereby earn higher wages over their careers? Considering "vertical" promotion potential may shift incentives for workers to switch their careers into the green sector despite short-term wage losses.

We analyze the resumes of 190,648 FFF workers who collectively underwent 600,000 job switches in 2000-2023 to study the patterns of upward mobility across sectors. Upward mobility is defined as the movement of FFF workers into managerial or science and engineering (SE) occupations, roles that consistently offer higher mobility and

[1] The full list of fossil fuel industries and associated occupations are provided in SI Table A.1 and A.2.

wages than FFF positions[4,2]. Rather than focusing on the immediate consequences of a single fossil fuel to green job transition, we take an "over the career" approach by identifying when each worker exits their first FFF job and tracing subsequent job switches across sectors and occupations over the remainder of the observed career (see Method section 6.1).

To classify green occupations, we adopt a broad definition that includes not only conventional green roles, such as wind turbine technicians and sustainability officers, but also managerial and technical occupations embedded within green industries, such as transportation managers, software developers, and financial quantitative analysts (see Method section 6.1 and SI Table A.1). This broader framework strengthens our analysis by recognizing that upward mobility may arise not only through narrowly defined "green" titles, but also through high-skill managerial and technical roles that are essential to the functioning and expansion of green industries despite their generic job titles (e.g., managers exist in many different sectors)[41,44].

Our cumulative wage analysis shows that FFF workers who ever transition into the green sector earn, on average, 10% higher cumulative wage over their careers than those who remain in fossil fuel jobs for their entire careers, highlighting the career-wide benefits of green transitions. This premium is partly explained by two patterns in our results. First, the green sector offers greater opportunities for upward mobility: for a given worker over the career, switching into the green sector is associated with about two times higher likelihood of holding managerial roles and 2.5 times higher likelihood of holding SE occupations than when job switches remain within the fossil fuel sector. Second, within these occupations, wages are higher in the green sector, about 8% for managerial roles and 27% for SE roles, relative to FFF jobs. The question, then, is how FFF workers typically obtain such positions. We show that access to these roles is associated with two distinct reskilling patterns: skill diversification is linked to managerial advancement, whereas engineering focused skill deepening increases the odds of entry into SE occupations.

[2] https://www.statista.com/statistics/218235/median-annual-wage-in-the-us-by-major-occupational-groups/

2 Upward mobility for FFF workers in the green sector

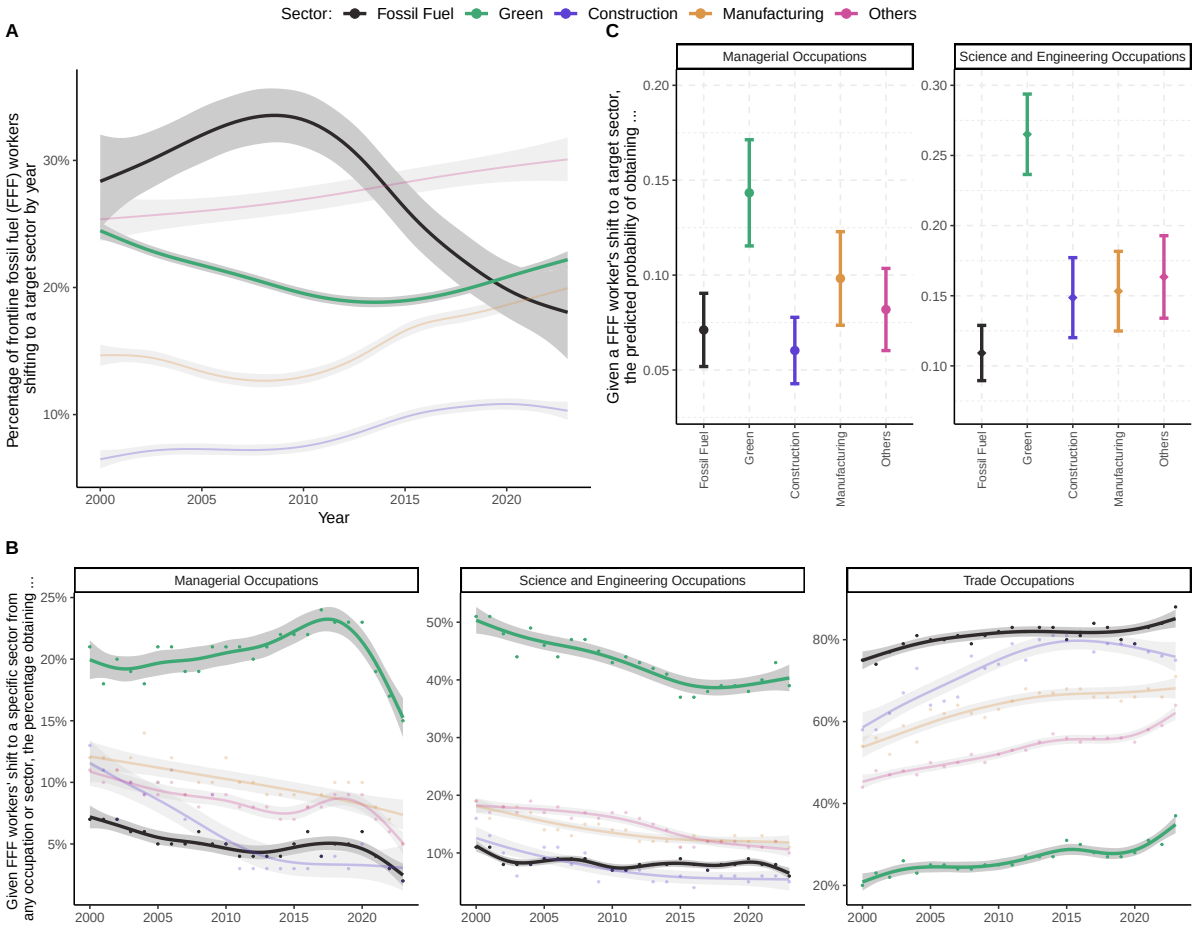


Fig. 1: FFF workers who, at some point in their career, switch to the green sector have more opportunities to achieve upward mobility to managerial and science and engineering (SE) occupations. A. The percentage of FFF workers switching into the green and other sectors each year. B. Given FFF workers' job switch into a specific sector at some point in their career, the percentage of workers that obtain managerial, SE, and trade occupations. C. Given FFF workers' job switch into a specific sector, the predicted probability of obtaining managerial or SE occupations.

In our data, 40.2% of FFF workers held at least one job in the green sector during their careers between 2000 and 2023. By contrast, 45.1% of FFF workers switch jobs within the fossil fuel sector or re-enter the fossil fuel sector at some point. Notably, the green sector has overtaken the fossil fuel sector as the main destination for workers who switch jobs since 2017. Over this period, the percentage of workers that shift to the green sector rises from 22% in 2017 to 25% in 2023, while the share of those who

shift or remain in the fossil fuel sector declines from 23% to 18% (Fig. 1A).

Do FFF workers who switch into the green sector, at some point in their careers, experience greater upward mobility than their peers in the fossil fuel sector? We begin with descriptive evidence from our sample (Fig. 1B). Among FFF workers who transitioned into the green sector, 15–24% subsequently moved into managerial roles, compared with only 2-7% of those who switched into fossil fuels. Similarly, 37-51% of the job switches to the green sector are to SE occupations, compared to only 6-11% in the fossil fuel sector. By contrast, 74-88% of job switches to the fossil fuel sector are to frontline occupations, while only 20-37% of job switches in the green sector are to trade occupations. Importantly, these upwardly mobile switches are rarely immediate; workers often take several steps across different jobs or industries before moving into green positions where upward mobility is realized.[3]

However, workers who switch to the green sector may differ systematically from those who remain in fossil fuel jobs in ways that also influence mobility. For example, workers who ever transition into the green sector are 25% more likely to hold a college degree than those who never do (see SI section 6.2 and 6.3). To account for these observable differences and construct a more comparable counterfactual, we estimate regression models that control for multiple individual characteristics and track changes in upward mobility as workers move across sectors (see Method section 6.3 and SI Table A.4). We find, over the career, job switches to the green sector have greater probabilities of landing in managerial and SE occupations (14.3% $\pm$ 1.4%, 26.5% $\pm$ 1.5%) than switches that remain within the fossil fuel sector (7.1% $\pm$ 0.9%, 10.9% $\pm$ 1.0%) (Fig. 1C)[4]. Because sector transitions are not randomly assigned, we interpret these estimates as associations and assess robustness using alternative definitions of green occupations (SI section4.1), models incorporating additional potential confounders (SI section 4.3.1), sample reweighting with nationally representative administrative data (SI section 4.2), and entropy balancing regressions (SI section 4.3). We also conduct a sensitivity analysis to probe the influence of potential unobserved

[3]Based on our data, FFF workers make, on average, three job transitions before attaining upwardly mobile positions in the green sector. SI section 6.8 also provides an example from our data.
[4]Average probabilities with standard errors are reported in parentheses.

confounding (SI section 4.4). Robustness analyses yield results consistent with the main findings, reducing, though not fully eliminating, bias from self-selection into the green sector.

3 Upwardly mobile FFF workers secure larger wages in the green sector

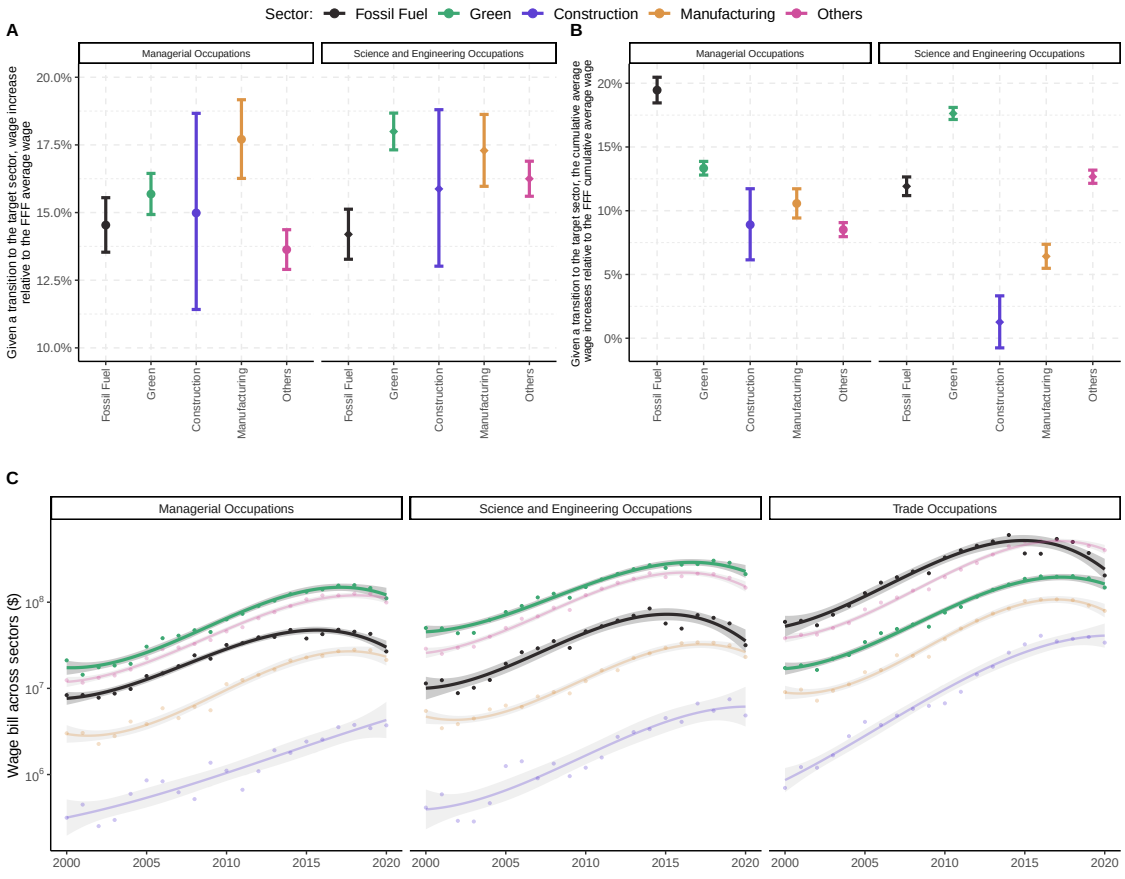


Fig. 2: Over their careers, FFF workers experience larger wage gains when transitioning into the green sector than when remaining in fossil fuel sector. A. Given a job shift into a specific sector, the predicted wage increase for those who secure managerial and SE occupations in that sector compared to average wages in FFF occupations. B. Over the course of their careers, the cumulative wage gain of FFF workers who ever transition into the target sector relative to the workers who remain in frontline fossil fuel jobs for their entire careers. C. The wage bill, i.e. the total payments to all workers, for managerial, SE and trade occupations in various sectors by year.

Is upward career mobility in the green sector reflected in the occupation title only or accompanied by higher wages too? Using regression estimates that adjust for

individual characteristics and other confounders, we first present wage changes for FFF workers who obtain the same upwardly mobile occupations in different sectors, benchmarked against the reference level of FFF occupations (Fig. 2A and SI section 3.2). We find that wage gains are larger when a worker secures SE occupations in the green sector (18.0% ± 0.3%) than when securing the same occupations in the fossil fuel sector (14.2% ± 0.4%). Wage gains are also higher for switches into managerial roles in the green sector (15.7% ± 0.3%) than for comparable switches within fossil fuel (14.5% ± 0.4%), although this difference is not statistically significant at the 95% confidence level. In other words, job switches into SE roles in green sector earn about 27% more than the same job switches in fossil fuel sector, whereas the corresponding difference for managerial roles is roughly 8%. A series of robustness checks, including alternative definitions of green occupations (SI section 4.1), sample reweighting (SI section 4.2), and entropy balancing (SI section 4.3), confirm results that remain consistent with those reported in this section.

We next examine how these wage differences vary over time (see SI Fig. A.1 and Fig. A.2). Comparing FFF workers who attain the same upwardly mobile occupation across sectors, those who enter SE roles in the green sector at any point between 2000 and 2023 consistently earn higher wages than when entering the same roles in the fossil fuel sector. For example, in 2022, they received a 5% higher wage increase compared to the same roles in the fossil fuel sector.[5] By contrast, for managerial occupations, the wage difference between green and fossil fuel employment is positive in only five years (2012, 2015, 2016, 2020, 2021) over the 2000-2023 period.

Do workers who, at some point in their careers, switch to the green sector experience long-term wage gains? To address this question, we compare average cumulative wages over workers' observed careers between workers who ever transition into the green sector and those who remain in fossil fuel employment over their career. On average, FFF workers who ever transition to the green sector earn 10% higher average cumulative wages over their careers than those who remain in the fossil fuel sector (see SI section 3.4 and Table A.6). These gains, however, vary markedly by

[5]Note the 2023 estimates are imprecise due to smaller number of observations

occupation. Workers who obtain managerial positions in the green sector enjoy an average cumulative wage increase of approximately 13%, while those who remain in the fossil fuel sector and move into the same occupations experience a larger increase of 20% (Fig. 2B). In contrast, FFF workers who switch into SE roles in the green sector achieve an 18% cumulative wage increase, compare to 12% increase among their counterparts in the fossil fuel sector (Fig. 2B).

Taken together, this evidence suggests that the overall wage premium (10%, results can be found in SI section A.6) enjoyed by green switchers can be partially attributed to the greater likelihood of upward mobility in the green sector. Even though average cumulative wages in fossil fuel managerial roles tend to be higher, the green sector offers substantially broader access to upward mobility, particularly into SE and managerial occupations, for FFF workers (see Fig.1 and SI Fig.A.38). This increased access effectively offsets the narrower but higher-paying managerial track in the fossil fuel sector, resulting in better aggregate wage outcomes for those who transition to green jobs.

This conclusion is further supported by analysis of the total wage bill and the number of FFF workers achieving upward mobility in each sector (see Fig.2C and SI Fig.A.38). The total wage bill captures both wage levels and the number of transitioning workers who reach each role, providing an aggregate measure of the scale of mobility. Between 2000 and 2023, FFF workers who obtained SE or managerial roles in the green sector collectively received a larger total wage bill than those who secured the same positions in the fossil fuel sector. Moreover, the number of FFF workers attaining upward mobility in the green sector is significantly higher than in the fossil fuel sector (Fig. A.38), underscoring both the broader opportunities for advancement and the substantial economic contribution of the green sector.

Looking at their career pathways into diverse sectors, FFF workers make job switches not only to the green sector, but also to the manufacturing and construction. For job shifts to the manufacturing sector face a reasonable probability of 10.0% $\pm$ 1.3% and 15.4% $\pm$ 1.4% of moving to managerial and SE occupations (Fig. 1C) and enjoy wage increases of 17.7% $\pm$ 0.63% and 17.2% $\pm$ 0.58% in these occupations,

with FFF average wages serving as baseline (Fig. 2A). Those job switches to the construction sector face a small probability 6.7% ± 1.0% to move to managerial occupations and a reasonable probability 15.5% ± 1.5% to move to SE occupations (Fig. 1C). However, the wage increases of moving into managerial and SE occupations in the construction sector (15.0 % ± 1.6%, 15.9% ± 1.3%) may not exceed that from comparable moves in the fossil fuel sector (14% ± 0.4%, 14% ± 0.4%) (Fig. 2A and SI Table A.5).

4 Skilling pathways to achieve upward mobility in the green sector

Policy discussion of a Just Transition (see SI section 7 for literature review on Just Transition) mostly focuses on horizontal career mobility from FFF jobs to trades jobs in the green sector because this strategy requires the least re-skilling. However, job transitions to green industry achieve greater vertical career mobility and a wage premium, so what kinds of skills and retraining could enable more FFF workers to pursue this strategy? To answer this question, we model the career mobility between occupations as a network based on their shared skill requirements.[6] Occupations are "closer" in the network if they have co-occurring skill requirements[2,4]. Workers can move more easily between occupations that have more skill co-occurrences and face difficulties moving between occupations that have limited skill co-occurrences. Workers can traverse this occupation network by accumulating skills through experience in different occupations over their career. For example, workers can achieve upward mobility by making strategic occupational changes into stepping-stone occupations and acquiring skills through work experience in those occupations[13,28,32].

We visualize the network of all 923 occupations in the US Bureau of Labor Statistics O*NET database by applying the network method[4] (see Method section 6.2 and SI section 3.5). FFF occupations are clustered and proximate to only a few SE occupations but separated from most SE and managerial occupations that form a distinct

[6]Data on skill requirements associated with each O*NET-SOC occupation are obtained from the O*NET database (version 28.1): https://www.onetcenter.org/db_releases.html

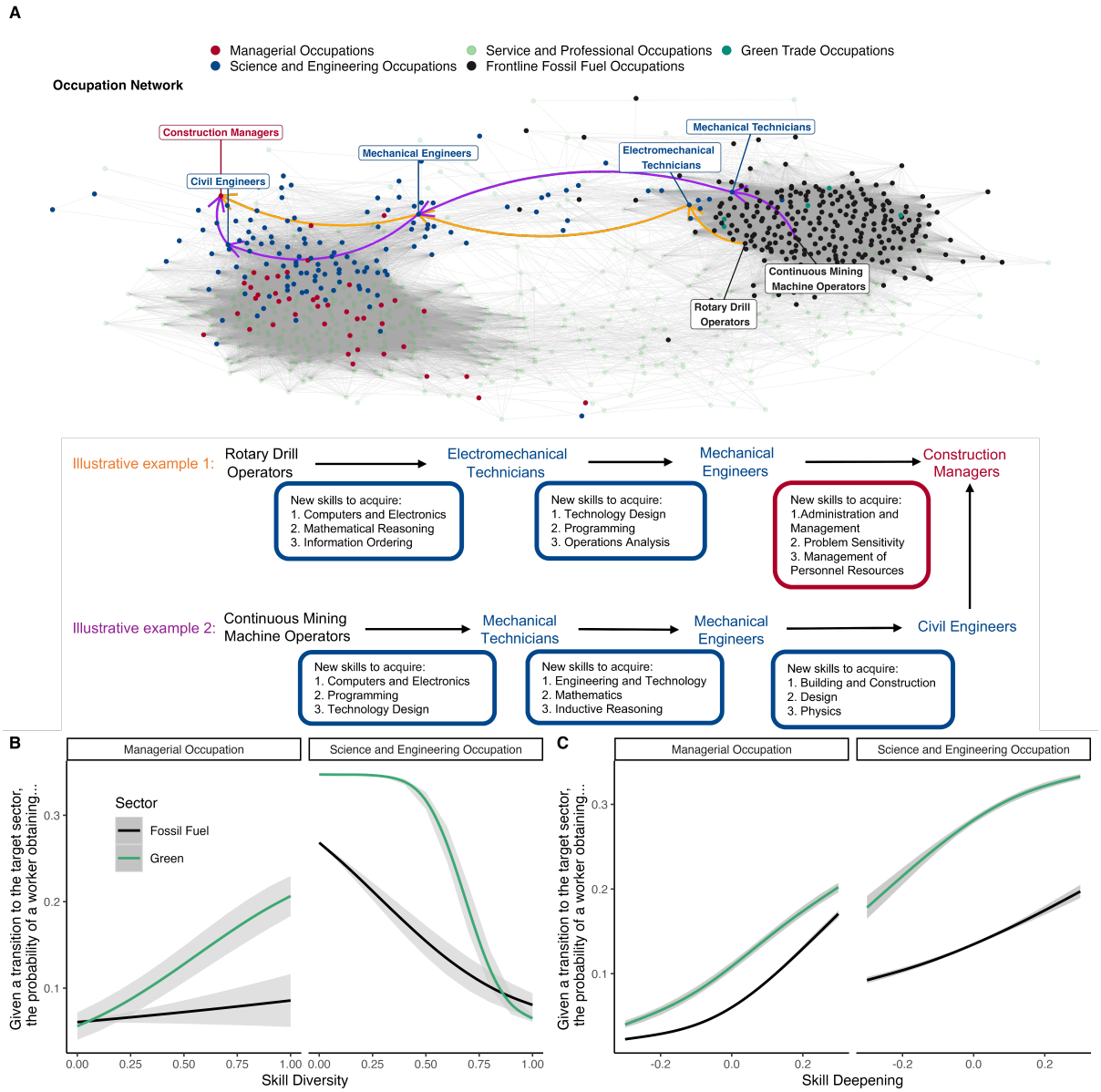


Fig. 3: Comparing the same worker across sector transitions, greater skill diversity is associated with a higher probability of entering managerial roles, whereas deeper SE skills are associated with a higher probability of entering SE roles. A. A network constructed from 923 US Bureau of Labor Statistics occupations connected by edges if they share similar skill requirements according to the O*NET database (see Method section 6.2 for construction details). FFF workers have skills that co-occur primarily in fossil fuel occupations, and these skills co-occur less frequently in SE and managerial occupations. We highlight two illustrative career pathways to demonstrate how workers can traverse the network from FFF to managerial or SE occupations. B. Given a job shift to the green or fossil fuel sector, the probability of securing managerial or SE occupations at different values of skill diversity (see SI section 3.6 for details). C. Given a job shift to the green or fossil fuel sector, the probability of securing managerial (SE) occupations at different values of managerial skill deepening (SE skill deepening). In B and C, the 95% CI associated with smoothed line are provided.

cluster (see Fig. 3A). This indicates that FFF skills co-occur in FFF occupations but co-occur less frequently in managerial and SE occupations. Nevertheless, FFF workers can still secure SE and managerial occupations with distinct skill sets by moving first to jobs with some skill co-occurrence with FFF jobs and acquiring skills through intermediate jobs over their careers. Based on our sample, only 3% percent of FFF workers secure SE or managerial occupations through intermediate jobs in the professional and service sectors, and thus, we do not study those pathways.

Among the 190,64 FFF workers, we observe thousands of unique career sequences, reflecting a large space of feasible transitions. To inform actionable policies, we focus on coherent patterns of job transitions that are associated with FFF workers' upward mobility over their careers. In particular, we observe FFF workers taking on a series of occupations in the green sector that are are associated with their incremental gains in skills and their subsequent entry into S&E or managerial occupations (see Fig. 3A). Notably, SE occupations both provide higher wages than frontline or trades positions and act as stepping-stone jobs to managerial occupations. Out of the 18,443 FFF workers who hold at least one managerial position in the green sector during their career, 11,035 (59.8%) hold a SE position in any sector prior to moving to the managerial position. As shown in illustrative example 1, in our data, 2,865 (1.9%) out of 152,500 rotary drill operators and 354 (0.8%) out of 44,451 continuous machine operators become mechanical engineers; while 1,714 (1.1%) out of 152,500 rotary drill operators and 945 out of 44,451 (2%) continuous machine operators become construction managers at some point in their careers (see Fig. 3A). Rotary drill operators can leverage their FFF skills that co-occur in electromechanical technician jobs (i.e., engineering and technology, physics and visualization) and acquire additional SE skills (i.e., computer and electronics, mathematic reasoning and information ordering) to become electromechanical technicians. Electromechanical technicians can then acquire more SE skills (i.e., technology design, programming and operations analysis) to become mechanical engineers. Mechanical engineers can diversify their skills, acquiring managerial skills (i.e., administration, managing personnel resources and problem sensitivity) to become construction managers. 72 rotary drill operators

become electromechanical technicians, 89 electromechanical technicians (from a variety of previous jobs) become mechanical engineers, and 594 mechanical engineers become construction managers. By contrast, illustrative example 2 is less viable with few workers making the intermediate move between mechanical technicians and mechanical engineers. While 87 continuous machine operators became mechanical technicians, only 8 mechanical technicians (from a variety of previous jobs) became mechanical engineers. 288 mechanical engineers became civil engineers and 227 civil engineers became construction managers.

More generally, using O*NET occupational skill profiles, we calculate: (1) the SE skill deepening index, which captures workers' accumulation of science and engineering skills by transitioning into jobs with higher associated SE skill requirements; (2) the managerial skill deepening index, defined analogously; and (3) the skill diversity index, which reflects the accumulation of a broader skill set by moving into jobs with more distinct skill profiles (see Method section 6.2 and SI section 3.5). Conceptually, skill deepening reflects vertical specialization, greater depth in a targeted domain, while the skill diversity index captures horizontal broadening, indicating exposure to a wider array of distinct capabilities. Regression models that control for multiple individual characteristics (SI section 3.6; Table A.7) show that greater skill diversity is associated with a higher probability of securing a managerial occupation but a lower probability of securing an SE occupation in the green sector (Fig. 3B).

Meanwhile, higher SE skill deepening is associated with a greater likelihood of holding an SE occupation in the green sector (Fig. 3C). A one standard deviation increase in a worker's SE skill deepening index is associated with a predicted probability of holding an SE occupation in the green sector of 30.0% $\pm$ 0.2%, compared with 28.1% $\pm$ 0.2% at the worker's mean level. The corresponding association is smaller in fossil fuel jobs. Turning to managerial occupations, a one standard deviation increase in managerial skill deepening is similarly associated with higher managerial attainment in the green sector, raising the predicted probability to 16.6% $\pm$ 0.3% from 12.2% $\pm$ 0.2% at the mean.

We confirm the robustness of our results by controlling for job network centrality

and time-varying skill differences (SI section 4.3.1), and using Jaccard similarity as an alternative measure of skill diversity (SI section 5). Findings remain consistent across specifications.

5 Discussion

To achieve a Just Transition, policymakers have focused on horizontal moves from frontline fossil fuel jobs to trade occupations in the green sector. The majority of workers may choose to make horizontal moves as it requires the least retraining. While the horizontal moves to the green sector lowers short-term frictions, our analysis reveals an important additional benefit: over the course of their careers, workers who switch from the fossil fuel sector to the green sector are more likely to attain upwardly mobile occupations, particularly in SE and managerial roles.

How many FFF workers might benefit from this upward mobility? At the aggregate level, 2.9% of all FFF workers experienced upward mobility through transition to the green sector between 2000 and 2023 (see SI section 6.1). National estimates further indicate that former FFF workers, who achieve upwardly mobile jobs, account for approximately 2% of all jobs in the green sector in 2023 (see SI section 6.1). Applying this share to employment projections from the U.S. Bureau of Labor Statistics, the projected 7.7% increase in green employment by 2033 would enable an additional 0.2% of the fossil fuel workforce to make upward career transitions in the green sector (see SI section 6.1).

These numbers indicate that only a subset of FFF workers have been able to secure SE and managerial positions in the green sector. However, upward mobility represents only one critical channel of benefit from green sector transitions. While managerial and SE roles constitute a limited share of jobs in any sector, and thus can be attained by only a subset of workers, these opportunities remain policy relevant, particularly because the green sector offers more such upward pathways than manufacturing or construction. Moreover, the gains from green sector transitions are not confined to the small fraction who ultimately enter managerial or SE roles. Among the 40% of

FFF workers who switch into the green sector at any point in their careers, we still observe long-run wage gains after accounting for upward mobility pathways: green switchers earn approximately 2% higher average cumulative wages than comparable workers who remain in fossil-fuel employment (see Fig. 1A and SI Table A.6). The modest share of workers attaining upwardly mobile jobs therefore reflects the scarcity of high level positions rather than negligible returns to transition, and points to the need for more ambitious transition policies that expand stepping-stone roles, reskilling pathways, and the overall supply of quality green jobs.

Trade occupations in the green sector tend to offer lower wages than their counterparts in fossil fuel[1,7,9,18,19,39] which feeds a concern that, in the short term, horizontal transitions from FFF jobs to comparable roles in the green sector may lead to wage loss. While this concern is valid in the short term, our analysis shows that over the course of their careers, FFF workers who switch to the green sector ultimately earn higher cumulative wages than those who remain in fossil fuel employment. Two key mechanisms contribute to this long run wage advantage. First, upwardly mobile occupations in the green sector offer significantly higher wages compared to frontline fossil fuel positions (see Fig. 2). Second, although managerial positions in the fossil fuel sector can be highly paid, access to these roles is limited in practice. By contrast, while managerial and SE jobs remain a small share of total employment in any sector, transition pathways into these roles are more accessible in the green sector for switching workers (Fig.1; SI Fig. A.38).

These findings suggest that temporary wage setbacks in the short term may be outweighed by longer-term prospects for career advancement and earnings growth in the green sector. Information about these long-term opportunities and the reskilling pathways they require can inform workforce development programs serving regions experiencing declines of fossil fuel jobs. This information is also useful for frontline fossil fuel workers who are considering the career-long costs and benefits of shifting to the green sector.

Importantly, the wage premium associated with SE and managerial occupations in the green sector creates a compelling economic incentive for reskilling. In particular,

the premium observed for SE roles in the green sector, even when compared to similar occupations in fossil fuels, reflects both the rising market value of specific green-related technical skills and the growing complexity and intensity of skill demands within the sector[17,41]. This wage advantage is further amplified by labor market shortages and recruitment challenges for green-skilled workers[36,40].

Our findings also indicate that the reskilling pathways to upward mobility differ by target occupation; skill diversification increases odds of a managerial job while skill deepening into science and engineering related skills increases odds of a SE occupation. The positive association between acquisition of SE skills and securing SE occupations in the green sector aligns with reports that green jobs require more technical skills than generic jobs[17,41]. Likewise, our observation of the positive association between diversity of skills and securing managerial occupations in the green sector aligns with reports of managers' tasks in the green sector require diverse skills, i.e., to restructure various aspects of their operations to innovate or adapt to green technologies, products and processes[3,5,21,44,46].

Our findings have three policy implications. First, the green sector is an important sector that offers upward mobility opportunities for FFF workers and hence, policies that support job growth in these sectors (e.g. the IRA, IJIA and the CHIPs Act)[10,23,25,30,31] can contribute to FFF workers' career advancement. Retrenchment of these policies[42], instead of shielding the careers of fossil fuel workers, would remove a strategy for FFF workers to secure upward mobility in their careers and thus hurt FFF workers and communities. Second, workforce development for skilled technical occupations in key technology areas, including green technologies, has been funded by the CHIPS Act[34]. These programs, when catering to FFF workers, should build not only skills that assist with the initial switch out of fossil fuel sector but also those that support longer-term upward career mobility in the green sector and provide guidance to workers on stepping-stone occupations that build on-the-job work experience[6] for that upward mobility. Third, our findings provide stronger economic justifications for the workforce development programs for FFF workers[38]. The lifetime earnings gain from the upward mobility in the green or manufacturing sectors imply that retraining

programs for frontline fossil fuel yields more favorable benefit-cost assessment than suggested by the myopic wage analysis of FFF workers' initial horizontal shift to trades occupations in the green sector.

Our work has several limitations. First, we track the long-term career benefits of FFF workers who did make the shift to the green sector. Complementing this study with interviews of FFF workers on factors that help or hinder their making such shifts would provide insights on how the pursuit of the career mobility in the green sector can be made feasible for more FFF workers. Second, our study contains limited observations for 2023, when congressional investments are beginning to spur green energy deployment and green manufacturing. Replicating our study when more deployment has proceeded and manufacturing plants have become operational would more fully capture FFF workers potential career mobility in the green sector. Third, we focus on fossil fuel workers who begin in frontline fossil fuel occupations, but future work should consider all workers in SE occupations in the fossil fuel sector and examine their skill and career pathways to move to SE occupations in the green and manufacturing sectors. Such moves could provide career progress for these workers while meeting the National Science Board[35,36] call to address severe shortages of the SE workforce in green and emerging technology sectors to enhance US economic competitiveness. Finally, our study does not rely on a strictly exogenous assignment of workers to different sectors. Consequently, our findings may be subject to selection biases. To mitigate such biases, we implement a series of robustness checks, including sample reweighting and entropy balancing (see SI section 4.2- 4.3). These additional tests reinforce our confidence in the interpretation of the main estimates, as they consistently yield results that are similar in both direction and magnitude to our main findings. However, we acknowledge that unobserved confounders may still be present. While our methods adjust for observable characteristics, they cannot fully eliminate selection bias arising from omitted variables. We conduct a sensitivity analysis following Cinelli and Hazlett[8] to assess the robustness of our estimates to potential unobserved confounding (see SI section 4.4)."

6 Method

6.1 Fossil fuel workers careers, occupations and sectors data

We identify frontline fossil fuel workers and track their careers using resume records from Revelio Lab that have been widely used for labor market analysis[14,26]. Revelio assigns each job using the Bureau of Labor Statistics (BLS) classification for SOC based on the tasks, skills and knowledge for each job, thus ensuring consistency between its data and government administrative data.

To identify workers with **frontline fossil fuel** experience, we use the Revelio database, selecting all individuals whose records include central occupations in fossil fuel industries and retrieving their complete resume histories through the end of 2023. Specifically, following Curtis, O'Kane and Park[11], we first identify fossil fuel industries based on NAICS codes, i.e., fossil fuel extractive industries and fossil fuel generation industries (SI Table A.1). We then adopt the approach of Muro et al.[33] to identify "central" occupations within each industry. Fossil fuel industries employ workers across the full SOC spectrum (SOC-11 to SOC-53). For each SOC in each of the fossil fuel industries, we calculate the ratio of (a) the share of occupations in an industry to (b) the share of occupations in the national economy. For each fossil fuel industry, we extract occupations whose ratio exceeds 1. To account for resume records missing NAICS codes, we additionally identify fossil fuel jobs using a keyword search on 1) job titles with terms including "coal", "petroleum", "fossil fuel", "shale" or "petrol," 2) workers' company names that belong to the list of top fossil fuel companies (see SI section 1). From the complete set of fossil fuel jobs, we then isolate **frontline fossil fuel** occupations by selecting workers' first recorded occupations in the fossil fuel sector within four two-digit SOC groups: SOC-47 (extraction and construction), SOC-49 (installation, maintenance, and repair), SOC-51 (production), and SOC-53 (transportation and material moving). A full list of frontline occupations is provided in SI Table A.2. Our approach yields 190,648 unique workers who have job transitions between 2000 and 2023.

We define **upwardly mobile occupations** as those in managerial or science and

engineering (SE) roles. Occupations are classified as managerial if their O*NET-SOC codes fall within the two-digit major group 11. Following the same classification logic, SE occupations are identified as those belonging to major groups 15 (Computer and Mathematical), 17 (Architecture and Engineering), and 19 (Life, Physical, and Social Science). For comparison, we define trade occupations as those in major groups 47, 49 , 51, and 53.

We construct a record of these workers' job transitions between 2000 and 2023, beginning from the point at which they exit their first frontline fossil fuel jobs and tracing their subsequent movements across occupations and sectors. We use a combination of the SOC code and the NAICS industrial code for each job to classify its unique sector (fossil fuel, green, manufacturing, construction, transportation and other) and its unique occupation on the occupation ladder.

To define **green occupations**, we use the Bureau of Labor Statistics (BLS) widely used list of green occupations that include mainstream and emerging green jobs. Our primary classification includes carbon trading, clean energy, energy, energy efficiency, energy engineering, energy trading, green construction, green infrastructure, renewable energy, solar, wind, sustainability, and transportation (SI Table A.3 provide the list of green occupations). We exclude occupations unlikely to be directly related to the green sector, such as brokerage clerks (SOC 43-4011.00), carpenters (SOC 47-2031.00), plumbers (SOC 47-2152.00), and roofers (SOC 47-2181.00).

Construction and manufacturing sectors are defined using Revelio's industry assignment for each job record, which follows the NAICS system. We classify a job as construction if its two-digit NAICS code is 23, and as manufacturing if its two-digit NAICS code is 31, 32, or 33. Job transitions that do not fall into the green, fossil fuel, construction, or manufacturing sectors are coded as "All other sectors" (e.g., real estate and rental and leasing).

We narrow our sample to the 190,648 FFF workers that made at least one job switch from their initial FFF occupation in the 2000-2023 period. Revelio provides wage estimates for each occupation using position-specific characteristics such as seniority and location, and draws on data from publicly available visa applications,

self-reported sources, and job postings. Revelio also provides workers' self-reported demographics, education, job locations and job start years.

To calculate the US-wide workforce in fossil fuel sector and in fossil fuel occupations, we apply the same FFF worker definitions to the BLS OWES data. Using the same data source, we aggregate all employment counts for all green industries listed in Table A.29 to calculate total green workforce (see SI section 6.1).

6.2 Fossil fuel workers skill deepening and skill diversity

We impute the skills of workers based on their Revelio-assigned SOC of the jobs they have held. BLS O*NET database details for each SOC the skills, ability and knowledge (hereafter skills) required for that occupation and rates the importance of these skills for a specific SOC.

We calculate the skill deepening index for workers prior to each of their job switches (see SI section 3.5 for details). First, we identify core skills as those skills that are rated as more important for managerial (SE) occupations. Second, for each SOC, we calculate its managerial (SE) skill relatedness based on each of its required core skills. Third, we calculate the change in managerial(SE) skill relatedness between each successive pair of jobs held by the worker prior to a job switch. Fourth, we calculate the cumulative change in the skill relatedness for each pairwise jobs, divided by the number of jobs held.

We also calculate the skill diversity index prior to each of their job switch (SI section 3.5). First, for each SOC, we define that the job requires a skill if its importance that job (normalized by the number of skills in that job) exceeds the average importance of that skill in all O*NET jobs. Second, we calculate the diversity in the skills required between each successive pair of jobs held by the worker prior to a job switch. Third, we calculate the cumulative skill diversity between each successive pair of jobs, divided by the number of jobs held.

6.3 Regression Analysis

We implement the following models to estimate the effects of green transition on career upward mobility and wage progression. In the analysis of career advancement, the comparison group consists of job switches within fossil fuel sector and their likelihood of moving into managerial or science and engineering roles. It is important to note that upward mobility is not typically achieved through immediate transitions from frontline fossil fuel jobs to target sectors. Instead, FFF workers often follow multi-step job switches before attaining upward mobility. In the wage analysis, occupation-wise comparisons are conducted between sectors, using the average wages of FFF jobs as the reference group.

$$\begin{aligned} y_{i,t} =& \beta_1 \text{Green Sector}_{i,t} + \beta_2 \text{Construction Sector}_{i,t} \\ &+ \beta_3 \text{Manufacturing Sector}_{i,t} + \beta_4 \text{Other Sectors}_{i,t} \\ &+ X'_{i,t}\Omega + Z'_i\Gamma + \delta_o + \tau_d + \epsilon_{it} \end{aligned} \tag{eq.1}$$

Observations are job switches in the 2000-2023 period. $y_{i,t}$ is the dummy for SE (managerial) occupation for models estimating the probability of obtaining SE (managerial) occupations and $y_{i,t}$ is log wages for models estimating the wage increases from job shifts to these occupations in the target sector at time t. $X_{i,t}$ represents time varying individual level covariates, including wages in the prior job and a factor variable for the year in which workers enter the labor market. Z_i captures time invariant individual characteristics, such as highest degree and gender. In the wage models, we also add the appropriate occupation variable SE (Managerial) $\text{Occupation}_{i,t}$ and the interaction variables $Sector_{i,t} \times \text{SE (Managerial) Occupation}_{i,t}$. We estimate fixed effect models to control for individual effects μ_i, year for the job switch λ_t, the origin state of the prior job δ_o and destination state of a job switch τ_d (SI Table A.4–A.5).

Our logit regression on skill pathways for upward mobility is:

$$\begin{aligned} y_{i,t} =& \beta_1 \textit{Green Sector}_{i,t} + \beta_2 \textit{Manufacturing Sector}_{i,t} + \beta_3 \textit{Construction Sector}_{i,t} \\ &+ \beta_4 \textit{Other Sector}_{i,t} + \beta_5 \textit{Skill Diversity}_{i,t} + \beta_6 \textit{Skill Deepening}_{i,t} \\ &+ \mu_i + \lambda_t + \delta_o + \tau_d + \epsilon_{it} \end{aligned} \tag{eq.2}$$

$y_{i,t}$ is the dummy for SE (managerial) occupation for models estimating the probability of entering SE (managerial) occupations (SI Table A.7). For the managerial occupation model, we add the interaction variable $\textit{Green Sector}_{i,t} \times \textit{Skill Diversity}_{i,t}$ and $\textit{Green Sector}_{i,t} \times \textit{Managerial Skill Deepening}_{i,t}$. For the SE occupation model, we add the variable $\textit{Green Sector}_{i,t} \times \textit{Skill Diversity}_{i,t}$ and $\textit{Green Sector}_{i,t} \times \textit{SE Skill Deepening}_{i,t}$.

7 Data Availability

This study uses several publicly available datasets from federal government sources: the O*NET database (https://www.dol.gov/agencies/eta/onet); Occupation Employment and Wage Statistics (https://www.bls.gov/oes/); and Longitudinal Employer-Household Dynamics (https://lehd.ces.census.gov/data/j2j_subsector_research.html).

This study also uses proprietary third-party resume dataset provided by Revelio Labs. We cannot make this proprietary data immediately available because of risks to individuals' privacy. Access to this data is available by contacting Morgan Frank (email: mrfrank@pitt.edu) or through the third-party data vendors.

8 Code availability

Code used for the data analysis and to produce figures and tables in this article is available at figshare (10.6084/m9.figshare.28828454).

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10 Contributions

QC: conceptualization, data collection, data analysis, writing (original draft). MA: conceptualization, writing (review and editing). MF: conceptualization, data collection, writing (review and editing). LS: data collection. SGR: conceptualization, writing (original draft).

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Supplementary Materials

1 Fossil Fuel Industry and Frontline Fossil Fuel Workers

We use a combination of (1) fossil fuel industries (identified with NAICS codes, 2017 version) and (2) occupations (identified with SOC codes) to identify occupations in the fossil fuel industry. First, as in Curtis, O'Kane and Park[14], we select the NAICS codes for fossil fuel industries. i.e., fossil fuel extractive industries and fossil fuel generation industries (SI Table A.1). Second, as in Muro et al.[37], we select the central occupations within each of these fossil fuel industries. Each industry hosts occupations classified across the entirety of SOC codes (from SOC-11 to SOC-53). For each SOC within each fossil fuel industry, we calculate the ratio between (a) the occupation's share within that industry and (b) its share in the national economy. For each industry, we retain occupations with a ratio greater than 1. We use this industry–occupation combination to collect all resume records for individuals who held fossil fuel positions meeting these criteria. In addition to this two-step procedure, we identify fossil fuel jobs among resume records missing NAICS codes by: (1) conducting a keyword search of job titles using the terms "coal," "petroleum," "fossil fuel," "shale," or "petrol"; and (2) compiling a list of top companies in each fossil fuel industry based on annual sales and matching company names in the resume data to this list.[1]

This procedure identifies workers across all occupations in the fossil fuel industry. To define frontline fossil fuel workers, we restrict the sample to occupations in the following SOC major groups: SOC 47 (Construction and Extraction), SOC 49 (Installation, Maintenance, and Repair), SOC 51 (Production), and SOC 53 (Transportation and Material Moving). Table A.2 presents the complete list of frontline fossil fuel occupations.

[1]Company names are obtained from NAICS Association, access at https://www.naics.com/search/.

Table A.1: List of Fossil Fuel Industries

NAICS	Industry
211120	Crude Petroleum Extraction
211130	Natural Gas Extraction
212111	Bituminous Coal and Lignite Surface Mining
212112	Bituminous Coal Underground Mining
212113	Anthracite Mining
213111	Drilling Oil and Gas Wells
213112	Support Activities for Oil and Gas Operations
213113	Support Activities for Coal Mining
221112	Fossil Fuel Electric Power Generation
221210	Natural Gas Distribution
237120	Oil and Gas Pipeline and Related Structures Construction
486110	Pipeline Transportation of Crude Oil
486210	Pipeline Transportation of Natural Gas

Table A.2: List of Frontline Fossil Fuel Occupation

O*NET	Occupation	O*NET	Occupation
47-1011.00	First-Line Supervisors of Construction Trades and Extraction Workers	51-4051.00	Metal-Refining Furnace Operators and Tenders
47-2011.00	Boilermakers	51-4052.00	Pourers and Casters, Metal
47-2021.00	Brickmasons and Blockmasons	51-4072.00	Molding, Coremaking, and Casting Machine Setters, Operators, and Tenders, Metal and Plastic
47-2031.00	Carpenters	51-4081.00	Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic
47-2051.00	Cement Masons and Concrete Finishers	51-4111.00	Tool and Die Makers
47-2071.00	Paving, Surfacing, and Tamping Equipment Operators	51-4121.00	Welders, Cutters, Solderers, and Brazers
47-2072.00	Pile Driver Operators	51-4122.00	Welding, Soldering, and Brazing Machine Setters, Operators, and Tenders
47-2132.00	Insulation Workers, Mechanical	51-4191.00	Heat Treating Equipment Setters, Operators, and Tenders, Metal and Plastic
47-2141.00	Painters, Construction and Maintenance	51-4193.00	Plating Machine Setters, Operators, and Tenders, Metal and Plastic
47-2151.00	Pipelayers	51-4199.00	Metal Workers and Plastic Workers, All Other
47-2152.00	Plumbers, Pipefitters, and Steamfitters	51-5112.00	Printing Press Operators
47-2171.00	Reinforcing Iron and Rebar Workers	51-6031.00	Sewing Machine Operators
47-2221.00	Structural Iron and Steel Workers	51-6061.00	Textile Bleaching and Dyeing Machine Operators and Tenders
47-3012.00	Helpers–Carpenters	51-6062.00	Textile Cutting Machine Setters, Operators, and Tenders
47-3013.00	Helpers–Electricians	51-6063.00	Textile Knitting and Weaving Machine Setters, Operators, and Tenders
47-3014.00	Helpers–Painters, Paperhangers, Plasterers, and Stucco Masons	51-6064.00	Textile Winding, Twisting, and Drawing Out Machine Setters, Operators, and Tenders
47-3015.00	Helpers–Pipelayers, Plumbers, Pipefitters, and Steamfitters	51-6091.00	Extruding and Forming Machine Setters, Operators, and Tenders, Synthetic and Glass Fibers
47-4051.00	Highway Maintenance Workers	51-6099.00	Textile, Apparel, and Furnishings Workers, All Other
47-4061.00	Rail-Track Laying and Maintenance Equipment Operators	51-7042.00	Woodworking Machine Setters, Operators, and Tenders, Except Sawing
47-4071.00	Septic Tank Servicers and Sewer Pipe Cleaners	51-8013.03	Biomass Plant Technicians
47-5011.00	Derrick Operators, Oil and Gas	51-8021.00	Stationary Engineers and Boiler Operators
47-5012.00	Rotary Drill Operators, Oil and Gas	51-8031.00	Water and Wastewater Treatment Plant and System Operators
47-5013.00	Service Unit Operators, Oil and Gas	51-8091.00	Chemical Plant and System Operators
47-5022.00	Excavating and Loading Machine and Dragline Operators, Surface Mining	51-8092.00	Gas Plant Operators
47-5023.00	Earth Drillers, Except Oil and Gas	51-8093.00	Petroleum Pump System Operators, Refinery Operators, and Gaugers
47-5041.00	Continuous Mining Machine Operators	51-8099.00	Plant and System Operators, All Other
47-5043.00	Roof Bolters, Mining	51-9011.00	Chemical Equipment Operators and Tenders
47-5044.00	Loading and Moving Machine Operators, Underground Mining	51-9012.00	Separating, Filtering, Clarifying, Precipitating, and Still Machine Setters, Operators, and Tenders
47-5049.00	Underground Mining Machine Operators, All Other	51-9021.00	Crushing, Grinding, and Polishing Machine Setters, Operators, and Tenders
47-5071.00	Roustabouts, Oil and Gas	51-9023.00	Mixing and Blending Machine Setters, Operators, and Tenders
47-5081.00	Helpers–Extraction Workers	51-9032.00	Cutting and Slicing Machine Setters, Operators, and Tenders
49-1011.00	First-Line Supervisors of Mechanics, Installers, and Repairers	51-9041.00	Extruding, Forming, Pressing, and Compacting Machine Setters, Operators, and Tenders
49-2021.00	Radio, Cellular, and Tower Equipment Installers and Repairers	51-9051.00	Furnace, Kiln, Oven, Drier, and Kettle Operators and Tenders
49-2092.00	Electric Motor, Power Tool, and Related Repairers	51-9061.00	Inspectors, Testers, Sorters, Samplers, and Weighers
49-2094.00	Electrical and Electronics Repairers, Commercial and Industrial Equipment	51-9111.00	Packaging and Filling Machine Operators and Tenders
49-2095.00	Electrical and Electronics Repairers, Powerhouse, Substation, and Relay	51-9124.00	Coating, Painting, and Spraying Machine Setters, Operators, and Tenders
49-3031.00	Bus and Truck Mechanics and Diesel Engine Specialists	51-9161.00	Computer Numerically Controlled Tool Operators
49-3042.00	Mobile Heavy Equipment Mechanics, Except Engines	51-9162.00	Computer Numerically Controlled Tool Programmers
49-9012.00	Control and Valve Installers and Repairers, Except Mechanical Door	51-9191.00	Adhesive Bonding Machine Operators and Tenders
49-9041.00	Industrial Machinery Mechanics	51-9192.00	Cleaning, Washing, and Metal Pickling Equipment Operators and Tenders
49-9043.00	Maintenance Workers, Machinery	51-9196.00	Paper Goods Machine Setters, Operators, and Tenders
49-9044.00	Millwrights	51-9198.00	Helpers–Production Workers
49-9045.00	Refractory Materials Repairers, Except Brickmasons	51-9199.00	Production Workers, All Other
49-9051.00	Electrical Power-Line Installers and Repairers	53-2012.00	Commercial Pilots
49-9052.00	Telecommunications Line Installers and Repairers	53-3032.00	Heavy and Tractor-Trailer Truck Drivers
49-9069.00	Precision Instrument and Equipment Repairers, All Other	53-5011.00	Sailors and Marine Oilers
49-9071.00	Maintenance and Repair Workers, General	53-5021.00	Captains, Mates, and Pilots of Water Vessels
49-9096.00	Riggers	53-6041.00	Traffic Technicians
49-9099.00	Installation, Maintenance, and Repair Workers, All Other	53-7011.00	Conveyor Operators and Tenders
51-2021.00	Coil Winders, Tapers, and Finishers	53-7021.00	Crane and Tower Operators
51-2041.00	Structural Metal Fabricators and Fitters	53-7041.00	Hoist and Winch Operators
51-4021.00	Extruding and Drawing Machine Setters, Operators, and Tenders, Metal and Plastic	53-7061.00	Cleaners of Vehicles and Equipment
51-4022.00	Forging Machine Setters, Operators, and Tenders, Metal and Plastic	53-7062.00	Laborers and Freight, Stock, and Material Movers, Hand
51-4023.00	Rolling Machine Setters, Operators, and Tenders, Metal and Plastic	53-7062.04	Recycling and Reclamation Workers
51-4031.00	Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic	53-7063.00	Machine Feeders and Offbearers
51-4032.00	Drilling and Boring Machine Tool Setters, Operators, and Tenders, Metal and Plastic	53-7064.00	Packers and Packagers, Hand
51-4033.00	Grinding, Lapping, Polishing, and Buffing Machine Tool Setters, Operators, and Tenders, Metal and Plastic	53-7071.00	Gas Compressor and Gas Pumping Station Operators
51-4034.00	Lathe and Turning Machine Tool Setters, Operators, and Tenders, Metal and Plastic	53-7072.00	Pump Operators, Except Wellhead Pumpers
51-4035.00	Milling and Planing Machine Setters, Operators, and Tenders, Metal and Plastic	53-7073.00	Wellhead Pumpers
51-4041.00	Machinists	53-7121.00	Tank Car, Truck, and Ship Loaders

2 Green Occupation List

To identify jobs in the green sector, we use SOC codes classified as green occupations by O*NET, maintained by the U.S. Bureau of Labor Statistics.[2] Our primary classification includes the following sectors: carbon trading, clean energy, energy, energy efficiency, energy engineering, energy trading, green construction, green infrastructure, renewable energy, solar, wind, sustainability, and transportation. We exclude occupations unlikely to be directly related to the green sector, such as brokerage clerks (SOC 43-4011.00), carpenters (SOC 47-2031.00), plumbers (SOC 47-2152.00), and roofers (SOC 47-2181.00).

To assess the robustness of our findings, we also implement a narrower definition of the green sector, restricting the sample to occupations directly related to solar, wind, hydro, biofuels, and nuclear energy (Section 4.1). Results based on this alternative classification are consistent with our main estimates.

Table A.3 presents the complete list of green sector occupations used for our main analysis.

Table A.3: List of Green Occupation

O*NET	Occupation	O*NET	Occupation
11-1011.03	Chief Sustainability Officers	17-3021.00	Aerospace Engineering and Operations Technologists and Technicians
11-1021.00	General and Operations Managers	17-3023.00	Electrical and Electronic Engineering Technologists and Technicians
11-3013.01	Security Managers	17-3024.00	Electro-Mechanical and Mechatronics Technologists and Technicians
11-3051.02	Geothermal Production Managers	17-3025.00	Environmental Engineering Technologists and Technicians
11-3051.03	Biofuels Production Managers	17-3026.00	Industrial Engineering Technologists and Technicians
11-3051.06	Hydroelectric Production Managers	17-3027.00	Mechanical Engineering Technologists and Technicians
11-3071.00	Transportation, Storage, and Distribution Managers	17-3027.01	Automotive Engineering Technicians
11-9021.00	Construction Managers	17-3029.08	Photonics Technicians
11-9041.00	Architectural and Engineering Managers	19-1013.00	Soil and Plant Scientists
11-9121.02	Water Resource Specialists	19-1029.04	Biologists
11-9199.01	Regulatory Affairs Managers	19-1031.02	Range Managers
11-9199.09	Wind Energy Operations Managers	19-2041.01	Climate Change Policy Analysts
11-9199.10	Wind Energy Development Managers	19-2041.03	Industrial Ecologists
11-9199.11	Brownfield Redevelopment Specialists and Site Managers	19-3011.01	Environmental Economists
13-1021.00	Buyers and Purchasing Agents, Farm Products	19-3051.00	Urban and Regional Planners
13-1022.00	Wholesale and Retail Buyers, Except Farm Products	19-3099.01	Transportation Planners
13-1081.01	Logistics Engineers	19-4012.00	Agricultural Technicians
13-1081.02	Logistics Analysts	19-4042.00	Environmental Science and Protection Technicians, Including Health
13-1199.00	Business Operations Specialists, All Other	19-4051.00	Nuclear Technicians
13-1199.04	Business Continuity Planners	25-1053.00	Environmental Science Teachers, Postsecondary
13-1199.05	Sustainability Specialists	33-9093.00	Transportation Security Screeners
13-2051.00	Financial and Investment Analysts	41-3031.00	Securities, Commodities, and Financial Services Sales Agents
13-2054.00	Financial Risk Specialists	41-4011.00	Sales Representatives, Wholesale and Manufacturing, Technical and Scientific Products
13-2099.01	Financial Quantitative Analysts	41-4011.07	Solar Sales Representatives and Assessors
15-1211.00	Computer Systems Analysts	43-5011.00	Cargo and Freight Agents
15-1211.01	Health Informatics Specialists	43-5011.01	Freight Forwarders
15-1212.00	Information Security Analysts	43-5071.00	Shipping, Receiving, and Inventory Clerks
15-1241.00	Computer Network Architects	47-1011.03	Solar Energy Installation Managers
15-1241.01	Telecommunications Engineering Specialists	47-2061.00	Construction Laborers
15-1243.00	Database Architects	47-2073.00	Operating Engineers and Other Construction Equipment Operators
15-1252.00	Software Developers	47-2111.00	Electricians
15-1254.00	Web Developers	47-2152.04	Solar Thermal Installers and Technicians
15-1299.01	Web Administrators	47-2231.00	Solar Photovoltaic Installers
15-1299.04	Penetration Testers	47-3019.00	Helpers, Construction Trades, All Other
15-1299.05	Information Security Engineers	47-4011.00	Construction and Building Inspectors
15-1299.07	Blockchain Engineers	47-4011.01	Energy Auditors
15-1299.08	Computer Systems Engineers/Architects	47-4099.00	Construction and Related Workers, All Other
15-1299.09	Information Technology Project Managers	47-4099.03	Weatherization Installers and Technicians
17-1011.00	Architects, Except Landscape and Naval	49-9021.00	Heating, Air Conditioning, and Refrigeration Mechanics and Installers
17-1012.00	Landscape Architects	49-9081.00	Wind Turbine Service Technicians
17-2011.00	Aerospace Engineers	49-9098.00	Helpers–Installation, Maintenance, and Repair Workers
17-2031.00	Bioengineers and Biomedical Engineers	51-1011.00	First-Line Supervisors of Production and Operating Workers
17-2051.00	Civil Engineers	51-8012.00	Power Distributors and Dispatchers
17-2051.01	Transportation Engineers	51-8013.00	Power Plant Operators
17-2071.00	Electrical Engineers	51-8013.04	Hydroelectric Plant Technicians
17-2072.00	Electronics Engineers, Except Computer	53-1042.00	First-Line Supervisors of Helpers, Laborers, and Material Movers, Hand
17-2131.00	Materials Engineers	53-1043.00	First-Line Supervisors of Material-Moving Machine and Vehicle Operators
17-2141.00	Mechanical Engineers	53-1049.00	First-Line Supervisors of Transportation Workers, All Other
17-2141.01	Fuel Cell Engineers	53-3053.00	Shuttle Drivers and Chauffeurs
17-2141.02	Automotive Engineers	53-4011.00	Locomotive Engineers
17-2161.00	Nuclear Engineers	53-4013.00	Rail Yard Engineers, Dinkey Operators, and Hostlers
17-2199.03	Energy Engineers, Except Wind and Solar	53-4099.00	Rail Transportation Workers, All Other
17-2199.07	Photonics Engineers	53-6051.00	Transportation Inspectors
17-2199.09	Nanosystems Engineers	53-6051.07	Transportation Vehicle, Equipment and Systems Inspectors, Except Aviation
17-2199.10	Wind Energy Engineers	53-6099.00	Transportation Workers, All Other
17-2199.11	Solar Energy Systems Engineers	53-7051.00	Industrial Truck and Tractor Operators

[2] Access at: https://www.onetonline.org/search/green_topics/

3 Regression Analysis: Methods and Tables of Results

3.1 Upward Mobility in the Green Sector

We estimate the effects of the green transition on upward mobility using the models described below. Our unit of observation is a job switch after workers leave their first frontline fossil fuel jobs. We benchmark switches into the green, construction, and manufacturing sectors against switches within the fossil fuel sector, and compare the probability that the destination job in each switch is managerial or S&E. From the initial exit onward, we follow workers' occupational and industry moves over time to trace their career trajectories. For each switch, the destination sector is coded as green, construction, manufacturing, or all other sectors, based on the sector of the post switch job. It is important to note that upward mobility rarely occurs through an immediate jump from a frontline fossil fuel job into a high-pay role. Instead, workers typically reach managerial or S&E positions through multiple steps of job changes across sectors. Accordingly, our switch level regressions capture whether a given move places a worker into a managerial or S&E job conditional on the destination sector, and do not require that the worker's immediately preceding job be in fossil fuel. The results, therefore, should not be interpreted as the probability of moving directly from a frontline fossil fuel job into a green managerial or S&E position in one step.

$$\begin{aligned} y_{i,t} =& \beta_1 \text{Green Sector}_{i,t} + \beta_2 \text{Construction Sector}_{i,t} \\ &+ \beta_3 \text{Manufacturing Sector}_{i,t} + \beta_4 \text{Other Sectors}_{i,t} \\ &+ X'_{i,t}\Omega + Z'_i\Gamma + \delta_o + \tau_d + \epsilon_{it} \end{aligned} \tag{eq.1}$$

Observations are job switches in the 2000–2023 period. $y_{i,t}$ is an indicator for whether the destination job is in an SE (managerial) occupation. The definition of green sector is based on list of occupations in Table A.3. Construction and manufacturing are defined from Revelio's NAICS based industry codes: construction is NAICS 23, and manufacturing is NAICS 31–33. Transitions not into the green, fossil fuel, construction, or manufacturing sectors are coded as "All other sectors". In the regression model, we set fossil fuel sector as the omitted referece category. $X_{i,t}$ represents time varying individual level covariates, including wages in the prior job and a factor variable for the year in which workers enter the labor market. Z_i captures time invariant individual characteristics, such as highest eduaction degree and gender. λ_t denotes fixed effects for the year of the job switch, and δ_o and τ_d capture fixed effects for the origin and destination states, respectively. In addition to baseline specifications, we estimate models that include individual fixed effects by adding μ_i.

The regression results are presented in Table A.4. Models with individual and year fixed effects construct the counterfactual that ask what a given worker's outcome would have been had they transitioned in the fossil fuel sector. Meanwhile, individual fixed effect further absorb time invariant unobservables that may jointly influence a worker's decision to transition into the green sector and their subsequent career advancement, such as talent or motivation. This approach also accounts for persistent individual preferences over job types, for example, workers who enjoy engineering are more likely to self-select into engineering-related positions in the green sector. In addition, we include state fixed effects to absorb time-invariant geographical factors, such as differences in industry composition, labor market conditions, and infrastructure across states.

Fig. 1C presents the results from the fixed effect regression models for managerial occupations and science and engineering (SE) occupations (Model 2 and 4). To calculate the predicted probability, we first generate counterfactual predictions under each sector for every observation, holding all other covariates at their observed values. Then, we compute the average of these predictions for each target sector. Lastly, standard errors are calculated using delta method. Thus, given FFF workers' job switch into a fossil fuel sector, the predicted probability of obtaining a managerial position is 7.1%. By the same method, given FFF workers' job switch into a green sector, the predicted probability of obtaining a managerial position is 13.4%.

We validate our findings through a series of robustness checks, including redefining green occupations (SI section 4.1); estimating models with additional potential confounders, such as an occupation's importance within job networks and career-long skill set differences (SI section 4.3.1); reweighting the sample based on nationally representative administrative data (SI section 4.2); and applying entropy balancing (SI sections 4.3.2, and 4.3.3). We also conduct a sensitivity analysis following Cinelli and Hazlett[9] to assess the robustness of our estimates to potential unobserved confounding (see SI section 4.4).

Table A.4: Upward Mobility in the Green Sector

	Managerial Occupation		Science and Engineering Occupation	
	Model1	Model2	Model3	Model4
Green Sector	1.401***	1.381***	1.752***	2.936***
	(0.029)	(0.038)	(0.031)	(0.040)
Construction Sector	0.149**	-0.112	0.118*	1.074***
	(0.045)	(0.094)	(0.050)	(0.087)
Manufacturing Sector	0.731***	0.693***	0.478***	1.046***
	(0.027)	(0.051)	(0.030)	(0.051)
Other Sectors	0.583***	0.365***	0.549***	1.293***
	(0.030)	(0.035)	(0.032)	(0.035)
College Dummy	0.180***		1.178***	
	(0.016)		(0.051)	
Gender Dummy	-0.079***		-0.249***	
	(0.021)		(0.024)	
Wage in Prior Job	0.924***	0.119***	0.799***	0.117***
	(0.012)	(0.024)	(0.022)	(0.026)
Year Entering Job Market	Yes	No	Yes	No
Individual Fixed Effect (FE)	No	Yes	No	Yes
Year FE	No	Yes	No	Yes
Origin State FE	No	Yes	No	Yes
Destination State FE	No	Yes	No	Yes
McFadden's Pseudo R2s	0.093	0.577	0.165	0.677
N. of observations	631,008	443,174	631,008	443,174

Notes:

[1] The observations are job switches of frontline fossil fuel (FFF) workers in 2000-2023. We estimate pooled models (columns 1 and 3) and fixed effect models (columns 2 and 4). Green sector, construction sector, manufacturing sector, and other sectors are dummy variables indicating the target sector into which FFF workers make their job switch. The omitted sector is the fossil fuel sector. The sector classifications are based on a combination of 2-digit NAICS codes and SOC codes (See Methods section 6.1). Wage in Prior Job is the wage of the worker in the prior job. Year Entering the Job Market indicates the first year a worker enters the job market. This captures the market conditions at the start of a worker's career that can have longer term influence on their careers. The fixed-effects model accounts for individual fixed effects, the state of the prior job, the state of the destination job, and the years in which job switches occur.

[2] *p<.10; **p<.05; ***p<.01.

3.2 Wage Increases and the Shift to the Green Sector

We use the same specification as in Model eq.1 to estimate average wage gains associated with upward mobility. Specifically, we examine wage changes when a given worker, at some point in their careers, enter a managerial or S&E position in the green sector versus other sectors. The reference group of all models is the average wage of FFF occupations. The observations are FFF workers' job switches in 2000-2023. The outcome $y_{i,t}$, is the inflation-adjusted log wages of individual i when switch to the target sector at time t. We augment the baseline model with an indicator for occupation type, SE (Managerial) $\text{Occupation}_{i,t}$ and the interaction variables, $Sector_{i,t} \times \text{SE (Managerial) Occupation}_{i,t}$, to allow wage effects to differ across managerial and S&E roles.

The full regression results are presented in Table A.5. Model 2 and 4 include individual and year fixed effects, which allow us to interpret the estimates as wage changes when a given worker switches across sectors. Individual fixed effects also control for time-invariant unobservables that may jointly influence a worker's decision to transition into the green sector and their associated wage outcomes. In addition,

we include state fixed effects to absorb persistent geographical factors that could affect wage levels.

Fig. 2A presents the results from model 4, with the full set of control variables. The predicted percentage wage increases when a job switch to managerial positions in the green sector, relative to staying in frontline fossil fuel jobs, are estimated by exponentiating the difference between the predicted wages when transitioning into managerial positions in the green sector and staying in frontline fossil fuel occupations. The predicted wage increases when FFF workers obtain a SE occupation in the green sector is calculated analogously.

We conduct multiple robustness check to support our finding, including alternative definitions of green occupations (SI section 4.1), models that account for additional potential confounders (SI section 4.3.1), sample reweighting based on nationally representative administrative data (SI section 4.2), and regressions based entropy balancing (SI section 4.3.2).

Table A.5: Green Transition and Wages

Outcome variable: log(Wages)				
	Model 1	Model 2	Model 3	Model 4
Green Sector	0.125***	0.064***	-0.002	0.010***
	(0.004)	(0.002)	(0.005)	(0.002)
Construction Sector	-0.097***	-0.004	-0.125***	-0.016***
	(0.004)	(0.004)	(0.005)	(0.004)
Manufacturing Sector	-0.034***	-0.006**	-0.070***	-0.024***
	(0.003)	(0.003)	(0.003)	(0.003)
Other Sectors	-0.049***	-0.013***	-0.083***	-0.027***
	(0.004)	(0.002)	(0.003)	(0.002)
Managerial Occupation			0.436***	0.136***
			(0.005)	(0.004)
Science & Engineering Occupation			0.319***	0.133***
			(0.004)	(0.004)
Green Sector× Managerial			-0.114***	0.010*
			(0.005)	(0.006)
Green Sector× Science & Engineering Occupation			0.060***	0.033***
			(0.007)	(0.005)
Construction Sector× Managerial Occupation			-0.061**	0.004
			(0.024)	(0.017)
Construction Sector× Science & Engineering Occupation			0.029**	0.015
			(0.014)	(0.013)
Manufacturing Sector× Managerial Occupation			-0.013**	0.027***
			(0.006)	(0.008)
Manufacturing Sector× Science & Engineering Occupation			0.036***	0.027***
			(0.007)	(0.007)
Other Sectors× Managerial Occupation			-0.099***	-0.008
			(0.006)	(0.005)
Other Sectors× Science & Engineering Occupation			0.092***	0.018***
			(0.007)	(0.005)
Individual FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Origin State FE	Yes	Yes	Yes	Yes
Destination State FE	Yes	Yes	Yes	Yes
R2 Adj.	0.142	0.580	0.223	0.595
N. of observations	442,216	442,216	441,036	441,036

Notes:

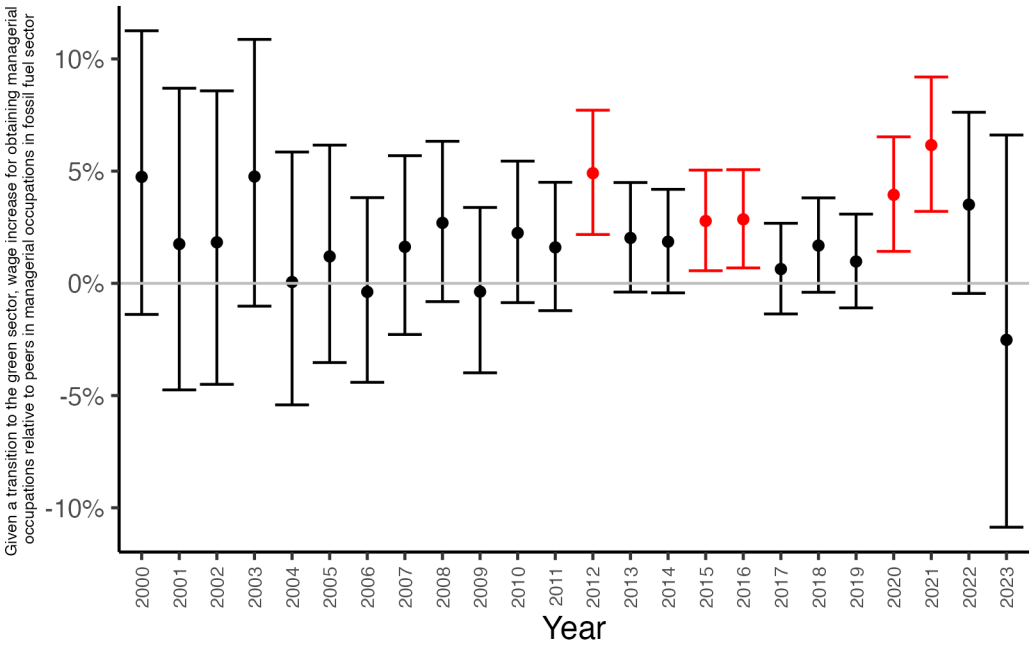
[1] The observations are job switches of frontline fossil fuel workers in 2000-2023. Green sector, construction sector, manufacturing sector, and other sectors are dummy variables indicating the target sector into which frontline fossil fuel (FFF) workers make their job switch. The omitted sector is the fossil fuel sector. The sector classifications are based on a combination of 2-digit NAICS codes and SOC codes (See Method Section 6.1). The managerial occupation dummy variable indicates the job switch is into a managerial occupation. The science and engineering occupation dummy variable indicates the job switch is into a science or engineering occupation. The models include individual fixed effects, the state of the prior job, the state of the destination job, and the years in which job switches occur.

[2] *p<.10; **p<.05; ***p<.01.

3.3 Wage Increases and the Shift to the Green Sector by Year

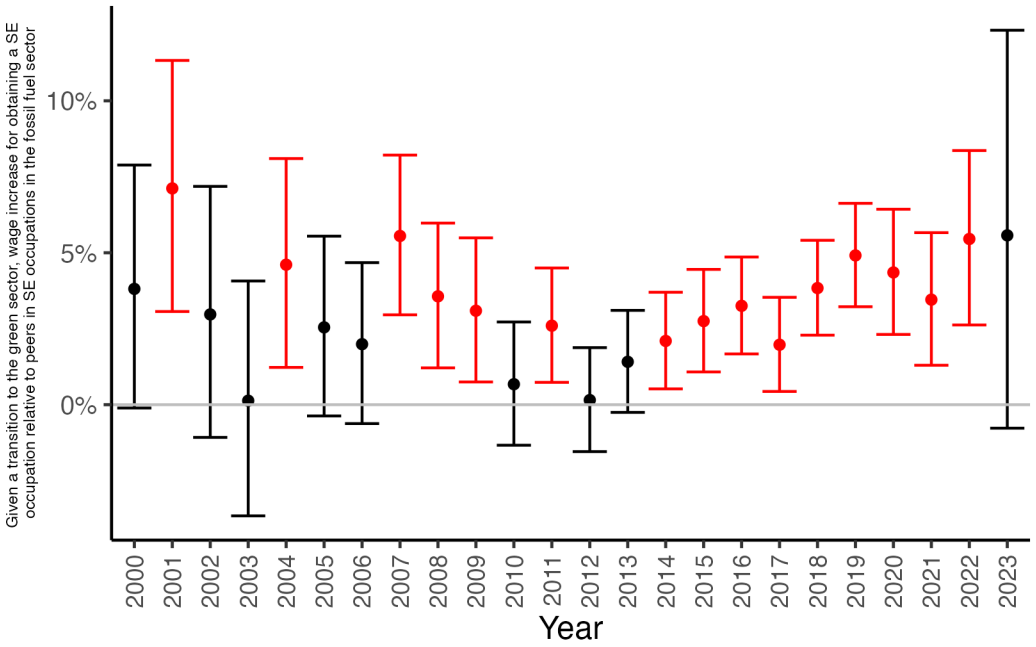
Fig. 2A in the main paper presents the average wage increase when a FFF worker switch to green sector and obtain managerial or SE positions. In this section, we examine how these wage gains vary by year by comparing the predicted wage change from obtaining managerial or SE positions in the green sector versus obtaining the same occupations while remaining in the fossil fuel sector. For a given worker, wages are consistently higher when holding SE occupations in the green sector than when holding the same SE occupations in the fossil fuel sector over 2000–2023 (Fig. A.2). In 2022, this premium is approximately 5% (Fig. A.2).[3] By contrast, the wage difference for a given worker holding managerial occupations in the green versus fossil fuel sector is positive in only five years, 2012, 2015, 2016, 2020, and 2021, during 2000–2023 (see Fig. A.1).

Fig. A.1: Wage Increases When a Given Worker Holds Managerial Occupations in the Green Sector Relative to the same positions in the Fossil Fuel Sector



[3]The 2023 estimates are imprecise due to the smaller number of observations.

Fig. A.2: Wage Increases When a Given Worker Holds SE Occupations in the Green Sector Relative to the same positions in the Fossil Fuel Sector

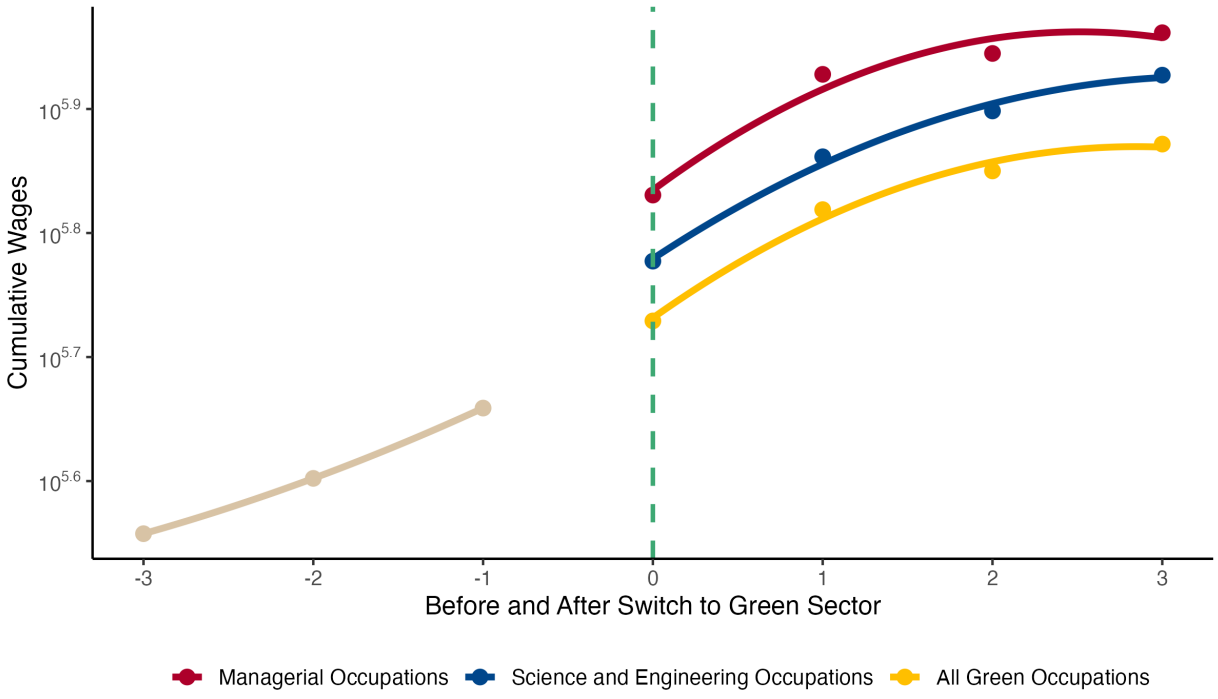


3.4 Cumulative Wages and the Shift to the Green Sector

Figure A.3 plots cumulative wage changes before and after a worker's transition to the green sector. We examine all workers who, at any point in their careers, transitioned to the green sector. The figure follows the structure of an event study plot: negative values on the x-axis represent job switches before the green transition, while positive values indicate switches occurring afterward. The y-axis reports cumulative wages, calculated as the product of years spent in a job and the average annual wage in that job. The green vertical line marks the transition into the green sector, and different colors represent the various occupations workers held. The grey line to the left of the transition shows the cumulative average wage trajectory prior to entry, while the red, blue, and orange lines to the right correspond to workers who obtain managerial positions, science and engineering roles, and the average for all green jobs, respectively. Notably, after entering the green sector, workers may switch to other green jobs or to jobs in the construction or manufacturing sectors.

The figure shows a sharp upward shift in cumulative wages at the point of transition, with the largest gains for workers moving into managerial positions, followed by those in science and engineering occupations. Taken together with the empirical evidence in section 3.2, these results indicate that upward mobility within the green sector not only provides an immediate wage increase for fossil fuel workers, but also yields a sustained, career-long boost in cumulative earnings.

Fig. A.3: Cumulative Wages Before and After Transition to the Green Sector



To more rigorously examine the relationship between cumulative wages and sector transitions, we use the regression model eq.2 that controls for workers' work experience (represented by the year they entered the job market), education level, and gender. Our outcome variable is the average cumulative wage, calculated by summing a worker's annualized, inflation-adjusted wages across all jobs up to a given

point in their career and then taking the mean. This approach isolates the effect of wage growth by removing the influence of job duration and the number of job transitions.

$$\begin{aligned}\text{Cumulative Wage}_i = &\beta_1 \text{Green Sector}_i + \beta_2 \text{Construction Sector}_i \\ &+ \beta_3 \text{Manufacturing Sector}_i + \beta_4 \text{Other Sectors}_i \\ &+ Z_i'\Gamma + \epsilon_i\end{aligned} \qquad \text{(eq.2)}$$

Different from eq.1, eq.2 compares average cumulative wages across workers based on whether they ever transition into a given sector at any point in their careers, regardless of the timing or number of switches. Accordingly, Green Sector$_i$ is an indicator equal to one if worker i ever transitions into the green sector during the observation window (and zero otherwise). Construction Sector$_i$ and Manufacturing Sector$_i$ are defined analogously. Fossil fuel sector serves as the omitted reference category. Z_i is a vector of time-invariant individual characteristics (e.g., gender and highest degree), and ϵ_i is an idiosyncratic error term. Coefficients β_1–β_4 therefore quantify differences in average cumulative wages relative to the reference group of workers who never transition into the focal sectors.

To account for the contribution of upward mobility to career-wide wage differences, we add controls for whether a worker ever enters a managerial occupation or an SE occupation. With these controls included, the coefficient on green sector transition captures the net career-wide wage difference associated with switching into the green sector, beyond the portion explained by upward mobility into managerial or SE roles (Model 2 in Table A.6). To further examine cumulative wage differences across sectors and occupations, we estimate an additional model that includes indicators for whether a worker ever transitions into the green, construction, or manufacturing sector and reaches a managerial or SE position at any point in the worker's career (Model 3 in Table A.6).

Model 1 Table A.6 shows a clear and statistically significant effect for workers who have ever transitioned into the green sector. The coefficient of 0.097 indicates that, over a career, a transition to the green sector increases a worker's cumulative wages by approximately 10% ($(exp(0.097) - 1) * 100$). After controlling for upward-mobility occupations, this association decreases to 2%, but still statistically significant. Model 3 further investigates the impact of specific occupations within these industries (results are shown in the main paper Fig. 2B). Among workers who achieve managerial positions, those in the fossil fuel sector maintain a considerable wage premium of 20%, which is larger than the 13% premium observed for their green sector counterparts. This finding suggests a persistent managerial wage advantage within the fossil fuel industry. By contrast, science and engineering roles display the opposite pattern: workers in these occupations earn 12% more than the average FFF workers when in the fossil fuel sector, but 18% more when in the green sector.

Taken together, the evidence suggests that the overall cumulative wage premium associated with transitioning to the green sector, as shown in Model 1 and 2, is largely driven by greater upward mobility into higher-paying occupations. This effect persists despite the fact that managerial positions in the fossil fuel sector offer substantially higher wages than comparable positions in the green sector.

Table A.6: Green Transition and Cumulative Average Earnings

Outcome Var.: log(Cumulative Average Wages)			
	Model1	Model2	
Green Sector	0.097***	0.016***	
	(0.002)	(0.002)	
Construction Sector	-0.067***	-0.062***	
	(0.003)	(0.003)	
Manufacturing Sector	-0.032***	-0.045***	
	(0.002)	(0.002)	
Other Sectors	-0.038***	-0.055***	
	(0.002)	(0.002)	
Managerial Occupation		0.140***	
		(0.002)	
Science and Engineering Occupation		0.186***	
		(0.002)	
Managerial Occupation in Fossil Fuel Sector			0.178***
			(0.004)
Science and Engineering Occupation in Fossil Fuel Sector			0.113***
			(0.003)
Managerial Occupation in Green Sector			0.125***
			(0.002)
Science and Engineering Occupation in Green Sector			0.162***
			(0.002)
Managerial Occupation in Construction Sector			0.085***
			(0.013)
Science and Engineering Occupation in Construction Sector			0.013
			(0.010)
Managerial Occupation in Manufacturing Sector			0.100***
			(0.005)
Science and Engineering Occupation in Manufacturing Sector			0.062***
			(0.005)
Managerial Occupation in Other Sectors			0.082***
			(0.003)
Science and Engineering Occupation in Other Sectors			0.119***
			(0.002)
College Degree	0.172***	0.113***	0.112***
	(0.002)	(0.002)	(0.002)
Male	0.006*	0.018***	0.019***
	(0.003)	(0.003)	(0.003)
Year Entering Job Market	Yes	Yes	
N. of observations	123,260	121,569	121,482

Notes:

[1] Green sector, construction sector, manufacturing sector, and other sectors are dummy variables indicating the target sector into which frontline fossil fuel (FFF) workers make their job switch. The omitted sector in model 1 is the fossil fuel sector. The sector classifications are based on a combination of 2-digit NAICS codes and SOC codes (See Method Section). The managerial occupation variable in each targeted sector is a dummy indicating whether a worker switches into a managerial role in that industry at any point in their career. The definition of science and engineering occupations in each sector follows the same approach. All models include fixed effects for the year of labor market entry, the state of the prior job, the state of the destination job, and the two-digit major occupation.

[2] *p<.10; **p<.05; ***p<.01.

3.5 Construction of the Skill Diversity and Skill Deepening Variables

We construct the skill diversity and skill deepening variables with the following steps. First, we obtain knowledge, skill, and ability requirement from O*NET database and represent them as a matrix (M), where each raw is an occupation and each column is a skill. We define $M_{js} = 1$ if job j requires skill s and its normalized importance score greater than the average importance in all occupations, and $M_{js} = 0$ otherwise. Second, following Aufiero et al. [1], we use eq.3 and eq.4 to compute similarity between two jobs j and j', and similarity between two skills s and s'.

$$B_{\text{Jobs}_{jj'}} = \frac{1}{\max(d_j, d_{j'})} \sum_s \frac{M_{js} M_{j's}}{u_s} \tag{eq.3}$$

$$B_{\text{Skills}_{ss'}} = \frac{1}{\max(u_s, u_{s'})} \sum_j \frac{M_{js} M_{js'}}{d_j} \tag{eq.4}$$

Where: $d_j = \sum_s M_{js}$ is the diversification of job j, representing how many different skills it requires. $u_s = \sum_j M_{js}$is the ubiquity of skill s, representing how common the skill is across different jobs.

Here, $B_{jj'}$ measures the similarity between each pair of occupations. To quantify dissimilarity, we use $1 - B_{jj'}$, where a higher value indicates greater dissimilarity between occupations. We then compute the average cumulative job dissimilarity based on workers' career histories to construct a measure of skill diversity.

We implement the following approach to calculate the managerial and SE skill deepening. First, we identify core managerial (SE) skills by comparing skill importance in managerial (SE) occupations to their importance in all other occupations. Skills that exhibit significantly higher importance in managerial (SE) occupations are classified as core managerial (SE) skills. Second, we compute the average managerial (SE) skill relatedness for each occupation using eq.5, which corresponds to the coherence score in economic complexity literature:

$$AB_j = \frac{\sum_{s,s'} M_{js} M_{js'} B_{ss'}}{\sum_{s,s'} M_{js} M_{js'}} \tag{eq.5}$$

It is important to note that M_{js} and $B_{ss'}$ represent subsets of the job-skill matrix (M) and the skill relatedness matrix, respectively, depending on whether the analysis focuses on managerial or SE occupations. For example, when calculating the average skill relatedness for managerial occupations, we consider only the subset of M_{js} corresponding to managerial positions and subset $B_{ss'}$ to include only managerial core skills. This approach ensures that AB_j captures the degree of interrelatedness among skills within a specific occupational domain. A higher value of AB_j indicates stronger interrelatedness among managerial (SE) skills within a given occupation.

After the average managerial (SE) skill relatedness is computed for each occupation, we measure changes in managerial (SE) skill relatedness between job transitions in workers' career histories. This change serves as a measure for managerial (SE) skill deepening. The underlying intuition is that if a worker consistently develops skills related to managerial (SE) roles, their skill relatedness should increase significantly over successive job transitions.

3.6 Skill Diversity, Skill Deepening and Upward Mobility in the Green Sector

We use the following model specification with logistic regression, where $y_{i,t}$ is the dummy for SE (managerial) occupation for models estimating the probability of entering SE (managerial) occupations (SI Table A.7). For the managerial occupation model, we add the interaction variable $Green\ Sector_{i,t} \times Skill\ Diversity_{i,t}$ and $Green\ Sector_{i,t} \times Managerial\ Skill\ Deepening_{i,t}$. For the SE occupation model, we add the variable $Green\ Sector_{i,t} \times Skill\ Diversity_{i,t}$ and $Green\ Sector_{i,t} \times SE\ Skill\ Deepening_{i,t}$.

$$\begin{aligned} y_{i,t} =& \beta_1 Green\ Sector_{i,t} + \beta_2 Manufacturing\ Sector_{i,t} \\ &+ \beta_3 Construction\ Sector_{i,t} + \beta_4 Other\ Sector_{i,t} \\ &+ \beta_5 Skill\ Diversity_{i,t} + \beta_6 Skill\ Deepening_{i,t} \\ &+ \mu_i + \lambda_t + \delta_o + \tau_d + \epsilon_{it} \end{aligned} \tag{eq.6}$$

Fig. 3B and 3C in the main paper report the association between skill diversity and the probability of obtaining managerial or SE occupations and the association between managerial skill deepening or SE skill deepening and the probability of obtaining managerial or SE occupations. The full regression results are presented in Table A.7. Model 1 and 2 examines the association between skill diversity (managerial skill deepening) and the probability of obtaining managerial occupations. Model 3 and 4 examines the association between skill diversity (SE skill deepening) and the probability of obtaining SE occupations in the green sector.

Individual fixed effects control for time-invariant confounders, such as talent, persistent preferences for certain occupations, and education level. SI section 4.3.1 introduces additional measures to address potential confounding, including controls for an occupation's importance within job networks and time-varying skill differences accumulated over a worker's career. SI 5 provides Jaccard similarity as an alternative measure of skill diversity and deepening as a sensitivity test. Results remain consistent with those reported in Table A.7.

Table A.7: Skill Diversity, Skill Deepening and Upward Mobility in the Green Sector

	Managerial Occupation		Science and Engineering Occupation	
	Model1	Model2	Model3	Model4
Green Sector	-0.160	1.415***	9.566***	3.227***
	(0.289)	(0.051)	(0.306)	(0.045)
Construction Sector	-0.036	-0.684***	1.191***	1.256***
	(0.100)	(0.123)	(0.093)	(0.095)
Manufacturing Sector	0.738***	0.466***	1.122***	1.107***
	(0.054)	(0.065)	(0.054)	(0.056)
Other Sectors	0.424***	-0.100**	1.413***	1.456***
	(0.037)	(0.043)	(0.038)	(0.038)
Skill Diversity	0.715*		-4.903***	
	(0.392)		(0.420)	
Managerial Skill Deepening		9.638***		
		(0.179)		
Science and Engineering Skill Deepening				4.572***
				(0.263)
Green Sector*Skill Diversity	2.933***		-11.122***	
	(0.491)		(0.521)	
Green Sector*Managerial Skill Deepening		-1.765***		
		(0.321)		
Green Sector*Science and Engineering Skill Deepening				2.896***
				(0.478)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Origin State FE	Yes	Yes	Yes	Yes
Destination State FE	Yes	Yes	Yes	Yes
McFadden's Pseudo R2s	0.602	0.645	0.698	0.700
N. of observations	418,457	354,622	418,457	405,774

Notes:

[1] The observations are job switches of frontline fossil fuel (FFF) workers in 2000-2023. Green sector, construction sector, manufacturing sector, and other sectors are dummy variables indicating the target sector into which FFF workers make their job switch. The omitted sector is the fossil fuel sector. The sector classifications are based on a combination of 2-digit NAICS codes and SOC codes (See Methods Section 6.1). We calculate (1) the SE skill deepening index, measured prior to a job switch, which captures workers' accumulation of SE skills by taking on jobs with greater core SE skills requirements; (2) the managerial skill deepening index, defined analogously; and (3) the skill diversity index, measured prior to a job switch, which captures workers' accumulation of diverse skills by taking on jobs with greater differences in skill requirements (see Methods section 6.2 and SI section 3.5).The models include individual fixed effects, the state of the prior job, the state of the destination job, and the years in which job switches occur fixed effects.

[2] *p<.10; **p<.05; ***p<.01.

3.7 R-learner Approach for Estimating Heterogeneity

We use the R-learner approach to estimate heterogeneous treatment effects[38]. The first step in the R-learner involves estimating the conditional expectation of the outcome Y given the covariates X: $\hat{m}(X) = \mathbb{E}[Y \mid X]$. Next, the R-learner estimates the propensity score by estimating equation $\hat{e}(X) = \mathbb{P}(W = 1 \mid X)$, where W indicate the treatment status. Using the outcome and propensity score models, residuals are then calculated for both the outcome and the treatment:$\tilde{Y}_i = Y_i - \hat{m}(X_i)$ and $\tilde{W}_i = W_i - \hat{e}(X_i)$. Finally, the R-learner estimates the heterogeneous treatment effect $(\tau(X))$ by regressing the outcome residuals $\tilde{Y}$ on the treatment residuals $\tilde{W}$. This is done by solving the following minimization problem:

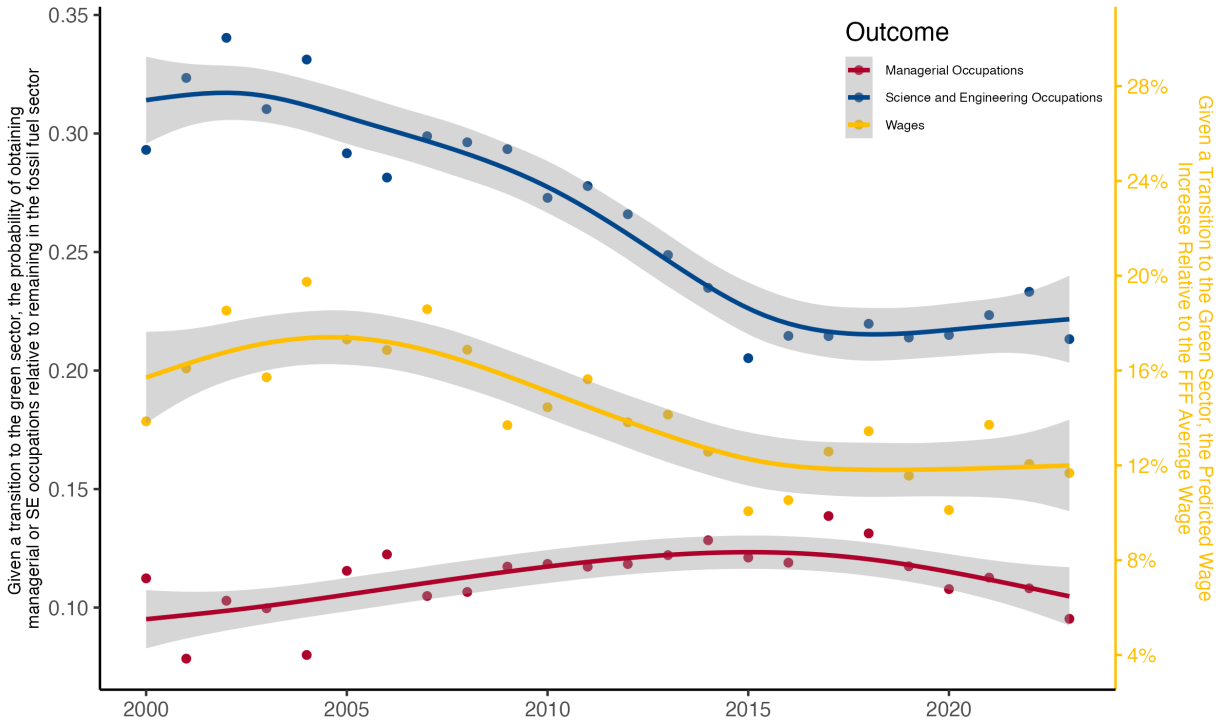
$$\hat{\tau}(X) = \arg\min_{\tau} \sum_{i} \left(\tilde{Y}_i - \tau(X_i)\tilde{W}_i\right)^2 + \lambda\mathcal{R}(\tau)$$

where $\lambda\mathcal{R}(\tau)$ is a regularization term that helps prevent overfitting.

In our paper, the treatment variable is a dummy variable for a job switch into the green sector. The control variables are workers' wages in their previous jobs, their highest level of education, gender, and the year they switched jobs. Additionally, lasso regression with 5-fold cross-validation is used to estimate the conditional expectation of the outcome Y and propensity score $\hat{e}(X)$.

The R-learner approach provides heterogeneous treatment effects for each individual in the dataset. To analyze trends over time, we calculate the average heterogeneous treatment effect for workers based on their job-switching year. Finally, we plot the average heterogeneous treatment effects by year in Fig. A.4B.

Fig. A.4: Effects of Transition to the Green Sector on Occupational Mobility and Wage Increases Over Time



Workers have a greater probability of moving to SE and managerial occupations

throughout the 2000-2023 period (see Fig. A.4). Nevertheless, the probability of FFF workers in the green sector securing SE occupations increases briefly in 2000-2002 and declines in 2003-2015 before stabilizing in the 2016-2023 period. In 2023, FFF workers in the green sector had a 21% probability to secure SE occupations relative to remaining in the fossil fuel sector. Unlike the shifts to SE occupations, the probability of shifting to managerial occupations in the green sector increases for a longer period (2000-2018) and declines later in 2019-2023. In 2023, FFF workers in the green sector had a 10% probability to secure managerial occupations.

Workers who secure occupations in green sector continue to enjoy a wage premium relative to the FFF average wages throughout 2000-2023, though that wage premium peaked at 20% in 2004 and declined to 13% by 2023 (see Fig. A.4). That smaller wage premium provides a weaker short-term incentive for FFF workers despite increased upward mobility over a career after a transition to the green sector.

4 Robustness Checks for Regression Estimates

To ensure the reliability of our findings, we conducted several robustness checks. In section 4.1, we demonstrate that the relationship between transitioning to the green sector and upward mobility into managerial or science and engineering occupations is not sensitive to alternative definitions of green occupations. We also implemented various statistical methods to address potential biases in our regression estimates. Specifically, we re-weight our data to reduce bias from sample selection issues in section 4.2. Furthermore, sections 4.3, 4.5, and 4.6 describe our approaches to mitigate the bias that can arise from workers' self-selection into the green sector. The results of our main regressions remain robust across all these checks.

4.1 Alternative Definitions of the Green Occupations

We use four alternative definitions of green occupations to re-estimate the core models reported in the main paper (Fig. 1B and 2A). Starting from the Bureau of Labor Statistics' classification of green sector occupations, we construct an initial list of core green occupations and expand it by incorporating additional matches identified through keyword searches of job titles and company names in the resume data, as well as by including workers employed at leading firms in green industries.

4.1.1 Approach 1: O*NET Green Core Occupations

Table A.8: List of Green Occupations Using Alternative Definition Approach 1

O*NET	Occupation	O*NET	Occupation
11-1011.03	Chief Sustainability Officers	17-3023.00	Electrical and Electronic Engineering Technologists and Technicians
11-3051.02	Geothermal Production Managers	17-3026.00	Industrial Engineering Technologists and Technicians
11-3051.03	Biofuels Production Managers	17-3029.08	Photonics Technicians
11-3051.04	Biomass Power Plant Managers	19-2041.01	Climate Change Policy Analysts
11-3051.06	Hydroelectric Production Managers	19-2041.02	Environmental Restoration Planners
11-9021.00	Construction Managers	19-2041.03	Industrial Ecologists
11-9041.00	Architectural and Engineering Managers	19-3011.01	Environmental Economists
11-9041.01	Biofuels/Biodiesel Technology and Product Development Managers	19-4051.00	Nuclear Technicians
11-9121.02	Water Resource Specialists	41-4011.07	Solar Sales Representatives and Assessors
11-9199.09	Wind Energy Operations Managers	47-1011.03	Solar Energy Installation Managers
11-9199.10	Wind Energy Development Managers	47-2061.00	Construction Laborers
11-9199.11	Brownfield Redevelopment Specialists and Site Managers	47-2111.00	Electricians
13-1199.05	Sustainability Specialists	47-2152.04	Solar Thermal Installers and Technicians
17-1011.00	Architects, Except Landscape and Naval	47-2231.00	Solar Photovoltaic Installers
17-2031.00	Bioengineers and Biomedical Engineers	47-4011.01	Energy Auditors
17-2041.00	Chemical Engineers	47-4099.00	Construction and Related Workers, All Other
17-2051.00	Civil Engineers	47-4099.03	Weatherization Installers and Technicians
17-2071.00	Electrical Engineers	49-9021.00	Heating, Air Conditioning, and Refrigeration Mechanics and Installers
17-2141.00	Mechanical Engineers	49-9081.00	Wind Turbine Service Technicians
17-2141.01	Fuel Cell Engineers	49-9098.00	Helpers–Installation, Maintenance, and Repair Workers
17-2141.02	Automotive Engineers	49-9099.01	Geothermal Technicians
17-2161.00	Nuclear Engineers	51-8012.00	Power Distributors and Dispatchers
17-2199.03	Energy Engineers, Except Wind and Solar	51-8013.03	Biomass Plant Technicians
17-2199.10	Wind Energy Engineers	51-8099.01	Biofuels Processing Technicians
17-2199.11	Solar Energy Systems Engineers		

We construct a core list of green occupations using Bureau of Labor Statistics data from the following sectors: (1) solar, (2) wind, (3) biofuels, (4) geothermal, (5) clean energy, and (6) sustainability.[4] To ensure that this list reflects occupations directly tied to the green sector, we exclude certain roles whose connection is indirect or peripheral, including landscape architects (SOC 17-1012.00), aerospace engineers (SOC 17-2011.00), aerospace engineering and operations technologists and technicians (SOC 17-3021.00), range manager (SOC 19-1031.02), urban and regional planners (SOC 19-3051.00), agricultural technicians (SOC 19-4012.00), sales representatives

[4] Access at: https://www.onetonline.org/search/green_topics/

(SOC 41-4011.00), plumbers (SOC 47-2152.00), and roofers (SOC 47-2181.00). The resulting set of core green occupations is presented in Table A.8.

We redefine our green transition variable following the above criteria and re-estimate the relationship between switching to the green sector and upward mobility. The results are presented in Table A.9. To enable a direct comparison with our original findings, we apply the same method to plot the predicted probability of obtaining managerial or science and engineering positions in each sector (Fig. A.5), as well as the associated wage gains relative to the average fossil fuel wage upon entering these roles (Fig. A.6).

Overall, we find that, over the course of a worker's career, transitioning to the green sector remains associated with a higher likelihood of upward mobility in both occupational advancement and wage growth, compared with job switches that remain within the fossil fuel sector. Under the revised definition, the magnitude of this mobility is even greater than reported in our main analysis. As shown in Fig.A.5, for a given worker after transitioning to the green sector, the predicted probability of holding a SE occupation is approximately 27.5%, compared with 26% in our main specification. The corresponding predicted increase in managerial attainment is 23%, compared with 14% in the main analysis. Consistent with these patterns, Fig.A.6 shows larger estimated wage gains for a given worker when holding upwardly mobile jobs, relative to the estimates reported in the main paper.

Table A.9: Robustness Check for Main Results Using Alternative Definition of Green Occupations (Approach 1)

	Managerial Occupations	Science and Engineering Occupations	log(Wages)
Green Sector	3.433***	2.010***	-0.071***
	(0.048)	(0.037)	(0.005)
Construction Sector	0.040	-0.316***	-0.029***
	(0.091)	(0.079)	(0.003)
Manufacturing Sector	0.801***	-0.324***	-0.033***
	(0.049)	(0.044)	(0.003)
Other Sectors	0.441***	0.023	-0.035***
	(0.031)	(0.028)	(0.002)
Managerial Occupation			0.123***
			(0.004)
Science and Engineering Occupation			0.128***
			(0.003)
Green Sector*Managerial Occupation			0.103***
			(0.007)
Green Sector*Science and Engineering Occupation			0.135***
			(0.006)
Construction Sector*Managerial Occupation			0.021
			(0.016)
Construction Sector*Science and Engineering Occupation			0.024*
			(0.013)
Manufacturing Sector*Managerial Occupation			0.040***
			(0.007)
Manufacturing Sector*Science and Engineering Occupation			0.033***
			(0.006)
Other Sectors*Managerial Occupation			0.004
			(0.005)
Other Sectors*Science and Engineering Occupation			0.024***
			(0.004)
Individual FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Origin State FE	Yes	Yes	Yes
Destination State FE	Yes	Yes	Yes
N. of observations	443,174	443,174	441,036

Notes:

[1] The observations are job switches of frontline fossil fuel (FFF) workers in 2000-2023. Green sector, construction sector, manufacturing sector, and other sectors are dummy variables indicating the target sector into which FFF workers make their job switch. The omitted sector is the fossil fuel sector. The sector classifications are based on a combination of 2-digit NAICS codes and SOC codes (See Methods section 6.1). The managerial occupation dummy variable indicates the job switch is into a managerial occupation. The science and engineering occupation dummy variable indicates the job switch is into a science or engineering occupation. The fixed-effects accounts for individual fixed effects, the state of the prior job, the state of the destination job, and the years in which job switches occur.

[2] *p<.10; **p<.05; ***p<.01.

Fig. A.5: Upward Mobility to Managerial and Science and Engineering Occupations Using Alternative Definition of Green Occupations (Approach 1)

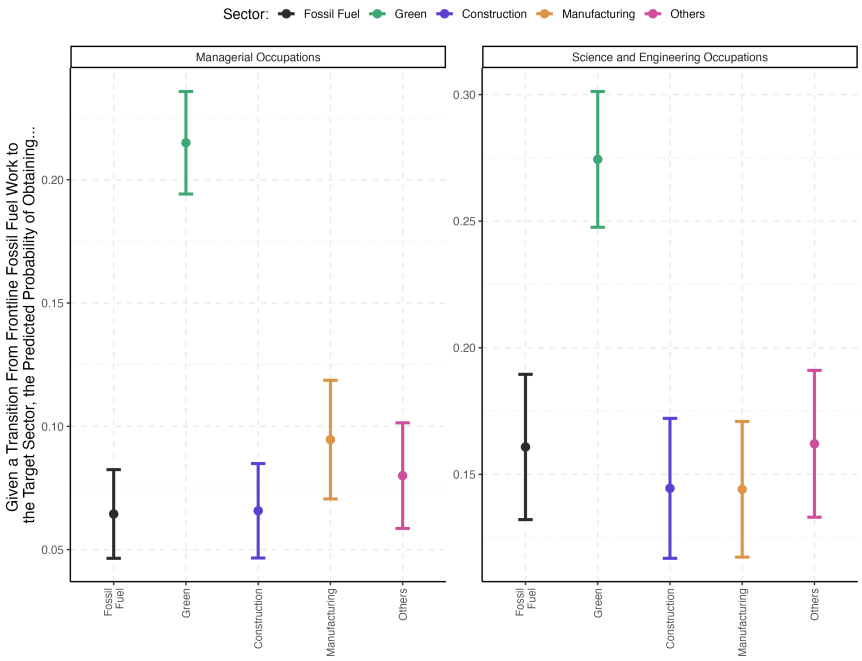
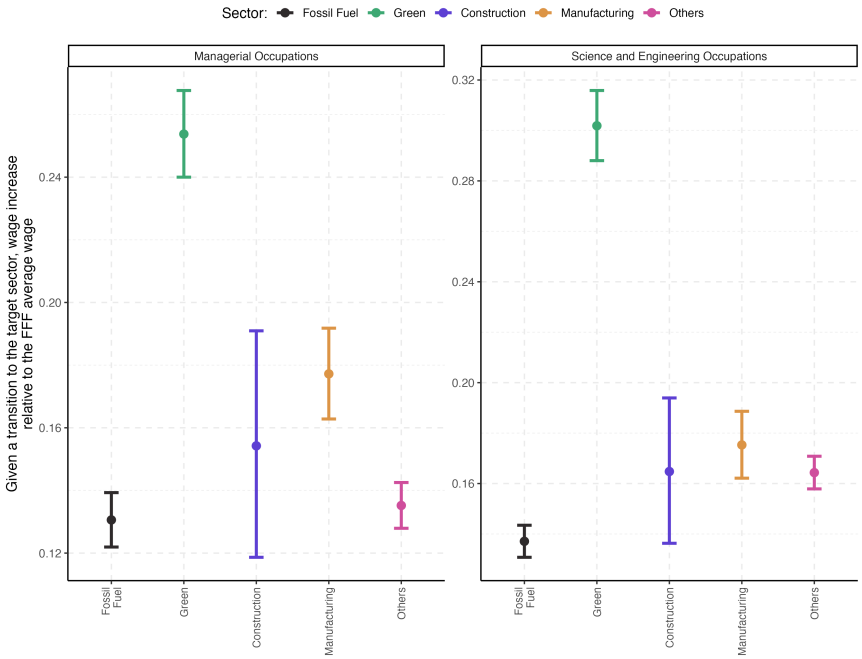


Fig. A.6: Wage Increase Using Alternative Definition of Green Occupations (Approach 1)



4.1.2 Approach 2: O*NET Green Core Occupations + Key Word Search on Job Titles

Building on the approach of Curtis, O'Kane and Park[14], which use keyword searches of job titles to identify green occupations, the second alternative definition extends Approach 1 by incorporating a keyword search of job titles in the resume data. The Revelio resume dataset provides raw job titles for each position a worker has held. Using these titles, we classify an occupation as green if it contains any of the predetermined keywords. This list was constructed by combining key terms from Curtis, O'Kane and Park[14], such as "solar," "photovoltaic," "wind turbine," and "wind energy", with additional keywords extracted from the job titles of core green occupations in Table A.8, as well as terms generated using ChatGPT, which was prompted to suggest industry-specific keywords to ensure broader coverage.

Using this expanded definition, we re-estimate the model. The regression results are reported in Table A.11 and Fig. A.7 and A.8 plot predicted probability. The findings are consistent with those from the first approach, though slightly smaller in magnitude, reaffirming that transitioning to the green sector increases the likelihood of upward mobility for a given FFF worker.

Table A.10: List of Green Key Words

Sector	Keyword	Sector	Keyword
Green energy	solar	EV	electric vehicle
Green energy	wind	EV	EV charging
Green energy	hydro	EV	EV infrastructure
Green energy	geothermal	EV	charging station
Green energy	renewable	EV	EV technician
Green energy	fuel cell	EV	EV manufacturing
Green energy	nuclear	EV	EV supply chain
Green energy	biofuels	EV	vehicle electrification
Green energy	biomass	EV	EV engineer
Green energy	energy efficiency	EV	battery electric vehicle
Battery	battery	EV	plug-in hybrid
Battery	battery engineer	EV	zero-emission vehicle
Battery	battery technician	EV	EV design
Battery	battery manufacturing	EV	EV software
Battery	grid storage	EV	mobility electrification
Battery	battery assembly	EV	EV maintenance
Battery	battery production	EV	EV systems
EV	EV	EV	EV testing

Table A.11: Robustness Check for Main Results Using Alternative Definition of Green Occupations (Approach 2)

	Managerial Occupations	Science and Engineering Occupations	log(Wages)
Green Sector	3.356***	1.975***	-0.060***
	(0.047)	(0.037)	(0.005)
Construction Sector	0.034	-0.315***	-0.029***
	(0.090)	(0.079)	(0.003)
Manufacturing Sector	0.796***	-0.325***	-0.032***
	(0.049)	(0.044)	(0.003)
Other Sectors	0.444***	0.025	-0.035***
	(0.031)	(0.028)	(0.002)
Managerial Occupation			0.123***
			(0.004)
Science and Engineering Occupation			0.129***
			(0.003)
Green Sector*Managerial Occupation			0.093***
			(0.007)
Green Sector*Science and Engineering Occupation			0.123***
			(0.006)
Construction Sector*Managerial Occupation			0.020
			(0.016)
Construction Sector*Science and Engineering Occupation			0.024*
			(0.013)
Manufacturing Sector*Managerial Occupation			0.040***
			(0.007)
Manufacturing Sector*Science and Engineering Occupation			0.033***
			(0.006)
Other Sectors*Managerial Occupation			0.004
			(0.005)
Other Sectors*Science and Engineering Occupation			0.023***
			(0.004)
Individual FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Origin State FE	Yes	Yes	Yes
Destination State FE	Yes	Yes	Yes
N. of observations	443,174	443,174	441,036

Notes:

[1] The observations are job switches of frontline fossil fuel (FFF) workers in 2000-2023. Green sector, construction sector, manufacturing sector, and other sectors are dummy variables indicating the target sector into which FFF workers make their job switch. The omitted sector is the fossil fuel sector. The sector classifications are based on a combination of 2-digit NAICS codes and SOC codes (See Methods section 6.1). The managerial occupation dummy variable indicates the job switch is into a managerial occupation. The science and engineering occupation dummy variable indicates the job switch is into a science or engineering occupation. The fixed-effects accounts for individual fixed effects, the state of the prior job, the state of the destination job, and the years in which job switches occur.

[2] *p<.10; **p<.05; ***p<.01.

Fig. A.7: Upward Mobility to Managerial and Science and Engineering Occupations Using Alternative Definition of Green Occupations (Approach 2)

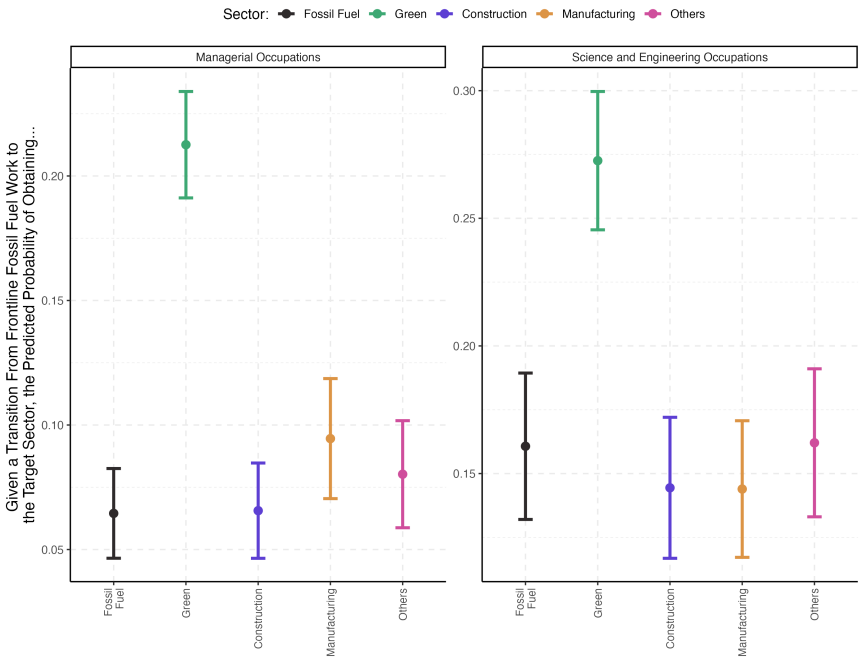
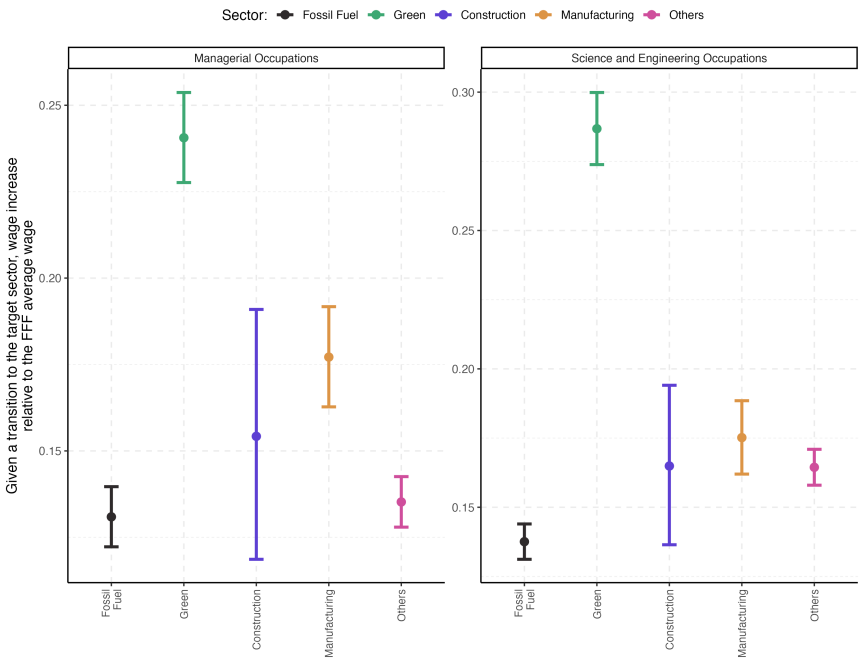


Fig. A.8: Wage Increase Using Alternative Definition of Green Occupations (Approach 2)



4.1.3 Approach 3: O*NET Green Core Occupations + Key Word Search on Job Titles and Company Names

The third alternative definition of green occupations further expands on the previous two approaches by including workers employed at companies whose names contain any of the keywords listed in Table A.10. We use company names in the resume data to identify these green employers.

Table A.12 presents results and Fig. A.9, and A.10 plot predicted probability. Using this revised definition, the results reaffirm our main findings, although the estimated upward mobility into managerial or science and engineering positions within the green sector is further lower than that reported under approaches 1 and 2.

Table A.12: Robustness Check for Main Results Using Alternative Definition of Green Occupations (Approach 3)

	Managerial Occupations	Science and Engineering Occupations	log(Wages)
Green Sector	3.334***	1.957***	-0.056***
	(0.047)	(0.037)	(0.004)
Construction Sector	0.034	-0.312***	-0.029***
	(0.090)	(0.079)	(0.003)
Manufacturing Sector	0.799***	-0.321***	-0.032***
	(0.049)	(0.044)	(0.003)
Other Sectors	0.445***	0.031	-0.035***
	(0.031)	(0.028)	(0.002)
Managerial Occupation			0.123***
			(0.004)
Science and Engineering Occupation			0.129***
			(0.003)
Green Sector*Managerial Occupation			0.088***
			(0.006)
Green Sector*Science and Engineering Occupation			0.119***
			(0.006)
Construction Sector*Managerial Occupation			0.020
			(0.016)
Construction Sector*Science and Engineering Occupation			0.024*
			(0.013)
Manufacturing Sector*Managerial Occupation			0.040***
			(0.007)
Manufacturing Sector*Science and Engineering Occupation			0.033***
			(0.006)
Other Sectors*Managerial Occupation			0.004
			(0.005)
Other Sectors*Science and Engineering Occupation			0.024***
			(0.004)
Individual FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Origin State FE	Yes	Yes	Yes
Destination State FE	Yes	Yes	Yes
N. of observations	443,174	443,174	441,036

Notes:

[1] The observations are job switches of frontline fossil fuel (FFF) workers in 2000-2023. Green sector, construction sector, manufacturing sector, and other sectors are dummy variables indicating the target sector into which FFF workers make their job switch. The omitted sector is the fossil fuel sector. The sector classifications are based on a combination of 2-digit NAICS codes and SOC codes (See Methods section 6.1). The managerial occupation dummy variable indicates the job switch is into a managerial occupation. The science and engineering occupation dummy variable indicates the job switch is into a science or engineering occupation. The fixed-effects accounts for individual fixed effects, the state of the prior job, the state of the destination job, and the years in which job switches occur.

[2] *p<.10; **p<.05; ***p<.01.

Fig. A.9: Upward Mobility to Managerial and Science and Engineering Occupations Using Alternative Definition of Green Occupations (Approach 3)

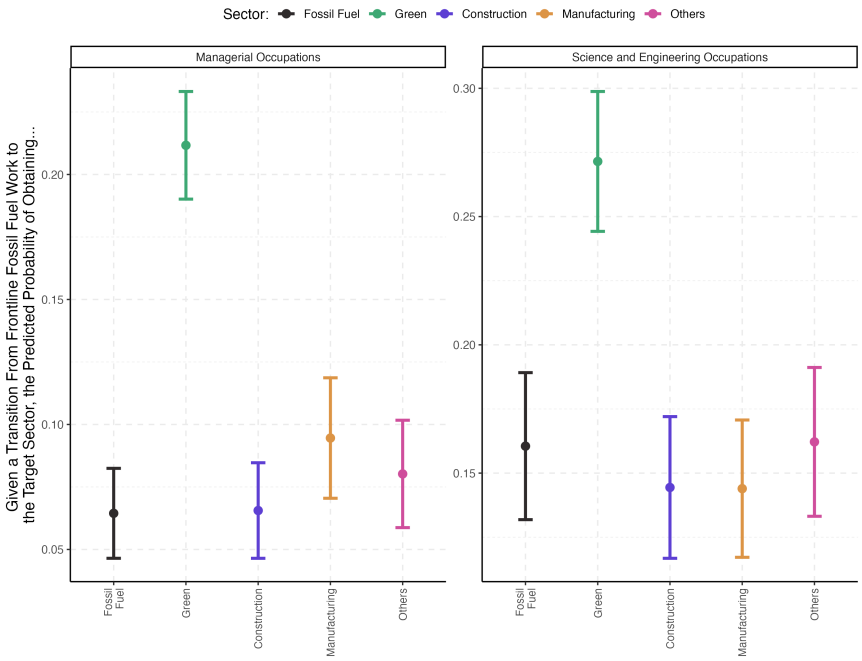
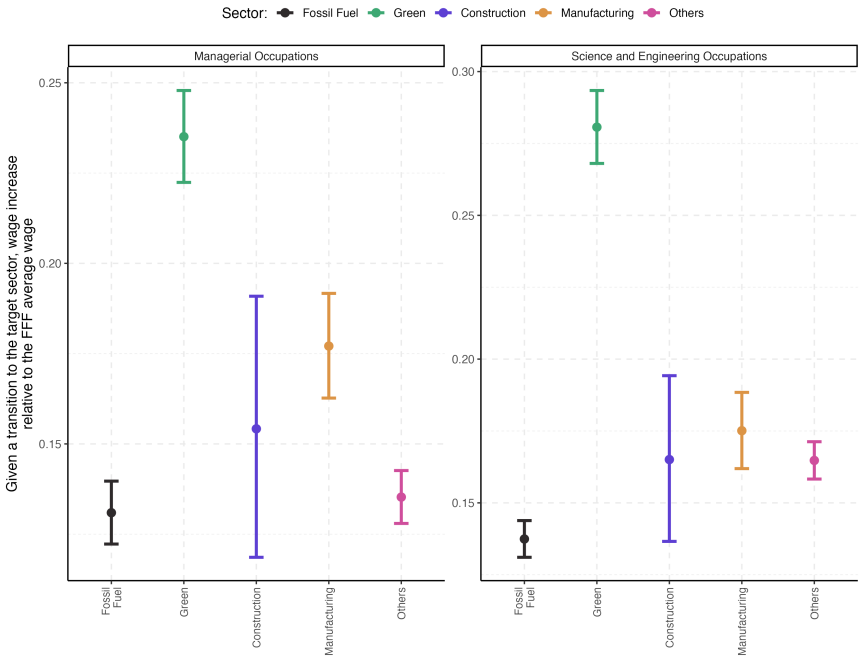


Fig. A.10: Wage Increase Using Alternative Definition of Green Occupations (Approach 3)



4.1.4 Approach 4: O*NET Green Core Occupations + Key Word Search on Job Titles and Company Names + Top Companies in the Green Sector

The final alternative definition of green occupations incorporates work experience at leading companies in green industries as an additional indicator of green employment. This approach is similar to the green occupation definition in Curtis, O'Kane and Park[14], who use top companies in solar, wind, EV battery, and EV manufacturing. We expand their classification of the green sector to include industries such as nuclear and geothermal. We begin by compiling a list of companies with the highest annual sales in the following green sectors: (1) hydro, (2) nuclear, (3) solar, (4) wind, (5) geothermal, (6) biomass, (7) electric vehicle manufacturing, and (8) battery manufacturing.[5] Table A.13 lists the top companies identified in each of these industries. In addition, we include workers with experience at traditional automobile manufacturers which are known to have EV production plans in certain states, as shown in Table A.14.[6]

Table A.13: List of Green Top Companies

Sector	Company	Sector	Company
Hydroelectric Power Generation	Salt Rver Prj AG Imprv Pwr Dst	Wind Electric Power Generation	Scout Clean Energy
Hydroelectric Power Generation	Salt River Project	Wind Electric Power Generation	Tri Global Energy
Hydroelectric Power Generation	Imperial Irrigation District	Wind Electric Power Generation	QED Wind Power
Hydroelectric Power Generation	Public Utlity Dst 1 Dglas Cnty	Geothermal Electric Power Generation	US Geothermal
Hydroelectric Power Generation	Public Utlity Dst 1 Clllam CNT	Geothermal Electric Power Generation	Integrated Geothermal
Hydroelectric Power Generation	Public Utility District	Geothermal Electric Power Generation	Fourth Wave Energy
Hydroelectric Power Generation	Eagle Creek Rnwble Enrgy Hldng	Biomass Electric Power Generation	Zilkha Biomass Crockett
Hydroelectric Power Generation	Hydro Development	Biomass Electric Power Generation	Drax Biomass
Hydroelectric Power Generation	Squam River Hydro	Biomass Electric Power Generation	Abengoa Energy Hybrid
Hydroelectric Power Generation	Black Bear So	Biomass Electric Power Generation	DTE Biomass Energy
Nuclear Electric Power Generation	Ultra Safe Nuclear	Biomass Electric Power Generation	Lignetics of Web
Nuclear Electric Power Generation	Power Advocate	Biomass Electric Power Generation	Northern Biomass
Nuclear Electric Power Generation	Kairos Power	Biomass Electric Power Generation	Aria Energy
Nuclear Electric Power Generation	Nuclear Service Organization	Biomass Electric Power Generation	Zilkha Biomass Power
Solar Electric Power Generation	Trinity Solar	Biomass Electric Power Generation	Lone Oak Energy
Solar Electric Power Generation	Oci Enterprises	Electric Vehicle Manufacturing	Tesla
Solar Electric Power Generation	Iap-Hill	Electric Vehicle Manufacturing	Rivian Automotive
Solar Electric Power Generation	Titan Solar Power	Electric Vehicle Manufacturing	Lucid Group
Solar Electric Power Generation	Centaurus Renewable	Electric Vehicle Manufacturing	Blue Bird
Solar Electric Power Generation	National Grid	Electric Vehicle Manufacturing	Faraday Future
Solar Electric Power Generation	Cypress Creek Renewable	Electric Vehicle Manufacturing	Nikola
Solar Electric Power Generation	Solv Energy	Electric Vehicle Manufacturing	Lordstown Motors
Solar Electric Power Generation	Aireko Energy	Electric Vehicle Manufacturing	Nu Ride
Solar Electric Power Generation	Heliogen	Battery Manufacturing	Clarios
Wind Electric Power Generation	EDP Renewables	Battery Manufacturing	Albemarle
Wind Electric Power Generation	Nextera Enrgy	Battery Manufacturing	QuantumScape
Wind Electric Power Generation	Vestas Blades America	Battery Manufacturing	Redwood Materials
Wind Electric Power Generation	Helix Generation	Battery Manufacturing	EnerSys
Wind Electric Power Generation	Eurus Energy America	Battery Manufacturing	Enovix
Wind Electric Power Generation	Iberdrola Renewable	Battery Manufacturing	Microvast
Wind Electric Power Generation	Southwest Windpower	Battery Manufacturing	Amprius Technologies

Table A.15 presents the regression results based on the above definition of green occupation. The estimated effect of transitioning to the green sector on the likelihood of obtaining a managerial position is larger than that reported in the main paper, and consistent with our theoretical expectations. Fig. A.11 and A.12 display the predicted probabilities of achieving upwardly mobile occupations and the associated wage increases relative to staying in fossil fuel sector. Both estimates are slightly higher than those reported in the main paper. Taken together, these findings reinforce our conclusion that the green sector offers greater opportunities for upward mobility than the fossil fuel sector.

[5]Top companies in hydro, nuclear, solar, wind, geothermal, and biomass are drawn from the NAICS Association, available at https://www.naics.com/six-digit-naics/?v=2022&code=22. Top companies in electric vehicles and batteries are obtained from Capital IQ, available at https://www.capitaliq.com/.

[6]Data comes from: https://www.thomasnet.com/insights/ev-manufacturing-plants-2/.

Table A.14: List of Key EV Manufacturing Plants Used in the Robustness Check (Approach 4)

Company	Location
BMW	South Carolina
Stellantis	Indiana
Samsung	Indiana
Hyundai	Georgia
Toyota	North Carolina
Volvo	South Carolina
Lucid	Arizona
Volkswagen	Tennessee
Nissan	Tennessee

Table A.15: Robustness Check for Main Results Using Alternative Definition of Green Occupations (Approach 4)

	Managerial Occupations	Science and Engineering Occupations	log(Wages)
Green Sector	3.326***	1.956***	-0.056***
	(0.047)	(0.037)	(0.004)
Construction Sector	0.033	-0.312***	-0.029***
	(0.090)	(0.079)	(0.003)
Manufacturing Sector	0.798***	-0.320***	-0.032***
	(0.049)	(0.044)	(0.003)
Other Sectors	0.446***	0.031	-0.035***
	(0.031)	(0.028)	(0.002)
Managerial Occupation			0.123***
			(0.004)
Science and Engineering Occupation			0.129***
			(0.003)
Green Sector*Managerial Occupation			0.088***
			(0.006)
Green Sector*Science and Engineering Occupation			0.118***
			(0.006)
Construction Sector*Managerial Occupation			0.020
			(0.016)
Construction Sector*Science and Engineering Occupation			0.024*
			(0.013)
Manufacturing Sector*Managerial Occupation			0.040***
			(0.007)
Manufacturing Sector*Science and Engineering Occupation			0.033***
			(0.006)
Other Sectors*Managerial Occupation			0.004
			(0.005)
Other Sectors*Science and Engineering Occupation			0.024***
			(0.004)
Individual FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Origin State FE	Yes	Yes	Yes
Destination State FE	Yes	Yes	Yes
N. of observations	443,174	443,174	441,036

Notes:

[1] The observations are job switches of frontline fossil fuel (FFF) workers in 2000-2023. Green sector, construction sector, manufacturing sector, and other sectors are dummy variables indicating the target sector into which FFF workers make their job switch. The omitted sector is the fossil fuel sector. The sector classifications are based on a combination of 2-digit NAICS codes and SOC codes (See Methods section 6.1). The managerial occupation dummy variable indicates the job switch is into a managerial occupation. The science and engineering occupation dummy variable indicates the job switch is into a science or engineering occupation. The fixed-effects accounts for individual fixed effects, the state of the prior job, the state of the destination job, and the years in which job switches occur.

[2] *p<.10; **p<.05; ***p<.01.

Fig. A.11: Upward Mobility to Managerial and Science and Engineering Occupations Using Alternative Definition of Green Occupations (Approach 4)

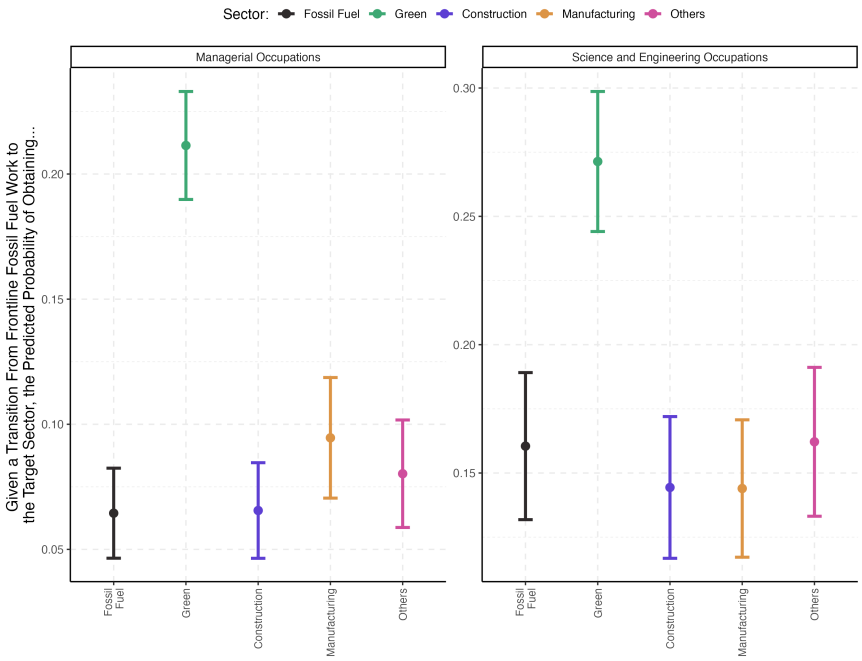
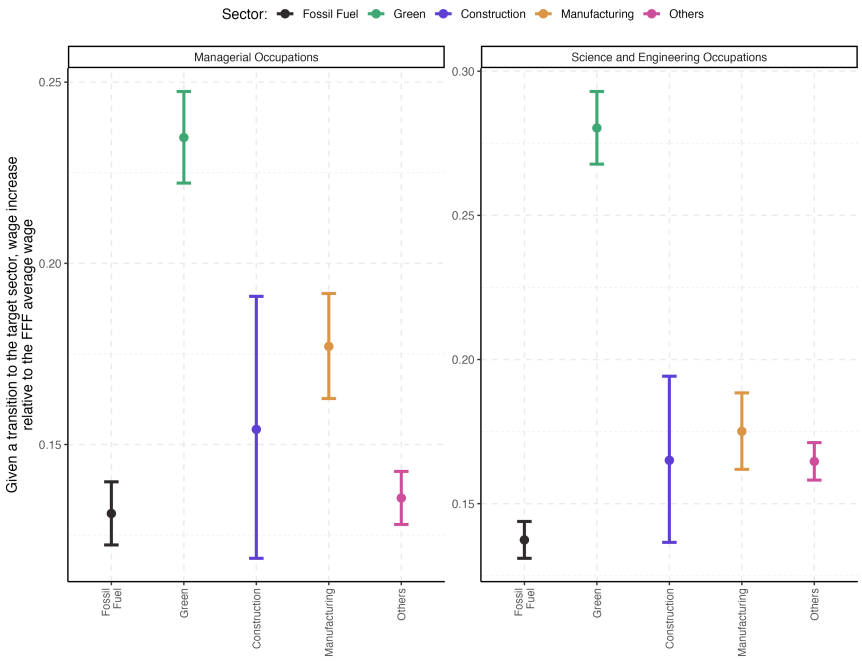


Fig. A.12: Wage Increase Using Alternative Definition of Green Occupations (Approach 4)



4.2 Addressing Sample Selection with Weighted Regressions

Our sample of FFF workers may overrepresent those who seek to shift out of the fossil fuel sector and thus post their resumes to LinkedIn (one of Revelio's sources of resumes). To address this issue, we estimate five regression models using alternative sample weights designed to better reflect the population.

We begin by comparing some statistics from the Revelio dataset and the Bureau of Labor Statistics (BLS) Occupational Employment and Wage Statistics (OEWS) dataset that reflect the national population. We find that relative to the BLS national level share of employment, the Revelio dataset has higher shares of employment for managerial and SE occupations (e.g. Managerial occupations SOC-11, Architecture and Engineering occupations SOC-17, Life, Physical and Social Science occupations SOC-19); but lower shares of employment for trades or frontline occupations (Construction and Extraction occupations SOC-47, Installation, Maintenance and Repair occupations SOC-49, Production occupations SOC-51, Transportation and Material Moving occupations SOC-53) (See Table A.16).

Next, we estimate five different weighted regressions.

1. Weighted by national occupation profiles (OCC)

We calculate the weights using (i) the national level share of employment in each occupation based on the BLS and (ii) the share of employment in each occupation based on the Revelio data.

2. Weighted by state and occupation profiles from BLS (State–OCC)

In this case, we calculate the appropriate weights using the share of employment in each occupation by state using the BLS OWES dataset and the analogous shares in the Revelio dataset.

3. Weighted by industry and occupation profiles from BLS (Ind–OCC)

In this case, we calculate the appropriate weights using the share of employment in each occupation by industry using the BLS OWES dataset and the analogous shares in the Revelio dataset.

4. Weighted by J2J state to state from LEHD (J2J: state to state)

A subset of job shifts involves workers' geographical mobility from one state to another state. We run weighted regressions to better mirror the job flows from one state to another as reflected in the national administrative data. We calculate the weights using (i) the job flows from one state to another from the Job-to-Job (J2J) Flows dataset from the Longitudinal Employer-Household Dynamics (LEHD) program and (ii) the job flows from one state to another from the Revelio dataset.

5. Weighted by J2J state-industry to state-industry from LEHD (J2J: state–ind to state–ind)

In this case, we calculate the job flows from one industry (based on the 2-digit NAICS code) in each state to other industries across US states using J2J data. We calculate the weights using (i) the state-industry job flows from the J2J data and (ii) the state-industry jobs flows from the Revelio data.

4.2.1 Revelio Job Profile versus BLS Industry Profile

Table A.16: Revelio Job Profile versus BLS Occupation Profile

SOC_Code	Title	Revelio_Percent	BLS_Percent
11-0000	Management Occupations	16.68	5.55
13-0000	Business and Financial Operations Occupations	9.38	5.51
15-0000	Computer and Mathematical Occupations	8.58	3.29
17-0000	Architecture and Engineering Occupations	5.73	1.83
19-0000	Life, Physical, and Social Science Occupations	3.66	0.66
21-0000	Community and Social Service Occupations	1.60	1.15
23-0000	Legal Occupations	1.59	0.70
25-0000	Educational Instruction and Library Occupations	5.72	1.85
27-0000	Arts, Design, Entertainment, Sports, and Media Occupations	8.35	1.45
29-0000	Healthcare Practitioners and Technical Occupations	3.60	5.97
31-0000	Healthcare Support Occupations	0.60	4.97
33-0000	Protective Service Occupations	0.74	1.10
35-0000	Food Preparation and Serving Related Occupations	2.57	10.39
37-0000	Building and Grounds Cleaning and Maintenance Occupations	0.98	2.99
39-0000	Personal Care and Service Occupations	1.45	2.30
41-0000	Sales and Related Occupations	8.11	11.43
43-0000	Office and Administrative Support Occupations	8.92	13.14
45-0000	Farming, Fishing, and Forestry Occupations	0.85	0.37
47-0000	Construction and Extraction Occupations	1.52	4.57
49-0000	Installation, Maintenance, and Repair Occupations	1.53	4.12
51-0000	Production Occupations	2.25	7.17
53-0000	Transportation and Material Moving Occupations	3.28	9.50

4.2.2 Weighted Regressions on Obtaining Managerial and SE Occupations, Given a Transition into a Target Sector

Fig. 1C in the main paper (we replicate these results in Fig. A.13) and Table A.4 in the SI section 3.1 report predicted probabilities of obtaining managerial and SE positions, for a given worker, following transitions into the green sector or other destination sectors. Table A.17 and Fig. A.14 present the results on upward mobility into managerial occupations in different sectors under different reweighting schemes. Table A.18 and Fig. A.15 present the results on upward mobility into SE occupations in different sectors under different reweighting schemes. In the unweighted regressions, predicted probabilities of obtaining managerial and SE positions are higher following transitions into the green sector than following transitions into the fossil fuel sector (Fig. A.13). We find consistent results in the weighted regressions (see Fig. A.14 and Fig. A.15).

We conclude that the results from the unweighted regressions are consistent with those from the weighted regressions.

Table A.17: Upward Mobility to Managerial Positions in the Green Sector (Weighted Regression)

	OCC	State-OCC	Ind-OCC	J2J: state to state	J2J: state-ind to state-ind
Green Sector	2.837***	1.601***	2.507***	1.720***	2.494***
	(0.054)	(0.039)	(0.055)	(0.048)	(0.126)
Construction Sector	0.311**	-0.288***	0.351**	-0.035	0.373
	(0.124)	(0.092)	(0.153)	(0.120)	(0.274)
Manufacturing Sector	1.078***	0.673***	1.346***	0.711***	1.144***
	(0.072)	(0.051)	(0.065)	(0.061)	(0.142)
Other Sectors	0.846***	0.306***	0.992***	0.355***	0.858***
	(0.048)	(0.035)	(0.051)	(0.043)	(0.111)
Individual FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Origin State FE	Yes	Yes	Yes	Yes	Yes
Destination State FE	Yes	Yes	Yes	Yes	Yes
McFadden's Pseudo R2s	0.725	0.612	0.655	0.607	0.706
N. of observations	443,174	443,174	443,174	443,174	443,174

Notes:

[1] The observations are job switches of frontline fossil fuel (FFF) workers in 2000-2023. OCC is the regression weighted by national occupational profiles based on BLS data. State-OCC is the regression weighted by state and occupational profiles based on BLS data. Ind-OCC is the regression weighted by industry and occupational profiles based on BLS data. J2J: state-to-state is the regression weighted by state-to-state job transitions based on the LEHD data. J2J: state–ind to state–ind is the regression weighted by state-industry to state-industry job transitions based on the LEHD data. Green sector, construction sector, manufacturing sector, and other sectors are dummy variables indicating the target sector into which FFF workers make their job switch. The omitted sector is the fossil fuel sector. The sector classifications are based on a combination of 2-digit NAICS codes and SOC codes (See Methods section 6.1). The fixed-effects accounts for individual fixed effects, the state of the prior job, the state of the destination job, and the years in which job switches occur.

[2] *p<.10; **p<.05; ***p<.01.

Fig. A.13: Upward Mobility in the Green Sector (Replication of Fig. 1C in the Main Result)

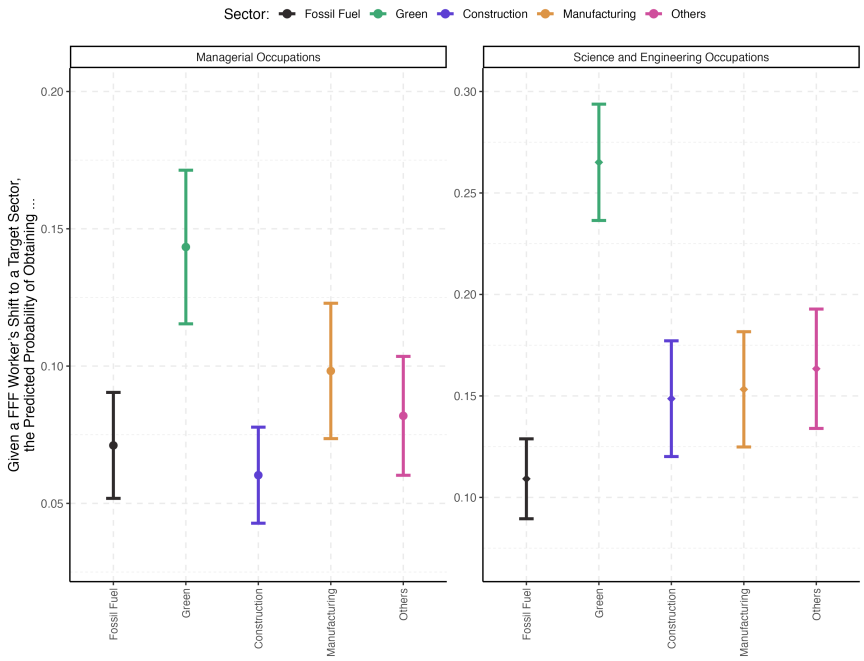


Table A.18: Upward Mobility to Science and Engineering Positions (Weighted Regression)

	OCC	State-OCC	Ind-OCC	J2J: state to state	J2J: state-ind to state-ind
Green Sector	4.240***	3.121***	4.204***	3.278***	3.649***
	(0.056)	(0.040)	(0.058)	(0.043)	(0.093)
Construction Sector	1.270***	0.915***	1.588***	1.006***	0.588***
	(0.116)	(0.085)	(0.148)	(0.088)	(0.199)
Manufacturing Sector	1.316***	1.019***	1.664***	1.049***	1.030***
	(0.071)	(0.051)	(0.066)	(0.052)	(0.102)
Other Sectors	1.586***	1.203***	1.925***	1.282***	1.383***
	(0.046)	(0.035)	(0.050)	(0.037)	(0.077)
Individual FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Origin State FE	Yes	Yes	Yes	Yes	Yes
Destination State FE	Yes	Yes	Yes	Yes	Yes
McFadden's Pseudo R2s	0.782	0.702	0.750	0.680	0.746
N. of observations	443,174	443,174	443,174	631,008	631,008

Notes:

[1] The observations are job switches of frontline fossil fuel (FFF) workers in 2000-2023. OCC is the regression weighted by national occupational profiles based on BLS data. State-OCC is the regression weighted by state and occupational profiles based on BLS data. Ind-OCC is the regression weighted by industry and occupational profiles based on BLS data. J2J: state-to-state is the regression weighted by state-to-state job transitions based on the LEHD data. J2J: state–ind to state–ind is the regression weighted by state-industry to state-industry job transitions based on the LEHD data. Green sector, construction sector, manufacturing sector, and other sectors are dummy variables indicating the target sector into which FFF workers make their job switch. The omitted sector is the fossil fuel sector. The sector classifications are based on a combination of 2-digit NAICS codes and SOC codes (See Methods section 6.1). The fixed-effects accounts for individual fixed effects, the state of the prior job, the state of the destination job, and the years in which job switches occur.

[2] *p<.10; **p<.05; ***p<.01.

Fig. A.14: Predicted Probability of Obtaining Managerial Occupations Based on Weighted Regression (Table A.17)

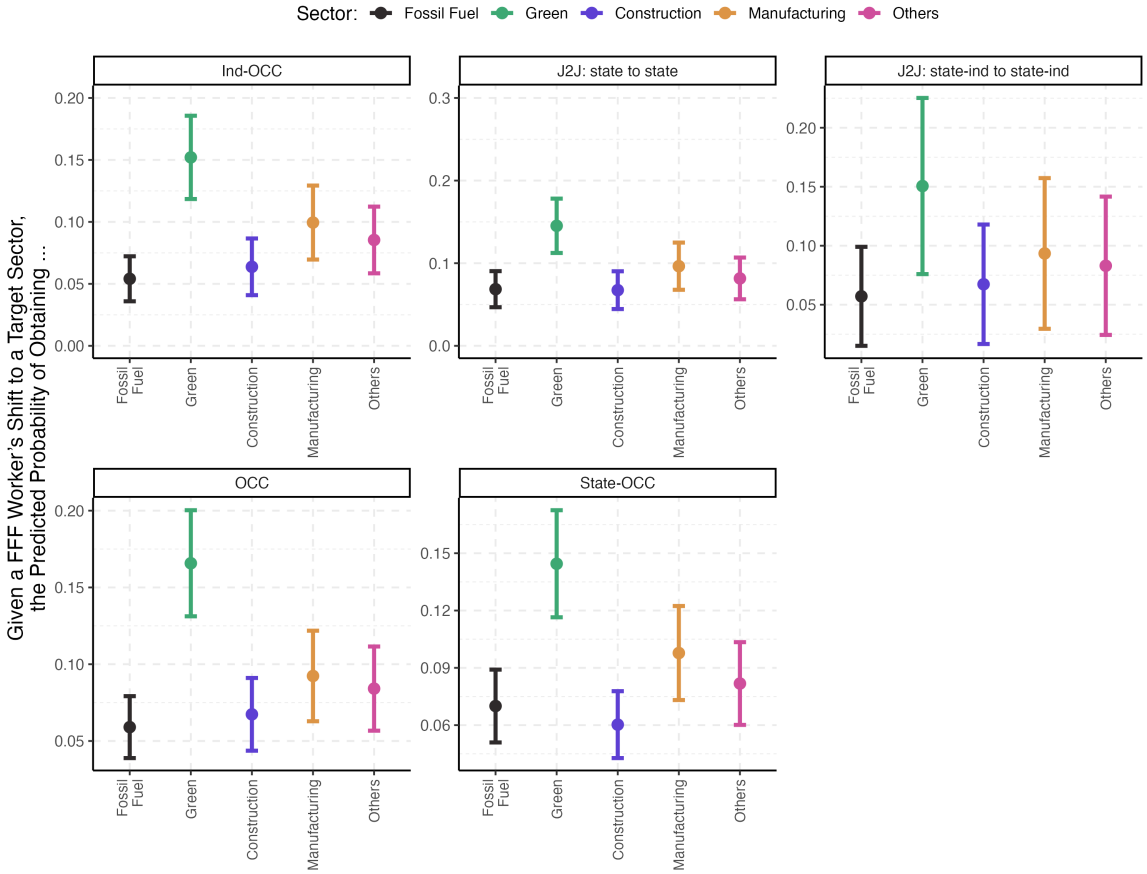
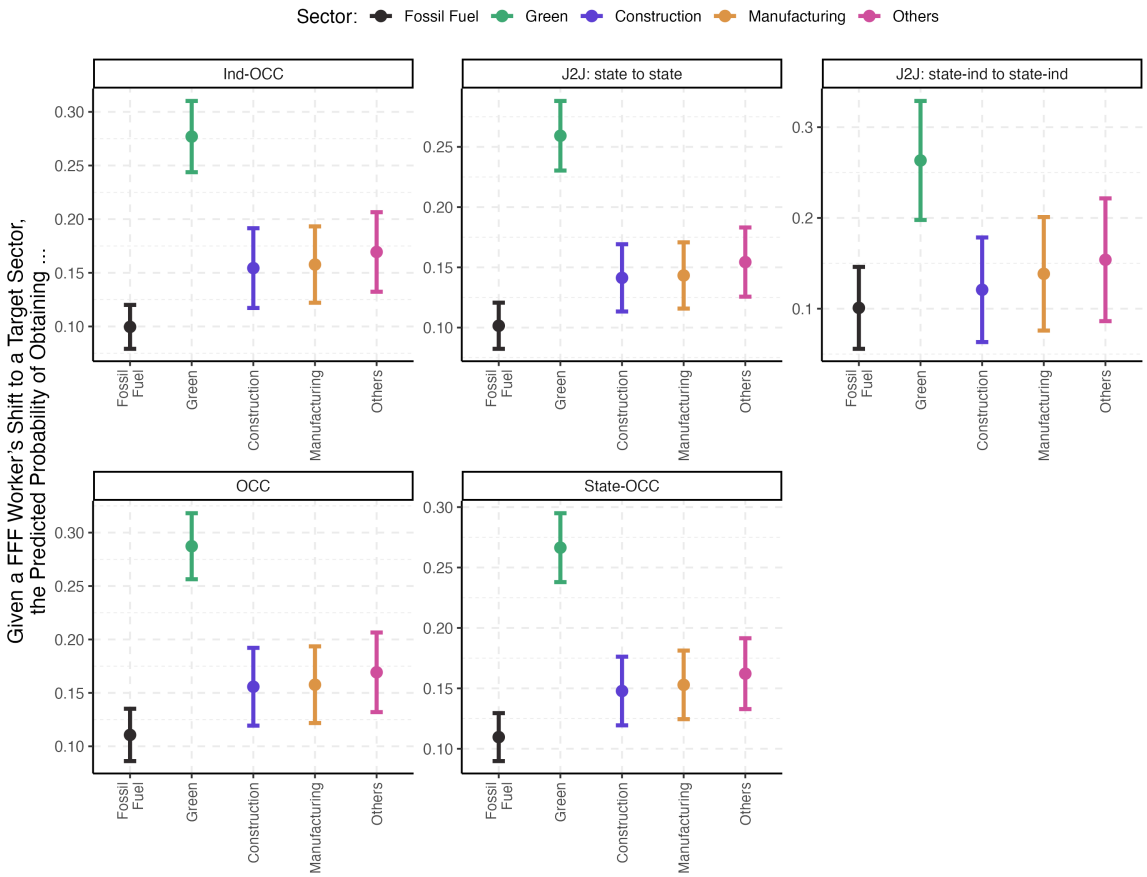


Fig. A.15: Predicted Probability of Obtaining Science and Engineering Occupations Based on Weighted Regression (Table A.18)



4.2.3 Weighted Regressions on the Wage Increases for Those Obtaining Managerial and SE Occupations, given a Transition into a Target Sector

Fig. 2A in the main paper (we replicate these results in Fig. A.16) and Table A.5 in the SI section 3.2 presents results on the wage increases for obtaining managerial and SE positions, given a worker's shift into the green or other sectors. Table A.19 and Fig. A.17 present the results on the wage increases under different reweighting schemes. Results from the unweighted regressions indicate larger wage increases when a FFF worker obtain managerial and SE positions in the green sector, relative to obtaining the same positions in the fossil fuel sector (Fig. 2A). We find consistent results in the weighted regressions.

Table A.19: Green Transition and Wages (Weighted Regression)

	OCC	State-OCC	Ind-OCC	J2J: state to state	J2J: state-ind to state-ind
Green Sector	0.007***	0.010***	0.011***	0.008***	0.013*
	(0.002)	(0.002)	(0.003)	(0.003)	(0.007)
Construction Sector	-0.017***	-0.016***	-0.023***	-0.017***	-0.014*
	(0.004)	(0.004)	(0.005)	(0.005)	(0.007)
Manufacturing Sector	-0.025***	-0.024***	-0.018***	-0.025***	-0.019***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)
Other Sectors	-0.024***	-0.026***	-0.022***	-0.026***	-0.023***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
Managerial Occupation	0.146***	0.137***	0.138***	0.134***	0.145***
	(0.006)	(0.005)	(0.007)	(0.005)	(0.013)
Science and Engineering Occupation	0.149***	0.134***	0.147***	0.131***	0.134***
	(0.005)	(0.004)	(0.006)	(0.005)	(0.013)
Green Sector*Managerial Occupation	0.028***	0.010*	0.019**	0.010	0.017
	(0.008)	(0.006)	(0.008)	(0.007)	(0.016)
Green Sector*Science and Engineering Occupation	0.023***	0.031***	0.023***	0.032***	0.028*
	(0.006)	(0.005)	(0.007)	(0.006)	(0.015)
Construction Sector*Managerial Occupation	-0.001	0.004	-0.020	0.008	-0.034
	(0.022)	(0.017)	(0.023)	(0.022)	(0.030)
Construction Sector*Science and Engineering Occupation	0.025	0.014	0.016	0.010	0.039
	(0.018)	(0.013)	(0.022)	(0.016)	(0.025)
Manufacturing Sector*Managerial Occupation	0.052***	0.028***	0.027***	0.035***	0.035**
	(0.011)	(0.008)	(0.009)	(0.009)	(0.016)
Manufacturing Sector*Science and Engineering Occupation	0.025***	0.026***	0.020**	0.027***	0.029*
	(0.009)	(0.007)	(0.008)	(0.008)	(0.017)
Other Sectors*Managerial Occupation	-0.013*	-0.008	-0.014*	-0.007	-0.022
	(0.007)	(0.005)	(0.007)	(0.006)	(0.014)
Other Sectors*Science and Engineering Occupation	0.011*	0.017***	0.008	0.018***	0.029**
	(0.006)	(0.005)	(0.006)	(0.006)	(0.014)
Individual FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Origin State FE	Yes	Yes	Yes	Yes	Yes
Destination State FE	Yes	Yes	Yes	Yes	Yes
R2 Adj.	0.604	0.596	0.636	0.610	0.707
N. of observations	441,036	441,036	441,036	441,036	441,036

Notes:

[1] The observations are job switches of frontline fossil fuel (FFF) workers in 2000-2023. OCC is the regression weighted by national occupational profiles based on BLS data. State-OCC is the regression weighted by state and occupational profiles based on BLS data. Ind-OCC is the regression weighted by industry and occupational profiles based on BLS data. J2J: state-to-state is the regression weighted by state-to-state job transitions based on the LEHD data. J2J: state–ind to state–ind is the regression weighted by state-industry to state-industry job transitions based on the LEHD data. Green sector, construction sector, manufacturing sector, and other sectors are dummy variables indicating the target sector into which FFF workers make their job switch. The omitted sector is the fossil fuel sector. The sector classifications are based on a combination of 2-digit NAICS codes and SOC codes (See Methods section 6.1). The fixed-effects accounts for individual fixed effects, the state of the prior job, the state of the destination job, and the years in which job switches occur.

[2] *p<.10; **p<.05; ***p<.01.

Fig. A.16: Wage Increases and the Shift to the Green Sector (Replication of Fig. 2A in the Main Result)

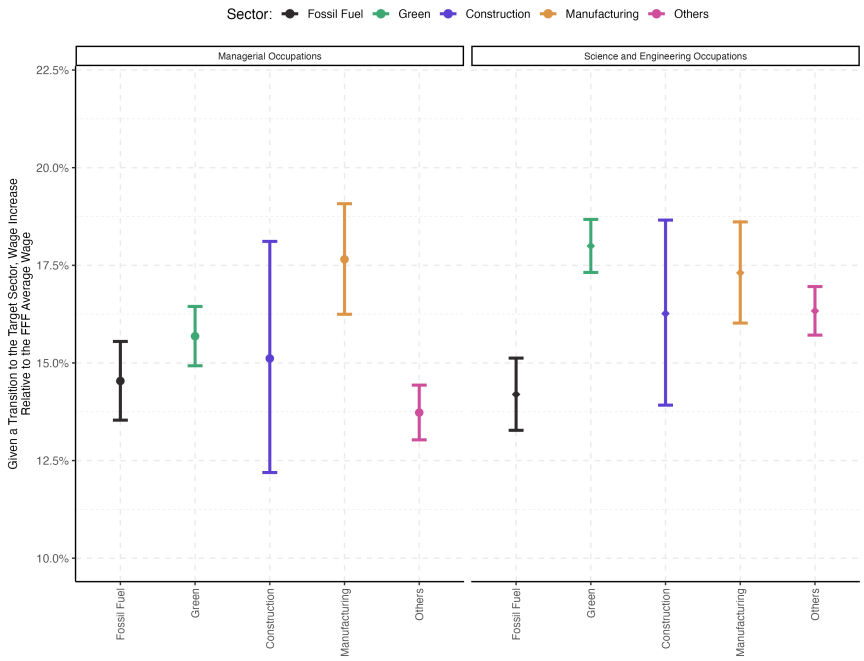
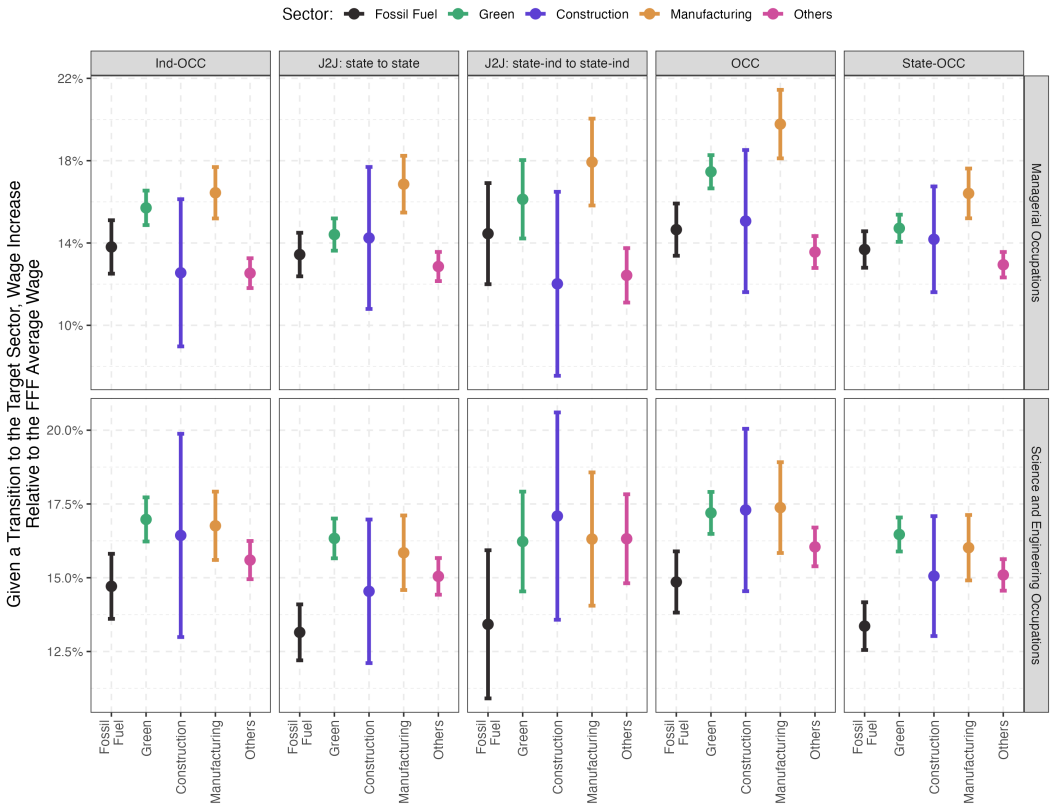


Fig. A.17: Wage Increases and the Shift to the Green Sector Based on Weighted Regression (Table A.19)



4.3 Addressing Workers' Self-Selection

A potential concern in our analysis is bias from workers' self-selection. Factors such as latent abilities, accumulated skill sets over the course of a career, the connectivity of a worker's current job within the occupation network, and career ambitions may all influence both sectoral transitions and upward mobility. To address this, we control for the influence of a worker's current occupation on career mobility as well as for skill sets accumulated prior to the job switch (section 4.3.1). We further mitigate self-selection bias by employing entropy balancing (sections 4.3.2 and 4.3.3). It is important to note that these methods substantially reduce potential bias, they cannot eliminate it entirely.

4.3.1 Adjusting for Workers' Occupation Centrality and Skill Sets

A potential self-selection concern arises if workers who intend to transition into the green sector are more likely to hold jobs with high connectivity and mobility within the occupational network. Such positions may inherently offer greater opportunities for advancement, making these workers more likely to attain managerial or science and engineering roles once they switch to the green sector. To address this concern, we construct a measure of occupation centrality based on eigenvector centrality within the job network.

Eigenvector centrality captures not only the number of connections an occupation has, but also the quality of those connections by assigning higher scores to occupations linked to other highly connected occupations. This allows us to account for both the connectivity and the mobility potential of an occupation within the network, thereby reducing bias from workers' selection into influential positions prior to transitioning. Our procedure proceeds in three steps. First, we construct the occupation network following the approach described in SI section 3.5. Second, we calculate the eigenvector centrality of each occupation using the method outlined in Bonacich [4]. Finally, we merge these centrality values with the occupation held prior to each job transition, resulting a measure of occupation centrality specific to the worker's position before switching jobs.

Another potential source of selection bias arises from the differences of skills and abilities that workers accumulate over their careers prior to switching jobs. For example, workers whose skill sets align more closely with the requirements of managerial roles in the green sector may be more likely to make such a transition. To address this concern, we construct a set of control variables capturing workers' accumulated skills and abilities before the job switch.

Specifically, we classify skills and abilities into seven broad categories: soft skills, cognitive abilities, physical abilities, social skills, system skills, business and management skills, and engineering and science skills. These categories are derived from the O*NET database, which specifies the detailed skills and abilities belonging to each category. Using the occupation–skill matrix (M) developed in section 3.5, we calculate the share of each skill category in the total skill requirements of an occupation. We then match these skill measures to the occupations held prior to each job transition and compute the cumulative average of each skill categories acquired over a worker's career up to that point. This process provides a set of final measures that capture the skill composition a worker has accumulated before making a job and sectoral transition.

Table A.20 reports regression results on upward mobility when a given FFF worker

switches into the green sector, after incorporating the additional control variables. Figures A.18 and A.19 present the predicted probabilities using the same methodology as in Figures 1 and 2 in the main paper.

Including these controls results in only modest changes to the estimated effects. The probabilities of transitioning into managerial or SE occupations increase slightly, whereas the associated wage gains upon obtaining these roles, decrease slightly, suggesting that occupation centrality and different skill sets do influence both job transition decisions and upward mobility. For instance, the predicted wage increase relative to the FFF average wage for a worker who transitions to the green sector and attains a SE occupation is approximately 17% with the additional controls, compared to 18% in the model without them.

Table A.20: Robustness Check of Occupation Centrality and Skill Set Differences

	Managerial Occupations	Science and Engineering Occupations	log(Wages)
Green Sector	1.590***	3.347***	0.020***
	(0.042)	(0.047)	(0.003)
Construction Sector	-0.263***	1.188***	-0.018***
	(0.100)	(0.094)	(0.004)
Manufacturing Sector	0.692***	1.235***	-0.023***
	(0.056)	(0.058)	(0.003)
Other Sectors	0.314***	1.501***	-0.024***
	(0.038)	(0.040)	(0.002)
Managerial Occupation			0.143***
			(0.005)
Science and Engineering Occupation			0.145***
			(0.004)
Green Sector*Managerial Occupation			0.003
			(0.006)
Green Sector*Science and Engineering Occupation			0.014***
			(0.005)
Construction Sector*Managerial Occupation			-0.002
			(0.018)
Construction Sector*Science and Engineering Occupation			0.009
			(0.014)
Manufacturing Sector*Managerial Occupation			0.024***
			(0.008)
Manufacturing Sector*Science and Engineering Occupation			0.020***
			(0.007)
Other Sectors*Managerial Occupation			-0.013**
			(0.006)
Other Sectors*Science and Engineering Occupation			0.010**
			(0.005)
Cumulative Avg. Soft Skills	-24.223***	6.604***	-0.712***
	(2.213)	(2.501)	(0.122)
Cumulative Avg. Cognitive Abilities	3.409***	-15.267***	0.106*
	(1.016)	(1.226)	(0.056)
Cumulative Avg. Physical Abilities	-23.578***	30.606***	-0.352***
	(1.636)	(1.732)	(0.085)
Cumulative Avg. Social Skills	43.493***	5.753	0.304
	(3.785)	(4.489)	(0.210)
Cumulative Avg. Systems Skills	-34.092***	6.576*	1.362***
	(3.053)	(3.446)	(0.154)
Cumulative Avg. Business and Management Skills	-30.816***	23.315***	0.101*
	(1.142)	(1.270)	(0.059)
Cumulative Avg. Engineering and Science Skills	1.067	-10.830***	-0.139***
	(0.752)	(0.806)	(0.038)
Occupation Centrality	0.544***	0.301***	0.011**
	(0.075)	(0.083)	(0.005)
Individual FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Origin State FE	Yes	Yes	Yes
Destination State FE	Yes	Yes	Yes
N. of observations	415,461	415,461	413,397

Notes:

[1] The observations are job switches of frontline fossil fuel (FFF) workers in 2000-2023. Green sector, construction sector, manufacturing sector, and other sectors are dummy variables indicating the target sector into which FFF workers make their job switch. The omitted sector is the fossil fuel sector. The sector classifications are based on a combination of 2-digit NAICS codes and SOC codes (See Methods section 6.1). The managerial occupation dummy variable indicates the job switch is into a managerial occupation. The science and engineering occupation dummy variable indicates the job switch is into a science or engineering occupation. The fixed-effects accounts for individual fixed effects, the state of the prior job, the state of the destination job, and the years in which job switches occur.

[2] *p<.10; **p<.05; ***p<.01.

Fig. A.18: Upward Mobility to Managerial and Science and Engineering Occupations By Adjusting Occupation Centrality and Skill Sets

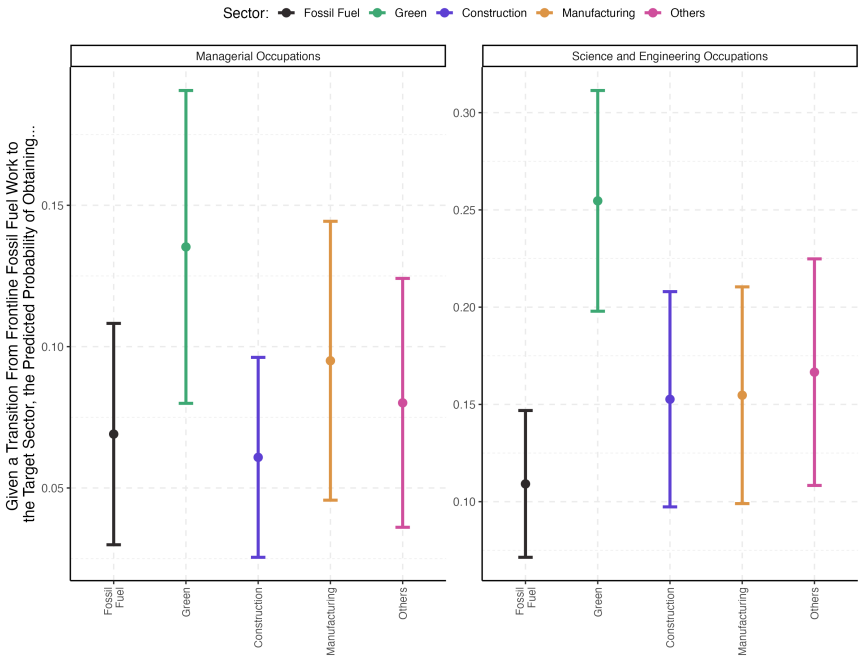


Fig. A.19: Wage Increase By Adjusting Occupation Centrality and Skill Sets

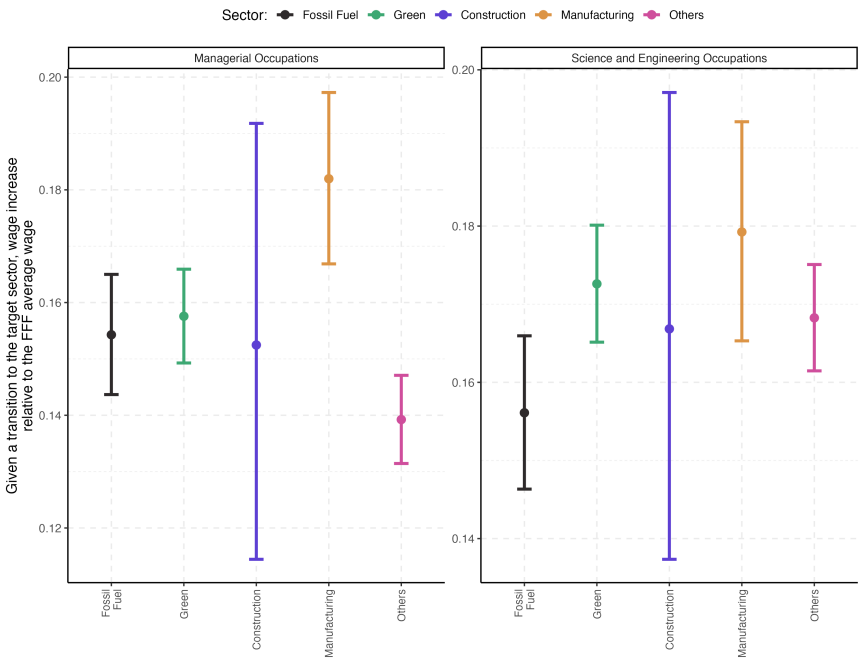


Table A.21 presents the regression results for skill diversity and deepening analysis after controlling for the occupation centrality variable. We do not include the accumulated skill set variables in these specifications because the primary objective of this analysis is to assess how skill diversity and skill deepening influence a worker's likelihood of achieving upward mobility. The construction of the skill diversity and skill deepening measures already incorporates information on skills across multiple categories; adding the accumulated skill set variables would therefore introduce multicollinearity.

To facilitate a direct comparison between the newly estimated results and those reported in the main paper, Fig. A.20 and A.21 illustrate the relationships between skill diversity, skill deepening, and upward mobility, respectively. The results reveal a consistent pattern: both skill diversity and skill deepening increase a worker's likelihood of attaining a managerial position, suggesting that a combination of broad, cross domain skills and strong domain specific knowledge in management is important for reaching managerial roles. This effect is particularly pronounced in the green sector, where transitions often require adaptability and leadership skills that span multiple domains.

In contrast, skill diversity is associated with a lower probability of entering science and engineering occupations, whereas skill deepening increases this probability. This implies that transitions into SE positions are more likely to succeed when a worker expands knowledge within engineering and technical domains rather than broadens skills across unrelated areas.

Taken together, the empirical results presented in this section confirm that our core findings are robust after accounting for both the importance and mobility of occupations within the job network, as well as differences in workers' skill profiles prior to job switching.

Table A.21: Robustness Check of Skill Diversity and Skill Deepening by Adding Occupation Centrality

	Managerial Occupation		Science and Engineering Occupation	
	Model1	Model2	Model3	Model4
Green Sector	-0.244	1.403***	9.592***	3.233***
	(0.288)	(0.051)	(0.308)	(0.045)
Construction Sector	-0.037	-0.705***	1.188***	1.255***
	(0.101)	(0.124)	(0.093)	(0.095)
Manufacturing Sector	0.742***	0.444***	1.125***	1.110***
	(0.054)	(0.065)	(0.055)	(0.056)
Other Sectors	0.423***	-0.123***	1.412***	1.457***
	(0.037)	(0.044)	(0.038)	(0.038)
Skill Diversity	-0.029		-5.438***	
	(0.401)		(0.422)	
Managerial Skill Deepening		10.221***		
		(0.186)		
Science and Engineering Skill Deepening				4.406***
				(0.263)
Green Sector*Skill Diversity	3.074***		-11.149***	
	(0.490)		(0.524)	
Green Sector*Managerial Skill Deepening		-1.828***		
		(0.320)		
Green Sector*Science and Engineering Skill Deepening				3.009***
				(0.480)
Occupation Centrality	-0.421***	0.792***	-0.840***	-0.534***
	(0.056)	(0.065)	(0.059)	(0.060)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Origin State FE	Yes	Yes	Yes	Yes
Destination State FE	Yes	Yes	Yes	Yes
McFadden's Pseudo R2s	0.601	0.643	0.699	0.7
N. of observations	418,457	354,622	418,457	405,774

Notes:

[1] The observations are job switches of frontline fossil fuel (FFF) workers in 2000-2023. Green sector, construction sector, manufacturing sector, and other sectors are dummy variables indicating the target sector into which FFF workers make their job switch. The omitted sector is the fossil fuel sector. The sector classifications are based on a combination of 2-digit NAICS codes and SOC codes (See Methods). The managerial occupation dummy variable indicates the job switch is into a managerial occupation. The science and engineering occupation dummy variable indicates the job switch to a science and engineering occupation. We calculate (1) the SE skill deepening index, measured prior to a job switch, which captures workers' accumulation of SE skills by taking on jobs with greater core SE skills requirements; (2) the managerial skill deepening index, defined analogously; and (3) the skill diversity index, measured prior to a job switch, which captures workers' accumulation of diverse skills by taking on jobs with greater differences in skill requirements (see Methods section 6.2).The models include individual fixed effects, the state of the prior job, the state of the destination job, and the years in which job switches occur.

[2] *p<.10; **p<.05; ***p<.01.

4.3.2 Entropy Balancing Using All Workers

We further validate our main results using entropy balancing, as developed by Hainmueller [23]. Entropy balancing reweights the control group (job switches that are not into the green sector) so that its covariate distribution, such as means and variances, exactly matches that of the treated group (job switches that are into the green sector). By achieving exact balance on observed characteristics, entropy balancing helps reduce bias from omitted variables that are correlated with these observables, such as skills and education. Although it cannot fully eliminate bias from unobserved confounders, it offers a robust method for mitigating selection bias, particularly when transitions into the green sector may be systematically influenced by pre-existing characteristics.

The covariates used for entropy balancing include gender, education level, work experience, prior job wages, the occupation centrality of prior jobs, and the skills accumulated over a worker's career. Fig. A.22 compares the mean differences in

Fig. A.20: Skill Diversity and Upward Mobility by Controlling for Occupation Centrality

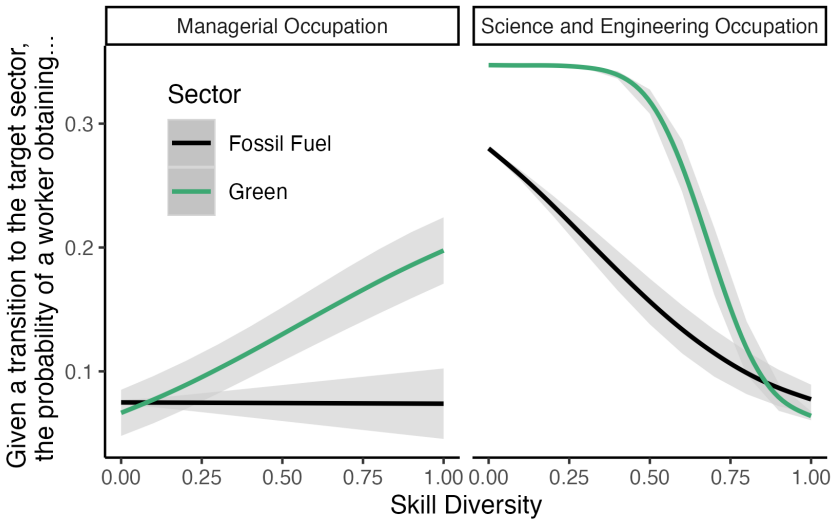
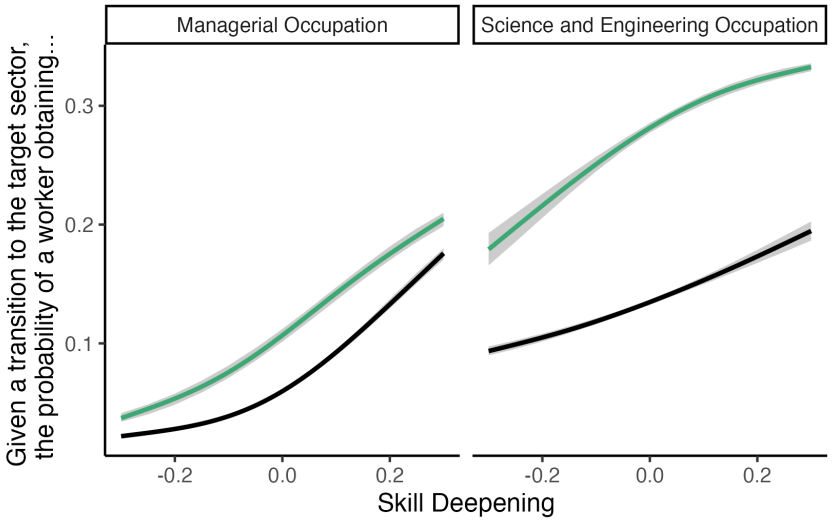
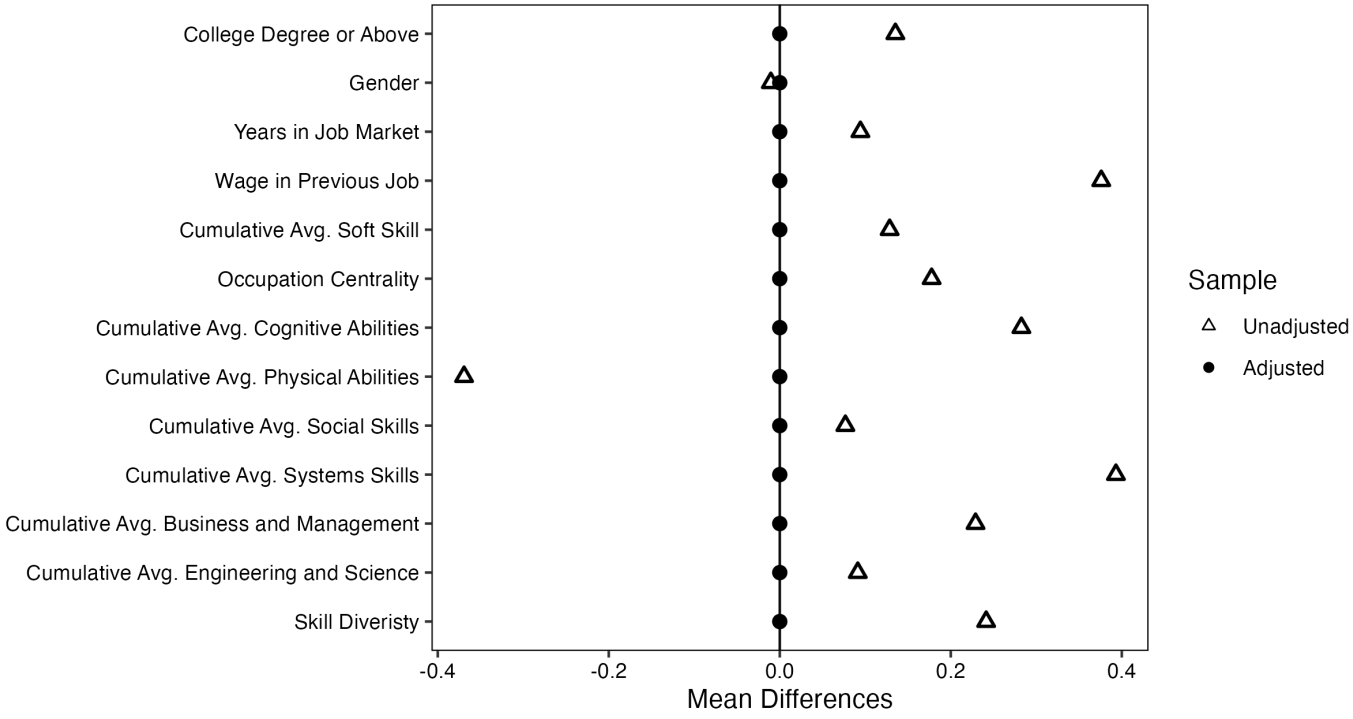


Fig. A.21: Skill Deepening and Upward Mobility by Controlling for Occupation Centrality



covariates between "treated" and "untreated" groups before applying the entropy balancing method (the unadjusted sample) and after applying the entropy balancing method (the adjusted sample). As theoretically expected, entropy balancing achieves exact mean balance in the covariates between the treatment and control groups.

Fig. A.22: Covariate Balance Before and After Entropy Balancing Using All Workers



Notes: All cumulative average skill categories represent the average proportion of each skill domain within the total skill requirements accumulated prior to each job switch (see SI section 4.3.1). All variables are continuous, except for "college degree or above" and "gender," which are binary indicators. To ensure comparability across variables, we compute standardized mean differences, defined as the mean differences divided by the pooled standard deviations, for continuous variables, and use differences in proportions for binary variables.

We estimate regression models on the weighted sample, including geographic and job transition year fixed effects. We do not include individual fixed effects in these specifications because the reweighting procedure is implemented at the level of job transitions rather than workers.

Table A.22 presents the regression results applying the entropy balancing method. Fig. A.23 and Fig. A.24 are based on the estimates from these regressions. These figures are analogous to the Fig. 1C and Fig. 2A in the main paper, which are based on the main regression results. The results from the entropy balancing method are largely consistent with our findings in model 1 and 3 in Table A.4 and model 3 in Table A.5). However, the estimated coefficients for upward mobility into managerial and SE occupations are slightly larger than those reported in the main paper. For instance, the likelihood of attaining an SE occupation when a worker switch to the green sector is 1.78 using entropy balancing (Table A.22), compared to 1.75 in the main model (Table A.4).

Table A.22: Robustness Check for Main Results Based on Entropy Balancing Using All Workers

	Managerial Occupations	Science and Engineering Occupations	log(Wages)
Green Sector	1.135***	1.779***	-0.041***
	(0.037)	(0.029)	(0.004)
Construction Sector	-0.236**	0.041	-0.120***
	(0.097)	(0.068)	(0.006)
Manufacturing Sector	0.512***	0.512***	-0.066***
	(0.039)	(0.030)	(0.003)
Other Sectors	0.099***	0.608***	-0.100***
	(0.026)	(0.038)	(0.004)
Managerial Occupation			0.283***
			(0.008)
Science & Engineering Occupation			0.214***
			(0.005)
Green Sector*Managerial Occupation			-0.038***
			(0.008)
Green Sector*Science and Engineering Occupation			0.055***
			(0.007)
Construction Sector*Managerial Occupation			0.015
			(0.024)
Construction Sector*Science and Engineering Occupation			0.004
			(0.015)
Manufacturing Sector*Managerial Occupation			-0.005
			(0.010)
Manufacturing Sector*Science and Engineering Occupation			0.001
			(0.010)
Other Sectors*Managerial Occupation			-0.035***
			(0.008)
Other Sectors*Science and Engineering Occupation			0.048***
			(0.008)
Year FE	Yes	Yes	Yes
Origin State FE	Yes	Yes	Yes
Destination State FE	Yes	Yes	Yes
N. of observations	415,270	415,270	411,184

Notes:
[1] The observations are job switches of frontline fossil fuel (FFF) workers in 2000-2023. Green sector, construction sector, manufacturing sector, and other sectors are dummy variables indicating the target sector into which FFF workers make their job switch. The omitted sector is the fossil fuel sector. The sector classifications are based on a combination of 2-digit NAICS codes and SOC codes (See Methods section 6.1). The managerial occupation dummy variable indicates the job switch is into a managerial occupation. The science and engineering occupation dummy variable indicates the job switch is into a science or engineering occupation. The fixed-effects accounts for individual fixed effects, the state of the prior job, the state of the destination job, and the years in which job switches occur.
[2] *p<.10; **p<.05; ***p<.01.

Fig. A.23: Predicted Probability of Obtaining Managerial or Science and Engineering Occupations Based on Entropy Balancing Using All Workers (Table A.22)

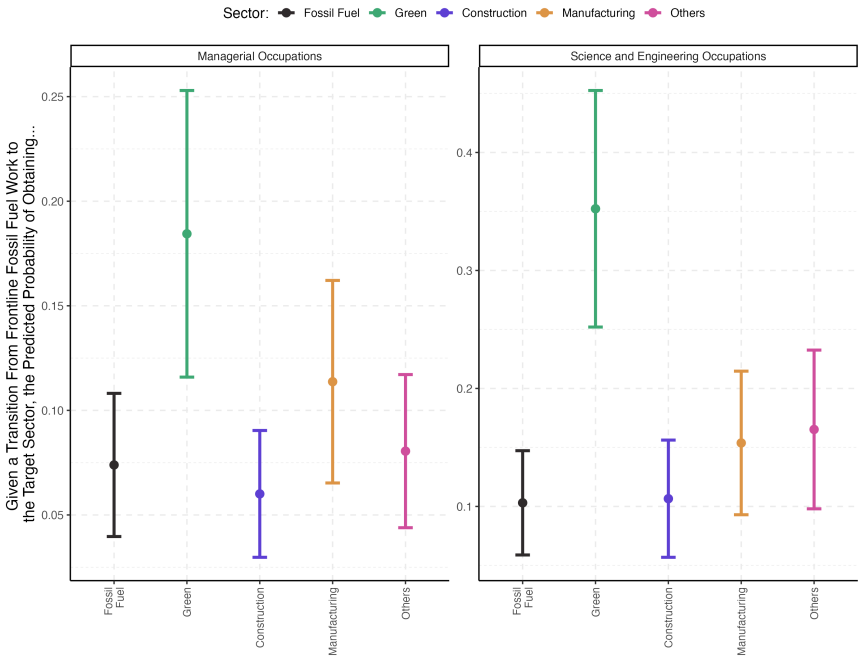
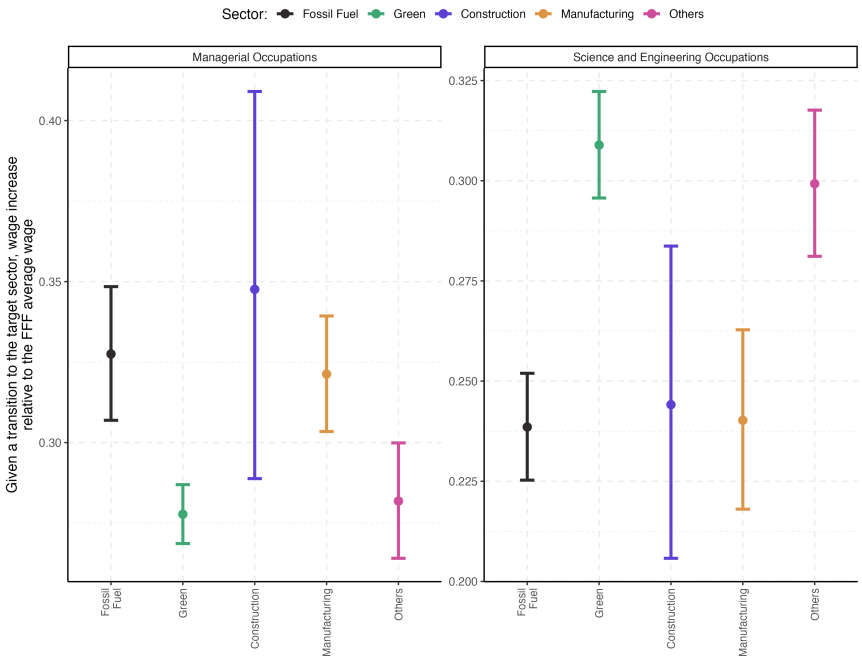


Fig. A.24: Wage Increases and the Shift to the Green Sector Based on Entropy Balancing Using All Workers (Table A.22)



4.3.3 Entropy Balancing: Green Switchers versus Workers in Fossil Fuel Sector

We also perform entropy balancing between workers who, at some point in their careers, transitioned to the green sector with workers who remained exclusively in the fossil fuel sector.

Table A.23 presents the regression results, while Figures A.25 and A.26 display the predicted probabilities of obtaining managerial or SE occupations and associated wage increases, respectively. As shown in Figure A.25 shows that the estimated effects of transitioning to the green sector on a worker's upward mobility into managerial and SE roles are consistent with our theoretical expectations. Notably, the magnitude of these effects is somewhat higher than those reported in the main paper. For example, the predicted probability of obtaining an SE occupation using entropy balancing is approximately 37%, compared to 26% in our main specification.

In sum, both entropy balancing approaches provide robust evidence that green sector offers greater opportunities for upward mobility than fossil fuel sector.

Table A.23: Robustness Check for Main Results Based on Entropy Balancing Using Green Switchers versus Workers in Fossil Fuel Sector

	Managerial Occupations	Science and Engineering Occupations	log(Wages)
Green Sector	1.098***	1.816***	-0.049***
	(0.031)	(0.033)	(0.004)
Construction Sector	-0.468***	-0.079	-0.125***
	(0.106)	(0.079)	(0.007)
Manufacturing Sector	0.496***	0.539***	-0.046***
	(0.042)	(0.029)	(0.004)
Other Sectors	0.064**	0.646***	-0.095***
	(0.032)	(0.048)	(0.004)
Managerial Occupation			0.280***
			(0.007)
Science & Engineering Occupation			0.215***
			(0.005)
Green Sector*Managerial Occupation			-0.031***
			(0.007)
Green Sector*Science and Engineering Occupation	0.056***		
			(0.007)
Construction Sector*Managerial Occupation			0.026
			(0.022)
Construction Sector*Science and Engineering Occupation			0.002
			(0.019)
Manufacturing Sector*Managerial Occupation			-0.025**
			(0.011)
Manufacturing Sector*Science and Engineering Occupation			-0.004
			(0.011)
Other Sectors*Managerial Occupation			-0.027***
			(0.006)
Other Sectors*Science and Engineering Occupation			0.039***
			(0.008)
Year FE	Yes	Yes	Yes
Origin State FE	Yes	Yes	Yes
Destination State FE	Yes	Yes	Yes
N. of observations	247,419	247,419	245,313

Notes:

[1] The observations are job switches of frontline fossil fuel (FFF) workers in 2000-2023. Green sector, construction sector, manufacturing sector, and other sectors are dummy variables indicating the target sector into which FFF workers make their job switch. The omitted sector is the fossil fuel sector. The sector classifications are based on a combination of 2-digit NAICS codes and SOC codes (See Methods section 6.1). The managerial occupation dummy variable indicates the job switch is into a managerial occupation. The science and engineering occupation dummy variable indicates the job switch is into a science or engineering occupation. The fixed-effects accounts for individual fixed effects, the state of the prior job, the state of the destination job, and the years in which job switches occur.

[2] *p<.10; **p<.05; ***p<.01.

Fig. A.25: Predicted Probability of Obtaining Managerial or Science and Engineering Occupations Based on Entropy Balancing Using Green Switchers versus Workers in Fossil Fuel Sector (Table A.22)

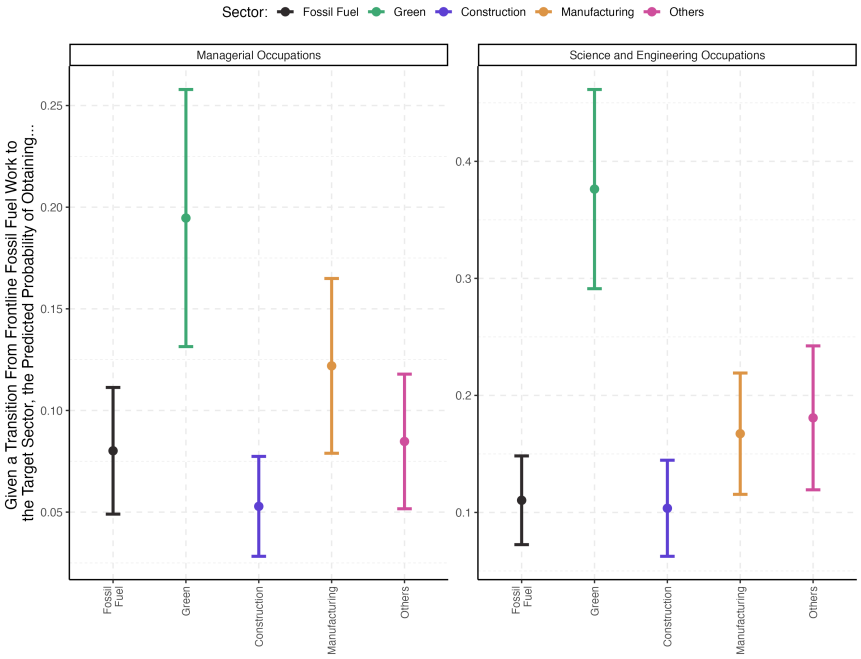
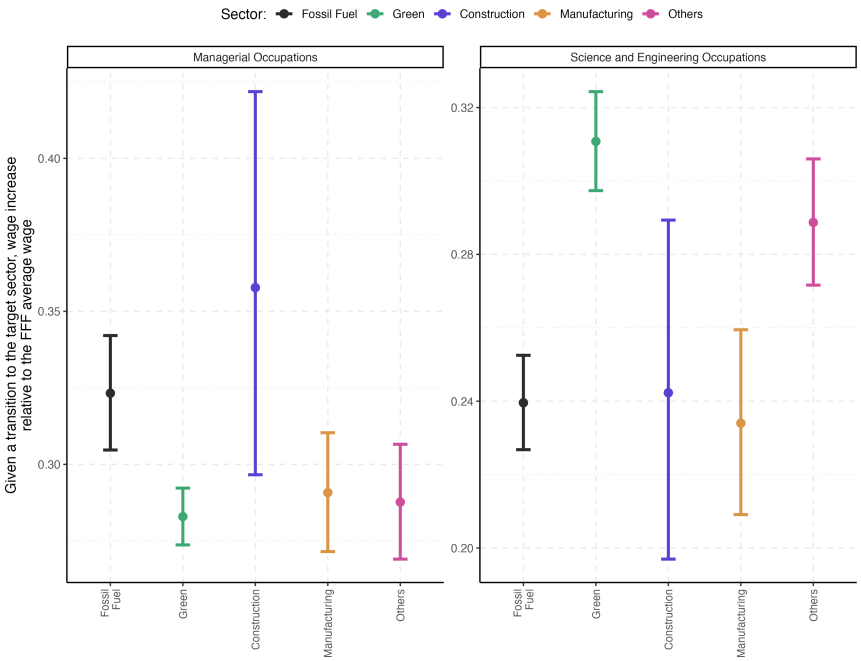


Fig. A.26: Wage Increases and the Shift to the Green Sector Based on Entropy Balancing Green Switchers versus Workers in Fossil Fuel Sector (Table A.22)



4.4 Sensitivity Analysis

We conduct several robustness checks to account for observable differences between transitions into the green sector and other job transitions in our data. However, there is still potential for differences based on unobservable factors. To estimate the sensitivity of our results to omitted variable bias, we conduct a sensitivity analysis to provide some bounds on the robustness of our estimates using the method detailed in Cinelli and Hazlett[9]. Our main analysis estimates the likelihood that a fossil fuel worker who switched to the green sector (the "treatment" variable) attains managerial or science & engineering (S&E) occupations (the outcome variable). Our sensitivity analysis quantifies the minimum strength of association that an unobserved confounder would need to have with both the "treatment" variable (transition to the green sector) and the outcome variable (attainment of managerial or SE occupations) to nullify the estimated relationship between these two variables. This minimum strength of association is known as the robustness value. We compare this robustness value with the explanatory power (partial R^2) of an independent variable that is strongly correlated with the outcome variable, i.e., college-level education and above. A high robustness value relative to that partial R^2 indicates that the unobserved confounder would need to be very strongly correlated to both the "treatment" and outcome variables to nullify our findings.

Table A.24, which is shown below, reports the results for the outcome of obtaining a managerial occupation. The analysis yields a robustness value ($RV_{q=1}$) of 12.9%, indicating that an unobserved confounder would need to explain at least 12.9% of the residual variance in both the treatment (green sector transition) and the outcome (obtain managerial occupation), after accounting for observed covariates, to fully explain away the observed effect. The value $RV_{q=1,\alpha=0.05}$ means that an unobserved confounder would need to be strong enough to account for at least 12.6% of the remaining variation in both the treatment and the outcome to reduce the estimated effect to a point where the 95% confidence interval includes zero, making the effect statistically insignificant. Lastly, the quantity $R^2_{Y\sim D|X}$ implies that, under the extreme assumption that unobserved confounders account for all residual variation in the outcome, they would still need to explain at least 1.9% of the residual variance in the treatment to nullify the estimated effect.

To assess the strength that an unobserved confounder would need to have to explain away our estimated effect, we use college degree or above as a benchmark variable. College-level education and above is a well-established determinant of career advancement and is strongly correlated with the outcome variable, making it a credible reference point for comparison.

Figure A.27 presents the sensitivity contour plot for the relationship between the switch to the green sector and the outcome of obtaining managerial occupations, using the binary variable college degree or above as the benchmark covariate. The x-axis represents the partial R^2 of a hypothetical unobserved confounder with the treatment (green sector transition), and the y-axis shows its partial R^2 with the outcome (managerial occupation). The contour lines indicate combinations of these R^2 values that would reduce the estimated effect to specific thresholds. Notably, the red diamond markers show that a confounder whose association with the treatment and outcome variables are three times the magnitude of the association between college-level education and the outcome variable would still not fully attenuate the estimated effect. Even in such a case, the estimated coefficient in our regression model would decline from 0.117 to 0.114. An omitted variable would need to be strongly correlated with

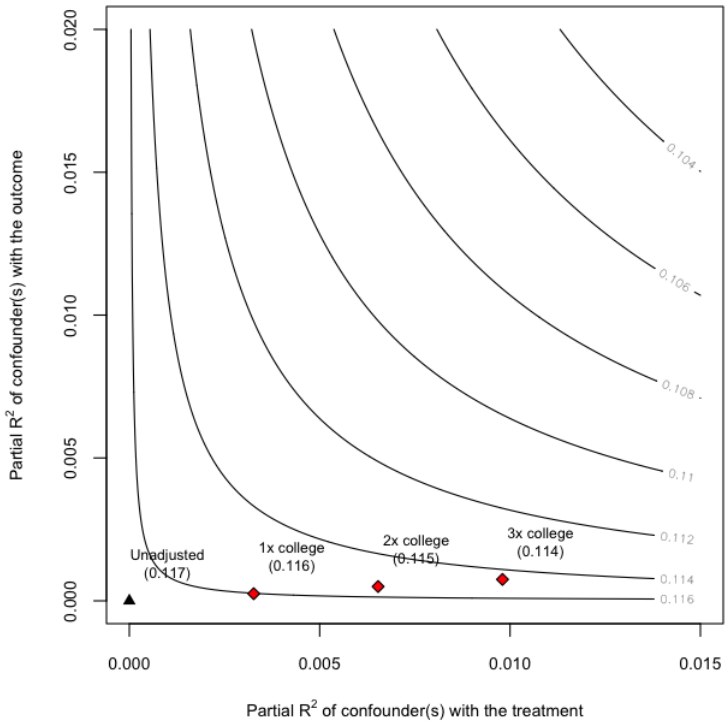
the "treatment" and outcome variables, much more so than the variable college-level education and above, to explain away the estimated association between the transition to the green sector and the attainment of managerial occupation. We conclude that the sensitivity analysis provides generous bounds under which our results are robust to omitted variable bias.

Table A.24: Sensitivity Analysis for Obtaining Managerial Occupations

Outcome: *Managerial Occupation*

Treatment:	Est.	S.E.	t-value	$R^2_{Y\sim D\|\mathbf{X}}$	$RV_{q=1}$	$RV_{q=1,\alpha=0.05}$
Green sector	0.117	0.001	91.974	1.9%	12.9%	12.6%
df = 443041						

Fig. A.27: Sensitivity Contour Plot of the Point Estimate of Attaining Managerial Occupations Using College Degree or Above as Benchmark Variable



Applying the same method, we implement sensitivity analysis for science and engineering occupations as an outcome. The robustness value reported in Table A.25, $RV_{q=1}$ is 21.8% suggests that, to completely explain away this effect, an unobserved confounder would need to explain at least 21.8% of the residual variance in both the treatment (green sector transition) and the outcome (science and engineering occupation), after accounting for all observed covariates. Meanwhile, $R^2_{Y\sim D|X}$ equals 5.8% tells us that, under an extreme assumption where omitted variables explain all remaining variation in the outcome, they would still need to explain at least 5.8% of the residual variance in the treatment to eliminate the observed effect. Finally, the value $RV_{q=1,\alpha=0.05}$ suggests that an unobserved confounder would need to account for at least 21.6% of the remaining variation in both the treatment and the outcome to

bring the lower bound of the 95% confidence interval to zero, meaning the effect is statistically insignificant.

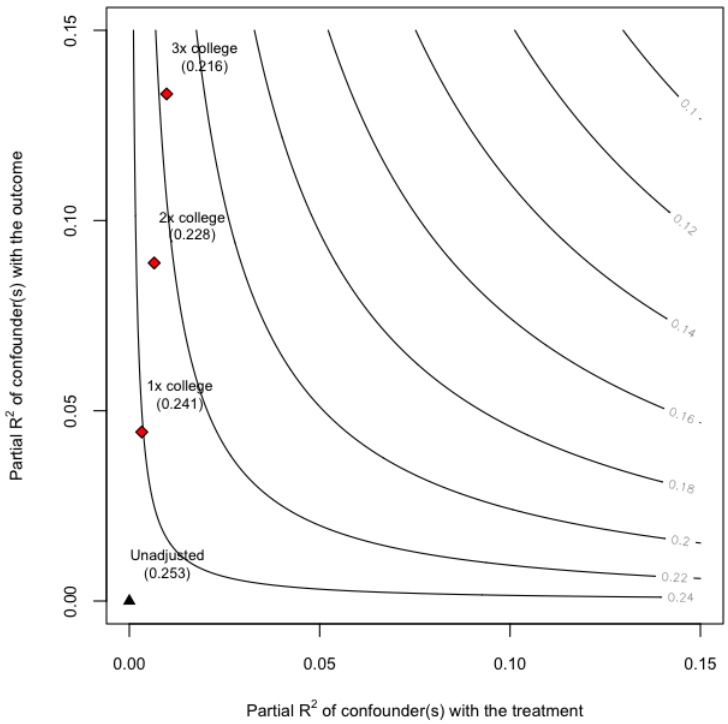
Figure A.28 presents the sensitivity contour plot for the relationship between the switch to the green sector and the outcome of obtaining SE occupations, using the binary variable college-level education and above as the benchmark covariate. The analysis shows that even an unobserved confounder with three times the strength of the association between college education and the outcome would not be sufficient to reduce the estimated effect to zero. In this scenario, the estimated regression coefficient remains at 0.216, well above zero, indicating that our results are robust to omitted variable bias.

Table A.25: Sensitivity Analysis for Obtaining Science and Engineering Occupations

Outcome: *Science and Engineering Occupation*

Treatment:	Est.	S.E.	t-value	$R^2_{Y\sim D\|\mathbf{X}}$	$RV_{q=1}$	$RV_{q=1,\alpha=0.05}$
Green sector	0.253	0.002	164.512	5.8%	21.8%	21.6%
df = 443041						

Fig. A.28: Sensitivity Contour Plot of the Point Estimate of Attaining SE Using College Degree or Above as Benchmark Variable



4.5 Addressing Self-Selection with the Instrumental Variable Method

We estimate the wage change associated with a fossil fuel worker switching into the green sector, relative to remaining in the fossil-fuel sector (Table A.5 Model 1). We find a wage premium in the green sector relative to the fossil fuel sector. Nevertheless, one source of bias in this estimate is that the wages in the green sector may influence workers' decision to make their job switch into the green sector. To reduce this bias (though we do not eliminate this bias), we estimate an instrumental variable regression using a Bartik-like instrumental variable[20].

We define the green energy Bartik instrument, $B_{i,t}$, for state i, at time t as the weighted sum of national trends using the local industry shares as weights: $B_{i,t} = \sum_{j=1}^{J} z_{i,j,0} g_{j,t}$, where $z_{i,j,0}$ represent the initial share of production in green energy industry j for state i, and $g_{j,t}$ indicates the growth of green energy industry j at the national level in year t. The initial share of green energy production j is the production of green energy j in 1970 divided by the total energy production in i in 1970. Green energy production j are green energy production from geothermal, biofuels, wind, solar, and hydropower. The total energy production is the energy production from these green energy sources plus coal, natural gas and oil. The data is from the U.S. Energy Information Administration.[7]

We postulate that the green energy Bartik instrument directly influences workers' probability of shifting to the green sector, but that the instrument does not directly influence workers' wages in the local labor market (though it does so indirectly through the channel of employment opportunities in the green sector). The intuition for this instrumental variable is as follows. National level shocks in the green energy production j (as captured by the growth rate of the green energy production j, i.e., the second component of the Bartik instrument) would have differential effects on the state level green energy production j. The differential effects depend on the state's initial level of green energy production j as measured in 1970 (i.e., the first component of the Bartik instrument). In other words, national level positive shocks would contribute to the larger production of green energy j in states with larger initial production of green energy j. These national level shocks would directly influence green sector employment in the local labor markets and thus workers' probability of shifting to the green sector. These national level shocks do not directly influence the wages in the local labor market (though these national level shocks can do so indirectly through the channel of increasing or decreasing employment opportunities in the green sector).

Table A.26 presents the results. We begin by considering the instrument quality. The F-statistics from the models are 20, which exceed the conventional cutoff of 10 for identifying weak instruments. This mitigates the concerns of weak instruments. The estimated coefficient for the green energy Bartik instrument in the first stage of the estimation models is positive and statistically significant. This estimate indicates a positive correlation between the size of the green energy sector in state i and time t (as captured by the green energy Bartik instrument) and frontline fossil fuel workers' shift into the green sector. This positive correlation corresponds to our expectation, based on our intuition for this instrument, as described earlier.

Next, we consider the results of the estimation models. These findings from the instrumental variable regressions align with our main results. The estimated coeffi-

[7]Data can be accessed at: https://www.eia.gov/beta/states/data

cient for the green sector is positive and statistically significant. Consistent with our main results, transitions into the green sector are associated with larger wage gains than job transitions within the fossil fuel sector.

We note that the IV estimates (0.628 in Table A.26) is larger than the OLS estimates in the main paper (0.064 in Model 1 Table A.5). This finding can be explained by the nature of these two estimation strategies. The OLS estimates capture the average treatment effect over the population, while the IV estimates capture the treatment effects on those that are treated. Because workers self-select into green jobs (and those that self-select may have other characteristics correlated with higher wages), it is unsurprising that the IV estimates of wages correlated to the shift to green sector is larger than the corresponding OLS estimates.

Table A.26: Green Transition and Wage Progression, IV Approach

	Model1
Second stage:	
Green Sector	0.628**
	(0.302)
R2 Adj.	0.424
First stage:	
Green Energy Bartik	0.131***
	(0.035)
R2 Adj.	0.532
Cragg-Donald F statistic	20
Num.Obs.	417627

Notes:
[1] *p<.10; **p<.05; ***p<.01.

4.6 Addressing Self-Selection by Estimating the Marginal Treatment Effect

One concern in our study is bias from workers' self-selection. Unobserved factors such as latent ability and career ambitions may shape both sector transitions and subsequent wages and mobility. To assess the role of selection on unobservables, we estimate marginal treatment effects (MTEs)[25–27] in a specification that controls for worker fixed effects. We use this framework to compare a given worker's wages when switching into the green sector versus switching into non-green sectors. The MTE identifies the wage effect for workers at the margin of choice—those who, given their observed characteristics and unobserved resistance to switching, are approximately indifferent between transitioning to the green sector and not doing so. In other words, we recover the wage impact for workers whose transition decision is most sensitive to small changes in the incentives to enter the green sector.

We conduct the analysis in following steps:

1. We define the potential outcomes:

$$Y = D \cdot Y(1) + (1 - D) \cdot Y(0).$$

where $Y(1)$ represents wages if transition to green, $Y(0)$ represents wages for not transition to green, D indicate green transition, X represent a vector of observed covariates.

2. We model a worker's decision to make a job switch into the green sector. Intuitively, a worker decides to make the switch into the green sector if the latent resistance (U_i) to make the switch (e.g., the cost of making the transition) is less than the benefit of making the switch. We estimate the propensity of receiving the treatment, i.e., making the shift to the green sector, using the following equation. $P(D = 1 \mid Z, X)$, where Z is instrumental variables and X are the control variables. Z is the green energy Bartik IV (estimated in section 4.5) and X are the dummy variables for the shift to the manufacturing sector, the dummy variable for the shift to the construction sector and the dummy variable for the shift to the other sectors.

3. Formally, MTE is defined as the derivative of the expected outcome with respect to the probability of treatment.

$$\text{MTE}(X = x_i, U_i = p) = \frac{\partial \mathbb{E}[Y_i(1) - Y_i(0) \mid X_i = x, P(Z_i) = p]}{\partial p}$$

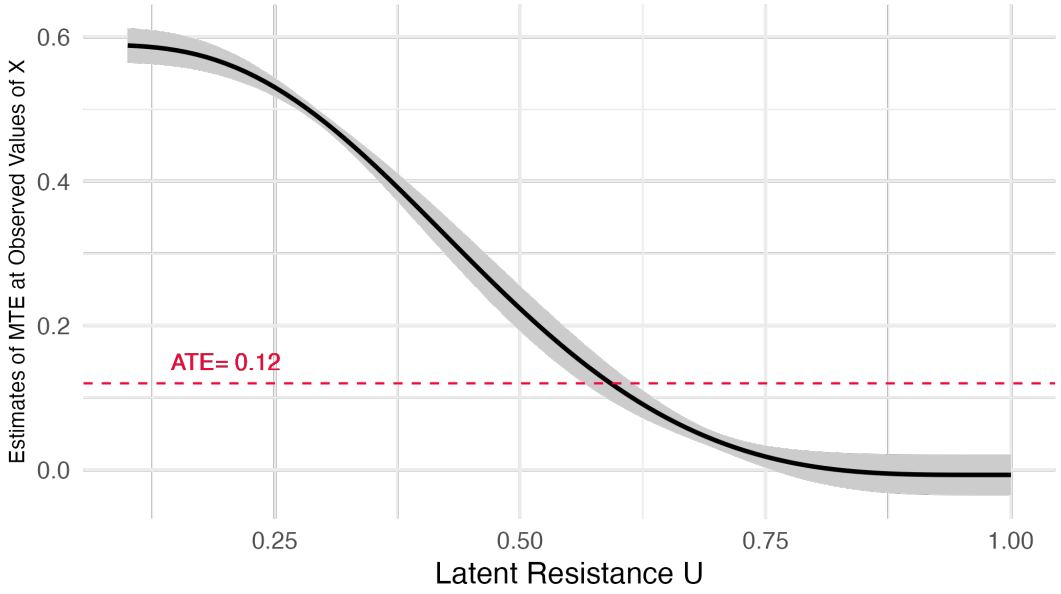
where X represents the observed covariates and U is a threshold that determines the individual i's likelihood of selecting into treatment. The technical details of estimating this equation can be found in Cornelissen et al. [12].

We estimate the MTE of the switch to the green sector on wages that are associated with each latent resistance U. Fig. A.29 presents the results. The y-axis indicates the wage increase of a worker with latent resistance U whose propensity to shift to the green sector is just slightly larger than their cost of making that shift.

Fig. A.29 shows that the MTE is declining as the latent resistance Uor the cost of making the transition increases. These results are consistent with our intuition that workers who self select into the green sector are those who have less latent

resistance to making that shift, and experience larger wage gains when they switch. We calculate the average treatment effect (ATE) from the estimates of the MTE over the distribution of the propensity score. Our estimate of the ATE is 0.12. This result is consistent with our OLS estimate of 0.06 in our main results, i.e., wages are higher for the same worker after switching into the green sector than when remaining in fossil-fuel employment.

Fig. A.29: Marginal Treatment Effect



5 Redefine the Skill Diversity and Skill Deepening Variables

In our main paper, we construct the skill diversity and the skill deepening variables using the skill progression network following the method used in Aufiero et al. [1]. In this section, we construct the skill diversity and the skill deepening variables using a different method. Specifically, we use Jaccard similarity to connect occupations and skills. Following the methodology applied in Lim, Aklin and Frank [33] and Frank et al. [16], we calculate Jaccard similarity of jobs and skills using the following equations:

$$B_{\text{Jobs}_{jj'}} = \frac{\sum_{j \in \text{Jobs}} \min(\text{M}_{j,s}, \text{M}_{j',s})}{\sum_{j \in \text{Jobs}} \max(\text{M}_{j,s}, \text{M}_{j',s})}$$

$$B_{\text{Skills}_{ss'}} = \frac{\sum_{j \in \text{Jobs}} \min(\text{M}_{j,s}, \text{M}_{j,s'})}{\sum_{j \in \text{Jobs}} \max(\text{M}_{j,s}, \text{M}_{j,s'})}$$

We set $M_{js} = 1$ if skill s is required for job j and its normalized importance exceeds the average importance of that skill across all occupations; otherwise, $M_{js} = 0$. The variable $B_{jj'}$ captures the similarity between two occupations j and j'. To represent dissimilarity, we calculate $1 - B_{jj'}$, where larger values reflect greater differences between occupations. Using workers' job histories, we then compute the cumulative average of these dissimilarity scores to develop an indicator of skill diversity.

To construct indicators of managerial and science and engineering skill deepening, we apply the same methodology outlined in Section 3.5, substituting the skill similarity matrix $B_{\text{Skills}_{ss'}}$ in eq.5 with Jaccard-based skill similarity measures.

We re-run the regressions in our main paper using this alternative definition for skill diversity and skill deepening. Table A.27 presents the results from these regressions. These results are consistent with our main results. For the same worker when switch to the green sector, greater skill diversity is associated with a higher probability of holding a managerial position but a lower probability of holding an SE occupation. For the same worker in green sector employment, stronger SE skill deepening is associated with a higher probability of holding an SE occupation, and greater managerial skill deepening is associated with an increased probability of holding a managerial occupation.

Table A.27: Skill Diversity, Skill Deepening and Upward Mobility in the Green Sector

	Managerial Occupation		Science and Engineering Occupation	
	Model1	Model2	Model3	Model4
Green Sector	0.667*	1.455***	11.741***	3.232***
	(0.365)	(0.051)	(0.389)	(0.045)
Construction Sector	-0.048	-0.657***	1.189***	1.265***
	(0.100)	(0.122)	(0.093)	(0.095)
Manufacturing Sector	0.731***	0.483***	1.116***	1.116***
	(0.054)	(0.065)	(0.054)	(0.056)
Other Sectors	0.415***	-0.070	1.404***	1.466***
	(0.037)	(0.043)	(0.038)	(0.038)
Skill Diversity	-0.208		-6.400***	
	(0.458)		(0.483)	
Managerial Skill Deepening		11.969***		
		(0.229)		
Science and Engineering Skill Deepening				5.247***
				(0.344)
Green Sector*Skill Diversity	1.317**		-13.191***	
	(0.554)		(0.590)	
Green Sector*Managerial Skill Deepening		-2.742***		
		(0.405)		
Green Sector*Science and Engineering Skill Deepening				4.636***
				(0.626)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Origin State FE	Yes	Yes	Yes	Yes
Destination State FE	Yes	Yes	Yes	Yes
McFadden's Pseudo R2s	0.601	0.643	0.699	0.7
N. of observations	418,457	354,622	418,457	405,774

Notes:

[1] The observations are job switches of frontline fossil fuel (FFF) workers in 2000-2023. Green sector, construction sector, manufacturing sector, and other sectors are dummy variables indicating the target sector into which FFF workers make their job switch. The omitted sector is the fossil fuel sector. The sector classifications are based on a combination of 2-digit NAICS codes and SOC codes (See Methods). The managerial occupation dummy variable indicates the job switch is into a managerial occupation. The science and engineering occupation dummy variable indicates the job switch to a science and engineering occupation. We calculate (1) the SE skill deepening index, measured prior to a job switch, which captures workers' accumulation of SE skills by taking on jobs with greater core SE skills requirements; (2) the managerial skill deepening index, defined analogously; and (3) the skill diversity index, measured prior to a job switch, which captures workers' accumulation of diverse skills by taking on jobs with greater differences in skill requirements (see Methods section 6.2).The models include individual fixed effects, the state of the prior job, the state of the destination job, and the years in which job switches occur.

[2] *p<.10; **p<.05; ***p<.01.

6 Additional Tables and Figures

6.1 Quantifying the Magnitude of Upward Mobility

Our core empirical results estimate the predicted probability of achieving upward mobility at the individual level. However, it is equally important to assess the overall economic significance of upward mobility for the entire FFF workers in the fossil fuel sector. This aggregate perspective helps to understand scale and potential impact of the overall mobility on the economy. Such measurement also carries direct policy relevance. By estimating the number of upwardly mobile positions that could be filled by former fossil fuel workers as the green sector expands, we provide policymakers with a actionable metric to evaluate the potential returns on green investment. This, in turn, can guide workforce transition strategies, training programs, and targeted economic policies aimed at maximizing the benefits of green transition.

To measure aggregate upward mobility, we proceed in four steps. First, we define upward mobility as the case in which FFF workers, at some point in their careers, obtain either managerial occupations or science and engineering occupations after leaving their first fossil fuel job. Importantly, this definition does not require that workers transition directly into the green sector to achieve upward mobility. In contrast, workers may take intermediary steps, switching to jobs in the fossil fuel, green, construction, or manufacturing sectors, before ultimately attaining upwardly mobile positions in the green sector. Second, we calculate the total number of upwardly mobile workers over the year between 2000 and 2023 in the targeted sectors, respectively. It is important to note that a worker may be counted more than once if they attain managerial or science and engineering positions in different sectors over the course of their career. Third, we identify the full population of FFF workers by aggregating all workers in fossil fuel industries (as listed in Table A.1) whose occupations fall within SOC 47 (Construction and Extraction), SOC 49 (Installation, Maintenance, and Repair), SOC 51 (Production), and SOC 53 (Transportation and Material Moving). This aggregation uses national industry-specific occupational employment data from the Bureau of Labor Statistics, resulting a total of approximately 1.4 million frontline fossil fuel workers. Finally, we compute the percentage of FFF workers who achieve upward mobility by dividing the total number of upwardly mobile workers by the total number of frontline fossil fuel workers.

Table A.28: Number of FFF Workers Obtaining Managerial or SE Positions After Transitioning to the Target Sector

From FF Sector to	# of People	% of All Frontline Fossil Fuel Workers
Fossil Fuel Sector	14054	0.9%
Green Sector	43819	2.9%
Construction Sector	1335	0.1%
Manufacturing Sector	7514	0.5%

Notes:

[1] Total upward mobility in each target sector is calculated by aggregating all unique workers who, at some point in their careers between 2000 and 2023, switched into managerial or science and engineering occupations within that sector. Importantly, a worker may be counted more than once if they attain managerial or science and engineering positions in different sectors over the course of their career.

[2] *p<.10; **p<.05; ***p<.01.

Table A.28 shows that the green sector offers the highest upward mobility opportunities for FFF workers. Among all FFF workers, 2.9% achieve upward mobility when transitioning to the green sector at some point of their career. In contrast, the corresponding share is only 1.0% for those who remain in the fossil fuel sector, and even lower for transitions into construction (0.1%) and manufacturing (0.5%). It is important to note that these numbers likely represent lower bound estimates of upward mobility rates in each sector. Because the Revelio dataset does not cover the full population of fossil fuel workers, some upwardly mobile individuals are not captured in the data. Even with this limitation, the results underscore the green sector's strong potential for career advancement among displaced fossil fuel workers. Continued investment in the green sector, leading to the creation of more high-quality jobs, is likely to absorb a larger share of former fossil fuel workers and provide them with substantially greater opportunities for upward mobility.

Table A.29: Green Industry Used to Calculate Total Green Workforce

NAICS Code	Industry Title
221111	Hydroelectric power generation
221113	Nuclear electric power generation
221114	Solar electric power generation
221115	Wind electric power generation
221116	Geothermal electric power generation
221117	Biomass electric power generation
221118	Other electric power generation
237130	Power and Communication Line and Related Structures Construction
238210	Electrical contractors and other wiring installation contractors
333600	Engine, turbine, and power transmission equipment manufacturing
335300	Electrical equipment manufacturing

To estimate the additional upward mobility opportunities for FFF workers if green sector keep growth, we proceed in three steps.

First, we calculate the share of upwardly mobile jobs filled by FFF workers. Using employment counts for all green industries listed in Table A.29 from the Bureau of Labor Statistics (BLS), we estimate the total green sector workforce at approximately 1.96 million. Of these, 43,819 upwardly mobile jobs are filled by FFF workers, representing about 2% of the total green workforce.

Second, we use BLS employment projections to estimate potential growth in green sector employment over the next decade, using 2023 employment as the baseline.[8] Under the BLS projection, total green sector employment in 2033 (as defined in Table A.29) is projected to reach 2.11 million, an increase of roughly 150,000 jobs, or 7.7% growth over ten years. Applying the 2% share of upwardly mobile jobs filled by FFF workers, this expansion would create approximately 3,020 additional upwardly mobile positions for fossil fuel workers.

Third, we explore alternative growth scenarios to illustrate the potential scale of opportunity if public and private investment in the green sector accelerates. Under a 20% growth scenario, green sector expansion would create an estimated 7,844 upwardly mobile jobs for FFF workers. A more ambitious 50% growth scenario would raise this figure to approximately 19,610 jobs.

[8]Employment projection data: https://www.bls.gov/emp/data.htm

Taken together, these estimates show that the opportunities pursued by a subset of FFF workers should not be overlooked by policymakers. While not all FFF workers will be able to secure such positions, given the limited availability of managerial and SE roles in the green sector, as in any other sector, they nonetheless represent an important avenue for upward mobility.

6.2 Personal Traits of Workers Who Transition to the Green Sector

To complement the regression analysis and inform more targeted workforce development strategies, we provide descriptive comparisons of personal and occupational traits between FFF workers who successfully transition into upwardly mobile roles in the green sector and those who remain in the fossil fuel sector (Fig.A.30, A.31, A.32).

To understand the extent to which workers' initial traits may influence their future upward mobility, Fig. A.30 compares baseline personal and occupational traits between frontline fossil fuel (FFF) workers who ultimately achieve upward mobility in the green sector (green switchers) and those who remain in the fossil fuel sector (fossil fuel stayers). Positive values indicate traits more prevalent among green switchers, while negative values indicate traits more common among fossil fuel stayers. Skills and abilities are categorized into seven dimensions, soft skills, cognitive abilities, physical abilities, social skills, system skills, business and management skills, and engineering and science skills, based on groupings derived from the O*NET database (see SI 4.3.1 for methodological details).

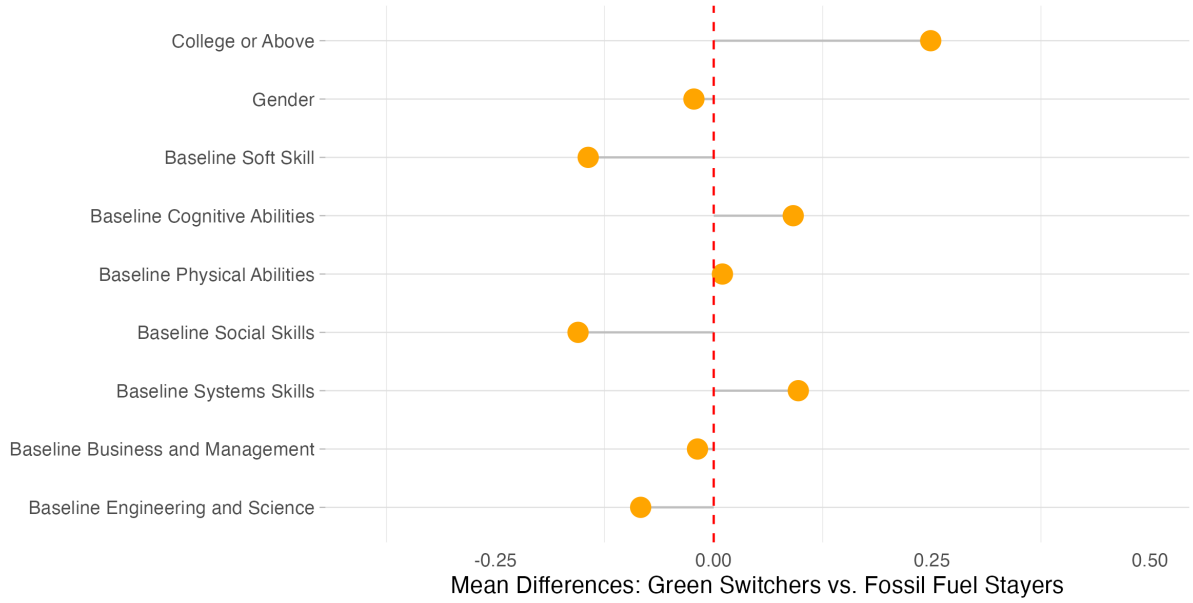
Green switchers exhibit slightly higher baseline cognitive abilities and systems skills, whereas fossil fuel stayers display marginally higher in soft and social skills. Differences across most other baseline skill domains, including business and management, engineering and science, and physical abilities, are relatively small, suggesting that initial occupational skill profiles alone do not strongly distinguish workers who transition successfully into the green sector.

However, one factor stands out: educational attainment. Workers who later transition into upwardly mobile roles in the green sector are substantially more likely to hold a college degree or higher. This pattern aligns with findings from Curtis, O'Kane and Park[14], who show that workers with only a high school education or less, as well as older workers, are significantly less likely to transition into green occupations. Together, this difference underscores the role of formal education as a key enabling factor for long-term mobility, even when initial occupational skill requirements are similar.

Figs.A.31 and A.32 further compare mean trait differences between workers who, at some point in their careers, transition to the green sector and advance into managerial or science and engineering roles, and those who remain in the fossil fuel sector. Cumulative average skill and ability scores are calculated based on attributes acquired across all jobs held up to each job transition.

For managerial roles (Fig. A.31), green switchers display markedly longer job experience, higher occupation centrality, and stronger scores across multiple skill categories, particularly in business and management skills. These patterns suggest that workers who move into green managerial positions often occupy highly connected roles in the occupational network before transitioning and cultivate broad, adaptable skill sets aligned with leadership demands. However, they score lower in engineering and science, and physical skills than fossil fuel stayers, reflecting a strategic shift toward management oriented competencies rather than technical specialization. Fossil

Fig. A.30: Baseline Personal Traits Differences Between Fossil Fuel Workers Who Ultimately Achieve Upward Mobility in Green Sector and Those Who Remain in Fossil Fuel



Notes: All baseline skill categories represent the proportion of each skill domain within the total skill requirements of the corresponding fossil fuel occupation (see section 4.3.1). All baseline variables are continuous, except for "college degree or above" and "gender," which are binary indicators. To ensure comparability across variables, we compute standardized mean differences, defined as the mean differences divided by the pooled standard deviations, for continuous variables, and use differences in proportions for binary variables.

fuel stayers' higher physical ability scores are consistent with the concentration of physically intensive occupations in the fossil fuel sector, which may be less transferable to managerial positions in the green economy.

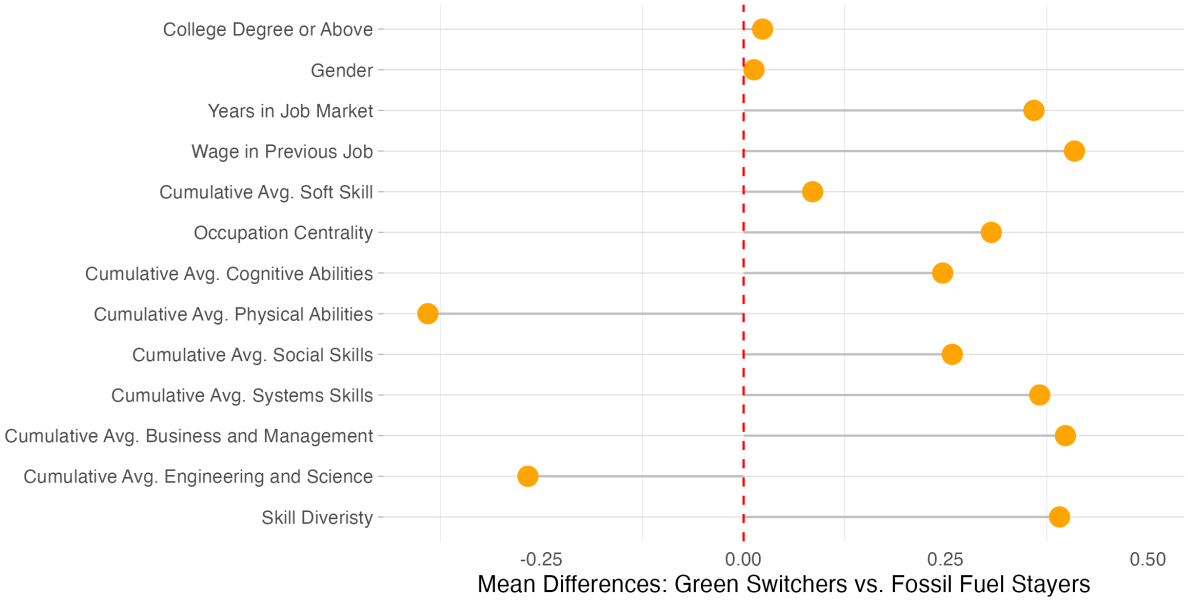
For science and engineering roles (Fig. A.32), green switchers have, on average, higher education levels, underscoring the importance of holding a college degree or higher in accessing these occupations, and significantly higher scores in systems skills and engineering and science skills. Differences in social skills and business and management skills are minimal, indicating that success in these technical positions is more closely tied to deep, specialized expertise than to broader interpersonal or managerial competencies.

Taken together, these findings reinforce our argument in section 4 that skill development is central to enabling displaced fossil fuel workers to capture upward mobility opportunities in the green sector. Workers seeking to transition must often break out of their existing fossil fuel occupational networks (as shown in Fig. 3) and move into roles that expand their skill sets, either by building strong technical expertise in science and engineering or by developing diverse competencies that include managerial and business skills.

From a workforce development and policy perspective, the evidence underscores the need for targeted and differentiated upskilling strategies. For those aiming to become engineers, investments should focus on deepening domain expertise in science and engineering. For those targeting managerial positions, training should prioritize broad skill diversification, leadership, and business management competencies.

Adopting this targeted approach would enhance the likelihood that fossil fuel workers can make successful transitions and fully capture the upward mobility opportunities emerging within the green economy.

Fig. A.31: Differences in Personal Traits Between Fossil Fuel Workers Who Transition to Green Sector and Become Managers and Those Who Remain in Fossil Fuel



Notes: All cumulative average skill categories represent the average proportion of each skill domain within the total skill requirements accumulated prior to each job switch (see SI section 4.3.1). All variables are continuous, except for "college degree or above" and "gender," which are binary indicators. To ensure comparability across variables, we compute standardized mean differences, defined as the mean differences divided by the pooled standard deviations, for continuous variables, and use differences in proportions for binary variables.

Fig. A.32: Differences in Personal Traits Between Fossil Fuel Workers Who Transition to Green Sector and Become Engineers and Those Who Remain in Fossil Fuel



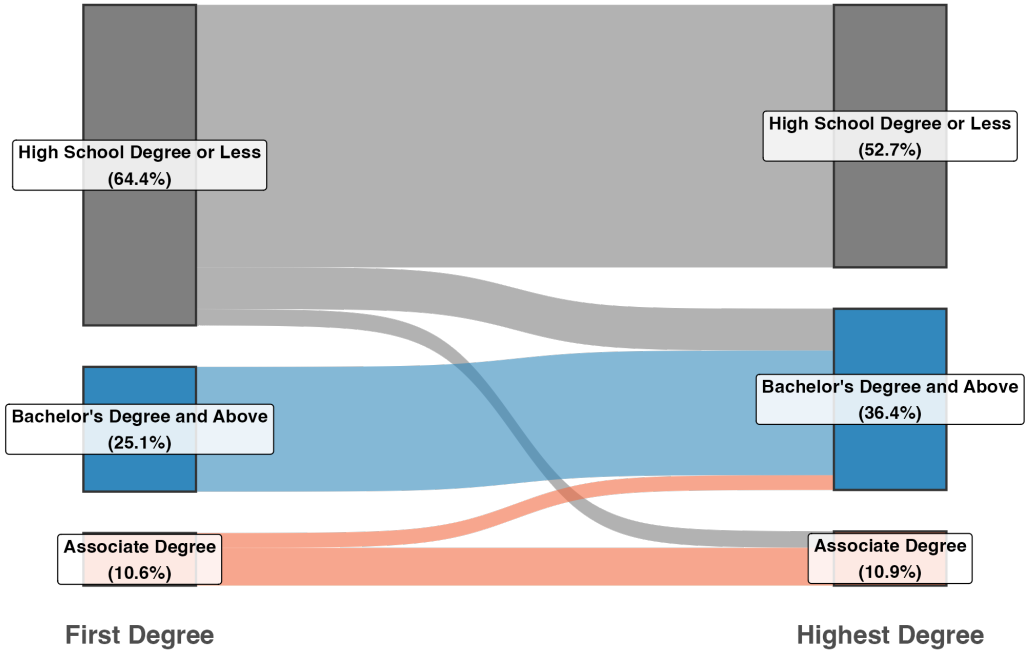
Notes: All cumulative average skill categories represent the average proportion of each skill domain within the total skill requirements accumulated prior to each job switch (see SI section 4.3.1). All variables are continuous, except for "college degree or above" and "gender," which are binary indicators. To ensure comparability across variables, we compute standardized mean differences, defined as the mean differences divided by the pooled standard deviations, for continuous variables, and use differences in proportions for binary variables.

6.3 Education Flow of Frontline Fossil Fuel Workers

Mean differences analysis reveals that workers who eventually transition to upward mobile positions in the green sector have higher educational attainment than those who remain in fossil fuels (see Fig. A.30). To be clear, for our regression analyses that examine the association between green transition and upward mobility (eq.1), we control for this difference using individual fixed effect, thereby restricting our comparison between a given worker over their career (SI section). In this section, we turn a different issue, i.e., the education mobility of fossil fuel workers.

Figure A.33 illustrates educational mobility among fossil fuel workers through a sankey diagram. The left side shows the distribution of workers' initial education levels, while the right side displays their highest degree obtained over their careers. The flows between these two stages reveal notable upward educational progression. While 64.4% of workers reported high school or less as their first degree, this proportion decreased to 52.7% for their highest degree attained. Conversely, the share holding a bachelor's degree or above increased from 25.1% to 36.4%, representing a 11 percentage point gain. These upward flows, particularly from high school credentials to bachelor's degrees, indicate that a substantial portion of the fossil fuel workforce pursued higher education mid-career. The associate degree category remained relatively stable (10.6% to 10.9%).

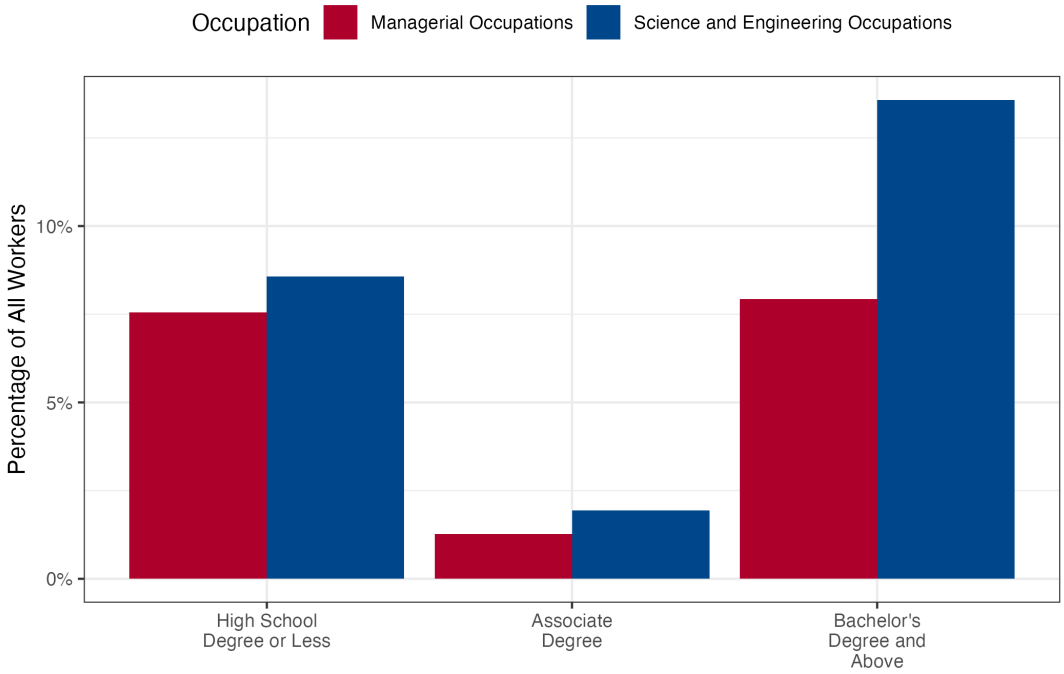
Fig. A.33: Education Flow of Frontline Fossil Fuel Workers



The relationship between education and upward mobility becomes clearer when examining occupational transitions. Figure A.34 shows the distribution of highest education degrees among fossil fuel workers who achieved upward mobility into managerial or science and engineering occupations. Workers with bachelor's degrees or above constitute the largest share of those reaching upward mobile positions, particularly in science and engineering roles (13.5% of all fossil fuel workers) compared

to managerial positions (8.0%). In contrast, workers with only high school degrees or less show more modest representation in both pathways (approximately 7-8.5%), while those with associate degrees represent the smallest share (1-2%). These patterns underscore that higher educational attainment, especially bachelor's degrees, serves as a critical enabler of upward occupational mobility for fossil fuel workers, with science and engineering pathways showing particularly strong educational requirements.

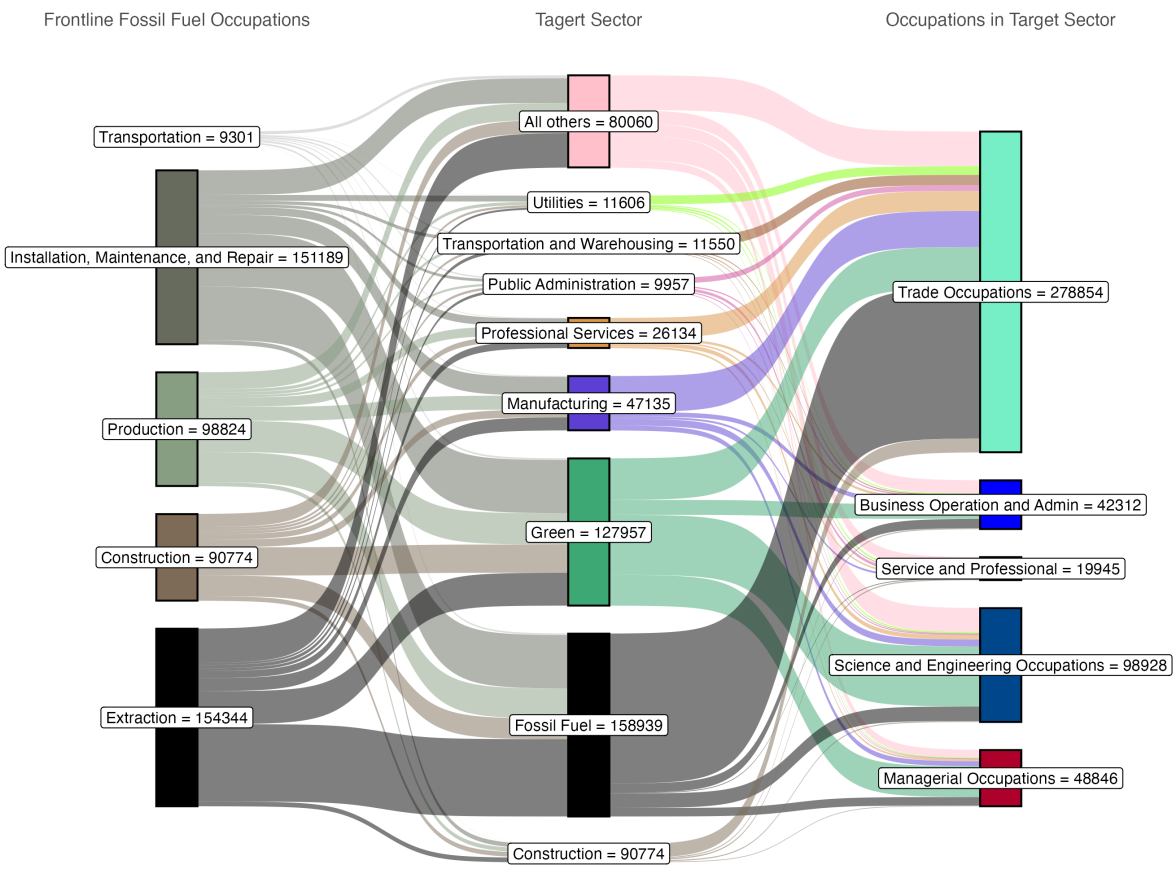
Fig. A.34: Educational Attainment of Workers and Upward Mobility



6.4 Sector and Occupation Flow of Frontline Fossil Fuel Workers

The observations are job switches from a prior frontline fossil fuel job. The diagram shows the job switches from frontline fossil fuel jobs into the different sectors, including the 4 major sectors that we focus on, i.e., the green, fossil fuel, manufacturing and construction sectors, and the job switches into different occupations, including the 3 major occupations that we focus on, i.e., managerial, science and engineering and trade occupations.

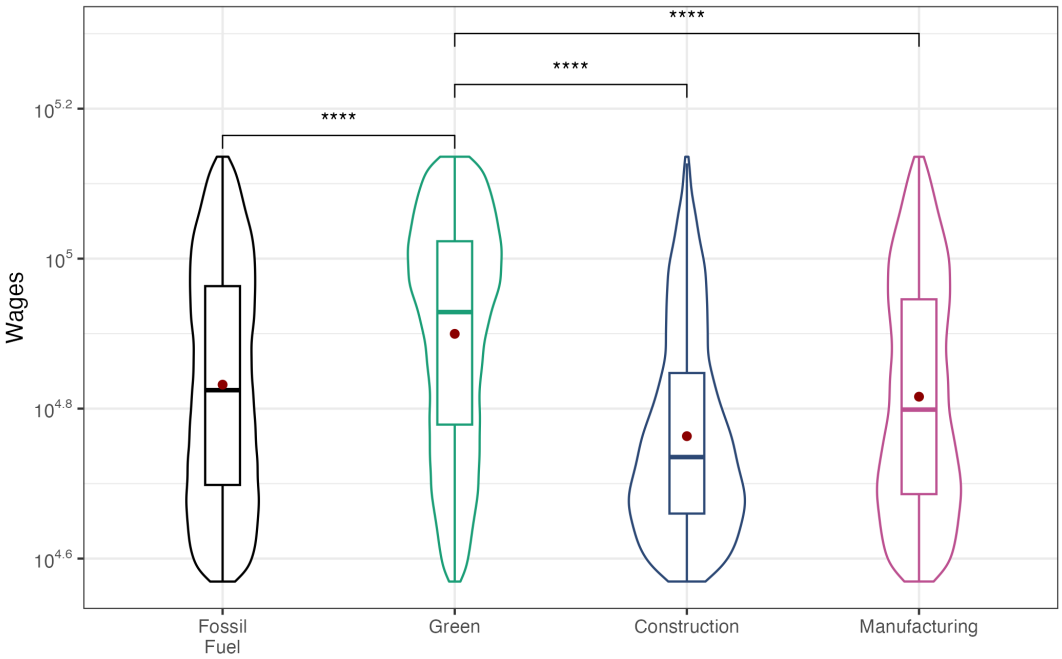
Fig. A.35: Job Flow of Frontline Fossil Fuel Workers



6.5 Distribution of Wages by Sector

Fig. A.36 shows green sector, on average, provide higher wages compare to fossil fuel sector. The green sector has the highest average wage of \$80K ± 2.7K , followed by the Fossil Fuel sector with an average of \$72K ± 2.6K. The Manufacturing sector has a lower average wage of \$70K ± 2.5K, while the Construction sector has the lowest average wage of \$62K ± 2.2K.

Fig. A.36: Distribution of Wages by Sector

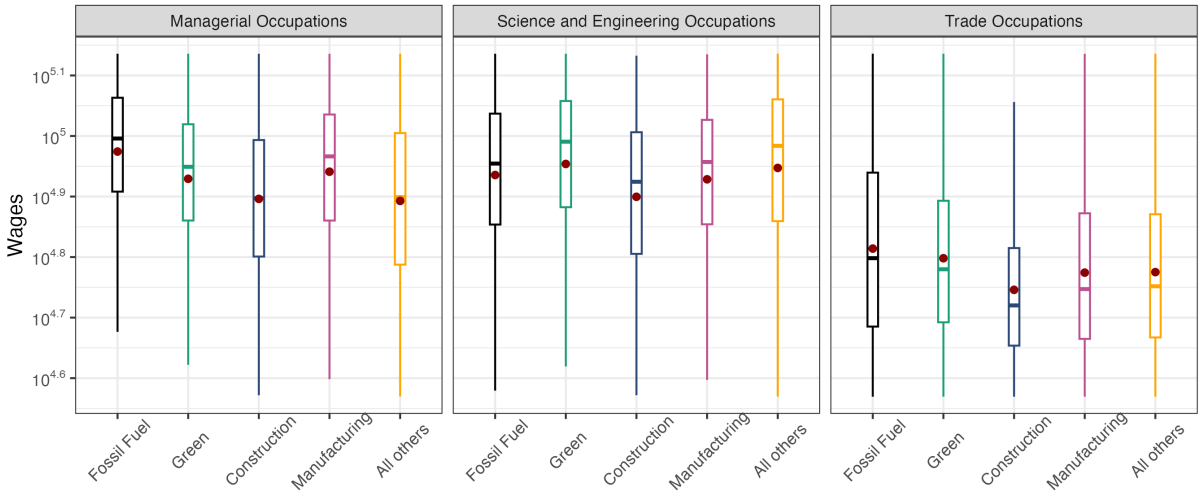


Note: Read dots represent the average wage.

6.6 Distribution of Wages by Sector and Occupation

Fig. A.37 display the distribution of wages across the key occupations and sectors we focus on. The red dots represents average wage estimated based on the data. The wage distribution in the first panel indicates that fossil fuel sectors, on average, offer higher salary for managerial positions (\$97K ± 23K) than green, construction, and manufacturing. Green sector provides slightly lower average wages (\$88K ± 23K) compared to fossil fuel and manufacturing but higher than construction sector. The second panel, however, shows that the green sector, on average, offers higher salaries (\$94K ± 26K) for workers transitioning into science and engineering positions compared to the fossil fuel (\$90K ± 24K). This indicates that the green sector places greater value on the technical expertise of its workforce. Lastly, trades occupations generally earn lower wages across all sectors, with the fossil fuel sector offering the highest, followed closely by the green sector, while the construction and manufacturing sectors provide the lowest wages.

Fig. A.37: Distribution of Wages by Sector and Occupation

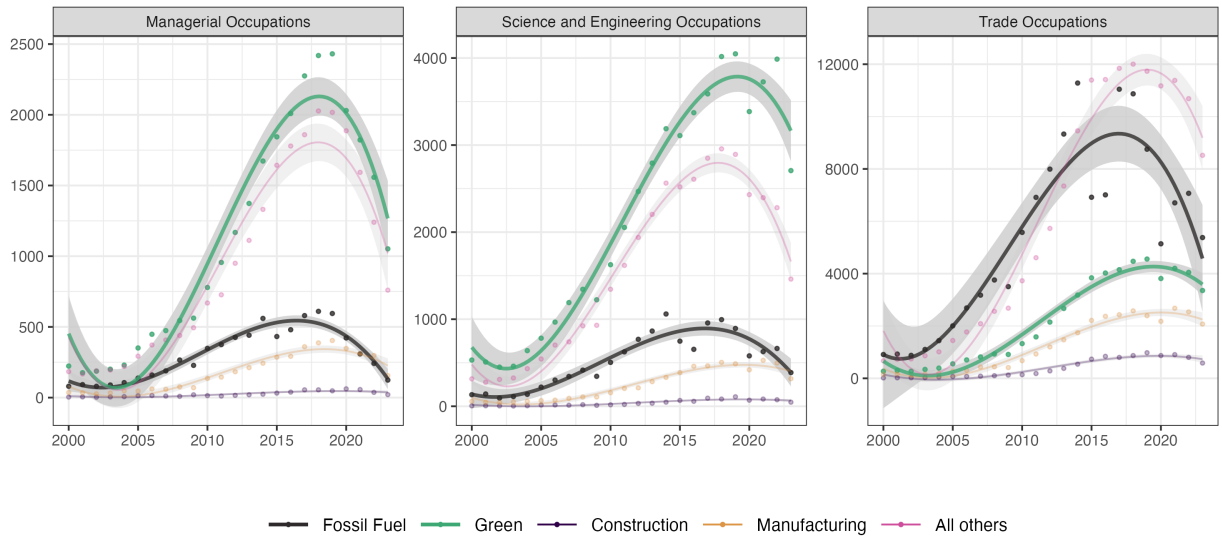


Note: Read dots represent the average wage.

6.7 Career Mobility in Numbers of People

Fig. A.38 indicates more FFF workers shifted to the managerial and SE occupations in the green sector than in the fossil fuel sector. The number of workers who secured managerial occupations (SE occupations) in the green sector rose since 2003, peaked at 2431 in 2019 (4048 in 2019) and declined to 1052 (2707) by 2023. Far fewer workers secure managerial and SE occupations in the fossil fuel sector, peaking at 610 at 2018 for managerial and 1060 SE occupations in 2014, and declining to only 124 managerial and 387 SE occupations by 2023.

Fig. A.38: Career Mobility Over Years

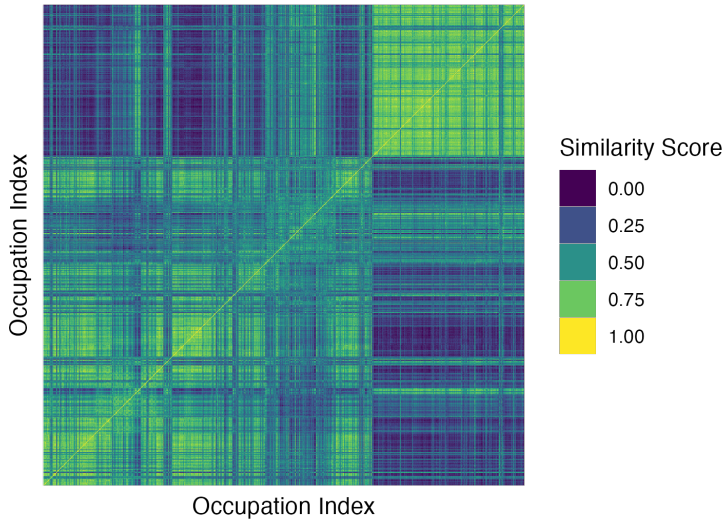


Note: Each dot represents the total number of workers transitioning into a managerial, science and engineering, or trades and labor role, by sector and year.

6.8 Job and Skill Similarity Matrix

Fig. A.39 visualizes the pairwise skill similarity scores between different occupations. The matrix compares occupations based on their shared skill sets, with both the x-axis and y-axis representing occupation indices. A similarity score of 1.00 (yellow) represents complete overlap in skill sets between two occupations, while a score of 0.00 (dark purple) indicates no overlap. The matrix highlights clusters of occupations with high similarity, suggesting groups of roles with overlapping or related skills, while areas with darker colors indicate occupations with distinct or unique skill requirements.

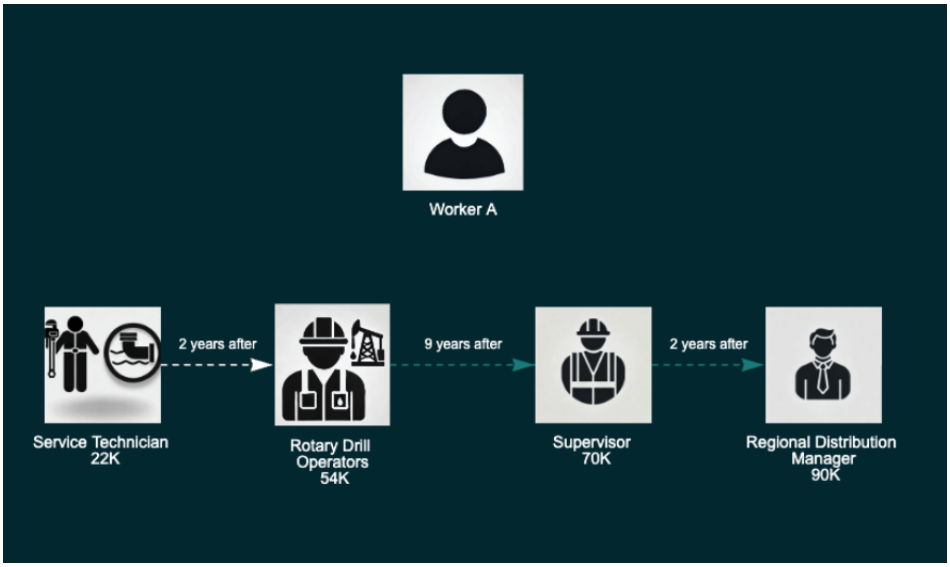
Fig. A.39: Matrix of Pairwise Skill Similarity Between Occupations



6.9 Example of Job Transitions for a FFF Worker

Figure A.40 illustrates an example of a real worker's career trajectory in our dataset. Worker A began their career as a Service Technician in the fossil fuel sector, earning $22K annually. After two years, Worker A transitioned to a role as a Rotary Drill Operator (annual wage: $54K), where they remained for nine years. Following this period, Worker A achieved a major career milestone by moving into the green sector as a First-Line Supervisor of Construction and Extraction Workers (annual wage: $70K). Just two years later, they advanced further to become a Regional Distribution Manager in the green sector, earning $90K annually. This trajectory highlights both the multiple transitions often required for frontline fossil fuel (FFF) workers to achieve upward mobility and the significant wage gains that can accompany successful transitions into managerial roles in the growing green economy.

Fig. A.40: Example of Job Transitions for a FFF Worker



7 Literature Review of the Just Transition

To position our research questions and our findings in the literature, we provide a review of the Just Transition literature. This literature examines the transition from a fossil fuel-based economy to a green energy-based economy or more broadly, to a low carbon economy. The literature recognizes that the transition can result in job losses for workers in the fossil fuel and energy intensive manufacturing sectors and adverse socioeconomic impacts to communities that are reliant on employment, tax revenue, and other resources from the carbon intensive sector[8,28,36,44]. The high concentration of workers in these carbon intensive sectors in specific geographical regions vulnerable to the energy transition amplifies the adverse impacts on communities in those regions[21,24]. The Just Transition literature examines the elements of an equitable transition (i.e., workers and communities securing livelihoods and quality lives and participating fully in the low carbon economy), factors that can impede a Just Transition, and explores public policies that can enable a Just Transition[6,8,40,42]. We provide a brief review of a selection of studies in the United States pertaining to the labor market aspects of the Just Transition literature (section 7.1 and 7.2). We also

provide a brief review of a selection of studies on other policies to support workers and communities for a Just Transition (section 7.3).

7.1 Job Transitions: Skills, Wages and Location of Jobs

Our study focuses on the vertical mobility of frontline fossil fuel workers and reskilling strategies used by workers who achieved upward mobility in the green sector over their careers. We describe how frontline fossil fuel workers that achieve upward mobility make a sequence of job changes over their career, moving from one job to another with greater overlap of skills. These sequential moves enable some frontline fossil fuel workers to eventually shift into science and engineering and managerial positions in the green sector, even if there is a sizable gap in skills between frontline fossil fuel jobs and science and engineering and managerial positions in the green sector. We also find larger cumulative wages throughout the careers of fossil fuel workers who secure science and engineering and manager positions.

Other important studies focus mainly on the horizontal mobility of workers from the fossil fuel sector to the green sector and compare the wages between these two jobs. These studies typically examine workers immediate shift from a fossil fuel job to a green job, rather than track workers' job switches over their career. These studies find that key factors that influence workers' transition between fossil fuel and green jobs are the extent of skill similarity, the differences in wages, and the co-location (or lack thereof) of fossil fuel and green jobs. We note that studies have used varying definitions of the "origin" jobs (e.g. fossil fuel, carbon-intensive, polluting or brown jobs) and the destination jobs (ranging from narrower definitions of jobs specific in wind, solar and EV and broader definitions of jobs defined as green by the US Bureau of Labor Statistics.[9] Therefore, comparisons across studies, if made, would need to be cognizant of these varying definitions.

One study that examines the transition of workers from the fossil fuel sector to the green sector estimates the magnitude of the workers that make such a transition and the characteristics of these workers. Curtis, O'Kane and Park [14] examines microdata of 130 million workers and their job history profile in the period 2005-2021. They use Lightcast data of online employment profiles, representing 300 million jobs. They find that the share of workers leaving a job in the dirty sector for the green jobs increased from less than 0.1% in 2005 to 0.7% in 2021, coinciding with the growth of jobs in the green sector. They note that the growth of jobs in the green sector can contribute to a rising rate of fossil fuel workers' transition to green jobs. Curtis, O'Kane and Park [14] define the green sector as the wind, solar and EV sectors; and define the jobs in carbon intensive sector to include all extraction workers, the coal, oil and natural gas sectors, and the five most energy intensive sectors. They find that the transition to green jobs varies across worker characteristics, i.e. workers with a high school degree or less and older workers are less likely to make the transition to green jobs. They also find that the transition to green jobs vary across cities and states. They note the reduction of opportunity to shift to fossil fuel jobs would reduce available jobs across the wage distribution and these impacts vary by geographical locations. Our findings on the share of fossil fuel workers that shift to the green sector are similar to those in Curtis, O'Kane and Park [14].

Several studies that focus on the horizontal mobility of fossil fuel workers to green jobs find a low skill "distance" between skills required in the fossil fuel and green

[9] Access at: https://www.onetonline.org/search/green_topics/

sectors, suggesting fossil fuel workers can potentially make the transition, provided they face no other frictions. However, the studies note that at least two factors impede the transition, first, those green jobs or alternative jobs that require similar skills to fossil fuel jobs pay less than the fossil fuel jobs, and second, new and expected green jobs are often not co-located with fossil fuel jobs.

An earlier study by Louie and Pearce[34] addresses the issue of skill distance between narrow sets of origin and destination jobs, i.e. from jobs specific in coal-mining and coal power plants (i.e., excluding jobs not specific to coal plants such as clerical workers) to solar photovoltaic jobs and estimate the potential costs of retraining. They match each coal specific occupation with a solar occupation that are closest in education, training and skill requirements. They find a varying need for retraining, estimating that 35% of workers in coal mining jobs and 57% of workers in coal power plants will need retraining to secure the closest solar photovoltaic occupation. They use data on education, training, and skill requirements for each coal-specific occupation from the BLS annual national industry specific Occupational Employment and Wage Statistics and for the solar photovoltaic occupation from the US Department of Energy's SunShot Initiative.

Other papers on horizontal mobility, while documenting that the short distance between skills between fossil fuel jobs and "closest" green jobs, underscore the frictions posed by the non-co-location of green jobs with fossil fuel jobs and the lower wages of green jobs that are "closest" in skills to fossil fuel jobs. Raimi and Greenspon[43] find that while there are many occupations that require the same skill sets as occupations in the coal, oil, and gas sector, those jobs offer significantly lower wages. Using the O*NET data on the level and importance of skills in diverse occupations, they conducted a detailed analysis of 31 occupations for which 5% of workers in these occupations are in the coal, oil, and gas sectors. They find that among these occupations, the higher-paying occupations have fewer good-matches among the alternatives with comparable pay than do lower-paying jobs. Moreover, workers in higher paying occupations in the fossil fuel sector will have to undertake many years of specialized training to shift to alternative occupations with similar high-level skills.

Greenspon and Raimi[22] find that alternative occupations that require similar skill sets in the local labor market pay lower wages than fossil fuel occupations. However, alternative occupations that pay similar wages and are growing in the local labor market require a different skill set than fossil fuel jobs. They focus on the local labor market, as represented by commuting zones, because historically, fossil fuel workers, particularly, coal workers in Appalachia, have exhibited limited geographical mobility to secure alternative jobs. They compare the skills in fossil fuel occupations and the skills in jobs that are growing by commuting zones among the 35 skills from O*NET.

Lim, Aklin and Frank[33] conclude that location, rather than skills, are the major barriers for fossil fuel extraction workers' transition to green jobs. They use BLS classification to define green occupations, using the narrow definition of occupations that are classified as emerging in renewable energy (and using alternative definitions as robustness checks). Using occupation skill profiles from the O*NET database, they find that skills of fossil fuel extraction workers are more similar to the skill requirements of green jobs than to those in other industries. Their analysis of metropolitan and non-metropolitan statistical areas finds that fossil fuel extraction workers are not co-located with current solar and wind power plants nor with the predicted locations of new green jobs. These predictions are based on BLS projections and historical employment data.

Marin and Chen[35] findings are relevant to the issue of the lack of co-location

of green and fossil fuel jobs. They highlight how investments into the green sector, spurred by green fiscal stimulus, would likely enter locations where workers in the local labor market already have pre-existing green skills. This investment pattern could result in fewer green jobs created in fossil fuel regions without pre-existing green jobs, thus making it less likely for new green jobs to be co-located with existing fossil fuel jobs. They document how the green part of the American Recovery and Reinvestment Act (ARRA) created jobs, but mainly in locations where the workforce already had pre-existing green skills, with green skills measured using the O*NET data. They estimate that $1 million in green ARRA investments created 15 new jobs in the post-ARRA period (2013-2017).

Saussay et al.[46], using the Lighthouse job posting data, similarly conclude that there is limited spatial overlap between the location of low-carbon jobs that are created and the location of high-carbon jobs that would be lost. Their definition of low-carbon jobs is based on a more comprehensive search of such jobs in the job posting data, i.e., they use a combination of key word searches, natural language processing, and expert survey. High carbon jobs are those linked to fossil fuels extraction and production.

As described earlier, several studies conclude limited skill gaps between fossil fuel jobs and the "closest" green jobs. However, a few studies conclude that there are notable skill gaps between fossil fuel and green jobs. Saussay et al.[46], using the Lighthouse job posting data, find that there are significant skill gaps between high-carbon jobs and low-carbon jobs. They consider five skill groups, i.e. cognitive, IT, management, social and technical skills. They find that low-carbon jobs are more likely to require skills across these five skill groups and more of the skills within each of the skill groups than high-carbon or generic jobs. They find that while low-carbon job postings offer a wage premium relative to high carbon jobs that require similar education and located in the same commuting zone, this wage premium has declined in the period 2010-2019. Nevertheless, they caution that their wage data had many missing values, and their wage regressions used only parsimonious control variables.

Another study on skills, Vona et al.[49], conclude that while generally there is a low skill distance between brown and green occupations, there are key exceptions. These two exceptions "for which skills for green jobs differ from non-green jobs are engineering skills for design and production of technology, and managerial skills for setting up and monitoring environmental organizational practices." They find that green occupations generally require routine tasks rather than complex tasks, suggesting that training efforts should be focused on technical training, rather than on advanced educational programs. Vona et al.[49] use the O*NET data to construct green general skills groups and the greenness of occupations. Occupations range from fully green occupations for which all specific tasks in the jobs are green tasks to least green occupations that only occasionally require the conduct of green specific tasks. Brown occupations are those occupations for which more than 10% of workers in these occupations are in pollution intensive industries, i.e. industries with greater share of energy costs to total production. They construct Green General Skills, a list of the 14 green general skills that are important tasks in greener occupations that are grouped into four macro-skill types, i.e. engineering and technical, science, operations management and monitoring.

While most studies note the non-co-location of fossil fuel and green jobs, Curtis, O'Kane and Park[14] draw a more optimistic conclusion on the potential co-location of wind and solar jobs and oil and gas jobs. They also draw a more optimistic conclusion on the wages of wind and solar jobs, finding that solar and wind jobs have

higher than average wages and finding higher wage premiums for those solar and wind jobs that have lower educational requirements. They implement strategies that can more comprehensively identify wind and solar jobs and thus avoid undercounting of these jobs. Using the Burning Glass (BG) job posting data (now Lightcast data), they conduct keyword searches using the terms solar, wind and photovoltaic of the job titles, BG occupation categories, and the listed skills for job listings. They also include all jobs in solar or wind firms (defined as firms whose job postings for a given year are solar or wind jobs exceed the specified threshold). Their study at the level of local labor markets, as represented by commuting zones, finds a positive correlation between the share of oil and natural gas employment and the share of solar or wind jobs in commuting zones. Additionally, they find significant growth of job postings in solar and wind jobs, i.e., the tripling of these job postings between 2010 and 2019.

7.2 Other Barriers to the Job Transition: preferences for green jobs, mobility/relocation, retraining and the political credibility of energy transition policies

Our study focuses on the vertical mobility of frontline fossil fuel workers and reskilling strategies used by workers that achieved upward mobility in the green sector over their careers. We recognize that our study does not investigate important barriers for fossil fuel workers to make the transition to the green sector. These include their preferences on green jobs or their attachment to fossil fuel jobs, their preference for relocating for new jobs or the historical pattern of mobility, and their preferences on reskilling and their desire for compensation during retraining.

Lim et al.[32] conduct a survey of over 3,000 respondents who are active on the labor market and live in coal communities in the United States. The forced-choice conjoint experiment on job preferences revealed that respondents impose a penalty on coal jobs, requiring higher wage offers from coal jobs than alternative jobs when other factors are held constant. Respondents were willing to undertake reskilling, even for extended periods, provided they receive compensation. Respondents expressed a strong preference for staying in their current location, preferring jobs that are located within commuting distance, even at the cost of lower compensation.

Studies show a mixed reception of fossil fuel workers to green jobs. On the one hand, several studies find that fossil fuel workers evaluate green jobs based on their attributes, rather than on ideological positions. Lim et al.[32] find that coal communities impose a penalty on coal jobs, calling into question the notion that coal workers have strong attachment to coal jobs. Similarly, Sicotte, Joyce and Hesse[48] finds that fossil fuels workers' support for or opposition against the green transition depends on their perception of the transferability of their skills to the green sector. In interviews of 48 union workers in the energy industry in New Jersey, New York and Pennsylvania, respondents were more supportive of the energy transition when they believed their skills are transferable to the green industry and their bargaining power would be protected or enhanced in the green sector[2]. Respondents were less supportive of the transition when they perceived that jobs in the renewable energy sector would provide lower wages, require less skills, and would be non-union positions that would weaken wages, benefits, work safety (e.g., for wind turbine jobs) and job security. Several studies report fossil fuel workers' willingness to shift to jobs in the green energy sector and members of fossil fuel communities' support of the green sector as an opportunity to diversify their economies, thus providing jobs for their communities

and stemming outmigration[6,13,15,17,47]. Nevertheless, there are some fossil fuel workers and some members of fossil fuel communities that take a negative view of the green sector, perceiving that that green energy had been unfairly privileged over fossil fuel energy and that green energy had caused job losses and economic decline in their communities[17,31,39,47]. Researchers note the importance of distinguishing the views of communities on the energy transition versus the political messaging from the fossil fuel industry that had constructed a selective narrative, reframing the history and culture of coal communities as synonymous to that of the coal industry[3,31].

Considering that many fossil fuel workers evaluate their potential shift to the green sector based on job attributes, several studies[11,29] emphasize the importance of improving the quality of green jobs to ensure they provide quality livelihoods for workers. These studies document negative aspects of green jobs in terms of workplace safety, though they do not provide comparative figures for the fossil fuel sector[11,29]. In a survey of 1,200 workers in the solar industry, wind industry, and clean energy manufacturing industry in Texas, one in four workers report seeing or experiencing work-related injuries, 43% report heat-related illnesses, and 6.4% of wind and solar workers report witnessing a fatality in the job site[11]. About 40%-70% of workers in the solar industry and clean energy manufacturing industry report the lack of benefits such as life insurance, retirement contributions, paid sick leave, or workers' compensation insurance. The study also reported racial and gender disparity in wages and benefits. Another study in New York similarly reports the lack of benefits in non-union solar jobs as well as racial disparities in wages and benefits[29]. The authors emphasize the importance of improving the quality of green jobs (including wages, benefits, and workplace safety).

On the issue of relocation to new jobs, several studies report that mixed willingness among fossil fuel workers to relocate away from their communities. Workers in the oil and gas sector that have relocated to pursue employment in offshore oil and gas fields and in onshore oil and gas fields such as North Dakota have greater mobility to relocate to alternative employment[22]. By contrast, workers in the coal sector, where multiple generations of family members had worked in the coal industry, such as in West Virginia, have less mobility to relocate to alternative employment[22]. Additionally, relocation out of coal counties in Appalachia that faced coal declines varied by educational level, with younger and more-educated workers most likely to out-migrate[30].

Studies report that low uptake of training and education in response to the expected or actual decline of fossil fuel jobs. Krause[30] finds that following coal declines, there is no increased postsecondary training investments, across variety of measures, including short-term credentials and community colleges. Krause[30] suggest that this pattern may be due to demand side factors (e.g. financial costs of attendance and informational barriers) and supply side factors (e.g. local governments lack the capacity to apply for grants to mount training programs).

Fossil fuel workers' willingness to retrain and relocate to green jobs also depends on their perception of the trajectory of the green sector and their expectations of the extent to which the federal or state governments will sustain longer-term support for the energy transition including support for the expansion of the green industry and workers' retraining[10,19,45]. Gazmararian and Tingley[19] discuss how fossil fuel workers and communities may not perceive long-term government energy transition policies as credible, especially when new administrations unwind the energy transition policies of past administrations[18]. They note that trust in government shapes workers' perception of the credibility of government policies, but that trust in governmental

entities delivering on promises is declining in regions that are adversely affected by the transition away from fossil fuels. Clarke et al.[10] discuss how policies can be more enduring if they provide benefits to local communities and win their support.

Several case studies examined the effectiveness of job retraining programs to help fossil fuel workers to transition to green jobs. Bottino[5] detail the opportunities offered by specific workforce training programs in economically distressed communities in coal regions and the challenges they face.

7.3 Multiple policies to support the Just Transition for workers and communities

While our study focuses narrowly on frontline fossil fuel workers upward mobility in the green sector, we acknowledge that the Just Transition literature points to the multiplicity of policies that are needed to support fossil fuel workers and communities to face the socioeconomic shocks from the energy transition[7,24,41].

Studies note the importance of providing a variety of support for fossil fuel workers and communities to achieve the outcome of a Just Transition. At the same time, broader support for workers and communities would entail greater financial costs, potentially for the state or federal governments. The costs for such programs would need to be balanced with the averted socioeconomic and psychological costs from fossil fuel workers not securing jobs (and facing permanent scarring in the labor market) and fossil fuel communities facing a downward economic spiral[8,24]. Pollin[41] distinguishes between the thin transition policies for workers that assist workers with job search, retraining and relocation programs, and more robust transition policies for workers that provide guaranteed reemployment, wage compensation to cover wage gaps, and pension guarantees for retiring workers. Cha[8] discussed how provision of financial assistance to participants in training programs are necessary to prevent enrollees from dropping out from these programs. Clarke et al.[10] discuss the need for policies that go beyond assistance to workers to provide benefits for fossil fuel communities, especially in those areas with limited employment opportunities. These include longer-term unemployment insurance, support for local government finances, and support for other public services[10]. Cha[8] and Clarke et al.[10] discusses social aspects of conceptualizing and implementing these policies, including with fossil fuel workers and communities' taking the lead on envisioning the policies, accounting for preferences and priorities, local strengths, and administrative capacity.

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