# Labor Reallocation, Green Subsidies, and Unemployment *

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*Abstract:* This paper analyzes the impact of green subsidies on employment. Using a multi-sector general equilibrium search model, I examine how the subsidies affect unemployment as well as the number of green, fossil, and remaining jobs. I underpin the analysis with novel empirical evidence on the distribution of jobs and job-to-job transitions in the United States. I find that the share of green jobs grew and the share of fossil jobs declined during 2013-2020. The majority of jobs are neither green nor fossil, however, and thus directly unaffected by climate policy. With regard to job-to-job transitions, the data suggests a high degree of movement between job types. Inserting the empirical estimates in the search model, I find that green subsidies reduce unemployment if they are financed in a non-distortionary manner. Paying for subsidies with distortionary labor taxes, in contrast, increases unemployment and makes the subsidies perform worse compared to a carbon tax. This is especially the case if preexisting distortions are high.

**Keywords:** Environmental labor economics, Green subsidies, Labor reallocation, Unemployment

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# 1 Introduction

Many countries are using green subsidies to decarbonize their economies. In the United States, the Inflation Reduction Act (IRA) of 2022 provides tax credits worth an estimated \$271 billion to clean sectors and technologies (Congressional Budget Office, 2022).[1] The European Union has given more than €800 billion in subsidies to renewable electricity sources since 2008 (European Commission, 2022). In addition, the European Commission has unveiled a Green Deal Industrial Plan to mobilize public funding and facilitate state aid for low-carbon projects.[2] China too has a history of supporting clean technologies, as exemplified by its renewable energy subsidies exceeding \$1 billion in 2017 (Qi et al., 2022).[3]

The adoption of green subsidies comes at a time of public concern about the impact of climate policy on jobs (Vona, 2019). Green subsidies are expected to shift labor demand to green sectors, which might cause workers in other parts of the economy to lose their jobs. Managing this risk requires an understanding of how green subsidies reallocate labor across sectors and affect unemployment. It is also important to understand the implications of adopting green subsidies as opposed to carbon taxes. Carbon taxes are widely advocated by economists because they internalize the damage from emissions. In practice, however, carbon taxes can face public opposition (Douenne and Fabre, 2022) and enjoy less support compared to green subsidies (Dechezleprêtre et al., 2022). In situations when carbon taxes cannot be implemented, it is valuable to understand the labor market implications of adopting green subsidies instead.

This paper analyzes the impact of green subsidies on employment. I develop a multi-sector general equilibrium search model to examine how the sub-

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[1] More than half of this amount is for low-carbon electricity production and investment, while the remainder is for carbon capture and storage, clean fuels, electric vehicle purchases, clean energy manufacturing, and private investments in energy efficiency and clean energy (Bistline, Mehrotra and Wolfram, 2023; CRFB, 2022).

[2] COM(2023) 62 final, available at https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52023DC0062.

[3] Qi et al. (2022) report subsidies of ¥7.538 billion. I convert this amount into dollars, giving \$1.1 billion, using the 2017 exchange rate from the OECD, available at https://data.oecd.org/conversion/exchange-rates.htm.

sidies affect the number of jobs by sector as well as overall unemployment. The model is characterized by search frictions in the labor market (Mortensen and Pissarides, 1994; Pissarides, 1985) that prevent firms from costlessly matching with job searchers. Unemployment in equilibrium is determined by the level of recruitment and redundancies. The green subsidies change the recruitment effort of firms which affects the level of employment.

The model is similar to the framework in Hafstead and Williams (2018). I extend their two-sector framework in a number of key ways.[4] First, I introduce an empirically relevant "neutral" sector that is not directly subjected to climate policy. My three-sector framework allows me to study labor movement between three distinct types of jobs: green, fossil and neutral jobs. Second, I apply my model to a different policy context by focusing on green subsidies. Third, I provide an empirical basis for the distribution of jobs and degree of labor mobility in the model. In particular, I use occupational survey data for the United States to estimate the number of green, fossil and neutral jobs, as well as job-to-job transitions. I use the job-to-job transition estimates to calibrate the ease at which workers move between sectors in the model. This enables me to study the employment effects of green subsidies for a more realistic degree of labor mobility.[5]

In the analysis, I compare a green subsidy to a carbon tax. Two reasons suggest employment outcomes might non-trivially differ across the instruments. First, their performance likely depends on how distortionary the financing mechanism (for a subsidy) and revenue recycling scheme (for a carbon tax) are. I examine this further by comparing employment outcomes for different ways of financing subsidies and recycling carbon tax revenue. Second, a subsidy and carbon tax might interact differently with preexisting tax distortions. Goulder, Hafstead and Williams (2016) show that a clean energy standard (equivalent to

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[4]Hafstead and Williams (2018) extend the one-sector framework of Shimer (2010) by modeling a clean and a dirty sector.

[5]There are three other differences with Hafstead and Williams (2018). First, I do not allow for an abatement activity. Abatement in my framework stems solely from reductions in the fossil sector's output. Second, I use a nested consumption structure. Third, I allow the degree of labor mobility to vary by sector.

a carbon tax plus a subsidy on fossil output) can be more cost-effective than a carbon tax because the standard exacerbates initial factor market distortions to a smaller extent.[6] I examine whether preexisting tax distortions alter the relative performance of green subsidies with respect to labor market outcomes.

The results are as follows. First, I find that a green subsidy can generate lower unemployment relative to a carbon tax. This result is sensitive, however, to the choice of financing mechanism. Financing a subsidy with (non-distortionary) lump sum taxes generates lower unemployment than a carbon tax. The unemployment rate even *decreases* from such a subsidy. A subsidy financed by distortionary payroll taxes, in contrast, generates employment losses and these losses exceed those from a carbon tax.

Second, the preexisting level of tax distortion has uneven effects across financing mechanisms. While the employment change from a subsidy financed by lump sum taxes is unaffected by the preexisting level of distortion, a subsidy paid for by payroll taxes generates higher unemployment when preexisting taxes are high. This suggests that a distortionary financing mechanism (such as payroll taxes) is especially disadvantageous if initial distortions are already high.

Third, in my empirical analysis, I find that the share of green and fossil jobs evolved in opposite directions in the United States during 2013-2020: green jobs became more prevalent while fossil jobs grew more scarce. However, while the share of green jobs increased, they account for a small share of all jobs. The vast majority of jobs, around 90%, are instead neutral. With regard to job transitions, the probability of moving to a green job is similar for green and fossil workers. Both worker types are far more likely to move to a neutral job, however, which highlights the relevance of neutral jobs for the green transition.

Fourth, by inserting the job transition estimates in the search model and solving for the steady state, I find evidence of a low degree of friction associated

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[6]Moreover, Hafstead and Williams (2018) show that the employment impacts of carbon taxes partly depend on how the recycling mechanism interacts with preexisting labor taxes. An increase in preexisting taxes has little effect on a carbon tax with lump sum transfers, but exacerbates employment losses from a carbon tax with payroll tax recycling.

with cross-sector matching. The low level of friction implies, in the model, that it is easy for workers to move across sectors and that the probability of a match is largely independent of a worker's employment history.

The paper relates to four strands of literature. The first examines the impact of environmental regulation on employment. A subset of studies use econometric methods (e.g., Chen et al., 2020; Popp et al., 2021 for green subsidies and Greenstone, 2002; Morgenstern, Pizer and Shih, 2002; Walker, 2011, 2013; Yip, 2018 for carbon taxes). A challenge for these studies is that employment in counterfactual (unregulated) sectors can be endogenous to environmental regulation due to workers moving between regulated and unregulated sectors (Hafstead and Williams, 2018). Econometric estimates of employment changes therefore risk being biased. An alternative approach is to employ general equilibrium methods. Such methods are well-suited for studying labor movement across sectors. They have generally been used, however, to analyze carbon taxes as opposed to green subsidies. A common result is that carbon taxes reallocate labor from fossil to green sectors and lead to a small increase in unemployment (Hafstead and Williams, 2018; Aubert and Chiroleu-Assouline, 2019; Carbone et al., 2020; Fernández Intriago, 2021; Heutel and Zhang, 2021; Hafstead, Williams and Chen, 2022; Finkelstein Shapiro and Metcalf, 2023; Castellanos and Heutel, 2024).

A study that does focus on green subsidies is Bistline, Mehrotra and Wolfram (2023). The authors examine the impact of the IRA on various macroeconomic outcomes. Using the Federal Reserve's FRBUS model, they find that the IRA generates a small increase in long run unemployment. Shimer (2013) analyzes the effect of a green subsidy and carbon tax on worker reallocation and unemployment in a theoretical framework.[7] I complement these studies by examining the employment impact of green subsidies in an analytically tractable numerical model. The tractability allows me to study the channels through which green subsidies affect labor markets. By using a three-sector framework, I can also

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[7]In contrast to my paper, Shimer (2013) assumes a fixed unemployment rate and does not model search frictions.

analyze the labor movement across sectors directly affected (green and fossil sectors) and unaffected (neutral sector) by climate policy.

The second related literature strand looks at the interaction between climate policy and the tax system. A large body of work has examined the impact of climate policy on voluntary labor supply and welfare in the presence of labor market distortions. These studies typically assume full employment and focus on environmental taxes (e.g., Bovenberg and de Mooij, 1994; Bovenberg and van der Ploeg, 1994; Goulder, 1995a,b; Parry, 1995; Bovenberg and Goulder, 1996; Goulder et al., 1999; Williams, 2002; Bento and Jacobsen, 2007; Carbone and Smith, 2008; Kaplow, 2012; Barrage, 2019). Some attention has also been paid to green subsidies (e.g., Fullerton, 1997; Parry, 1998; Fullerton and Metcalf, 2001; Kaplow, 2012). These studies emphasize two opposing effects of a revenue-neutral subsidy in the presence of full employment and preexisting labor taxes: a revenue-financing effect and a tax-interaction effect (Parry, 1998). The revenue-financing effect corresponds to the welfare loss from financing a subsidy with distortionary labor taxes as opposed to with lump sum taxes. The tax-interaction effect denotes the welfare gain from the subsidy increasing voluntary labor supply in the green sector. The manner in which these effects trade off influences a subsidy's impact on total labor supply and welfare.

I contribute to this literature by relaxing the full employment assumption. In particular, I examine how green subsidies affect involuntary unemployment given various financing mechanisms and preexisting levels of tax distortion. No study has, to the best of my knowledge, investigated these issues in a microfounded model of unemployment. By focusing on subsidies, my paper complements previous work on the interplay between carbon taxes, preexisting distortions, and unemployment resulting from search frictions (Bovenberg, 1997; Bovenberg and van der Ploeg, 1998a; Wagner, 2005; Hafstead and Williams, 2018), wage bargaining (Carraro, Galeotti and Gallo, 1996; Koskela and Schöb, 1999), wage rigidity (Bovenberg and van der Ploeg, 1996, 1998b), and union monopoly power (Nielsen, Pedersen and Sørensen, 1995).

Third, my paper relates to the search literature.[8] Search models are a well-established theory of equilibrium unemployment and have been used to investigate a range of labor market and macroeconomic issues (see e.g. Hall, 2005; Shimer, 2005; Hagedorn and Manovskii, 2008; Hall and Milgrom, 2008; Yedid-Levi, 2016; Ljungqvist and Sargent, 2017). They have also been applied in the context of environmental regulation (Shimer, 2013; Hafstead and Williams, 2018; Aubert and Chiroleu-Assouline, 2019; Fernández Intriago, 2021; Hafstead, Williams and Chen, 2022; Finkelstein Shapiro and Metcalf, 2023). A key feature of search models is the matching function that determines the number of hires in a period. Shimer (2010) uses a matching function that depends on a sector's recruitment effort and unemployment rate. Hafstead and Williams (2018) extend this function to a multi-sector framework characterized by matching within and across sectors.[9] A key parameter in their matching function is the degree of friction associated with cross-sector matching. I calibrate this parameter on the basis of longitudinal occupational data for the United States. In doing so, I allow the parameter to vary by sector to reflect differences in labor mobility across sectors.

The final literature strand to which my paper relates empirically measures the number of green jobs. A challenge for these studies is that no standard definition of green jobs exists. A common approach is to base the definition on whether a job is located in a green sector (see e.g. Curtis and Marinescu, 2022; Colmer, Lyubich and Voorheis, 2023; Curtis, O'Kane and Park, 2023). A drawback of this approach is that it ignores jobs benefiting from the low-carbon transition in non-green sectors (e.g., environmental engineering positions in construction). One way to capture these jobs is to shift the unit of analysis to a more granular level by focusing on occupational task content. Tasks are commonly used as the unit of analysis in the labor economics literature when

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[8]Two important contributions to this literature are Pissarides (1985) and Mortensen and Pissarides (1994).

[9]Most studies in the search literature use a one-sector matching function. Two exceptions are Hafstead and Williams (2018) and Yedid-Levi (2016) who extend the function to multiple sectors. Hafstead and Williams (2018) represent a clean and a fossil sector, while Yedid-Levi (2016) models a consumption and an investment sector.

assessing the incidence of labor market events (Acemoglu and Autor, 2011; Autor, 2013). A seminal example is Autor, Levy and Murnane (2003) who show that the impact of computerization on jobs depends on whether job tasks are complements or substitutes to computers. The green transition can be analyzed through a similar task-based lens. The green transition has created a need for new tasks (e.g., the installation of solar panels). Jobs involving many of these tasks can be thought of as green because they will likely benefit from the green transition. A recent literature strand has adopted such a task-based approach by defining green jobs as jobs involving a high share of green tasks (e.g., Vona et al., 2018; Vona, Marin and Consoli, 2019; Chen et al., 2020; Popp et al., 2021). An advantage of this definition is that it captures jobs benefiting from the green transition, irrespective of the sector in which the jobs are located.

I use a task-based approach to measure the number of green jobs in the United States. In particular, I define green jobs as jobs involving a high share of green tasks and use this definition to quantify the occupations that are green. By also measuring the number of fossil and neutral jobs, I estimate the distribution of jobs and job-to-job transition patterns in the United States. The job-to-job transition estimates are used to calibrate the degree of labor mobility across sectors in my search model.

The paper is structured as follows. Section 2 estimates the distribution of jobs and job-to-job transitions in the United States. Section 3 describes the search model. Section 4 details the calibration procedure, including how the job transition estimates from Section 2 are used to calibrate the degree of labor mobility in the model. Section 5 presents the results from the numerical analysis. Section 6 concludes.

## 2 Estimating the distribution of jobs and job transitions

This section empirically estimates the distribution of jobs and job-to-job transitions in the United States. Section 2.1 gives an overview of the data, while

Section 2.2 describes the job classification procedure. Section 2.3 presents the estimates.

## 2.1 Occupation data

To empirically analyze job patterns over time, I require longitudinal data on occupations. I obtain such data from the Survey of Income and Program Participation (SIPP). SIPP is a representative longitudinal survey of the U.S. population that is administered annually by the U.S. Census Bureau. The survey follows individuals over four years and asks them about their monthly occupation.[10] I make use of two panels: one for the period 2013-2016 and another for 2017-2020.[11] This gives me monthly employment data over an eight-year span (2013-2020).[12,13]

The next step is to classify the occupations in SIPP as "green", "fossil" or "neutral". I describe the classification procedure in the following section.

## 2.2 Classifying jobs by type

### 2.2.1 Defining green jobs

Distinguishing green jobs is challenging since no standard definition exists (Peters, Eathington and Swenson, 2011; Deschenes, 2013; Consoli et al., 2016; Vona, 2021). One approach is to define them as jobs contributing to a greener production process. This definition encompasses jobs related to improving energy efficiency, reducing pollution, and managing waste. An alternative is to focus on the product or service associated with a job. Elliott and Lindley (2017)

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[10]Some respondents report multiple jobs in a month. I determine their main job based on the highest average number of hours worked. If there is a tie, I choose the job with the highest income or, if a tie remains, the first job that month.

[11]The 2013-2016 and 2017-2020 panels surveyed 42,323 and 30,441 persons respectively.

[12]The sample changes across panels and I can therefore only observe an individual's employment history over a four-year period.

[13]The occupations in the 2013-2016 and 2017-2020 panels use Census Occupation codes (versions 2010 and 2018 respectively). I translate these codes to the 6-digit 2010 Standard Occupational Classification (SOC) system using crosswalks from the U.S. Census Bureau, available at https://www.census.gov/topics/employment/industry-occupation/guidance/code-lists.html. 42 out of 518 occupations in the 2017-2020 panel have a one-to-many mapping that would give respondents multiple jobs in a given month. To achieve a one-to-one mapping from each Census code, I choose the modal SOC code in the 2013-2016 panel (see the first SOC code per Census category in Table A.1 in Appendix A).

define jobs as green if they are involved in producing goods and services that create environmental benefits or conserve natural resources. Curtis and Marinescu (2022) call solar and wind power jobs green, while Curtis, O'Kane and Park (2023) use a broader scope by also counting jobs associated with electric vehicle production. Colmer, Lyubich and Voorheis (2023) focus on the energy sector and base their definition on whether a firm is engaged in green energy activities.

I adopt a different approach by defining green jobs on the basis of their task content. In particular, I consider jobs involving a high share of green tasks to be green. A task-based approach has been used by a number of recent studies (Consoli et al., 2016; Bowen, Kuralbayeva and Tipoe, 2018; Vona et al., 2018; Vona, Marin and Consoli, 2019; Chen et al., 2020; Rutzer, Niggli and Weder, 2020; Popp et al., 2021) and is consistent with the standard view in labor economics of a job as a collection of tasks. Jobs with a high share of green tasks can be considered green because workers devote much of their time to green activities.

A task-based definition has a number of advantages (Vona, Marin and Consoli, 2019; Vona, 2021). First, the unit of analysis is the tasks carried out by a worker. The definition therefore centers around the characteristics of a job, as opposed to a broader unit such as a sector. Second, it accounts for green jobs that are present in multiple sectors. For instance, energy engineers work in both polluting and non-polluting sectors. Restricting the scope of green jobs to non-polluting sectors would overlook some of these positions. Third, it allows for a non-binary definition of green jobs. This is advantageous since not all green jobs are fully green. A task-based approach allows for a proportional relationship between the degree to which an occupation is green and the share of tasks devoted to green activities. Fourth, it captures jobs indirectly created by the green transition, including jobs outside of energy and manufacturing (e.g., in consulting or construction). Capturing these jobs can be difficult due to a lack of green production data.

I define an occupation as green if its share of green tasks equals or exceeds

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a threshold $\alpha$.[14] I assume $\alpha = 50\%$ in my main specification and conduct sensitivity on this value in Section 2.3. I operationalize the green job definition using the U.S. Occupational Information Network (O*NET) database. O*NET is funded by the U.S. Department of Labor and is the main source of occupational information in the United States. Version 24.1 of the database contains detailed task information for 974 occupations on an 8-digit O*NET-SOC level.[15] The information includes task descriptions, task importance scores, and a classification of tasks as green or non-green.[16] Following Vona, Marin and Consoli (2019), I take a weighted average of the green tasks using the importance scores as weights. This gives the share of green tasks by 8-digit occupation $\kappa$:[17]

$$GreenShare_\kappa = \frac{\sum_\nu \iota_{\nu\kappa} \, \mathbb{1}_{\nu \in \texttt{green}}}{\sum_\nu \iota_{\nu\kappa}},$$

where $\iota \in \{1, 2, 3, 4, 5\}$ is an importance score for task $\nu$ and $\mathbb{1}$ is an indicator variable for green tasks.[18] I aggregate the shares to a 6-digit level by taking

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[14]This approach is similar to Vona et al. (2018) who define an occupation as green if it contains more than 10% of green tasks.

[15]O*NET collects the information by surveying a random sample of employees from a representative sample of U.S. firms. The surveys are complemented with input from expert panels and desk research by occupational analysts (Peterson et al., 2001).

[16]O*NET classified the tasks as follows (Dierdorff et al., 2009; O*NET, 2010). Job titles relating to the green economy were first identified in the literature, where the "green economy" was defined as "encompass(ing) the economic activity related to reducing the use of fossil fuels, decreasing pollution and greenhouse gas emissions, increasing the efficiency of energy usage, recycling materials, and developing and adopting renewable sources of energy" (Dierdorff et al., 2009, p. 3). The job titles were grouped into occupations and the occupations were sorted into three groups:

1. Occupations experiencing more demand, but no change in task content, from green economy activities and technologies;

2. Occupations seeing changes in task content from green economy activities and technologies; and

3. Occupations created from green economy activities and technologies.

Green task research was thereafter conducted. The research consisted of reviewing the literature and online sources (e.g., job descriptions, employment databases, and career information websites) to identify tasks affected by green economy activities and technologies. These tasks were labeled green. Occupations in the first group were assigned zero green tasks since their tasks are by definition unaffected by the green economy. Occupations in the third group were created from the green economy and thus all their tasks were labeled green. For occupations in the second group, only tasks affected by green economy activities and technologies were labeled green.

[17]$GreenShare_\kappa \geq 0.5$ for 41 occupations (see Table A.2 in Appendix A).

[18]O*NET assigns the importance scores on the basis of employee surveys and occupational experts. The scores range from 1 (not important) to 5 (very important). 24 occupations lack scores for some tasks. I assign these tasks the minimum score for that occupation in line with Vona, Marin and Consoli (2019).

an average across the 8-digit occupations (see Appendix B for the aggregation procedure). 11 occupations on a 6-digit level have a green task share of at least 50%. I call these occupations "green".

### 2.2.2 Defining fossil jobs

Data on fossil tasks does not exist. I therefore define fossil jobs as those disproportionately found in emissions-intensive ("dirty") sectors using a two-step procedure.[19]

First, I identify a set of dirty sectors. To do this, I obtain facility-level greenhouse gas emissions data for the year 2019 from the Greenhouse Gas Reporting Program of the Environmental Protection Agency.[20] I aggregate the data to a sector-level and combine them with employment data from the Occupational Employment and Wage Statistics program of the Bureau of Labor Statistics (BLS).[21] This allows me to calculate emissions intensity by sector. I call a sector dirty if it lies in the top five percent of the employment-weighted emissions intensity distribution. Table C.4 in Appendix C lists the sectors that are classified as dirty.

Second, I define fossil jobs by taking advantage of sector information in SIPP. Each survey respondent reports both their occupation and sector in which they work.[22] I classify an occupation as fossil if it is at least eight times more likely than the average occupation to be found in one of the dirty sectors.[23] This gives

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[19]The procedure has similarities to Vona et al. (2018).

[20]The emissions are $CO_2$, Methane, Nitrous Oxide, HFC, PFC, $SF_6$, $NF_3$, and other greenhouse gas emissions (that account for less than 0.05% of total emissions).

[21]Specifically, I aggregate the emissions data to a 4-digit North American Industry Classification System (NAICS) level.

[22]The sectors in the 2013-2016 and 2017-2020 SIPP panels use versions 2012 and 2017 respectively of the Census Industry system. I convert the codes in the 2013-2016 panel to version 2017 using a crosswalk from the U.S. Census Bureau, available at https://www.census.gov/topics/employment/industry-occupation/guidance/code-lists.html.

[23]Before classifying the occupations, I harmonize the sector codes. SIPP uses the Census Industry system while the dirty sector classification uses NAICS. I convert the dirty sector classification to the Census Industry system using crosswalks from the U.S. Census Bureau, available at https://www.census.gov/topics/employment/industry-occupation/guidance/code-lists.html. A challenge when crosswalking is that not all dirty sectors map to a unique Census code. Some have a many-to-one mapping, while others are not explicitly in the crosswalk. Appendix C explains how these issues are resolved.

63 fossil jobs (see Table A.3 in Appendix A).[24]

## 2.3 Estimation results

I apply the classification scheme to the jobs in SIPP and call any job that is neither green nor fossil neutral. Section 2.3.1 shows the distribution of jobs. Section 2.3.2 presents job-to-job transition estimates.

### 2.3.1 Distribution of jobs

Fig. 1 shows the evolution of green and fossil jobs in the United States. The share of green jobs increased from 1.5% to 1.7% between 2013 and 2020.[25] The share of fossil jobs, in contrast, decreased by 0.6 percentage points during this period. The combined share of green and fossil jobs remained below 10%. The vast majority of jobs are therefore neutral.
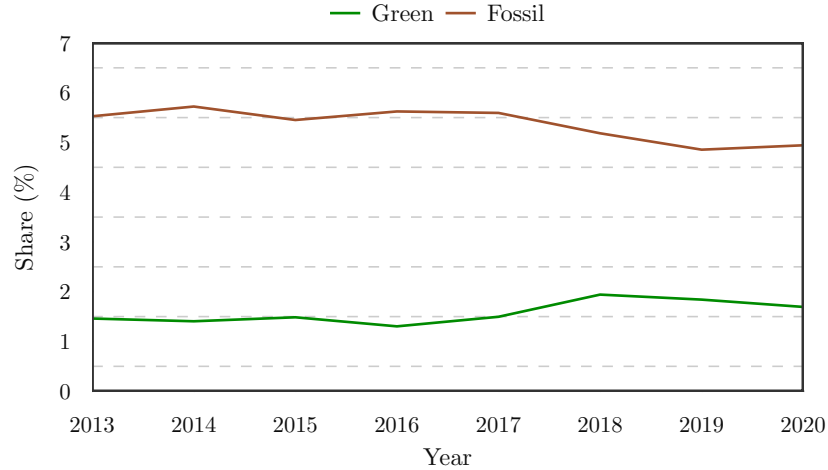


**Figure 1:** Green and fossil job shares in the United States

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[24]Two jobs are both green and fossil: "17-2141 - Mechanical Engineers" and "51-9199 - Production Workers, All Other". I classify them as green in line with Vona et al. (2018).

[25]The green job share is slightly lower than previous estimates that typically range from 2-3% (Deschenes, 2013; Elliott and Lindley, 2017; Cedefop, 2019; Vona, Marin and Consoli, 2019). It is higher relative to two recent studies that use a narrower definition of green jobs. Curtis, O'Kane and Park (2023) find that jobs related to electric vehicle production, solar power, and wind power accounted for 0.8% of jobs on average during 2005-2019. Curtis and Marinescu (2022) estimate that 0.2% of job postings in 2019 were solar and wind jobs.

I conduct four sensitivity tests on these findings. First, I vary the green task share threshold $\alpha$ in the green job definition. I have so far assumed that green jobs involve at least 50% of green tasks. Panel (a) of Figure D.1 and Panel (a) of Figure D.2 in Appendix D show how varying this threshold impacts the proportion of green and fossil jobs respectively. Using a lax threshold of $\alpha = 10\%$ gives unrealistically many green jobs and fewer fossil jobs. Using a restrictive threshold of $\alpha = 100\%$ does not drastically change the job distribution relative to the main specification ($\alpha = 50\%$). The green job definition in the main specification is thus already restrictive.

While changing the green job definition affects the composition of jobs, the trends over time are qualitatively robust. The share of clean jobs increases and the share of fossil jobs decreases. In addition, the vast majority of jobs are neutral. The share of neutral jobs exceeds 80% in all years and specifications.

The remaining three sensitivity tests further vary the green and fossil job definitions. Panel (b) restricts the task data to occupations' "core" tasks.[26] The green task shares are thereby calculated on the basis of the most important tasks for each occupation. Panel (c) removes all green jobs in dirty sectors (see Table C.4 in Appendix A for these sectors). Workers vulnerable to climate policy, owing to their sector, but that can potentially transition to green sectors, thanks to their green job, are omitted as a result. Panel (d) removes all fossil jobs in non-dirty sectors. This restricts the fossil jobs to those that are most vulnerable to climate policy (i.e., those in dirty sectors).

In all three cases, the qualitative insights from before hold: the share of clean jobs increases over time, the share of fossil jobs decreases over time, and the majority of jobs are neutral.

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[26]O*NET classifies tasks as "core" and "supplemental". Core tasks are critical to an occupation. They are tasks for which job incumbents report a relevance score of at least 67% and for which the mean importance score is at least 3 (see https://www.onetonline.org/help/online/scales).

### 2.3.2 Job-to-job transitions

Figure 2 shows job-to-job transition probabilities by worker and job type. The probability of starting a green job is similar for green workers (1%) and fossil workers (5%). All workers are most likely to start a neutral job. This highlights the important role neutral jobs play in the economy, which largely stems from the abundance of these jobs.
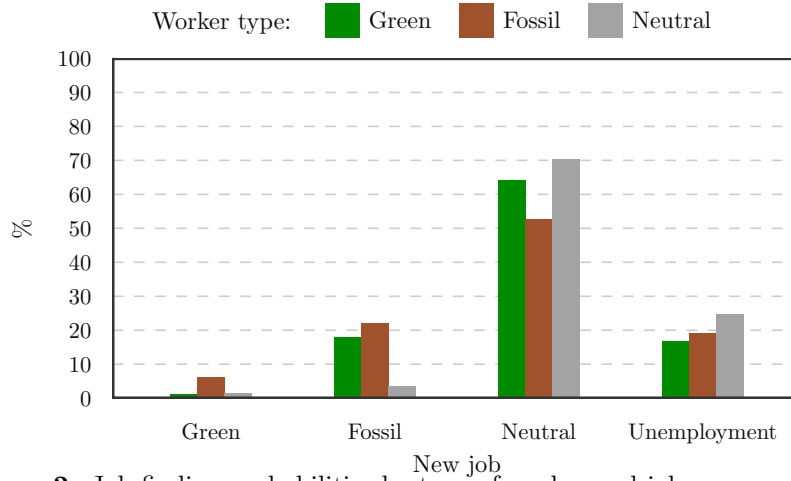


**Figure 2:** Job finding probabilities by type of worker and job

I conduct a similar sensitivity analysis as in Section 2.3.1. Figure D.3 in Appendix D shows how the job transition probabilities vary with $\alpha$. Figures D.4-D.6 repeat this exercise assuming only core tasks, no green jobs in dirty sectors, and only fossil jobs in dirty sectors respectively. The probability of transitioning to a green job remains similar for green and fossil workers in all specifications, and the likelihood of transitioning to a neutral job is always highest. The qualitative insights from the main specification are therefore corroborated.

Finally, I estimate the distribution of workers starting each job type. The results are shown in Table 1. 1% of workers starting a green job were green (i.e., previously had a green job), while 21% were fossil and 78% were neutral. The diagonal elements of the table correspond to the transitions between jobs of the same type. Green workers accounted for 1% of new green jobs, while fossil

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workers accounted for a quarter of new fossil jobs. The vast majority (94%) of neutral jobs were absorbed by neutral workers, owing in part to the prevalence of these workers.

I will use the diagonal elements in Table 1 to calibrate the degree of labor mobility in the search model. I elaborate on the model and calibration procedure in the following two sections.

**Table 1:** Distribution of new jobs by type of worker and job

| Worker type | New job | | |
|---|---|---|---|
| | Green | Fossil | Neutral |
| Green | 0.01 | 0.07 | 0.02 |
| Fossil | 0.21 | 0.25 | 0.04 |
| Neutral | 0.78 | 0.68 | 0.94 |

*Note:* Each column sums to unity.

## 3   Search model

I employ a multi-sector general equilibrium search model to study the effects of green subsidies. The model builds on Hafstead and Williams (2018) and is characterized by search frictions in the labor market. The search frictions imply that it takes time for job searchers to match with firms. Unemployment in equilibrium is determined by the amount of hiring and job loss. Hiring takes the form of an endogenous job matching process. Once a worker and firm match, they negotiate wages and hours worked according to Nash bargaining. The worker then joins the firm in the following period. An exogenous number of workers $\pi$ lose their job at the end of each period. I assume that only unemployed workers search for jobs. I elaborate on the model below.

### 3.1   Basic set-up

The model is characterized by $t = \{0, 1, 2, ...\}$ months.[27] There are three sectors $i, j, k \in \mathcal{J} = \{\texttt{f}, \texttt{g}, \texttt{z}\}$ that require labor to produce output. Firms in the fossil

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[27]I suppress the time subscript henceforth to simplify the notation.

sector ($j = \mathtt{f}$) generate emissions in production, while firms in the green ($j = \mathtt{g}$) and neutral ($j = \mathtt{z}$) sectors are emissions-free.

There are $n_j$ workers employed in sector $j$ and $u_i$ unemployed workers that previously worked in sector $i$. Total employment is given by $\bar{n} := \sum_j n_j$ and total unemployment is $\bar{u} := \sum_i u_i$. The overall workforce is normalized to unity, meaning $\bar{n} + \bar{u} = 1$.

## 3.2 Firms

Firms recruit workers and assign them to either a production technology or a matching technology. The production technology generates revenue while the matching technology allows the firm to recruit more workers. I refer to workers using the production technology as "production workers" and workers using the matching technology as "recruiters". Workers are identical meaning firms are indifferent between assigning them to either technology. Let $l_j$ denote the number of production workers and $n_j - l_j = v_j$ the number of recruiters in a sector. Both production workers and recruiters are paid wage $w_j$ and work $h_j$ hours.

### 3.2.1 Production

The production technology exhibits constant returns to scale and converts labor into output $y_j$ according to

$$y_j = \zeta l_j h_j, \tag{1}$$

where $\zeta$ is labor productivity. The output is sold at net price $p_j^y$. Firms in the fossil sector generate $\epsilon$ emissions from each unit of output. Total emissions $e$ are given by

$$e = \epsilon y_{\mathtt{f}}.$$

### 3.2.2 Matching

Recruiters use a constant-returns-to-scale matching technology

$$
m_{ij} = \mu_j v_j h_j u_i \left[ \xi_j \underbrace{\left( \sum_k v_k h_k \right)}_{\text{Total recruitment}}^{-\gamma} \underbrace{\overline{u}}_{\substack{\text{Total unem.}}}^{\gamma-1} + (1 - \xi_j) \underbrace{(v_j h_j)}_{\substack{\text{Firm } j\text{'s recruitment}}}^{-\gamma} \underbrace{u_i}_{\substack{\text{Unem. of } i}}^{\gamma-1} \delta_{ij} \right],
$$

$$(2)$$

where $\mu_j$ is matching efficiency, $\gamma$ is the elasticity of matching with respect to unemployment, $\delta_{ij}$ is the Kronecker delta that equals 1 for $i = j$ and 0 otherwise, and $\xi_j \in [0,1]$ controls the degree of cross-sector matching. The number of matches $m_{ij}$ between unemployed workers $i$ and firms $j$ depends positively on the firms' own recruitment effort and the unemployment rate in sector $i$. Conversely, it depends negatively on the aggregate recruitment effort in the economy (as more effort by other firms reduces the likelihood of a match for firm $j$) and the total unemployment rate (as more competition from other job-seekers makes a match less likely for workers $i$).

The parameter $\xi_j$ controls the degree of friction associated with cross-sector matching.[28] If $\xi_j = 0$, there is no cross-sector matching, meaning a worker previously employed in sector $j$ can only find a job in sector $j$. If $\xi_j = 1$, matching does not depend on a worker's employment history, implying that workers $i$ and $j \neq i$ are equally likely to match with sector $j$. For values of $\xi_j$ in between zero and one, the share of cross-sector matching for sector $j$ is proportional to $\xi_j$ (holding all variables constant).

The degree of labor market tightness determines the ease at which workers can find a job and the amount of recruitment effort that firms must exert to hire workers. There are three measures of labor market tightness: the ratio of sector $j$'s recruitment effort to unemployment in sector $i$ ($\theta_{ij}$), the ratio of sector $j$'s recruitment effort to total unemployment ($\theta_j$), and the ratio of total

---

[28]I let $\xi_j$ vary by sector in contrast to Hafstead and Williams (2018).

recruitment effort to total unemployment ($\theta$):

$$\theta_{ij} = \frac{v_j h_j}{u_i},$$

$$\theta_j = \frac{v_j h_j}{\overline{u}},$$

$$\theta = \frac{\sum_j v_j h_j}{\overline{u}}.$$

Recruitment productivity $q_j$ corresponds to the number of matches from a unit of recruitment effort, and the probability $\phi_{ij}$ of worker $i$ finding a job in sector $j$ equals the number of matches between $i$ and $j$ divided by the unemployment rate in sector $i$:

$$q_j = \frac{\sum_i m_{ij}}{v_j h_j}, \tag{3}$$

$$\phi_{ij} = \frac{m_{ij}}{u_i}. \tag{4}$$

Inserting Eq. 2 into Eqs. 3 and 4 gives the recruitment productivity and job-finding probability as functions of labor market tightness:

$$q_j = \mu_j \Big[ \xi_j \theta^{-\gamma} + (1 - \xi_j) \theta_{jj}^{-\gamma} \Big], \tag{5}$$

$$\phi_{ij} = \mu_j \Big[ \xi_j \theta_j \theta^{-\gamma} + (1 - \xi_j) \theta_{ij}^{1-\gamma} \delta_{ij} \Big]. \tag{6}$$

Recruitment productivity $q_j$ is decreasing in labor market tightness: a tighter labor market, from either an increase in recruitment effort or a decrease in unemployment, means recruiters have to exert more effort to hire a given number of workers. The probability of finding a job $\phi_{ij}$ is increasing in labor market tightness measures $\theta_j$ and $\theta_{ij}$ since a worker $i$ is more likely to find a job in sector $j$ if recruitment there increases or competition from other workers decreases. The probability of finding a job is, in contrast, decreasing in $\theta$ because higher recruitment effort by other sectors means worker $i$ can more easily find a job outside of sector $j$.

### 3.2.3 Firm's problem

Let $\overline{v}_j$ be the recruitment ratio, equal to the share of workers assigned to recruitment (Shimer, 2010; Hafstead and Williams, 2018):

$$\overline{v}_j = \frac{v_j}{n_j}. \tag{7}$$

The firm's problem is to choose the recruitment ratio that maximizes the value of the firm. The value of the firm corresponds to revenue from selling output minus after-tax labor costs plus expected future profits. Denoting values in the next period with an apostrophe, the Bellman equation is

$$J(n_j) = \max_{\overline{v}_j} \left[ p_j^y \zeta h_j n_j (1 - \overline{v}_j) - (1 + \tau^P) n_j h_j w_j + \mathbb{E}\left[ p_j^a J(n_j') \right] \right], \tag{8}$$

where $\tau^P$ is a payroll tax, $p_j^a$ is the firm's discount rate and the price of an Arrow security, and employment in the next period $n_j'$ equals current employment minus layoffs plus new hires:

$$n_j' = n_j - \pi n_j + q_j \overline{v}_j h_j n_j. \tag{9}$$

Denoting partial derivatives with subscripts, the first-order condition with respect to $\overline{v}_j$ gives

$$p_j^y \zeta = q_j \mathbb{E}\left[ p_j^a J_{n_j}' \right], \tag{10}$$

where $J_{n_j}' := \partial J(n_j')/\partial n_j$ is the value in the next period of employing a worker today. The left-hand side of Eq. 10 is a production worker's output. The right-hand side is the present value of the profits that a recruiter indirectly generates from hiring more workers. The equality sign in Eq. 10 implies that a firm must be indifferent between assigning a worker to production and recruitment.

I obtain $J_{n_j}$ by differentiating Eq. 8 with respect to the number of workers $n_j$. This gives the envelope condition

$$J_{n_j} = p_j^y \zeta h_j - (1 + \tau^P) h_j w_j + (1 - \pi) \mathbb{E}\left[ p_j^a J_{n_j}' \right].$$

The condition states that the value of a worker equals the marginal product minus after-tax wage payments plus the present value of the worker in the following period given that they remain with the firm.

## 3.3 Household

The workers own the firms and belong to a representative household. The household pools workers' income together and fully insures workers against temporary income shocks (e.g., from unemployment or wage changes).[29] The assumption of full insurance, dating back to Merz (1995), is common in the search literature and simplifies the household's problem (Hall, 2009). It implies that the household equalizes the marginal utility of consumption across workers in order to maximize their combined utility.

Workers get utility from consumption $\overline{C}$ and disutility from work. Consumption is separable from leisure and identical across employed and unemployed workers. The utility function is

$$U(\overline{C}, h_j) = \log(\overline{C}) - \frac{\psi\chi}{1+\chi} h_j^{1+\frac{1}{\chi}},$$

where $\psi$ is a parameter representing disutility from work and $\chi$ is the Frisch elasticity of labor supply. The aggregate consumption good $\overline{C}$ is a nested constant elasticity of substitution (CES) aggregate of consumption goods $r \in \mathcal{R} = \{\texttt{f},\texttt{g},\texttt{z},\texttt{fg}\}$. Fig. 3 displays the nesting structure. The fossil and green goods trade-off in a bottom nest with elasticity $\sigma^{fg}$. The aggregate good $\overline{C}$ is produced in a top nest by combining the fossil-green composite good ($r = \texttt{fg}$) with the neutral good and elasticity $\sigma$. The goods take the form of

$$C_r = \varrho_r \left(\frac{\overline{p}}{p_r}\right)^{\sigma} \overline{C} \qquad\qquad \forall r \in \{\texttt{fg},\texttt{z}\}, \qquad\qquad (11)$$

$$C_r = \varrho_r \left(\frac{p_{\texttt{fg}}}{p_r}\right)^{\sigma^{fg}} C_{\texttt{fg}} \qquad\qquad \forall r \in \{\texttt{f},\texttt{g}\}, \qquad\qquad (12)$$

where $\varrho_r$ are (scaled) CES share parameters and $p_r$ is the gross price of good $r$. The gross price of the aggregate good $\overline{p}$ and of the fossil-green composite $p_{\texttt{fg}}$ are defined by

$$\overline{p} = \left(\varrho_{\texttt{fg}} p_{\texttt{fg}}^{1-\sigma} + \varrho_{\texttt{z}} p_{\texttt{z}}^{1-\sigma}\right)^{\frac{1}{1-\sigma}},$$

$$p_{\texttt{fg}} = \left(\varrho_{\texttt{f}} p_{\texttt{f}}^{1-\sigma^{fg}} + \varrho_{\texttt{g}} p_{\texttt{g}}^{1-\sigma^{fg}}\right)^{\frac{1}{1-\sigma^{fg}}}.$$

---

[29]Blundell, Pistaferri and Preston (2008) find evidence that all households besides the poorest insure themselves against temporary income shocks.
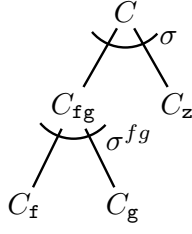
**Figure 3:** Consumption nesting structure

An employed worker receives gross labor income $w_j h_j$ and pays labor income tax $\tau^L$. An unemployed worker gets a fixed unemployment benefit $b_j$. All workers receive an equal transfer amount from the government. The total transfer amount summed across workers is $T$. The unemployment benefits and transfers are valued at $\overline{p}$. Workers own assets and the total assets of the representative household is $a$.

The household's problem is to choose the level of consumption $\overline{C}$ and the value of the next period's assets $a'$ that maximize lifetime utility subject to an intertemporal budget constraint and laws of motion for employment and unemployment. The Bellman equation is

$$V\big(a, n_{\mathcal{J}}, u_{\mathcal{J}}\big) = \max_{\overline{C}, a'} \left[ \sum_j n_j U\big(\overline{C}, h_j\big) + \sum_i u_i U\big(\overline{C}, 0\big) + \beta \mathbb{E}\Big[ V\big(a', n'_{\mathcal{J}}, u'_{\mathcal{J}}\big) \Big] \right],$$
(13)

subject to

$$\overline{p}\overline{C} + p^a a' \leq \sum_j (1 - \tau^L) n_j w_j h_j + \sum_i u_i \overline{p} b_j + a + \overline{p} T,$$

$$n'_j = n_j - \pi n_j + \sum_i \phi_{ij} u_i \qquad\qquad \forall j, \qquad (14)$$

$$u'_i = \pi n_i + u_i (1 - \sum_j \phi_{ij}) \qquad\qquad \forall i. \qquad (15)$$

Eq. 14 states that employment in the next period corresponds to current employment minus layoffs plus the number of unemployed workers that find a job. Eq. 15 indicates that unemployment in the next period corresponds to layoffs plus the number of unemployed workers that do not find a job.

The first-order condition with respect to consumption is

$$\frac{1}{\overline{C}} = \lambda\overline{p},$$

where $\lambda$ is the Lagrange multiplier for the budget constraint. The marginal utility of consumption, in other words, equals the cost (in terms of utility) of paying price $\overline{p}$ for an additional unit of consumption.

The first-order condition with respect to next period's assets $a'$ equates the present value of one unit of future assets with the cost of this unit, such that

$$\beta\mathbb{E}\left[V'_{a'}\right] = \lambda p^a. \tag{16}$$

Differentiating Eq. 13 with respect to current assets gives the envelope condition

$$V_a = \lambda,$$

which holds in every period implying

$$V'_{a'} = \lambda'. \tag{17}$$

Combining Eqs. 16 and 17 gives the Euler equation

$$p^a = \beta\frac{\lambda'}{\lambda}.$$

The equation states that the price of an Arrow security must equal the discounted intertemporal ratio of the marginal utility of income.

To obtain $V_{n_{\mathcal{J}}}$ and $V_{u_{\mathcal{J}}}$, I differentiate Eq. 13 with respect to employment and unemployment in each sector to get the envelope conditions

$$V_{n_j} = U\left(\overline{C}, h_j\right) + \lambda\left(1 - \tau^L\right)w_j h_j + \beta\left((1 - \pi)\mathbb{E}\left[V'_{n_j}\right] + \pi\mathbb{E}\left[V'_{u_j}\right]\right) \qquad \forall j, \tag{18}$$

$$V_{u_i} = U\left(\overline{C}, 0\right) + \lambda\overline{p}b + \beta\left(\mathbb{E}\left[V'_{u_i}\right] + \sum_j \phi_{ij}\left(\mathbb{E}\left[V'_{n_j}\right] - \mathbb{E}\left[V'_{u_i}\right]\right)\right) \qquad \forall i. \tag{19}$$

Eq. 18 states that the value (for the household) of having a worker employed in sector $j$ corresponds to the worker's utility plus the value of after-tax labor

income plus the discounted expected value in the next period if the worker is employed with probability $1 - \pi$ and unemployed with probability $\pi$. Eq. 19 indicates that the value of having a worker unemployed in sector $i$ corresponds to the worker's utility plus the value of unemployment benefits and the discounted expected value in the next period if the worker is unemployed or finds a job with probability $\sum_j \phi_{ij}$.

## 3.4 Wages and hours

Upon matching, a worker and firm divide the match surplus according to Nash bargaining. The match surplus is the value to the firm of an additional worker $J_{n_j}$ plus the value to the worker of being hired $V_{n_j} - V_{u_j}$. The Nash bargaining problem is to choose the wage and hours that maximize a Cobb-Douglas function of the match surplus components:

$$\max_{w_j, h_j} J_{n_j}^{\eta} \left[ V_{n_j} - V_{u_j} \right]^{1-\eta} \quad \forall j,$$

where $\eta \in [0, 1]$ denotes the firm's bargaining power. Solving gives the following respective equilibrium conditions for hours and wages:[30]

$$(1 + \tau^P)\psi h_j^{\frac{1}{\chi}} = (1 - \tau^L)\lambda p_j^n \zeta \quad \forall j, \tag{20}$$

$$(1 - \tau^L)h_j w_j = (1 - \eta)\left[\frac{1 - \tau^L}{1 + \tau^P}p_j^n \zeta h_j\right]$$

$$+ \eta\left[\frac{\psi \chi h_j^{1+\frac{1}{\chi}}}{\lambda(1 + \chi)} + \bar{p}b_j + \beta\frac{\sum_i \phi_{ji}\left(V'_{n_i} - V'_{u_j}\right)}{\lambda}\right] \quad \forall j. \tag{21}$$

Eq. 20 states that the disutility from working one hour equals the after-tax value that this hour generates in production. The equation implies that hours in equilibrium maximize the value of the match surplus.

Eq. 21, meanwhile, implies that the match surplus is split between the worker and firm according to a constant share rule. A worker's after-tax wage income equals a weighted average of the marginal product of labor (first square bracket) and the marginal rate of substitution between consumption and leisure

---

[30]The derivations of Eqs. 20 and 21 are analogous to the derivations for a one-sector framework in Shimer (2010). They are therefore omitted here for the sake of conciseness.

(second square bracket), where the weights correspond to the bargaining powers of the worker and firm. The marginal product of labor typically exceeds the marginal rate of substitution as a result of the search frictions in the labor market (Shimer, 2010). Eq. 21 implies that a worker captures a larger share of this difference if their bargaining power $1 - \eta$ increases.

## 3.5 Government, climate policy, and market clearing

The government has access to two climate policy instruments. The first is a subsidy $s$ on the green sector's output and the second is a tax $\tau^E$ on the fossil sector's emissions. The net price $p_j^y$ corresponds to the gross price $p_j$ adjusted for any subsidy receipts and emissions tax payments, meaning

$$
p_j^y = \begin{cases} p_j + s & \text{for } j = \text{g}, \\ p_j - \tau^E & \text{for } j = \text{f}, \\ p_j & \text{for } j = \text{z}. \end{cases}
$$

The government collects revenue from a labor income tax, payroll tax and carbon tax, and returns the revenue as lump sum transfers, unemployment benefits, and subsidy payments. The government's budget constraint is

$$
\left( \tau^L + \tau^P \right) \sum_j n_j w_j h_j + \tau^E e = T + \sum_i u_i \overline{p} b_i + s y_{\text{g}}.
$$

Finally, the market for each good clears implying

$$
y_j \geq C_j \quad \perp p_j \quad \forall j, \tag{22}
$$

where $\perp$ indicates complementarity between the market clearing condition and gross price $p_j$.

## 3.6 Fundamental surplus ratio

As shown by Ljungqvist and Sargent (2017), the magnitude of the employment change from a productivity shock depends on the fundamental surplus ratio.[31] The ratio is defined as

$$
\frac{\hat{y}_{n_j} - Z_j}{\hat{y}_{n_j}},
$$

---

[31] A lower fundamental surplus ratio implies larger employment changes from climate policy, while a higher ratio implies smaller changes.

where $\hat{y}_{n_j}$ is the after-tax marginal product of labor

$$\frac{1 - \tau^L}{1 + \tau^P} p_j^n \zeta h_j,$$

and $Z_j$ is the flow value of unemployment, equal to the value of leisure plus unemployment benefits

$$\frac{\psi \chi h_j^{1+\frac{1}{\chi}}}{\lambda(1 + \chi)} + \overline{p} b_j.$$

# 4   Calibration

I calibrate the model to the U.S. economy in 2019. Some parameter values are based on the literature and data sources (Section 4.1), while others are estimated using the search model in the no-policy steady state (Section 4.2). Table 2 summarizes the calibration.

**Table 2:** Calibration overview

| Direct calibration | | |
|---|---|---|
| Quit rate | $\pi$ | 0.037 |
| Bargaining power of employer | $\eta$ | 0.5 |
| Matching elasticity | $\gamma$ | 0.5 |
| Discount rate | $\beta$ | 0.997 |
| Frisch elasticity of labor supply | $\chi$ | 1 |
| Elasticity in the bottom consumption nest | $\sigma^{fg}$ | 0.75 |
| Elasticity in the top consumption nest | $\sigma$ | 0.5 |
| Labor income tax | $\tau^L$ | 0.29 |
| Payroll tax | $\tau^P$ | 0.15 |
| | | |
| No-policy steady state calibration | | |
| Switching friction in sector $j \in \{\mathtt{f},\mathtt{g},\mathtt{z}\}$ | $\xi_j$ | 0.75, 1, 1 |
| Matching efficiency in sector $j \in \{\mathtt{f},\mathtt{g},\mathtt{z}\}$ | $\mu_j$ | 3.953, 3.841, 3.841 |
| Labor productivity | $\zeta$ | 3.202 |
| Disutility of work | $\psi$ | 5.931 |
| CES share of good $r \in \{\mathtt{f},\mathtt{g},\mathtt{z},\mathtt{gf}\}$ | $\varrho_r$ | 0.73, 0.27, 0.93, 0.07 |
| Unemployment benefits in sector $j \in \{\mathtt{f},\mathtt{g},\mathtt{z}\}$ | $b_j$ | 0.264, 0.277, 0.277 |
| Emissions factor of the fossil sector | $\epsilon$ | 0.0075 |

## 4.1   Direct calibration

The average job separation rate in the United States was 3.7% in 2019 according to the Job Openings and Labor Turnover Survey of the BLS.[32] I set $\pi$ equal to this value. The bargaining power is split equally across firms and workers ($\eta = 0.5$), which is standard in the literature (see e.g. Finkelstein Shapiro and Metcalf, 2023; Ljungqvist and Sargent, 2017; Mortensen and Pissarides, 1999). Regarding the elasticity of matches with respect to unemployment $\gamma$, Petrongolo and Pissarides (2001) recommend a value of $0.5 - 0.7$ based on a literature review, while Hall (2005) and Shimer (2005) estimate values of 0.235 and 0.72 respectively using survey data. I adopt a middle value of $\gamma = 0.5$, which is also the approach of Yedid-Levi (2016) and Hafstead and Williams (2018).

The average real interest rate in the United States was 3.43% in 2019,[33] which translates into a monthly discount rate $\beta$ of $1.0343^{-1/12} = 0.997$. The Frisch elasticity of labor supply $\chi$ is equalized to unity in line with Hall and Milgrom (2008). I set the elasticity of substitution between the green-fossil composite and the neutral good $\sigma$ to 0.5, which is a standard value in aggregated CES consumption structures (see e.g. Landis, Fredriksson and Rausch, 2021). The elasticity between the fossil and green good $\sigma^{fg}$ is set to a higher level (0.75) in order to reflect the larger switch in consumption from fossil to green goods as a result of climate policy.

Tax data for the United States in 2019 were obtained from the OECD.[34] The average marginal rate of federal and state labor income taxes was 29%, while the average marginal payroll tax, consisting of social security contributions of employers and workers, was 15%. I therefore set $\tau^L = 0.29$ and $\tau^P = 0.15$.

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[32]Available at https://data.bls.gov/timeseries/JTS000000000000000TSR.

[33]See the World Bank at https://data.worldbank.org/indicator/FR.INR.RINR?view=chart.

[34]See "Table I.4. Marginal personal income tax and social security contribution rates on gross labour income", available at https://stats.oecd.org/index.aspx?DataSetCode=TABLE_I4#.

## 4.2 Calibration using the no-policy steady state

I make five assumptions in the no-policy steady state. First, I set $\bar{u} = 5.9\%$ to mirror the average unemployment rate in the United States during 2000-2019.[35] This implies $\bar{n} = 1 - \bar{u} = 94.1\%$. Second, I distribute total employment $\bar{n}$ and total consumption $\overline{C}$ across sectors in proportion to the employment shares in 2019 in Fig. 1. The employment shares are 1.8%, 4.9% and 93.3% for the green, fossil and neutral sectors respectively. Third, without loss of generality, I normalize prices, total consumption, and workers' time endowment to unity. Fourth, I assume that one third of the time endowment (i.e., eight hours per day) is spent working, meaning $h_j = 1/3$. Fifth, I assume the share of within-sector matches correspond to the diagonal elements in Table 1. In particular, let $\omega_j$ denote the share of within-sector matches such that

$$\omega_j = \frac{m_{jj}}{\sum_i m_{ij}}. \tag{23}$$

I assume $\omega_j$ equals the diagonal elements in Table 1, i.e. the share of workers starting job $j$ that previously had the same job $i = j$. Thus, $\omega_{\mathrm{f}} = 0.25, \omega_{\mathrm{g}} = 0.01$ and $\omega_{\mathrm{z}} = 0.94$.

### 4.2.1 Calibrating $\xi_j$

To estimate $\xi_j$, I first rearrange Eqs. 3 and 4 and substitute them into Eq. 23 to get[36]

$$\omega_j = \frac{u_j \phi_{jj}}{v_j h_j q_j} \quad \forall j.$$

Substituting for $\phi_{jj}$ using Eq. 6 and then for $\mu_j$ using Eq. 5 gives

$$\omega_j = \frac{u_j \left[ \xi_j \theta_j \theta^{-\gamma} + (1 - \xi_j)\theta_{jj}^{1-\gamma} \right]}{v_j h_j \left[ \xi_j \theta^{-\gamma} + (1 - \xi_j)\theta_{jj}^{-\gamma} \right]} \quad \forall j. \tag{24}$$

---

In the steady state, Eq. 24 links $\xi_j$ to the variables $\{u_{\mathtt{f}}, u_{\mathtt{g}}, u_{\mathtt{z}}\}$ and to exogenous parameters. To see why $v_j$ is exogenous, I first note that Silva and Toledo (2009) find that the cost of recruiting one worker is approximately 4% of a quarterly wage. Assuming this cost is borne in terms of hours, recruitment productivity $q_j = 1/(\frac{1}{3} \times 3 \times 0.04) = 25$ by Eq. 3. Since employment in the steady state is constant, Eqs. 7 and 9 imply that $v_j$ is determined exogenously by $v_j = n_j \pi/(q_j h_j)$.

To define the three unknowns $\{u_{\mathtt{f}}, u_{\mathtt{g}}, u_{\mathtt{z}}\}$, I recall that employment and unemployment are constant in the steady state. Eqs. 14 and 15 therefore imply

$$u_j = \frac{\sum_i u_i \phi_{ij}}{\sum_i \phi_{ji}} \quad \forall j,$$

which, using Eq. 6, can be rewritten as

$$u_j = \frac{\sum_i u_i \mu_j \left[ \xi_j \theta_j \theta^{-\gamma} + (1 - \xi_j) \theta_{ij}^{1-\gamma} \delta_{ij} \right]}{\sum_i \mu_i \left[ \xi_i \theta_i \theta^{-\gamma} + (1 - \xi_i) \theta_{ji}^{1-\gamma} \delta_{ij} \right]} \quad \forall j. \tag{25}$$

Eqs. 24 and 25 contain two unknowns ($\xi_j$ and $u_j$) in the no-policy steady state.[37] Solving for $\xi_j$ and $u_j$ using both equations gives

$$\xi_j = \begin{cases} 0.75 & \text{for } j = \mathtt{f}, \\ 1 & \text{for } j = \mathtt{g}, \\ 1 & \text{for } j = \mathtt{z}, \end{cases}^{38}$$

$$u_j = \begin{cases} 0.002 & \text{for } j = \mathtt{f}, \\ 0.001 & \text{for } j = \mathtt{g}, \\ 0.056 & \text{for } j = \mathtt{z}. \end{cases}$$

The values of $\xi_j$ imply a high degree of cross-sector matching. This is especially the case in the green and neutral sectors, where matching is independent of a worker's employment history. Fossil and green workers are therefore as likely as neutral workers, everything else equal, to match with neutral firms. Similarly, fossil and neutral workers are equally likely as green workers to match with green firms. Turning to the values of $u_j$ in the no-policy steady state, we see that there

---

[37] Note that $\mu_j$ is determined by $\xi_j$ and $\{u_{\mathtt{f}}, u_{\mathtt{g}}, u_{\mathtt{z}}\}$ by Eq. 5.
[38] I restrict $\xi_j$ to a maximum value of 1 as this represents an extreme whereby matching does not depend on a worker's employment history.

are many more unemployed workers in the neutral sector. This largely stems from the neutral sector being bigger.

### 4.2.2 Calibrating the remaining parameters

The matching efficiency $\mu_j$ is pinned down by rearranging Eq. 5 to $\mu_j = q_j/(\xi_j\theta^{-\gamma} + (1 - \xi_j)\theta_{jj}^{-\gamma})$. Labor productivity $\zeta$ is obtained by rearranging Eq. 1 to $\zeta = y_g/(l_g h_g)$ and setting $y_g = n_g$, $l_g = n_g - \upsilon_g$, and $h_g = 1/3$.[39] I pin down the disutility of work $\psi$ by the hour bargaining condition in Eq. 20. The CES consumption shares $\varrho_r$ are obtained from Eqs. 11 and 12. Similarly to Hafstead and Williams (2018), unemployment benefits $b_j$ are endogenously determined by the wage bargaining condition in Eq. 21. I get $b_f = 0.264, b_g = 0.277$ and $b_z = 0.277$.[40] The values imply replacement rates of 40.2%, 42.2% and 42.2% for the fossil, green and neutral sectors respectively. These are similar to the 41% in Hafstead and Williams (2018) and lie in between the 25% and 50% in Hall and Milgrom (2008) and Finkelstein Shapiro and Metcalf (2023) respectively.

The emissions factor $\epsilon$ is parametrized using a similar procedure as in Hafstead and Williams (2018). First, I note that total personal consumption expenditure in the United States was \$14.4 trillion in 2019,[41] while carbon dioxide emissions were 5.262 billion tons.[42] The emissions per dollar of consumption were therefore 0.0004 $tCO_2$. Second, I adjust this number for the fact that only the fossil sector emits in my model. The fossil sector accounts for 4.9% of total consumption (that equals one) in the initial steady state, meaning its emissions factor is 0.0075 $tCO_2$ per unit of output.

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[39] I pin down $\zeta$ using the green sector. The choice of sector is arbitrary since $y_j/l_j$ and $1/h_j$ are identical across sectors in the no-policy benchmark.

[40] In contrast to Hafstead and Williams (2018), my unemployment benefits vary by sector because of the sector-specific $\xi_j$. This implies different flow values of unemployment (0.593, 0.607, 0.607) and fundamental surplus ratios (0.100, 0.080, 0.080) in the fossil, green and neutral sectors respectively. I examine the implications of varying the unemployment benefits in Section 5.4.

[41] See "Table 2.3.5U." under "Section 2 Personal Consumption Expenditures", available from the Bureau of Economic Analysis at: `https://apps.bea.gov/iTable/?isuri=1&reqid=19&step=4&categories=flatfiles&nipa_table_list=1`.

[42] See the "Inventory of U.S. Greenhouse Gas Emissions and Sinks", available from the EPA at: `https://www.epa.gov/ghgemissions/inventory-us-greenhouse-gas-emissions-and-sinks`.

# 5 Numerical analysis

This section presents the employment outcomes from a green subsidy and a carbon tax. Section 5.1 assumes that the government finances the subsidy and recycles the carbon tax revenue in a non-distortionary manner. Section 5.2 relaxes this assumption, while Section 5.3 looks at the effects of changing the level of preexisting distortions in the economy. Section 5.4 presents a sensitivity analysis. The abatement level is fixed throughout. The level is set such that the 10-year subsidy expenditure in Section 5.1 equals the \$271 billion in the IRA.

## 5.1 Climate policy with lump sum taxes

### 5.1.1 Total employment impact

Fig. 4 shows the change in total employment from a subsidy and a carbon tax when the government uses lump sum taxes to balance its budget.[43] A subsidy increases steady state employment by 0.04 percentage points. A carbon tax, in contrast, reduces it by 0.01 percentage points. A subsidy therefore outperforms a carbon tax and generates small employment gains when financed in a non-distortionary manner.

### 5.1.2 Sector-level impacts

In the following, I decompose the employment impacts by sector. I begin with the green subsidy and thereafter turn to the carbon tax.

#### 5.1.2.1 Subsidy

Panel (a) of Fig. 5 shows that a subsidy increases employment in the green sector and decreases employment in the fossil and neutral sectors.[44] Table 3 sheds

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[43]The lump sum taxes are positive in the context of a subsidy and negative (i.e., equivalent to transfers) in the context of a carbon tax.

[44]The transition to the steady state is quick, which partly stems from the high values of $\xi_j$. The fossil sector has a lower value of $\xi_j$. Firms there consequently face more hiring friction because their matching depends on a job searcher's employment history. These firms adjust their hiring more gradually, as Fig. 5 shows. The green and neutral sectors, in contrast, have a value of $\xi_j = 1$ and do not face any cross-sector matching frictions. Firms in these sectors can adjust their hiring more quickly, which explains why the green and neutral sectors reach the steady state faster in Fig. 5.
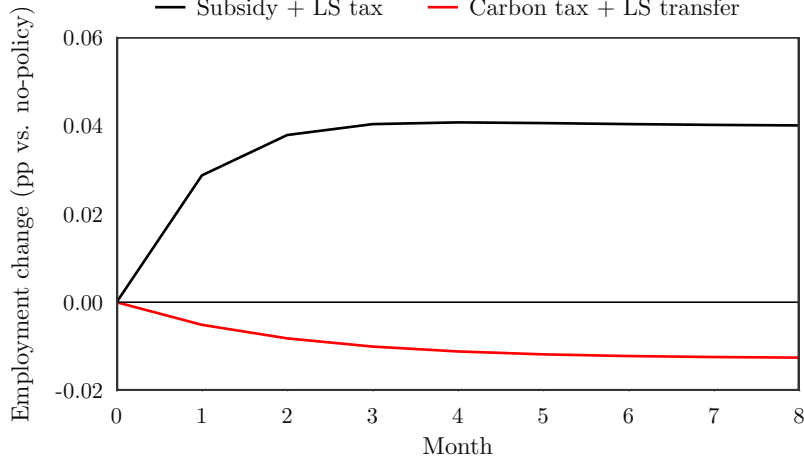
**Figure 4:** Employment change from a green subsidy and carbon tax with lump
sum taxes and transfers

*Note:* "LS" is short for lump sum.

light on the mechanisms.[45] A subsidy induces consumers to substitute towards
the green good by lowering its price $p_{\mathbf{g}}$ relative to other goods. Firms in the
green sector respond by demanding more workers and increasing recruitment.
Employment in the green sector consequently expands.[46] The opposite occurs
in the fossil and neutral sectors. Goods there become relatively more expensive
which reduces demand for them and induces firms to hire fewer workers.

Table 4 decomposes the change in recruitment $v_j q_j h_j$ in the initial period
and in the steady state. Firms in the green sector hire more recruiters $v_j$
immediately after the subsidy is introduced, while firms elsewhere hire fewer
recruiters. Recruitment productivity $q_j$ initially decreases in the green sector

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[45]Employment contracts by more in the fossil sector compared to the neutral sector in
Table 3. The opposite is true, however, in Fig. 5. The discrepancy arises from reporting
differences. Table 3 reports the employment change in percentage terms while Fig. 5 reports
it in percentage points. The fossil sector is smaller than the neutral sector, which makes its
employment change smaller in percentage points.

[46]The large employment gains in the green sector occur in spite of its comparatively high
benchmark fundamental surplus ratio (see footnote 40). The employment gains might have
been even larger if the no-policy steady state calibration resulted in a lower fundamental
surplus ratio. Table 9 provides some evidence of this. The table shows the fundamental
surplus ratio in the benchmark and employment change by sector for alternative calibrations.
A much lower fundamental surplus ratio in the green sector (from a higher $q_{\mathbf{g}}$ or higher $\eta$) is
associated with larger employment gains there.
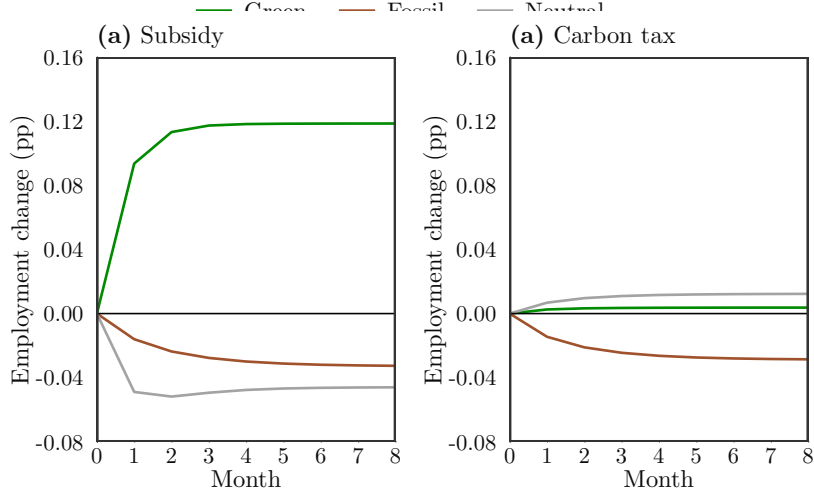
**Figure 5:** Employment change by sector from a green subsidy and carbon tax with lump sum taxes and transfers

**Table 3:** Steady state changes from a subsidy by sector (in percent relative to no-policy)

|         | Gross price $p_j$ | Output $y_j$ | Recruitment $v_j q_j h_j$ | Employment $n_j$ |
|---------|------|------|------|------|
| Green   | 0    | 8.5  | 8.5  | 8.5  |
| Fossil  | 12.5 | -0.6 | -0.7 | -0.7 |
| Neutral | 12.5 | 0.0  | -0.1 | -0.1 |

*Note*: The gross price of the green good $p_g$ does not change as it is the numeraire.

because the labor market there becomes tighter (as a result of the higher recruitment effort). In the fossil sector, in contrast, the labor market becomes slacker which increases recruitment productivity. The values of $v_j$, $q_j$ and $h_j$ converge to similar levels across sectors in the steady state.[47] The steady state is characterized by more recruiters $v_j$, lower recruitment productivity $q_j$ (because of a tighter labor market), and slightly more hours worked $h_j$.

Table 4 also depicts worker-level outcomes. The subsidy benefits workers in the green sector. They receive a higher wage and are more likely to find a job immediately after the subsidy is implemented. In the steady state, wages and

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[47]The values are, however, not identical because the degree of friction associated with cross-sector matching $\xi_j$ varies across sectors.

job-finding probabilities converge to similar levels across sectors.[48] The levels are higher than in the no-policy benchmark, implying that the subsidy increases wages and the likelihood of finding a job.

**Table 4:** Changes from a subsidy by sector and time period (in percent relative to no-policy)

| | | Firm-level | | | | Worker-level | |
|---|---|---|---|---|---|---|---|
| | | Number of recruiters $v_j$ | Recruitment productivity $q_j$ | Hours worked $h_j$ | | Job-finding probability $\sum_j \varphi_{ij}$ | After-tax real wage $(1-\tau^L)w_i/\overline{p}$ |
| Green | $t = 0$ | 168.0 | -0.7 | 5.4 | 0.9 | 2.9439 | |
| | SS | 9.2 | -0.7 | 0.1 | 0.7 | 0.1707 | |
| Fossil | $t = 0$ | -9.4 | 0.7 | -0.2 | -0.5 | -0.0304 | |
| | SS | -0.1 | -0.7 | 0.1 | 0.7 | 0.1709 | |
| Neutral | $t = 0$ | -0.8 | -0.7 | 0.0 | 0.9 | 0.1443 | |
| | SS | 0.6 | -0.7 | 0.1 | 0.7 | 0.1707 | |

*Note*: "SS" denotes the steady state.

#### 5.1.2.2 Carbon tax

Panel (b) of Fig. 5 displays the sector-level results for a carbon tax. Three insights emerge with respect to how the carbon tax compares to the subsidy. First, a carbon tax generates a smaller reallocation of labor across sectors.

Second, the two instruments have opposite effects on employment in the neutral sector. A subsidy decreases employment there while a carbon tax increases it. The discrepancy stems from how the instruments affect the neutral good's price. A subsidy makes the neutral good more expensive relative to an average consumption basket, which reduces recruitment in the neutral sector. A carbon tax, conversely, makes the neutral good relatively cheaper and thus increases recruitment in the neutral sector (Table 5).

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[48]The wage changes in Table 4 explain why employment decreases by more in the fossil sector compared to the neutral sector in Table 3. The steady state wage is slightly higher in the fossil sector compared to the neutral sector. Workers in the fossil sector face less outside competition because $\xi_f < 1$ implies that firms there face frictions when matching with workers from other sectors. Workers in the neutral sector, in contrast, are not shielded from outside competition because $\xi_z = 1$. The fact that $\xi_f < \xi_z$ means workers in the fossil sector have a stronger bargaining position and can demand a higher wage. The higher wage reduces the value of a match for firms in the fossil sector. These firms consequently recruit fewer workers, which explains why employment contracts to a larger extent in the fossil sector.

**Table 5:** Steady state changes from a carbon tax by sector (in percent relative to no-policy)

|  | Gross price $p_j$ | Output $y_j$ | Recruitment $v_j q_j h_j$ | Employment $n_j$ |
|---|---|---|---|---|
| Green | 0 | 0.2 | 0.23 | 0.23 |
| Fossil | 1.1 | -0.6 | -0.61 | -0.61 |
| Neutral | 0.0 | -0.0 | 0.01 | 0.01 |

*Note*: The gross price of the green good $p_g$ does not change as it is the numeraire.

Third, a subsidy produces much larger employment gains in the green sector compared to a carbon tax. A subsidy, when financed in a non-distortionary manner, reduces labor costs in the green sector which counteracts distortions from preexisting labor taxes. A carbon tax, in contrast, does not reduce distortions when the tax revenue is recycled in a lump sum fashion. Fig. 5 therefore highlights a key advantage of subsidies (when financed by lump sum taxes), namely that they counteract initial distortions in the green sector by making it cheaper to recruit workers there.

The previous paragraph touches on an important issue, namely that the performance of subsidies and carbon taxes depends on how distortionary they are. I have assumed until now that the government finances subsidies and recycles carbon tax revenue in a non-distortionary manner. This assumption might be unrealistic since governments in practice use distortionary labor taxes. If such taxes are used to finance subsides and recycle carbon revenue, the climate policy instruments might perform differently. I turn to this issue next.

## 5.2 Climate policy with labor taxes

The black lines in Fig. 6 show the employment impact of a subsidy given different financing methods. The solid black line is the same as in Fig. 4 and represents a situation in which the government finances a subsidy with lump sum taxes. Employment increases in this case. The dashed black line depicts the employment change if the government instead increases payroll taxes to finance the subsidy. The job gains thereby disappear and employment instead

falls. The choice of financing mechanism therefore has a notable impact on employment.

The financing mechanism affects a subsidy's relative performance to a carbon tax. Fig. 6 shows that while a subsidy outperforms a carbon tax when financed by lump sum taxes, the inverse is true when the subsidy is paid for by payroll taxes. An implication is that subsidies are especially advantageous when lump sum taxes are available. If this is not the case, Fig. 6 suggests that a carbon tax generates more favorable employment outcomes.
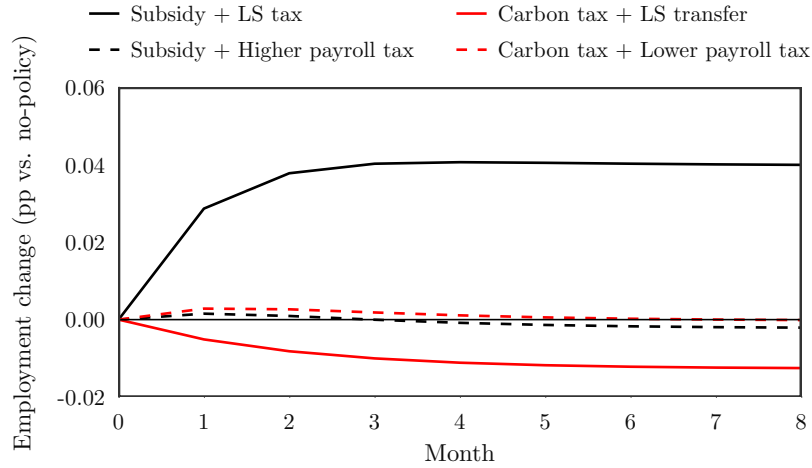


**Figure 6:** Employment change from a green subsidy and carbon tax by financing/recycling mechanism

*Note:* "LS" is short for lump sum.

Fig. 7 decomposes the employment change from a subsidy by sector and financing mechanism. A subsidy reallocates labor to the green sector, irrespective of the financing mechanism. However, the reallocation is much smaller when the subsidy is paid for by payroll taxes. The reason is twofold. First, higher payroll taxes increase the level of distortion in the green sector by making it costlier to hire workers. This reduces output and recruitment relative to a subsidy financed by lump sum taxes (Table 6). Second, a payroll tax-financed subsidy offsets preexisting distortions in the green sector by less because it induces a

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lower subsidy rate.[49] The subsidy rate is lower because each dollar in subsidy payments increases production costs in the fossil sector (from the higher payroll taxes). Output, and consequently emissions, therefore contract by more for a given subsidy level when payroll taxes finance the subsidy. The lower subsidy rate further slows down recruitment in the green sector and contributes to the smaller employment gains there.[50]
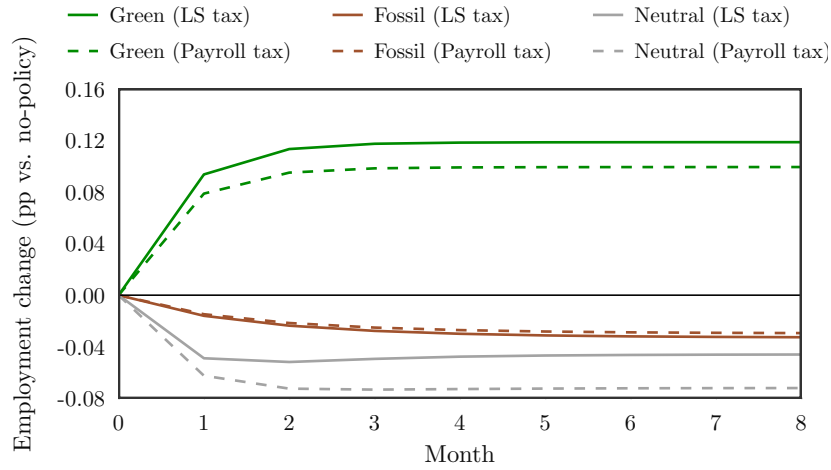


**Figure 7:** Employment change from a green subsidy by sector and financing mechanism

*Note:* "LS tax" refers to a subsidy financed by lump sum taxes.

A take-away from the above is that the financing mechanism matters because it influences the level of distortion in the labor market. A question is whether the discrepancy across financing mechanisms changes with the degree of preexisting distortions. I investigate this issue in the following section.

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[49]The subsidy decreases from 1 to 0.6 cents per dollar of green output when switching from lump sum to payroll taxes.

[50]While switching from lump sum to payroll taxes decreases green and neutral employment in Fig. 7, it increases employment slightly in the fossil sector. Financing via payroll taxes decreases labor demand in the green sector which leads to a smaller outflow of workers from the fossil sector. This offsets the employment losses from the higher payroll taxes and explains why employment slightly increases in the fossil sector.

**Table 6:** Steady state changes from a subsidy by financing mechanism and sector (in percent relative to no-policy)

|  |  | Output $y_j$ | Recruitment $v_j q_j h_j$ |
|---|---|---|---|
| Subsidy with lump sum tax | Green | 8.5 | 8.5 |
|  | Fossil | -0.6 | -0.7 |
|  | Neutral | 0.0 | -0.1 |
| Subsidy with payroll tax | Green | 7.1 | 7.1 |
|  | Fossil | -0.6 | -0.6 |
|  | Neutral | -0.1 | -0.1 |

*Note*: Output $y_j$ in the fossil sector is constant since the abatement level is fixed.

## 5.3 Preexisting distortions

Fig. 8 shows the total employment impact of a subsidy given various financing mechanisms and benchmark labor tax rates. A higher level of preexisting distortions (represented by a 40% increase in $\tau^P$ and $\tau^L$ in the no-policy benchmark) has heterogeneous effects across financing mechanisms. Employment is lower if the subsidy is financed by payroll taxes but unchanged if lump sum taxes are used. Financing a subsidy via payroll taxes is therefore less attractive if the labor market is already distorted. This is also true relative to a carbon tax. Fig. 9 shows that the carbon tax is less affected by the level of preexisting distortions. The employment losses from a payroll tax-financed subsidy therefore grow relative to a carbon tax when the labor market is initially more distorted.

A subsidy financed by payroll taxes performs worse in the presence of high preexisting distortions because the distortions dampen economic activity and erode the tax base. To finance a given subsidy level, payroll taxes thereby need to increase by a larger amount. The higher payroll taxes increase labor costs, reduce recruitment, and ultimately decrease employment.
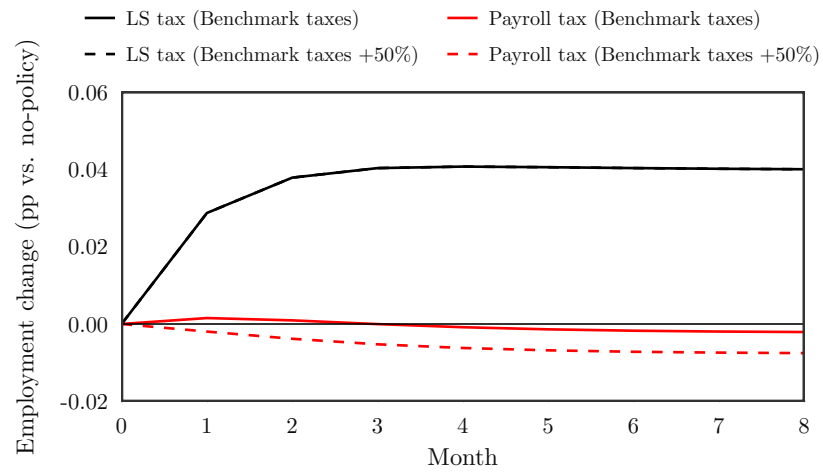
**Figure 8:** Employment change from a green subsidy by financing mechanism and benchmark tax rates

*Note:* "LS tax" refers to a subsidy financed by lump sum taxes.
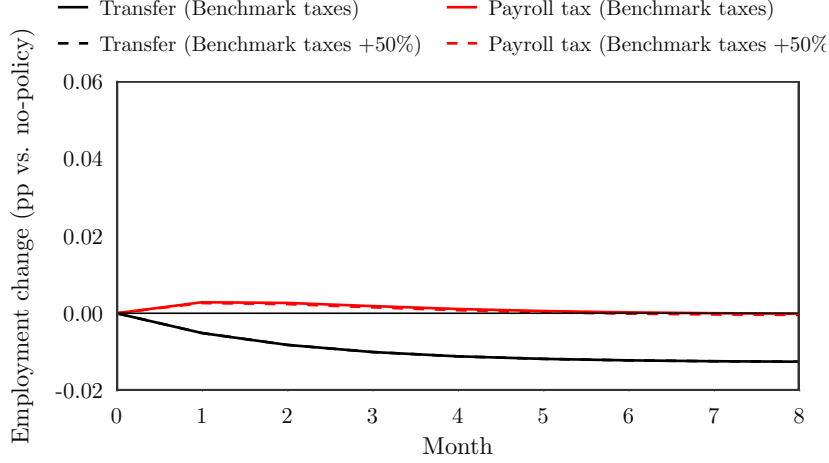
**Figure 9:** Employment change from a carbon tax by recycling mechanism and benchmark tax rates

## 5.4 Sensitivity analysis

This section looks at how the employment outcomes vary with key parameters. The analysis is carried out by recalibrating the disutility of work $\psi$ and unemployment benefits $b_j$ in the no-policy benchmark. Table 7 presents the results. The qualitative effects are generally robust. A non-distortionary subsidy always produces employment gains.[51] Using a distortionary financing mechanism, in contrast, increases unemployment. A carbon tax produces employment losses irrespective of the recycling mechanism. The losses are smaller when the revenue is recycled via lower payroll taxes.

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[51]I refer to a subsidy financed by lump sum taxes as "non-distortionary" and a subsidy financed by payroll taxes as "distortionary" in this section. To be sure, both subsidies distort. However, only the latter's financing mechanism is distortionary.

**Table 7:** Employment change by policy instrument and parameter (in percentage points relative to no-policy)

|  | Subsidy + LS tax | Subsidy + Payroll tax | Carbon tax + LS transfer | Carbon tax + Payroll tax |
|---|---|---|---|---|
| Baseline | 0.039 | -0.003 | -0.014 | -0.000 |
| $q_j$ up by 50% | 0.059 | -0.005 | -0.020 | -0.000 |
| $q_j$ down by 50% | 0.018 | -0.001 | -0.006 | -0.000 |
| $\eta = 0.7$ | 0.087 | -0.009 | -0.029 | -0.001 |
| $\eta = 0.3$ | 0.015 | -0.001 | -0.005 | -0.000 |
| $\gamma = 0.75$ | 0.020 | -0.001 | -0.007 | -0.000 |
| $\gamma = 0.25$ | 0.059 | -0.005 | -0.020 | -0.001 |
| $\chi = 2$ | 0.029 | -0.002 | -0.010 | -0.000 |
| $\chi = 0.5$ | 0.046 | -0.004 | -0.017 | -0.000 |
| $\sigma_{\mathtt{fg}} = 0.95$ | 0.021 | -0.001 | -0.013 | -0.000 |
| $\sigma_{\mathtt{fg}} = 0.55$ | 0.194 | -0.019 | -0.015 | -0.000 |
| $\sigma = 0.6$ | 0.063 | -0.006 | -0.012 | -0.000 |
| $\sigma = 0.4$ | 0.028 | -0.002 | -0.015 | -0.000 |

*Note:* "LS" is short for lump sum.

Looking at the subsidy outcomes in Table 7, we see that changing recruitment productivity $q_j$ in the benchmark has an uneven impact across financing mechanisms. A higher $q_j$ means a unit of recruitment effort $\upsilon_j h_j$ generates more matches. A subsidy financed by non-distortionary taxes increases recruitment effort (see Table 8) and therefore generates more matches when $q_j$ is high. The opposite occurs if a subsidy is financed by payroll taxes. Recruitment effort then decreases (Table 8), meaning a higher $q_j$ result in fewer matches and more unemployment.

A higher bargaining power of firms $\eta$ increases the flow value of unemployment and reduces the fundamental surplus ratio.[52,53] A small fundamental surplus ratio means that a productivity shock has a large percentage impact on profits because profits are initially small (Ljungqvist and Sargent, 2017). There

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[52]The relationship between $\eta$ and the flow value of unemployment in my analysis is similar to Hagedorn and Manovskii (2008). They find empirical evidence of small profits and only moderately procyclical wages. They argue that the latter indicates a high bargaining power of firms, which, together with small profits, imply that the flow value of unemployment is high. The same relationship is evident in my no-policy calibration. A higher value of $\eta$ raises the flow value of unemployment because unemployment benefits $b_j$ increase. The larger flow value of unemployment, in turn, reduces the fundamental surplus ratio.

[53]As shown in Table 9, a higher $\eta$ increases the average flow value of unemployment in the benchmark from 0.61 to 0.63, and reduces the average fundamental surplus ratio in the benchmark from 0.08 to 0.04.

is consequently a strong incentive to adjust recruitment in response to a productivity shock. The shock is positive in the context of a non-distortionary subsidy, meaning the recruitment and employment gains grow. Conversely, the shock is negative for a distortionary subsidy, meaning employment declines by more.

A higher elasticity of matching with respect to unemployment $\gamma$ reduces the matching efficiency $\mu_j$.[54] The lower $\mu_j$ reduces the number of matches from a unit of recruitment effort. This weakens the employment gains from a non-distortionary subsidy. On the other hand, the number of matches from a distortionary subsidy falls by less, which reduces the employment losses from such a subsidy.

Increasing the labor supply elasticity $\chi$ makes workers react more on the intensive margin to wage changes. For the case of a non-distortionary subsidy, the wage change is positive, meaning hours increase (Table 8). This crowds out labor supply on the extensive margin and reduces the employment gains. For the case of a distortionary subsidy, the wage change is negative. Hours therefore decrease (Table 8) while labor supply on the extensive margin rises.

A higher elasticity of substitution between the fossil and green good $\sigma_{\text{fg}}$ decreases the required subsidy rate (Table 8). This weakens the magnitude of the employment effects.

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[54]This can be seen by rearranging Eq. 5 to $\mu_j = q_j / (\xi_j \theta^{-\gamma} + (1 - \xi_j) \theta_{jj}^{-\gamma})$.

**Table 8:** Subsidy rate and change in recruitment effort and hours from a subsidy by financing mechanism and parameter value

| | % change in recruitment effort $\frac{\sum_j v_j h_j n_j}{\sum_j n_j}$ | | % change in hours $\frac{\sum_j h_j n_j}{\sum_j n_j}$ | | Subsidy rate $s$ | |
|---|---|---|---|---|---|---|
| | LS | Payroll | LS | Payroll | LS | Payroll |
| Baseline | 0.66 | -0.13 | 0.071 | -0.003 | 0.69 | 0.58 |
| $q_j$ up by 50% | 1.04 | -0.17 | 0.062 | -0.003 | 0.71 | 0.58 |
| $q_j$ down by 50% | 0.25 | -0.10 | 0.081 | -0.002 | 0.68 | 0.58 |
| $\eta = 0.7$ | 1.59 | -0.25 | 0.051 | -0.003 | 0.72 | 0.58 |
| $\eta = 0.3$ | 0.19 | -0.10 | 0.081 | -0.002 | 0.68 | 0.58 |
| $\gamma = 0.75$ | 1.00 | -0.14 | 0.081 | -0.002 | 0.68 | 0.58 |
| $\gamma = 0.25$ | 0.32 | -0.11 | 0.062 | -0.003 | 0.71 | 0.58 |
| $\chi = 2$ | 0.46 | -0.11 | 0.105 | -0.004 | 0.72 | 0.58 |
| $\chi = 0.5$ | 0.80 | -0.15 | 0.043 | -0.002 | 0.67 | 0.58 |
| $\sigma_{\mathtt{fg}} = 0.95$ | 0.36 | -0.07 | 0.039 | -0.001 | 0.37 | 0.33 |
| $\sigma_{\mathtt{fg}} = 0.55$ | 3.22 | -0.62 | 0.411 | -0.019 | 5.04 | 2.07 |
| $\sigma = 0.6$ | 1.03 | -0.25 | 0.118 | -0.006 | 1.17 | 0.88 |
| $\sigma = 0.4$ | 0.49 | -0.08 | 0.051 | -0.001 | 0.49 | 0.43 |

*Note:* "LS" refers to a subsidy financed by lump sum taxes. "Payroll" refers to a subsidy financed by payroll taxes. The change in recruitment effort and hours is reported as the percentage change in the steady state value. The subsidy rate is given in cents per dollar of green output.

Finally, increasing the elasticity of substitution between the green-fossil composite and the neutral good $\sigma$ amplifies the employment outcomes from a subsidy. A higher $\sigma$ induces more consumer substitution from the neutral to the cheaper green good. More workers consequently flow from the neutral to the green sector. This crowds out some of the worker reallocation from the fossil sector. A higher subsidy rate is required to counterbalance this crowding out effect (Table 8). The higher subsidy is beneficial in the context of a non-distortionary subsidy since employment increases to a larger extent. In contrast, payroll taxes must increase to cover a higher distortionary subsidy, which reduces employment by more.

**Table 9:** Outcomes from a non-distortionary subsidy by sector and parameter value

| | Benchmark unemployment benefits | | | Benchmark flow value of unemployment | | | | Benchmark fundamental surplus ratio | | | | Employment change (pp) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | g | f | z | g | f | z | mean | g | f | z | mean | g | f | z |
| Baseline | 0.28 | 0.26 | 0.28 | 0.61 | 0.59 | 0.61 | 0.61 | 0.08 | 0.10 | 0.08 | 0.08 | 0.12 | -0.03 | -0.05 |
| $q_j$ up by 50% | 0.29 | 0.28 | 0.29 | 0.62 | 0.61 | 0.62 | 0.62 | 0.05 | 0.07 | 0.05 | 0.05 | 0.12 | -0.03 | -0.03 |
| $q_j$ down by 50% | 0.23 | 0.20 | 0.23 | 0.56 | 0.53 | 0.56 | 0.56 | 0.16 | 0.20 | 0.16 | 0.16 | 0.12 | -0.03 | -0.06 |
| $\eta = 0.7$ | 0.31 | 0.30 | 0.31 | 0.63 | 0.63 | 0.63 | 0.63 | 0.04 | 0.05 | 0.04 | 0.04 | 0.12 | -0.03 | -0.00 |
| $\eta = 0.3$ | 0.21 | 0.18 | 0.21 | 0.54 | 0.51 | 0.54 | 0.54 | 0.18 | 0.23 | 0.18 | 0.18 | 0.12 | -0.03 | -0.07 |
| $\gamma = 0.75$ | 0.28 | 0.26 | 0.28 | 0.61 | 0.59 | 0.61 | 0.61 | 0.08 | 0.10 | 0.08 | 0.08 | 0.12 | -0.03 | -0.06 |
| $\gamma = 0.25$ | 0.28 | 0.26 | 0.28 | 0.61 | 0.59 | 0.61 | 0.61 | 0.08 | 0.10 | 0.08 | 0.08 | 0.12 | -0.03 | -0.03 |
| $\chi = 2$ | 0.17 | 0.15 | 0.17 | 0.61 | 0.59 | 0.61 | 0.61 | 0.08 | 0.10 | 0.08 | 0.08 | 0.12 | -0.04 | -0.06 |
| $\chi = 0.5$ | 0.39 | 0.37 | 0.39 | 0.61 | 0.59 | 0.61 | 0.61 | 0.08 | 0.10 | 0.08 | 0.08 | 0.12 | -0.03 | -0.04 |
| $\sigma_{\mathtt{fg}} = 0.95$ | 0.28 | 0.26 | 0.28 | 0.61 | 0.59 | 0.61 | 0.61 | 0.08 | 0.10 | 0.08 | 0.08 | 0.08 | -0.03 | -0.02 |
| $\sigma_{\mathtt{fg}} = 0.55$ | 0.28 | 0.26 | 0.28 | 0.61 | 0.59 | 0.61 | 0.61 | 0.08 | 0.10 | 0.08 | 0.08 | 0.58 | -0.05 | -0.34 |
| $\sigma = 0.6$ | 0.28 | 0.26 | 0.28 | 0.61 | 0.59 | 0.61 | 0.61 | 0.08 | 0.10 | 0.08 | 0.08 | 0.21 | -0.04 | -0.11 |
| $\sigma = 0.4$ | 0.28 | 0.26 | 0.28 | 0.61 | 0.59 | 0.61 | 0.61 | 0.08 | 0.10 | 0.08 | 0.08 | 0.08 | -0.03 | -0.02 |

*Note:* The "mean" columns denote weighted averages, where the weights are the sectors' benchmark unemployment rates. The no-policy benchmark is identical across financing mechanisms and climate policy instruments. The "Employment change" refers to the change in steady state employment relative to the no-policy benchmark.

# 6 Conclusion

This paper examines the effects of green subsidies on employment. I use a multi-sector general equilibrium search model to analyze how green subsidies impact the number of jobs in green, fossil and neutral sectors, and in the economy as a whole. A key parameter in the analysis is $\xi_j$ that controls the frictions associated with cross-sector matching. I calibrate this parameter using longitudinal survey data on occupations for the United States. This allows me to investigate the impact of green subsidies for a more realistic degree of labor mobility across sectors.

My empirical analysis suggests that the majority of jobs in the United States are neutral and thus directly unaffected by carbon taxes or green subsidies. Green jobs are becoming increasingly prevalent and accounted for slightly less than five percent of all jobs in 2020. The share of fossil jobs, in contrast, decreased by almost a percentage point during 2013-2020. When looking at the composition of job changes in this period, I find some heterogeneity across sectors. Less than one third of recruited workers in the green and fossil sectors previously had the same type of job (i.e., a green and a fossil job respectively), while this share is considerably higher in the neutral sector. I use the shares of within-sector job changes to calibrate $\xi_j$ and find evidence of low levels of friction associated with cross-sector matching (i.e., high values of $\xi_j$) in the no-policy steady state of the search model.

In the numerical analysis, I find that green subsidies reduce unemployment if they are paid for by non-distortionary taxes. If such taxes are unavailable and instead replaced by distortionary labor taxes, a subsidy increases unemployment and generates larger employment losses compared to a carbon tax. The choice of financing mechanism is therefore an important determinant of a subsidy's overall employment impact.

Across sectors, a subsidy generates a higher level of labor reallocation compared to a carbon tax. In particular, a subsidy increases employment in the green sector and reduces employment in fossil and neutral sectors to a larger ex-

tent. The higher degree of labor reallocation compared to a carbon tax suggests that a subsidy is the least preferable instrument if the priority is to minimize worker displacement in polluting sectors.

Finally, the results indicate that the preexisting level of labor market distortion can affect the performance of green subsidies. The effect is heterogeneous across financing mechanisms. A subsidy paid for by non-distortionary taxes generates the same employment change independent of the preexisting level of distortion, while the employment losses from a subsidy financed by labor taxes grow with the preexisting distortions. Financing a subsidy with lump sum, as opposed to labor, taxes is therefore especially advantageous if the labor market is initially distorted.

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# Appendix A: Occupations

**Table A.1:** 2018 Census codes with a one-to-many mapping to SOC

| Census code | Census title | SOC code | SOC title | SOC share in SIPP |
|---|---|---|---|---|
| 0335 | Entertainment and Recreation Managers | 11-9199 | Managers, All Other | 1 |
| | | 11-9071 | Gaming Managers | 0 |
| 0705 | Project Management Specialists | 11-9199 | Managers, All Other | 0.77 |
| | | 15-1199 | Computer Occupations, All Other | 0.16 |
| | | 13-1199 | Business Operations Specialists, All Other | 0.06 |
| 0960 | Other Financial Specialists | 13-2051 | Financial Analysts | 0.88 |
| | | 13-2099 | Financial Specialists, All Other | 0.12 |
| 1022 | Software Quality Assurance Analysts and Testers | 15-113X | Software Developers, Applications and Systems Software | 0.67 |
| | | 15-1199 | Computer Occupations, All Other | 0.33 |
| 1032 | Web and Digital Interface Designers | 15-1199 | Computer Occupations, All Other | 0.73 |
| | | 15-1134 | Web Developers | 0.27 |
| 1065 | Database Administ-rators and Architects | 15-1199 | Computer Occupations, All Other | 0.86 |
| | | 15-1141 | Database Administrators | 0.14 |
| 1108 | Computer Occup-ations, All Other | 15-1199 | Computer Occupations, All Other | 0.94 |
| | | 43-9011 | Computer Operators | 0.06 |
| 1555 | Other Engineering Technologists and Technicians, Except Drafters | 17-3020 | Engineering Technicians, Except Drafters | 1 |
| | | 55-3010 | Military Enlisted Tactical Operations and Air/Weapons Specialists and Crew Members | 0 |
| 1935 | Environmental Science and Geoscience Technicians | 19-4090 | Miscellaneous Life, Physical, and Social Science Technicians | 0.98 |
| | | 19-4041 | Geological and Petroleum Technicians | 0.02 |
| 2435 | Librarians and Media Collections Specialists | 25-90XX | Other Education, Training, and Library Workers | 0.52 |
| | | 25-4021 | Librarians | 0.48 |
| 2545 | Teaching Assistants | 25-1000 | Postsecondary Teachers | 0.63 |
| | | 25-9041 | Teacher Assistants | 0.37 |
| 2865 | Media and Communication Workers, All Other | 27-3090 | Miscellaneous Media and Communication Workers | 0.7 |
| | | 27-3010 | Announcers | 0.3 |
| 2905 | Broadcast, Sound, and Lighting Technicians | 27-4010 | Broadcast and Sound Engineering Technicians and Radio Operators | 1 |
| | | 27-4099 | Media and Communication Equipment Workers, All Other | 0 |

**Table A.1:** 2018 Census codes with a one-to-many mapping to SOC (continued)

| Census code | Census title | SOC code | SOC title | SOC share in SIPP |
|---|---|---|---|---|
| 3545 | Miscellaneous Health Technologists and Technicians | 29-2050 | Health Practitioner Support Technologists and Technicians | 0.86 |
|  |  | 29-2090 | Miscellaneous Health Technologists and Technicians | 0.14 |
| 3550 | Other Healthcare Practitioners and Technical Occupations | 29-2071 | Medical Records and Health Information Technicians | 0.69 |
|  |  | 29-9000 | Other Healthcare Practitioners and Technical Occupations | 0.31 |
| 3870 | Police Officers | 33-3051 | Police and Sheriff's Patrol Officers | 1 |
|  |  | 33-3052 | Transit and Railroad Police | 0 |
| 4055 | Fast Food and Counter Workers | 35-3021 | Combined Food Preparation and Serving Workers, Including Fast Food | 0.67 |
|  |  | 35-3022 | Counter Attendants, Cafeteria, Food Concession, and Coffee Shop | 0.33 |
| 4330 | Supervisors of Personal Care and Service Workers | 39-1021 | First-Line Supervisors of Personal Service Workers | 0.86 |
|  |  | 39-1010 | First-Line Supervisors of Gaming Workers | 0.14 |
| 4435 | Other Entertainment Attendants and Related Workers | 39-3090 | Miscellaneous Entertainment Attendants and Related Workers | 1 |
|  |  | 39-3021 | Motion Picture Projectionists | 0 |
| 4461 | Embalmers, Crematory Operators and Funeral Attendants | 39-9099 | Personal Care and Service Workers, All Other | 0.86 |
|  |  | 39-40XX | Embalmers and Funeral Attendants | 0.14 |
| 5040 | Communications Equipment Operators, All Other | 27-4010 | Broadcast and Sound Engineering Technicians and Radio Operators | 1 |
|  |  | 43-2099 | Communications Equipment Operators, All Other | 0 |
| 6115 | Fishing and Hunting Workers | 45-3011 | Fishers and Related Fishing Workers | 1 |
|  |  | 45-3021 | Hunters and Trappers | 0 |
| 6305 | Construction Equipment Operators | 47-2073 | Operating Engineers and Other Construction Equipment Operators | 0.98 |
|  |  | 47-2071 | Paving, Surfacing, and Tamping Equipment Operators | 0.02 |
|  |  | 47-2072 | Pile-Driver Operators | 0 |
| 6410 | Painters and Paperhangers | 47-2141 | Painters, Construction and Maintenance | 1 |
|  |  | 47-2142 | Paperhangers | 0 |
| 6850 | Underground Mining Machine Operators | 47-5040 | Mining Machine Operators | 0.54 |
|  |  | 53-7030 | Dredge, Excavating, and Loading Machine Operators | 0.46 |
|  |  | 47-5061 | Roof Bolters, Mining | 0 |
|  |  | 53-7111 | Mine Shuttle Car Operators | 0 |

**Table A.1:** 2018 Census codes with a one-to-many mapping to SOC (continued)

| Census code | Census title | SOC code | SOC title | SOC share in SIPP |
|---|---|---|---|---|
| 6950 | Other Extraction Workers | 47-50XX | Other Extraction Workers | 0.53 |
| | | 47-5040 | Mining Machine Operators | 0.47 |
| | | 47-5081 | Helpers–Extraction Workers | 0 |
| 7640 | Other Installation, Maintenance, and Repair Workers | 49-909X | Other Installation, Maintenance, and Repair Workers | 1 |
| | | 49-9097 | Signal and Track Switch Repairers | 0 |
| 7905 | Computer Numerically Controlled Tool Operators and Programmers | 51-9199 | Production Workers, All Other | 0.89 |
| | | 51-4010 | Computer Control Programmers and Operators | 0.11 |
| 7925 | Forming Machine Setters, Operators, and Tenders, Metal and Plastic | 51-4021 | Extruding and Drawing Machine Setters, Operators, and Tenders, Metal and Plastic | 0.81 |
| | | 51-4022 | Forging Machine Setters, Operators, and Tenders, Metal and Plastic | 0.12 |
| | | 51-4023 | Rolling Machine Setters, Operators, and Tenders, Metal and Plastic | 0.07 |
| 8025 | Other Machine Tool Setters, Operators, and Tenders, Metal and Plastic | 51-4032 | Drilling and Boring Machine Tool Setters, Operators, and Tenders, Metal and Plastic | NA[†] |
| | | 51-4034 | Lathe and Turning Machine Tool Setters, Operators, and Tenders, Metal and Plastic | NA[†] |
| | | 51-4035 | Milling and Planing Machine Setters, Operators, and Tenders, Metal and Plastic | NA[†] |
| 8225 | Other Metal Workers and Plastic Workers | 51-4199 | Metal Workers and Plastic Workers, All Other | 1 |
| | | 51-4081 | Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic | 0 |
| | | 51-4191 | Heat Treating Equipment Setters, Operators, and Tenders, Metal and Plastic | 0 |
| | | 51-4192 | Layout Workers, Metal and Plastic | 0 |
| | | 51-4193 | Plating and Coating Machine Setters, Operators, and Tenders, Metal and Plastic | 0 |
| | | 51-4194 | Tool Grinders, Filers, and Sharpeners | 0 |

**Table A.1:** 2018 Census codes with a one-to-many mapping to SOC (continued)

| Census code | Census title | SOC code | SOC title | SOC share in SIPP |
|---|---|---|---|---|
| 8365 | Textile Machine Setters, Operators, and Tenders | 51-6064 | Textile Winding, Twisting, and Drawing Out Machine Setters, Operators, and Tenders | 0.74 |
| | | 51-6063 | Textile Knitting and Weaving Machine Setters, Operators, and Tenders | 0.21 |
| | | 51-6062 | Textile Cutting Machine Setters, Operators, and Tenders | 0.05 |
| | | 51-6061 | Textile Bleaching and Dyeing Machine Operators and Tenders | 0 |
| 8465 | Other Textile, Apparel, and Furnishings Workers | 51-6099 | Textile, Apparel, and Furnishings Workers, All Other | 1 |
| | | 51-6091 | Extruding and Forming Machine Setters, Operators, and Tenders, Synthetic and Glass Fibers | 0 |
| | | 51-6092 | Fabric and Apparel Patternmakers | 0 |
| 8555 | Other Woodworkers | 51-7099 | Woodworkers, All Other | 1 |
| | | 51-7030 | Model Makers and Patternmakers, Wood | 0 |
| 8990 | Other Production Workers | 51-9199 | Production Workers, All Other | 1 |
| | | 51-9141 | Semiconductor Processors | 0 |
| 9005 | Supervisors of Transportation and Material Moving Workers | 53-1000 | Supervisors of Transportation and Material Moving Workers | 0.56 |
| | | 39-1021 | First-Line Supervisors of Personal Service Workers | 0.44 |
| 9141 | Shuttle Drivers and Chauffeurs | 53-3020 | Bus Drivers | 0.62 |
| | | 53-3041 | Taxi Drivers and Chauffeurs | 0.38 |
| 9265 | Other Rail Transportation Workers | 53-4010 | Locomotive Engineers and Operators | 0.64 |
| | | 53-40XX | Subway, Streetcar, and Other Rail Transportation Workers | 0.36 |
| | | 53-4021 | Railroad Brake, Signal, and Switch Operators | 0 |
| 9365 | Transportation Service Attendants | 53-6031 | Automotive and Watercraft Service Attendants | 0.84 |
| | | 53-60XX | Other Transportation Workers | 0.16 |
| 9430 | Other Transportation Workers | 53-60XX | Other Transportation Workers | 1 |
| | | 53-6011 | Bridge and Lock Tenders | 0 |
| 9570 | Conveyor, Dredge, and Hoist and Winch Operators | 53-7030 | Dredge, Excavating, and Loading Machine Operators | 0.85 |
| | | 53-7041 | Hoist and Winch Operators | 0.15 |
| | | 53-7011 | Conveyor Operators and Tenders | 0 |
| 9760 | Other Material Moving Workers | 53-7199 | Material Moving Workers, All Other | 0.53 |
| | | 53-7030 | Dredge, Excavating, and Loading Machine Operators | 0.47 |
| | | 53-7121 | Tank Car, Truck, and Ship Loaders | 0 |

*Note:* The last column shows the distribution of SOC codes in the 2013-2016 SIPP panel. To acheive a one-to-one mapping, I choose the most frequent SOC code (i.e., the SOC code with the highest share in the last column).

[†]The SOC codes mapping to Census code "8025" are not present in the 2013-2016 SIPP panel. I therefore map this Census code to the first SOC category "51-4032 - Drilling and Boring Machine Tool Setters, Operators, and Tenders, Metal and Plastic".

**Table A.2:** O*NET occupations with *GreenShare* $\geq 0.5$

| O*NET-SOC code | O*NET-SOC title | Total tasks | Green tasks | *GreenShare* |
|---|---|---|---|---|
| 11-1011.03 | Chief Sustainability Officers | 18 | 18 | 1 |
| 11-3051.02 | Geothermal Production Managers | 17 | 17 | 1 |
| 11-3051.03 | Biofuels Production Managers | 14 | 14 | 1 |
| 11-3051.04 | Biomass Power Plant Managers | 18 | 18 | 1 |
| 11-3051.06 | Hydroelectric Production Managers | 19 | 19 | 1 |
| 11-9041.01 | Biofuels/Biodiesel Technology and Product Development Managers | 19 | 19 | 1 |
| 11-9121.02 | Water Resource Specialists | 21 | 21 | 1 |
| 11-9199.09 | Wind Energy Operations Managers | 16 | 16 | 1 |
| 11-9199.10 | Wind Energy Project Managers | 15 | 15 | 1 |
| 11-9199.11 | Brownfield Redevelopment Specialists and Site Managers | 22 | 22 | 1 |
| 13-1199.01 | Energy Auditors | 21 | 21 | 1 |
| 13-1199.05 | Sustainability Specialists | 14 | 14 | 1 |
| 17-2081.00 | Environmental Engineers | 28 | 28 | 1 |
| 17-2081.01 | Water/Wastewater Engineers | 27 | 27 | 1 |
| 17-2141.01 | Fuel Cell Engineers | 26 | 26 | 1 |
| 17-2199.03 | Energy Engineers | 21 | 21 | 1 |
| 17-2199.10 | Wind Energy Engineers | 16 | 16 | 1 |
| 17-2199.11 | Solar Energy Systems Engineers | 13 | 13 | 1 |
| 17-3025.00 | Environmental Engineering Technicians | 26 | 26 | 1 |
| 19-1013.00 | Soil and Plant Scientists | 27 | 17 | 0.62 |
| 19-1031.01 | Soil and Water Conservationists | 33 | 33 | 1 |
| 19-2041.01 | Climate Change Analysts | 14 | 14 | 1 |
| 19-2041.02 | Environmental Restoration Planners | 22 | 22 | 1 |
| 19-2041.03 | Industrial Ecologists | 38 | 38 | 1 |
| 19-3011.01 | Environmental Economists | 19 | 19 | 1 |
| 19-4091.00 | Environmental Science and Protection Technicians, Including Health | 26 | 26 | 1 |
| 41-3099.01 | Energy Brokers | 16 | 16 | 1 |
| 41-4011.07 | Solar Sales Representatives and Assessors | 13 | 13 | 1 |
| 47-1011.03 | Solar Energy Installation Managers | 15 | 15 | 1 |
| 47-2231.00 | Solar Photovoltaic Installers | 26 | 26 | 1 |
| 47-4041.00 | Hazardous Materials Removal Workers | 21 | 21 | 1 |
| 47-4099.02 | Solar Thermal Installers and Technicians | 21 | 21 | 1 |
| 47-4099.03 | Weatherization Installers and Technicians | 18 | 18 | 1 |
| 49-9081.00 | Wind Turbine Service Technicians | 13 | 13 | 1 |
| 49-9099.01 | Geothermal Technicians | 24 | 24 | 1 |
| 51-8099.01 | Biofuels Processing Technicians | 19 | 19 | 1 |
| 51-8099.03 | Biomass Plant Technicians | 16 | 16 | 1 |
| 51-8099.04 | Hydroelectric Plant Technicians | 21 | 21 | 1 |
| 51-9199.01 | Recycling and Reclamation Workers | 18 | 18 | 1 |
| 53-1021.01 | Recycling Coordinators | 23 | 23 | 1 |
| 53-7081.00 | Refuse and Recyclable Material Collectors | 16 | 16 | 1 |

**Table A.3:** Fossil occupations

| SOC code | SOC title |
|---|---|
| 11-3051 | Industrial Production Managers |
| 11-9041 | Architectural and Engineering Managers |
| 17-2041 | Chemical Engineers |
| 17-2110 | Industrial Engineers, Including Health and Safety |
| 17-2121 | Marine Engineers and Naval Architects |
| 17-2131 | Materials Engineers |
| 17-2171 | Petroleum Engineers |
| 17-3020 | Engineering Technicians, Except Drafters |
| 19-2030 | Chemists and Materials Scientists |
| 19-4011 | Agricultural and Food Science Technicians |
| 19-4031 | Chemical Technicians |
| 43-5061 | Production, Planning, and Expediting Clerks |
| 47-5010 | Derrick, Rotary Drill, and Service Unit Operators, Oil, Gas, and Mining |
| 47-5021 | Earth Drillers, Except Oil and Gas |
| 47-5040 | Mining Machine Operators |
| 47-50XX | Other extraction workers |
| 49-2091 | Avionics Technicians |
| 49-9010 | Control and Valve Installers and Repairers |
| 49-9043 | Maintenance Workers, Machinery |
| 49-9044 | Millwrights |
| 49-904X | Industrial and refractory machinery mechanics |
| 49-9096 | Riggers |
| 49-9098 | Helpers–Installation, Maintenance, and Repair Workers |
| 51-1011 | First-Line Supervisors of Production and Operating Workers |
| 51-2011 | Aircraft Structure, Surfaces, Rigging, and Systems Assemblers |
| 51-2031 | Engine and Other Machine Assemblers |
| 51-2041 | Structural Metal Fabricators and Fitters |
| 51-2090 | Miscellaneous Assemblers and Fabricators |
| 51-3020 | Butchers and Other Meat, Poultry, and Fish Processing Workers |
| 51-3091 | Food and Tobacco Roasting, Baking, and Drying Machine Operators and Tenders |
| 51-3093 | Food Cooking Machine Operators and Tenders |
| 51-3099 | Food Processing Workers, All Other |
| 51-4021 | Extruding and Drawing Machine Setters, Operators, and Tenders, Metal and Plastic |
| 51-4022 | Forging Machine Setters, Operators, and Tenders, Metal and Plastic |
| 51-4031 | Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic |
| 51-4033 | Grinding, Lapping, Polishing, and Buffing Machine Tool Setters, Operators, and Tenders, Metal and Plastic |
| 51-4050 | Metal Furnace Operators, Tenders, Pourers, and Casters |
| 51-4070 | Molders and Molding Machine Setters, Operators, and Tenders, Metal and Plastic |
| 51-4111 | Tool and Die Makers |
| 51-4199 | Metal Workers and Plastic Workers, All Other |
| 51-6063 | Textile Knitting and Weaving Machine Setters, Operators, and Tenders |

**Table A.3:** Fossil occupations (continued)

| SOC code | SOC title |
|---|---|
| 51-6064 | Textile Winding, Twisting, and Drawing Out Machine Setters, Operators, and Tenders |
| 51-7041 | Sawing Machine Setters, Operators, and Tenders, Wood |
| 51-7042 | Woodworking Machine Setters, Operators, and Tenders, Except Sawing |
| 51-8031 | Water and Wastewater Treatment Plant and System Operators |
| 51-8090 | Miscellaneous Plant and System Operators |
| 51-9010 | Chemical Processing Machine Setters, Operators, and Tenders |
| 51-9020 | Crushing, Grinding, Polishing, Mixing, and Blending Workers |
| 51-9041 | Extruding, Forming, Pressing, and Compacting Machine Setters, Operators, and Tenders |
| 51-9051 | Furnace, Kiln, Oven, Drier, and Kettle Operators and Tenders |
| 51-9061 | Inspectors, Testers, Sorters, Samplers, and Weighers |
| 51-9111 | Packaging and Filling Machine Operators and Tenders |
| 51-9191 | Adhesive Bonding Machine Operators and Tenders |
| 51-9195 | Molders, Shapers, and Casters, Except Metal and Plastic |
| 51-9196 | Paper Goods Machine Setters, Operators, and Tenders |
| 51-9197 | Tire Builders |
| 51-9198 | Helpers–Production Workers |
| 53-5011 | Sailors and Marine Oilers |
| 53-6031 | Automotive and Watercraft Service Attendants |
| 53-7021 | Crane and Tower Operators |
| 53-7051 | Industrial Truck and Tractor Operators |
| 53-7070 | Pumping Station Operators |
| 53-7199 | Material Moving Workers, All Other |

# Appendix B: Aggregating the O*NET task data

O*NET provides task data on an 8-digit occupational level. I aggregate the data to a 6-digit level to align them with SIPP. The task data in O*NET are given for 974 occupations that map to 774 6-digit parent groups. 677 occupations map to a unique parent group. The aggregation is straightforward in these cases. It is more difficult for occupations sharing a parent group. Simply averaging the green task shares of these occupations is inappropriate when they have different weights in the parent group. This is the case when the parent group includes an occupation ending in ".00" (i.e., an occupation corresponding to a 6-digit parent group) as this occupation should get more weight. For instance, the occupation "19-3011.00 - Economists" is much broader than "19-3011.01 - Environmental Economists" and should get more weight in the parent group "19-3011 - Economists".

I use a procedure based on Vona, Marin and Consoli (2019) to account for weight differences across occupations. The procedure is as follows. If an occupation corresponding to the parent group (i.e., ending in ".00") has zero or relatively few green tasks, I assign a green task share of zero to the parent group. In all other cases, I average the green task shares across the occupations in the parent group.[55]

Table B.1 shows how this procedure is implemented. The number of total and green tasks are listed by occupation in the third and fourth columns, where the occupations are sorted by 6-digit parent group. The last column indicates whether the parent group is assigned a green task share of zero ("Zero") or an average of the occupations' green task shares ("Mean").

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[55]Four 6-digit groups are special cases and exempted from the aggregation procedure (see the note at the bottom of Table B.1 for more details). Vona, Marin and Consoli (2019) make similar adjustments for these groups.

**Table B.1:** Task aggregation procedure for O*NET occupations with a many-to-one mapping to a 6-digit level

| O*NET-SOC code | O*NET-SOC title | Total tasks | Green tasks | Method |
|---|---|---|---|---|
| 11-1011.00 | Chief Executives | 31 | 0 | Zero |
| 11-1011.03 | Chief Sustainability Officers | 18 | 18 | |
| 11-2011.00 | Advertising and Promotions Managers | 26 | 0 | Zero |
| 11-2011.01 | Green Marketers | 16 | 16 | |
| 11-3051.00 | Industrial Production Managers | 14 | 0 | Zero |
| 11-3051.01 | Quality Control Systems Managers | 27 | 0 | |
| 11-3051.02 | Geothermal Production Managers | 17 | 17 | |
| 11-3051.03 | Biofuels Production Managers | 14 | 14 | |
| 11-3051.04 | Biomass Power Plant Managers | 18 | 18 | |
| 11-3051.05 | Methane/Landfill Gas Collection System Operators | 21 | 21 | |
| 11-3051.06 | Hydroelectric Production Managers | 19 | 19 | |
| 11-3071.01 | Transportation Managers | 28 | 6 | Mean |
| 11-3071.02 | Storage and Distribution Managers | 31 | 7 | |
| 11-3071.03 | Logistics Managers | 30 | 9 | |
| 11-9013.01 | Nursery and Greenhouse Managers | 20 | 0 | Mean$^\dagger$ |
| 11-9013.02 | Farm and Ranch Managers | 27 | 4 | |
| 11-9013.03 | Aquacultural Managers | 19 | 0 | |
| 11-9041.01 | Biofuels/Biodiesel Technology and Product Development Managers | 19 | 19 | |
| 11-9121.00 | Natural Sciences Managers | 16 | 0 | Zero |
| 11-9121.01 | Clinical Research Coordinators | 33 | 0 | |
| 11-9121.02 | Water Resource Specialists | 21 | 21 | |
| 11-9199.01 | Regulatory Affairs Managers | 27 | 4 | Mean |
| 11-9199.02 | Compliance Managers | 30 | 6 | |
| 11-9199.03 | Investment Fund Managers | 20 | 0 | |
| 11-9199.04 | Supply Chain Managers | 30 | 9 | |
| 11-9199.07 | Security Managers | 30 | 0 | |
| 11-9199.08 | Loss Prevention Managers | 27 | 0 | |
| 11-9199.09 | Wind Energy Operations Managers | 16 | 16 | |
| 11-9199.10 | Wind Energy Project Managers | 15 | 15 | |
| 11-9199.11 | Brownfield Redevelopment Specialists and Site Managers | 22 | 22 | |
| 13-1041.01 | Environmental Compliance Inspectors | 26 | 0 | Mean |
| 13-1041.02 | Licensing Examiners and Inspectors | 12 | 0 | |
| 13-1041.03 | Equal Opportunity Representatives and Officers | 19 | 0 | |
| 13-1041.04 | Government Property Inspectors and Investigators | 14 | 0 | |
| 13-1041.06 | Coroners | 20 | 0 | |
| 13-1041.07 | Regulatory Affairs Specialists | 32 | 6 | |

**Table B.1:** Task aggregation procedure for O*NET occupations with a many-to-one mapping to a 6-digit level (continued)

| O*NET-SOC code | O*NET-SOC title | Total tasks | Green tasks | Method |
|---|---|---|---|---|
| 13-1081.00 | Logisticians | 22 | 0 | Zero |
| 13-1081.01 | Logistics Engineers | 30 | 11 | |
| 13-1081.02 | Logistics Analysts | 31 | 6 | |
| 13-1199.01 | Energy Auditors | 21 | 21 | Mean |
| 13-1199.02 | Security Management Specialists | 24 | 0 | |
| 13-1199.03 | Customs Brokers | 23 | 0 | |
| 13-1199.04 | Business Continuity Planners | 21 | 0 | |
| 13-1199.05 | Sustainability Specialists | 14 | 14 | |
| 13-1199.06 | Online Merchants | 34 | 0 | |
| 13-2099.01 | Financial Quantitative Analysts | 21 | 5 | Mean |
| 13-2099.02 | Risk Management Specialists | 24 | 4 | |
| 13-2099.03 | Investment Underwriters | 19 | 2 | |
| 13-2099.04 | Fraud Examiners, Investigators and Analysts | 23 | 0 | |
| 15-1199.01 | Software Quality Assurance Engineers and Testers | 28 | 0 | Mean |
| 15-1199.02 | Computer Systems Engineers/Architects | 28 | 0 | |
| 15-1199.03 | Web Administrators | 35 | 0 | |
| 15-1199.04 | Geospatial Information Scientists and Technologists | 24 | 2 | |
| 15-1199.05 | Geographic Information Systems Technicians | 19 | 5 | |
| 15-1199.06 | Database Architects | 18 | 0 | |
| 15-1199.07 | Data Warehousing Specialists | 18 | 0 | |
| 15-1199.08 | Business Intelligence Analysts | 17 | 0 | |
| 15-1199.09 | Information Technology Project Managers | 21 | 0 | |
| 15-1199.10 | Search Marketing Strategists | 36 | 0 | |
| 15-1199.11 | Video Game Designers | 24 | 0 | |
| 15-1199.12 | Document Management Specialists | 23 | 0 | |
| 17-2051.00 | Civil Engineers | 17 | 8 | Mean |
| 17-2051.01 | Transportation Engineers | 26 | 6 | |
| 17-2072.00 | Electronics Engineers, Except Computer | 22 | 5 | Value of |
| 17-2072.01 | Radio Frequency Identification Device Specialists | 21 | 0 | 17-2072.00[‡] |
| 17-2081.00 | Environmental Engineers | 28 | 28 | Mean |
| 17-2081.01 | Water/Wastewater Engineers | 27 | 27 | |
| 17-2141.00 | Mechanical Engineers | 28 | 8 | Mean |
| 17-2141.01 | Fuel Cell Engineers | 26 | 26 | |
| 17-2141.02 | Automotive Engineers | 25 | 8 | |

**Table B.1:** Task aggregation procedure for O*NET occupations with a many-to-one mapping to a 6-digit level (continued)

| O*NET-SOC code | O*NET-SOC title | Total tasks | Green tasks | Method |
|---|---|---|---|---|
| 17-2199.01 | Biochemical Engineers | 35 | 12 | Mean |
| 17-2199.02 | Validation Engineers | 22 | 2 | |
| 17-2199.03 | Energy Engineers | 21 | 21 | |
| 17-2199.04 | Manufacturing Engineers | 24 | 4 | |
| 17-2199.05 | Mechatronics Engineers | 23 | 3 | |
| 17-2199.06 | Microsystems Engineers | 31 | 6 | |
| 17-2199.07 | Photonics Engineers | 26 | 5 | |
| 17-2199.08 | Robotics Engineers | 24 | 2 | |
| 17-2199.09 | Nanosystems Engineers | 25 | 9 | |
| 17-2199.10 | Wind Energy Engineers | 16 | 16 | |
| 17-2199.11 | Solar Energy Systems Engineers | 13 | 13 | |
| 17-3023.01 | Electronics Engineering Technicians | 19 | 0 | Mean |
| 17-3023.03 | Electrical Engineering Technicians | 24 | 5 | |
| 17-3024.00 | Electro-Mechanical Technicians | 12 | 1 | Mean |
| 17-3024.01 | Robotics Technicians | 23 | 2 | |
| 17-3027.00 | Mechanical Engineering Technicians | 18 | 0 | Zero |
| 17-3027.01 | Automotive Engineering Technicians | 18 | 5 | |
| 17-3029.01 | Non-Destructive Testing Specialists | 16 | 0 | Mean |
| 17-3029.02 | Electrical Engineering Technologists | 20 | 8 | |
| 17-3029.03 | Electromechanical Engineering Technologists | 17 | 5 | |
| 17-3029.04 | Electronics Engineering Technologists | 23 | 4 | |
| 17-3029.05 | Industrial Engineering Technologists | 23 | 4 | |
| 17-3029.06 | Manufacturing Engineering Technologists | 29 | 8 | |
| 17-3029.07 | Mechanical Engineering Technologists | 21 | 3 | |
| 17-3029.08 | Photonics Technicians | 30 | 6 | |
| 17-3029.09 | Manufacturing Production Technicians | 30 | 6 | |
| 17-3029.10 | Fuel Cell Technicians | 16 | 16 | |
| 17-3029.11 | Nanotechnology Engineering Technologists | 17 | 6 | |
| 17-3029.12 | Nanotechnology Engineering Technicians | 19 | 3 | |
| 19-1031.01 | Soil and Water Conservationists | 33 | 33 | Mean |
| 19-1031.02 | Range Managers | 16 | 0 | |
| 19-1031.03 | Park Naturalists | 18 | 0 | |
| 19-2041.00 | Environmental Scientists and Specialists, Including Health | 22 | 0 | Mean* |
| 19-2041.01 | Climate Change Analysts | 14 | 14 | |
| 19-2041.02 | Environmental Restoration Planners | 22 | 22 | |
| 19-2041.03 | Industrial Ecologists | 38 | 38 | |
| 19-3011.00 | Economists | 13 | 0 | Zero |
| 19-3011.01 | Environmental Economists | 19 | 19 | |

**Table B.1:** Task aggregation procedure for O*NET occupations with a many-to-one mapping to a 6-digit level (continued)

| O*NET-SOC code | O*NET-SOC title | Total tasks | Green tasks | Method |
|---|---|---|---|---|
| 19-4011.01 | Agricultural Technicians | 26 | 3 | Mean |
| 19-4011.02 | Food Science Technicians | 15 | 0 | |
| 19-4041.01 | Geophysical Data Technicians | 21 | 5 | Mean |
| 19-4041.02 | Geological Sample Test Technicians | 17 | 3 | |
| 19-4051.01 | Nuclear Equipment Operation Technicians | 20 | 7 | Zero** |
| 19-4051.02 | Nuclear Monitoring Technicians | 19 | 0 | |
| 19-4099.01 | Quality Control Analysts | 26 | 0 | Mean |
| 19-4099.02 | Precision Agriculture Technicians | 22 | 7 | |
| 19-4099.03 | Remote Sensing Technicians | 22 | 3 | |
| 41-3031.01 | Sales Agents, Securities and Commodities | 19 | 0 | Mean |
| 41-3031.02 | Sales Agents, Financial Services | 8 | 0 | |
| 41-3031.03 | Securities and Commodities Traders | 22 | 2 | |
| 41-4011.00 | Sales Representatives, Wholesale and Manufacturing, Technical and Scientific Products | 36 | 5 | Value of 41-4011.00$^{\ddagger}$ |
| 41-4011.07 | Solar Sales Representatives and Assessors | 13 | 13 | |
| 43-5011.00 | Cargo and Freight Agents | 24 | 0 | Zero |
| 43-5011.01 | Freight Forwarders | 31 | 6 | |
| 47-1011.00 | First-Line Supervisors of Construction Trades and Extraction Workers | 15 | 0 | Zero |
| 47-1011.03 | Solar Energy Installation Managers | 15 | 15 | |
| 47-2152.01 | Pipe Fitters and Steamfitters | 20 | 3 | Mean |
| 47-2152.02 | Plumbers | 23 | 9 | |
| 47-4099.02 | Solar Thermal Installers and Technicians | 21 | 21 | Mean |
| 47-4099.03 | Weatherization Installers and Technicians | 18 | 18 | |
| 49-3023.01 | Automotive Master Mechanics | 24 | 0 | Mean |
| 49-3023.02 | Automotive Specialty Technicians | 26 | 12 | |
| 49-9021.01 | Heating and Air Conditioning Mechanics and Installers | 26 | 7 | Mean |
| 49-9021.02 | Refrigeration Mechanics and Installers | 21 | 0 | |
| 51-8099.01 | Biofuels Processing Technicians | 19 | 19 | Mean |
| 51-8099.02 | Methane/Landfill Gas Generation System Technicians | 17 | 17 | |
| 51-8099.03 | Biomass Plant Technicians | 16 | 16 | |
| 51-8099.04 | Hydroelectric Plant Technicians | 21 | 21 | |

**Table B.1:** Task aggregation procedure for O*NET occupations with a many-to-one mapping to a 6-digit level (continued)

| O*NET-SOC code | O*NET-SOC title | Total tasks | Green tasks | Method |
|---|---|---|---|---|
| 53-1021.00 | First-Line Supervisors of Helpers, Laborers, and Material Movers, Hand | 24 | 0 | Zero |
| 53-1021.01 | Recycling Coordinators | 23 | 23 | |
| 53-6051.01 | Aviation Inspectors | 15 | 0 | Mean |
| 53-6051.07 | Transportation Vehicle, Equipment and Systems Inspectors, Except Aviation | 21 | 9 | |
| 53-6051.08 | Freight and Cargo Inspectors | 20 | 0 | |

*Note:* †Occupation "11-9041.01 - Biofuels/Biodiesel Technology and Product Development Managers" was originally in parent group "11-9041 - Architectural and Engineering Managers". The green task share of this parent group ("11-9041.00") is 19% and therefore much lower than the 100% of "11-9041.01". The occupation "11-9041.01" was moved to parent group "11-9013" that contains similar occupations, while parent group "11-9041" was removed.

‡The values of the ".00" parent group were chosen because this occupation is more important.

*The parent group was not assigned zero green tasks because occupations "19-2041.01" - "19-2041.03" have 100% green tasks and can jointly be considered of similar importance to the parent group.

**The parent group was assigned zero green tasks since occupations in the nuclear power sector are typically not considered green (Bowen and Kuralbayeva, 2015).

# Appendix C: Crosswalking from NAICS to the Census Industry system

I harmonize the dirty sector classification with SIPP by crosswalking the codes in the classification from a 4-digit NAICS level to the Census Industry system. The crosswalking is straightforward for sectors with a unique Census mapping. It is more complicated in two other instances.

First, multiple sectors sometimes map to the same Census code. This is problematic when only some of the sectors are dirty, since it implies that the Census code is only partly dirty. Table C.1 lists these Census codes.

Second, some dirty sectors lack a mapping to a Census code. They are instead indirectly mapped through parent groups (on a 2-digit or 3-digit level) or subcategories (on a 5-digit or 6-digit level).

Table C.2 lists the parent groups in the crosswalk containing both dirty and non-dirty sectors. An example is Census code "3895". It maps to the 3-digit NAICS code "377" that has three 4-digit codes, of which only one is dirty. The Census code is therefore only partly dirty.

Table C.3 lists the dirty sectors that are indirectly mapped through subcategories. Sector "2213 - Water, Sewage and Other Systems", for instance, has two subcategories "22131" and "22133" that map to Census code "0670" - Water, Steam, Airconditioning, and Irrigation systems". It is not clear which subcategory accounts for the dirty part of "2213". If not all of them do, the Census code is only partly dirty.

Tables C.1-C.3 contain in total 18 Census codes that I consider partly dirty and that I add to the list of dirty sectors (see Table C.4). In addition, I include three Census codes that are typically thought of as dirty: "4490 - Petroleum and petroleum products merchant wholesalers", "5090 - Gasoline stations", and "5680 - Fuel dealers".

**Table C.1:** 4-digit NAICS sectors, of which some are dirty, with a many-to-one mapping to the Census Industry system

| NAICS code | NAICS title | Dirty NAICS? | Census code | Census title | Call Census code dirty? |
|---|---|---|---|---|---|
| 3344 | Semiconductor and Other Electronic and Component Manufacturing | Yes | 3390 | Electronic component and product manufacturing, n.e.c. | Yes |
| 3346 | Manufacturing and Reproducing Magnetic and Optical Media | No | | | |
| 3351 | Electric Lighting Equipment Manufacturing | No | 3490 | Electric lighting and electrical equipment manufacturing, and other electrical component manufacturing, n.e.c. | Yes |
| 3353 | Electrical Equipment Manufacturing | No | | | |
| 3359 | Other Electrical Equipment and Component Manufacturing | Yes | | | |
| 3361 | Motor Vehicle Manufacturing | Yes | 3570 | Motor vehicles and motor vehicle equipment manufacturing | Yes |
| 3362 | Motor Vehicle Body and Trailer Manufacturing | No | | | |
| 3363 | Motor Vehicle Parts Manufacturing | No | | | |
| 5611 | Office Administrative Services | No | 7780 | Other administrative and other support services | No[†] |
| 5612 | Facilities Support Services | Yes | | | |
| 5619 | Other Support Services | No | | | |
| 6112 | Junior Colleges | No | 7870 | Colleges, universities, and professional schools, including junior colleges | No[†] |
| 6113 | Colleges, Universities, and Professional Schools | Yes | | | |

*Note:* [†]I do not call this Census code dirty as it is typically not thought of as a sector most vulnerable to decarbonization.

**Table C.2:** 2-digit and 3-digit NAICS codes in the crosswalk with some dirty 4-digit sectors

| NAICS code in crosswalk | Share of 4-digit NAICS codes that are dirty | Census code | Census title | Call Census code dirty? |
|---|---|---|---|---|
| Part of 311 | 8/9 | 1290 | Not specified food industries | Yes |
| Part of 331 and 332 | 5/14 | 2990 | Not specified metal industries | Yes |
| Part of 31-33 | 41/86 | 3990 | Not specified manufacturing industries | Yes |
| 488 | 1/6 | 6290 | Services incidental to transportation | No[†] |
| 562 | 2/3 | 7790 | Waste management and remediation services | No[‡] |

*Note:* [†]I do not call this Census code dirty since only one out of six NAICS codes are dirty.

[‡]I do not call this Census code dirty as it is typically not thought of as a sector most vulnerable to decarbonization.

**Table C.3:** Dirty NAICS sectors with subcategories that map to a Census code

| Dirty NAICS code | Dirty NAICS title | NAICS code in crosswalk | NAICS title in crosswalk | Census code | Census title | Call Census code dirty? |
|---|---|---|---|---|---|---|
| 2213 | Water, Sewage and Other Systems | 22131 22133 | Water Supply and Irrigation Systems Steam and Air-Conditioning Supply | 0670 | Water, Steam, Air-conditioning, and Irrigation systems | Yes |
| | | 22132 | Sewage Treatment Facilities | 0680 | Sewage Treatment Facilities | Yes |
| 3132 | Fabric Mills | 31321 31322 31323 | Broadwoven Fabric Mills Narrow Fabric Mills and Schiffli Machine Embroidery Nonwoven Fabric Mills | 1480 | Fabric mills, except knitting mills | Yes[†] |
| 3132 | Fabric Mills | 31324 3151 | Knit Fabric Mills Apparel Knitting Mills | 1670 | Knitting Fabric Mills, and Apparel Knitting Mills | No[†] |
| 3141 | Textile Furnishings Mills | 31411 | Carpet and Rug Mills | 1570 | Carpet and Rug Mills | Yes[‡] |
| 3141 | Textile Furnishings Mills | 31412 3149 | Curtain and Linen Mills Other Textile Product Mills | 1590 | Textile Product Mills, Except Carpet and Rug | No[‡] |
| 3241 | Petroleum and Coal Products Manufacturing | 32411 | Petroleum Refineries | 2070 | Petroleum refining | Yes[*] |
| 3241 | Petroleum and Coal Products Manufacturing | 32412 32419 | Asphalt Paving, Roofing, and Saturated Materials Manufacturing Miscellaneous petroleum and coal products | 2090 | Miscellaneous petroleum and coal products | Yes[*] |
| 3262 | Rubber Product Manufacturing | 32621 | Tire Manufacturing | 2380 | Tire Manufacturing | Yes |
| | | 32622 32629 | Rubber and Plastics Hoses and Belting Manufacturing Other Rubber Product Manufacturing | 2390 | Rubber Products, Except Tires, Manufacturing | Yes |
| 3271 | Clay Product and Refractory Manufacturing | 32711 | Pottery, Ceramics, and Plumbing Fixture Manufacturing | 2470 | Pottery, Ceramics, and Plumbing Fixture Manufacturing | Yes |
| | | 327120 | Clay Building Material and Refractories Manufacturing | 2480 | Clay Building Material and Refractories Manufacturing | Yes |
| 3364 | Aerospace Product and Parts Manufacturing | 336411 336412 336413 | Aircraft Manufacturing Aircraft Engine and Engine Parts Manufacturing Other Aircraft Parts and Auxiliary Equipment Manufacturing | 3580 | Aircraft and parts manufacturing | Yes |
| | | 336414 336415 336419 | Guided Missile and Space Vehicle Manufacturing Guided Missile and Space Vehicle Propulsion Unit and Propulsion Unit Parts Manufacturing Other Guided Missile and Space Vehicle Parts and Auxiliary Equipment Manufacturing | 3590 | Aerospace products and parts manufacturing | Yes |

*Note:* [†]I call Census code "1480" dirty as it maps to most subcategories of dirty NAICS code "3132". I call Census code "1670" non-dirty as NAICS code "3151" is not dirty.

[‡]NAICS code "3149" is not dirty and I therefore call Census code "1590" non-dirty. NAICS code "3141" is dirty. I attribute the dirty part of this code to subcategory "31411". Thus, I call Census code "1570" dirty.

*The parent 4-digit NAICS code is "3241 - Petroleum and Coal Products Manufacturing". I consider this NAICS code as well as its subcategories dirty. I therefore call Census codes "2070" and "2090" dirty.

**Table C.4:** Dirty Census sectors

| Census code | Census title |
|---|---|
| 0370 | Oil and gas extraction |
| 0380 | Coal mining |
| 0390 | Metal ore mining |
| 0470 | Nonmetallic mineral mining and quarrying |
| 0480 | Not specified type of mining |
| 0490 | Support activities for mining |
| 0570 | Electric power generation, transmission and distribution |
| 0580 | Natural gas distribution |
| 0590 | Electric and gas, and other combinations |
| 0670 | Water, steam, air-conditioning, and irrigation systems |
| 0680 | Sewage treatment facilities |
| 0690 | Not specified utilities |
| 1070 | Animal food, grain and oilseed milling |
| 1080 | Sugar and confectionery products |
| 1090 | Fruit and vegetable preserving and specialty food manufacturing |
| 1170 | Dairy product manufacturing |
| 1180 | Animal slaughtering and processing |
| 1280 | Seafood and other miscellaneous foods, n.e.c. |
| 1290 | Not specified food industries |
| 1370 | Beverage manufacturing |
| 1390 | Tobacco manufacturing |
| 1480 | Fabric mills, except knitting mills |
| 1490 | Textile and fabric finishing and fabric coating mills |
| 1570 | Carpet and rug mills |
| 1870 | Pulp, paper, and paperboard mills |
| 2070 | Petroleum refining |
| 2090 | Miscellaneous petroleum and coal products |
| 2170 | Resin, synthetic rubber, and fibers and filaments manufacturing |
| 2180 | Agricultural chemical manufacturing |
| 2190 | Pharmaceutical and medicine manufacturing |
| 2270 | Paint, coating, and adhesive manufacturing |
| 2280 | Soap, cleaning compound, and cosmetics manufacturing |
| 2290 | Industrial and miscellaneous chemicals |
| 2380 | Tire manufacturing |
| 2390 | Rubber products, except tires, manufacturing |
| 2470 | Pottery, ceramics, and plumbing fixture manufacturing |
| 2480 | Clay building material and refractories manufacturing |
| 2490 | Glass and glass product manufacturing |
| 2570 | Cement, concrete, lime, and gypsum product manufacturing |
| 2590 | Miscellaneous nonmetallic mineral product manufacturing |
| 2670 | Iron and steel mills and steel product manufacturing |
| 2680 | Aluminum production and processing |
| 2690 | Nonferrous metal (except aluminum) production and processing |
| 2770 | Foundries |
| 2990 | Not specified metal industries |
| 3180 | Engine, turbine, and power transmission equipment manufacturing |

**Table C.4:** Dirty Census sectors (continued)

| Census code | Census title |
|---|---|
| 3390 | Electronic component and product manufacturing, n.e.c. |
| 3490 | Electric lighting and electrical equipment manufacturing, and other electrical component manufacturing, n.e.c. |
| 3570 | Motor vehicles and motor vehicle equipment manufacturing |
| 3580 | Aircraft and parts manufacturing |
| 3590 | Aerospace products and parts manufacturing |
| 3670 | Railroad rolling stock manufacturing |
| 3770 | Sawmills and wood preservation |
| 3780 | Veneer, plywood, and engineered wood products |
| 3990 | Not specified manufacturing industries |
| 4490 | Petroleum and petroleum products merchant wholesalers |
| 5090 | Gasoline stations |
| 5680 | Fuel dealers |
| 6270 | Pipeline transportation |

# Appendix D: Figures
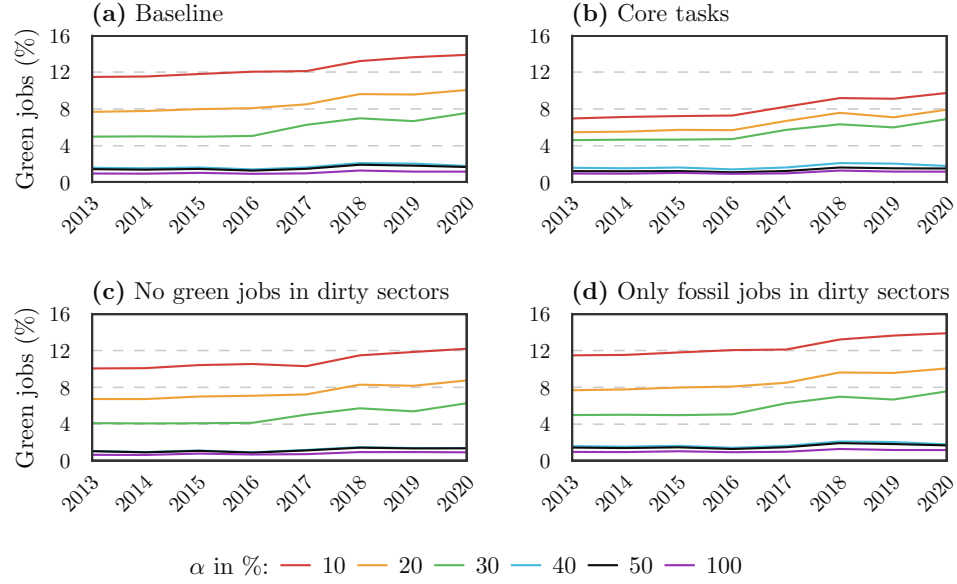


**Figure D.1:** Green job share over time by sensitivity test (panels) and $\alpha$ (lines)



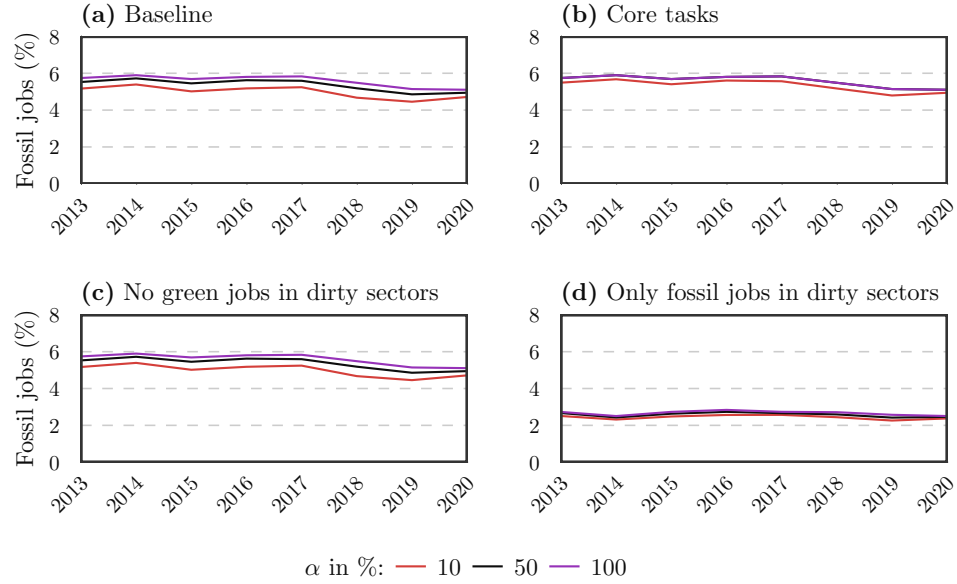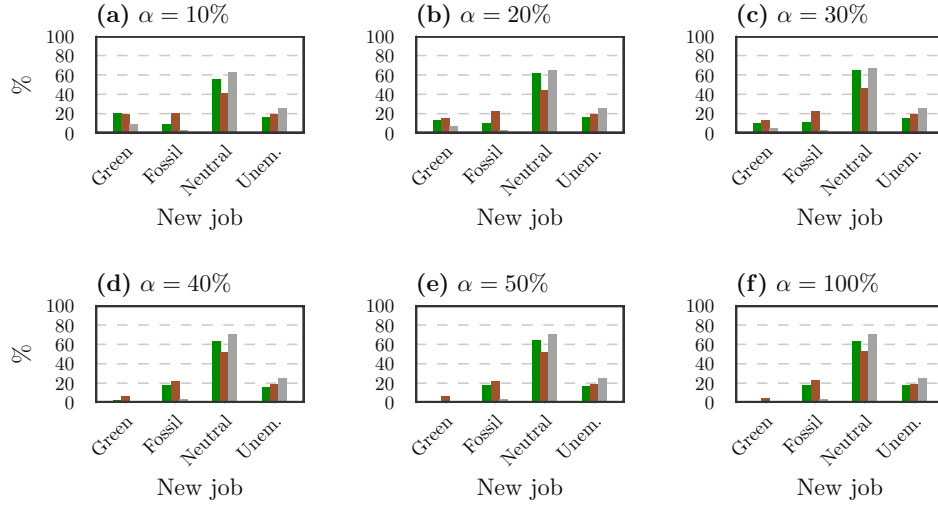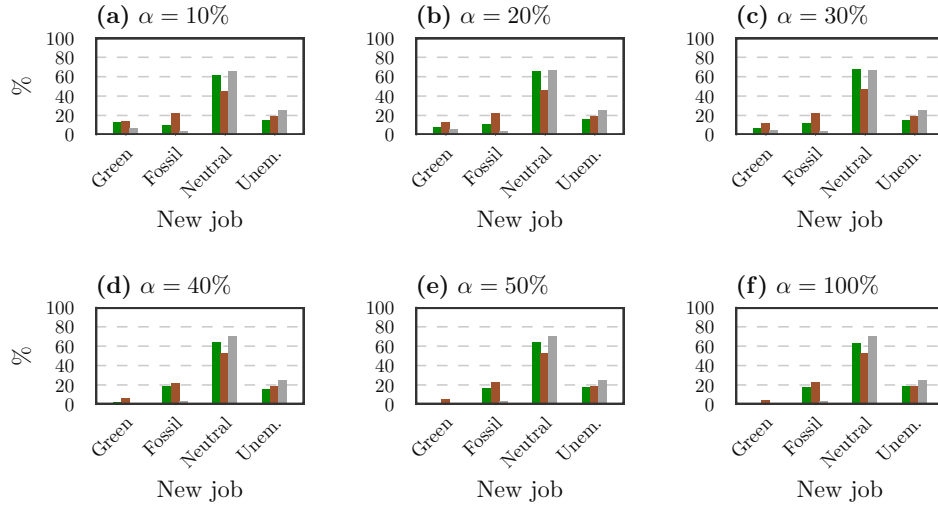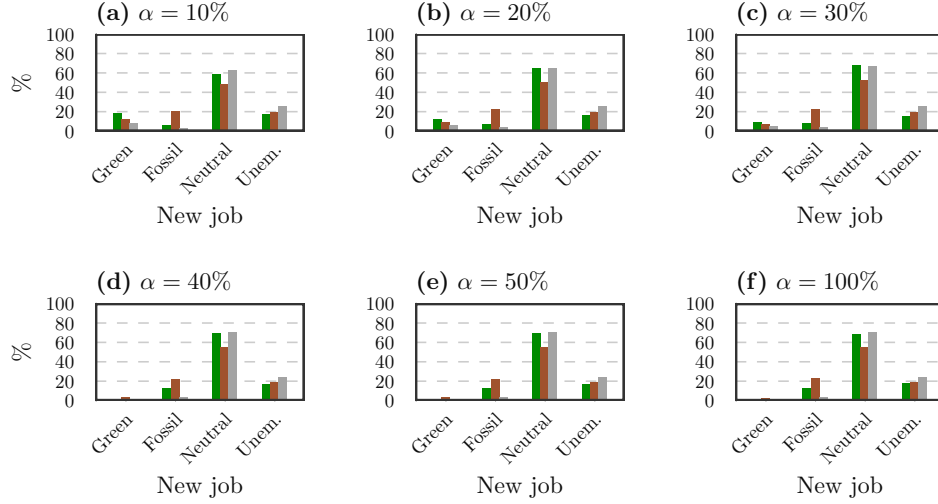**Figure D.2:** Fossil job share over time by sensitivity test (panels) and $\alpha$ (lines)

**(a)** $\alpha = 10\%$

**(b)** $\alpha = 20\%$

**(c)** $\alpha = 30\%$

**(d)** $\alpha = 40\%$

**(e)** $\alpha = 50\%$

**(f)** $\alpha = 100\%$

Worker type: ■ Green ■ Fossil ■ Neutral

**Figure D.3:** Job-finding probability by $\alpha$, type of job, and worker type



**(a)** $\alpha = 10\%$

**(b)** $\alpha = 20\%$

**(c)** $\alpha = 30\%$

**(d)** $\alpha = 40\%$

**(e)** $\alpha = 50\%$

**(f)** $\alpha = 100\%$

Worker type: ■ Green ■ Fossil ■ Neutral

**Figure D.4:** Job-finding probability by $\alpha$, type of job, and worker type (assuming only core tasks)

**Figure D.5:** Job-finding probability by $\alpha$, type of job, and worker type (assuming no green jobs in dirty sectors)
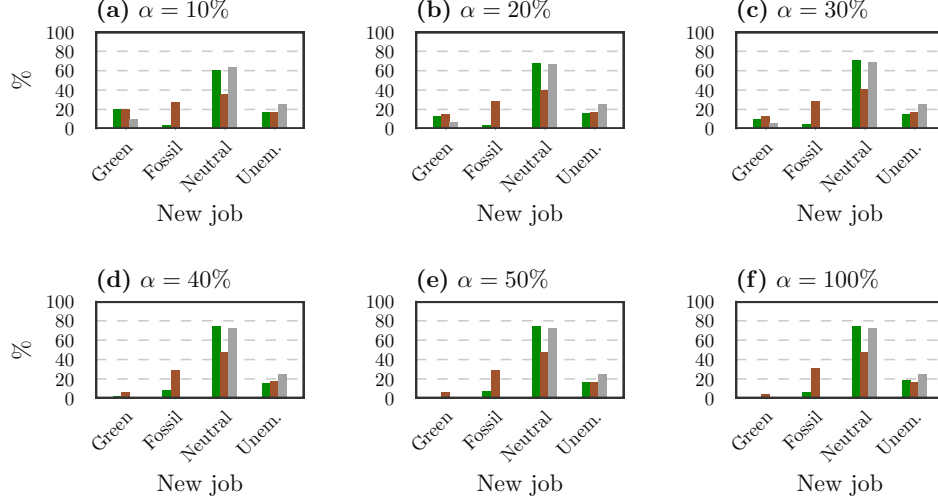


**Figure D.6:** Job-finding probability by $\alpha$, type of job, and worker type (assuming only fossil jobs in dirty sectors)