Labor Reallocation, Green Subsidies, and Unemployment *

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Abstract: This paper analyzes the impact of green subsidies on employment. I develop a general equilibrium search model to examine how the subsidies affect unemployment as well as the number of green, fossil, and remaining "neutral" jobs. The analysis is underpinned by novel empirical estimates of the distribution of jobs and job-to-job transitions in the United States. The estimates indicate that the share of green jobs grew and the share of fossil jobs declined during 2013-2020. The majority of jobs are neutral, however, and therefore neither green nor fossil. With regard to job-to-job transitions, the data shows that fossil workers rarely start green jobs and more often reallocate to neutral jobs. 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 hundreds of billions of dollars in tax credits to clean sectors and technologies.[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). While green subsidies are expected to benefit workers performing environmentally related tasks (e.g., installing solar panels), they might also shift labor demand away from emissions-intensive sectors. A risk is that displaced workers in these sectors do not find work elsewhere and become unemployed. Managing this risk requires an understanding of how green subsidies affect the reallocation of workers and unemployment. It is also important to understand the implications of choosing green subsidies over 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

[1] The total amount of IRA tax credits is uncertain because most of the tax credits are uncapped. Bistline, Mehrotra and Wolfram (2023) estimate in their main scenario that the tax credits are worth $781 billion, while Congressional Budget Office (2022) value them at $271 billion. The tax credits are intended for low-carbon electricity production and investment, 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`.

labor market implications of adopting green subsidies instead.

This paper analyzes the impact of green subsidies on employment. I develop a general equilibrium search model to examine how the subsidies affect the number of green, fossil, and remaining "neutral" jobs, as well as overall unemployment. The model is characterized by search frictions in the labor market (Pissarides, 1985; Mortensen and Pissarides, 1994) that prevent firms from matching with job searchers at zero cost. Unemployment in equilibrium is determined by the number of matches and redundancies. The green subsidies affect the recruitment effort of firms which changes the number of matches and unemployment.

The model builds on the framework in Hafstead and Williams (2018). I extend their two-sector framework in a number of ways.[4] First, I account for an empirically relevant "neutral" job type that is not directly affected by climate policy. This 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 jobs 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, the instruments' performance likely depends on how distortionary the financing mechanism (for a subsidy) and revenue recycling scheme (for a car-

[4] Hafstead and Williams (2018) model a clean and a dirty sector. Their framework is an extension of the one-sector model of Shimer (2010).

[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 fossil firms' output. Second, I use a nested consumption structure. Third, I allow for a heterogeneous degree of labor mobility in the model. In particular, I relax the assumption that all firms face the same level of friction when matching with workers of a different type.

bon 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 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 can be summarized 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 green 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 resulting 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 largely 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 the empirical analysis, I find that green and fossil jobs evolved in opposite directions in the United States during 2013-2020: green jobs became more prevalent while the number of fossil jobs declined. However, while green jobs are becoming more common, they account for a small share of all jobs. The vast majority of jobs, above 90% in the main specification, are neutral. With

[6] Moreover, Hafstead and Williams (2018) show that the employment impact of carbon taxes partly depends 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.

regard to job transitions, I find that workers are unlikely to move from fossil to green jobs. This reinforces the insight from previous studies that workers in emissions-intensive sectors can find it difficult to exploit the job opportunities created by the green transition (Walker, 2013; Saussay et al., 2022; Colmer, Lyubich and Voorheis, 2023; Curtis, O'Kane and Park, 2023; Colmer et al., 2024). However, my results also show that many fossil workers reallocate to neutral jobs. Fossil workers are in fact likelier to start a neutral job than any other kind of job. Neutral jobs should therefore not be overlooked in the context of the green transition. While the discussion on jobs and the green transition typically revolves around enabling fossil workers to reallocate to green jobs, it is important to note that many work opportunities are neutral. My results suggest that displaced workers from the transition exploit these opportunities, meaning the reallocation will not solely be from fossil to green jobs.

Fourth, by inserting the job transition estimates in the search model and solving for the steady state, I am able to calibrate the degree of friction firms face when matching with workers of a different type. I find evidence of a low degree of friction, implying that firms and workers of different types can easily match. The degree of labor mobility across job types is consequently high in the model.

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 U.S. model (FRBUS), 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 the labor market. By using a three-job framework, I can also analyze the labor movement across jobs directly affected (green and fossil jobs) and unaffected (neutral jobs) by climate policy.

The second related literature strand looks at the interaction between environmental regulation and the tax system. A large body of work has examined the impact of environmental regulation 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, 1995b,a; 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

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

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 of green workers. 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 (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. Shimer (2010) develops a one-sector matching function that depends on firms' recruitment effort and the unemployment rate. Hafstead and Williams (2018) extend this function to a multi-good framework characterized by matching within and across job types.[9] A key parameter in their matching function is the degree of

[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

friction associated with matching between firms and workers of different types. 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 firm type to reflect differences in labor mobility throughout the economy.

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. One approach is to use a sector-based definition (Curtis and Marinescu, 2022; Colmer, Lyubich and Voorheis, 2023; Curtis, O'Kane and Park, 2023) by calling jobs related to, for instance, wind or solar power green. A limitation of this approach is that it ignores jobs in non-green sectors, even if these jobs benefit from the low-carbon transition (e.g., climate change analysts and environmental engineers working in the public sector). One way to also capture these jobs is to look at the task content of occupations. Tasks are commonly used as the unit of analysis in the labor economics literature when 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 tasks are complements or substitutes to computers. The green transition can be analyzed through a similar task-based lens. The transition has created a need for new tasks and this will benefit jobs involving these "green" tasks. The defining feature of a green job can therefore be viewed as the share of green tasks it involves. A recent literature strand has adopted such a task-based approach by defining green jobs on the basis of their task content (e.g., Vona et al., 2018; Vona, Marin and Consoli, 2019; Chen et al., 2020; Popp et al., 2021).

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 number of 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.

sectors. Hafstead and Williams (2018) represent a clean and a dirty good, while Yedid-Levi (2016) models a consumption and an investment good.

The job-to-job transition estimates are used to calibrate the degree of labor mobility in the 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 measure job patterns over time, I obtain longitudinal data on occupations 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]

[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

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) 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; Saussay et al., 2022) and offers several 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

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).

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 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 a threshold α.[14] I assume $\alpha = 50\%$ in the 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

[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 not directly affected 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 tech-

(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 κ:[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 ν and $\mathbb{1}$ is an indicator variable for green tasks.[18] I aggregate the shares to a 6-digit level by taking 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" (see Table A.3 in Appendix A for a list of these occupations).

2.2.2 Defining fossil jobs

The green transition will shift demand away from emissions-intensive ("dirty") sectors. I define fossil jobs as jobs disproportionately found in these sectors. The fossil workers in my analysis represent the workers likely to become displaced from the green transition as a result of their sector.[19] I use a two-step procedure to identify the fossil jobs.[20]

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 (GHGRP) of the Environmental Protection Agency.[21] I aggregate the data to a sector-level and combine them with employment data from the Oc-

nologies 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).

[19] Data on dirty tasks does not exist. With a task-based definition, the fossil jobs would have been the jobs most vulnerable to the green transition. Instead, with my sector-based approach, the fossil jobs represent the jobs in the most vulnerable *sectors*. While workers in dirty sectors are likely to become displaced, some will be able to transition to jobs with similar tasks in non-dirty sectors. Thus, while a sector-based approach captures the workers likely to become displaced, a task-based approach captures the workers likely to struggle to find a new job with a similar task profile.

[20] The procedure bears similarities with Vona et al. (2018).

[21] The GHGRP requires large emitters to report direct (scope 1) emissions on a facility-level. The emitters are power plants, oil and gas systems, and industrial sectors (including underground coal mines). 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).

cupational Employment and Wage Statistics program of the Bureau of Labor Statistics (BLS).[22] 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-level information in SIPP. Each survey respondent reports both their occupation and sector in which they work.[23] 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.[24] This gives 63 fossil jobs (see Table A.4 in Appendix A).[25]

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. These shares are similar in magnitude to Saussay et al. (2022) and broadly in line with the range of 2-3% in Deschenes (2013); Elliott and Lindley (2017); Cedefop (2019); Vona, Marin and Consoli (2019).[26] The share of fossil jobs, in contrast,

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

[23] 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`.

[24] 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.

[25] 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).

[26] The green job shares in Fig. 1 are higher than two recent studies for the United States. Both studies use a narrower definition of green jobs. Curtis, O'Kane and Park (2023) find

decreased from 5.5% to 4.9% during 2013-2020. The combined share of green and fossil jobs remained below 10% in each year. The vast majority of jobs are therefore neutral.

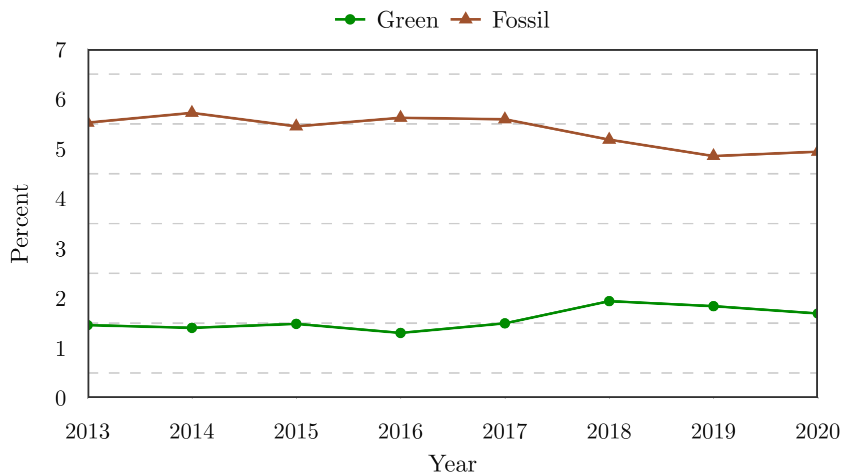

Figure 1: Green and fossil jobs over time
Note: The figure shows the percent of green and fossil jobs in the United States during 2013-2020.

I conduct a number of sensitivity tests on these findings. First, I vary the green task share threshold α in the green job definition. I have so far assumed that green jobs involve at least 50% of green tasks. Panel (a) of Fig. D.1 and Panel (a) of Fig. 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

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.

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 sensitivity tests are as follows. Panel (b) of Figs. D.1-D.2 restricts the task data to occupations' "core" tasks.[27] 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). Panel (e) restricts dirty sectors to sectors in the top 1% (as opposed to top 5%) of emissions intensity. Panel (f) restricts fossil jobs to jobs that are above 10 times (as opposed to 8 times) more likely than the average job to be found in a dirty sector.

In all five 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.

2.3.2 Job-to-job transitions

Fig. 2 shows job-to-job transition probabilities by worker and job type.[28] The probability of starting a green job is 12% for green workers and 5% for fossil

[27] 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).

[28] A job transition in SIPP occurs when the occupation code changes. Some transitions, however, occur between jobs sharing an occupation code. For instance, a waiter switching restaurants is a job change although the occupation code does not change. I need to account for such job changes to avoid underreporting the number of transitions between jobs of the same type. I do this in four ways. First, I assume that a worker moving from one sector to another reflects a job change (e.g., because a worker has moved to another company). Second, I exploit the fact that SIPP reports the month in which a job starts and ends in each year. SIPP assigns January as the starting month if a job continues from the previous year. I assume a job change takes place if the starting month is not January. For instance, a job ending in February and another starting in March implies a job change. Third, occupations in SIPP are assigned unique identifiers to allow tracking a job over multiple years. I assume that any change in the identifier corresponds to a job change. Finally, I assume the first job following an unemployment spell constitutes a job change, irrespective of whether the job shares an occupation code with the job preceding the unemployment spell.

workers. All worker types are most likely to transition to a neutral job.[29] For fossil workers, the probability exceeds 40%. The high probability highlights the relevance of neutral jobs for the green transition and suggests that workers displaced from the transition are more likely to start a neutral, as opposed to a green, job.

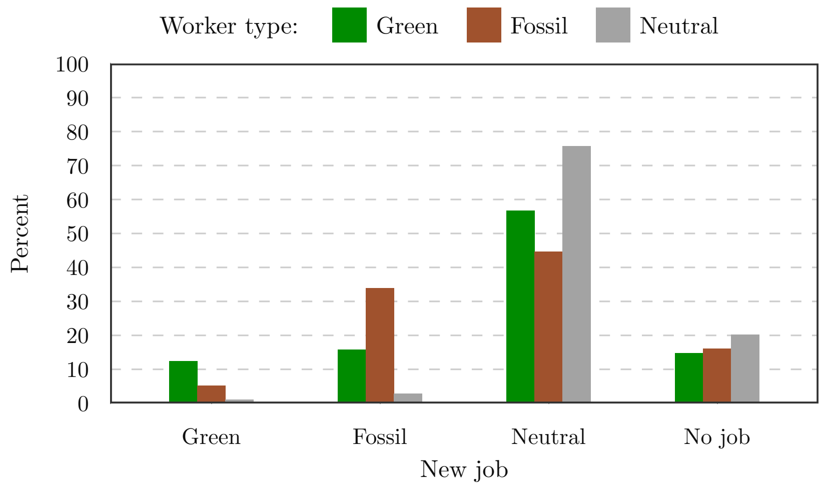

Figure 2: Job finding probability by type of worker and job

Note: The figure shows the probability of transitioning to a green job, fossil job, neutral job, or unemployment by worker type (green, fossil, or neutral) in the United States during 2013-2020.

I conduct a similar sensitivity analysis as in Section 2.3.1. Fig. D.3 in Appendix D shows how the job transition probabilities vary with α. Figs. 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. Figs. D.7-D.8 vary α assuming more narrow definitions of dirty sectors and fossil jobs respectively. In all figures, green workers are more likely than fossil workers to transition to a green job, and the likelihood of transitioning to a neutral job is highest for all worker types. The qualitative insights from the main specification are therefore corroborated.

Finally, I estimate the distribution of workers starting each job. The results are shown in Table 1. 14% of workers starting a green job were green (i.e.,

[29] This is largely due to the abundance of these jobs.

previously had a green job), while 18% were fossil and 68% were neutral. The diagonal elements of the table correspond to the transitions between jobs of the same type. Green workers accounted for 14% of new green jobs, and fossil workers started 39% of new fossil jobs. The vast majority (95%) of neutral jobs were absorbed by neutral workers, due in part to the prevalence of these workers.

Table 1: Distribution of workers starting each job

	New job		
Worker type	Green	Fossil	Neutral
Green	0.14	0.06	0.01
Fossil	0.18	0.39	0.03
Neutral	0.68	0.56	0.95

Note: The table shows the distribution of workers (green, fossil, or neutral) starting a green, fossil, or neutral job in the United States during 2013-2020. The share of green, fossil, and neutral workers was 1.6%, 5.4%, and 93.1% respectively during 2013-2020. These shares, as well as some columns in the table, sum imperfectly to unity due to rounding.

The diagonal elements of Table 1 are used to provide an empirical basis for the degree of labor mobility in the search model. This procedure is elaborated on in Section 4. I describe the search model in the following section.

3 Search model

I employ a 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 a Nash bargaining process. The worker then joins the firm in the following period. An exogenous number of workers π 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.[30] There are three firm types $i, j, k \in \mathcal{J} = \{\texttt{f},\texttt{g},\texttt{z}\}$ that require labor to produce output. Fossil firms ($j = \texttt{f}$) generate emissions in production, while green firms ($j = \texttt{g}$) and neutral firms ($j = \texttt{z}$) are emissions-free.

A worker's type is given by their most recent workplace. This gives three worker types $i, j, k \in \mathcal{J} = \{\texttt{f},\texttt{g},\texttt{z}\}$. There are n_j workers employed at firm j and u_i unemployed workers that previously worked for firm i. Total employment is given by $\overline{n} \coloneqq \sum_j n_j$ and total unemployment is $\overline{u} \coloneqq \sum_i u_i$. The overall workforce is normalized to unity, meaning $\overline{n} + \overline{u} = 1$.

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 employed by a firm. 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 ζ is labor productivity. The output is sold at net price p^y_j. Fossil firms generate ϵ emissions from each unit of output. Total emissions e are given by

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

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

3.2.2 Matching

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

$$m_{ij} = \mu_j \upsilon_j h_j u_i \left[\xi_j \underbrace{\left(\sum_k \upsilon_k h_k \right)}_{\substack{\text{Total}\\ \text{recruitment}}}^{-\gamma} \underbrace{\overline{u}}_{\substack{\text{Total}\\ \text{unem.}}}^{\gamma-1} + (1-\xi_j) \underbrace{(\upsilon_j h_j)}_{\substack{\text{Firm } j\text{'s}\\ \text{recruitment}}}^{-\gamma} \underbrace{u_i}_{\substack{\text{Unem.}\\ \text{of } i}}^{\gamma-1} \delta_{ij} \right], \tag{2}$$

where μ_j is matching efficiency, γ is the elasticity of matching with respect to unemployment, δ_{ij} is the Kronecker delta that equals 1 for $i = j$ and 0 otherwise, and $\xi_j \in [0, 1]$ controls the degree of matching between firms and workers of different types. The number of matches m_{ij} between unemployed worker i and firm j depends positively on the firm's own recruitment effort and the unemployment rate of worker 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 worker i).

The parameter ξ_j controls the degree of friction associated with cross-type matching.[31] If $\xi_j = 0$, a firm j can only recruit workers of type j, meaning there is no cross-type matching. If $\xi_j = 1$, matching does not depend on a worker's type, implying that workers i and $j \neq i$ are equally likely to match with firm j. For values of ξ_j in between zero and one, the share of cross-type matches for firm j is proportional to ξ_j.

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 firm j's recruitment effort to the number of unemployed workers of type i (θ_{ij}), the ratio of firm j's recruitment effort to total unemployment (θ_j), and the ratio of

[31] I let ξ_j vary by firm j in contrast to Hafstead and Williams (2018).

total recruitment effort to total unemployment (θ):

$$\theta_{ij} = \frac{\upsilon_j h_j}{u_i},$$
$$\theta_j = \frac{\upsilon_j h_j}{\overline{u}},$$
$$\theta = \frac{\sum_j \upsilon_j h_j}{\overline{u}}.$$

Recruitment productivity q_j corresponds to the number of matches from a unit of recruitment effort, and the probability ϕ_{ij} of worker i matching with firm j equals the number of matches between them divided by the number of unemployed workers of type i:

$$q_j = \frac{\sum_i m_{ij}}{\upsilon_j h_j}, \tag{3}$$
$$\phi_{ij} = \frac{m_{ij}}{u_i}. \tag{4}$$

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 ϕ_{ij} is increasing in labor market tightness measures θ_j and θ_{ij} since a worker i is more likely to find a job at firm j if the firm's recruitment increases or competition from other workers decreases. The probability of finding a job at firm j is, in contrast, decreasing in θ because higher recruitment effort by other firms means worker i can more easily find a job outside of firm j.

3.2.3 Firm's problem

Firms must decide how to divide workers between production and recruitment. Let $\overline{\upsilon}_j$ be the recruitment ratio, equal to the share of workers assigned to recruitment (Shimer, 2010; Hafstead and Williams, 2018):

$$\overline{\upsilon}_j = \frac{\upsilon_j}{n_j}. \tag{7}$$

The firm's problem is to choose the recruitment ratio that maximizes its value. 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

$$J(n_j) = \max_{\overline{\upsilon}_j} \Big[p^y_j \zeta h_j n_j \big(1 - \overline{\upsilon}_j\big) - \big(1 + \tau^P\big) n_j h_j w_j + \mathbb{E}\Big[p^a J(n'_j)\Big]\Big], \tag{8}$$

where τ^P is a payroll tax, p^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:

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

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

$$p^y_j \zeta = q_j \mathbb{E}\Big[p^a J'_{n_j}\Big], \tag{10}$$

where $J'_{n_j} \coloneqq \partial J(n'_j)/\partial n_j$ 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

$$J_{n_j} = p^y_j \zeta h_j - \big(1 + \tau^P\big) h_j w_j + (1 - \pi)\mathbb{E}\Big[p^a J'_{n_j}\Big].$$

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).[32] 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 C and disutility from work. Consumption is separable from leisure and identical across employed and unemployed workers. The utility function is

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

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

$$c_r = \varrho_r \left(\frac{p_{\texttt{fg}}}{p_r}\right)^{\sigma^{fg}} c_{\texttt{fg}} \qquad \forall r \in \{\texttt{f,g}\}, \tag{11}$$

$$c_r = \varrho_r \left(\frac{p^C}{p_r}\right)^{\sigma^C} C \qquad \forall r \in \{\texttt{fg}, \texttt{z}\}, \tag{12}$$

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

[32] Blundell, Pistaferri and Preston (2008) find evidence that all households besides the poorest insure themselves against temporary income shocks.

are defined by

$$p_{\mathtt{fg}} = \left(\varrho_{\mathtt{f}} p_{\mathtt{f}}^{1-\sigma^{fg}} + \varrho_{\mathtt{g}} p_{\mathtt{g}}^{1-\sigma^{fg}}\right)^{\frac{1}{1-\sigma^{fg}}},$$
$$p^{C} = \left(\varrho_{\mathtt{fg}} p_{\mathtt{fg}}^{1-\sigma^{C}} + \varrho_{\mathtt{z}} p_{\mathtt{z}}^{1-\sigma^{C}}\right)^{\frac{1}{1-\sigma^{C}}}.$$

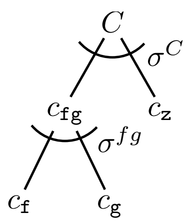

Figure 3: Consumption structure

Note: The figure shows the consumption structure. The fossil and green goods produce a composite good in a bottom nest. The composite good combines with the neutral good in an upper nest to create the aggregate consumption good.

An employed worker receives gross labor income $w_j h_j$ and pays labor income tax τ^L. An unemployed worker gets fixed unemployment benefits b_i. 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 p^C. Workers own assets and the total assets of the representative household is a.

The household's problem is to choose the level of consumption 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

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

subject to

$$
\begin{aligned}
p^C C + p^a a' &\leq \sum_j (1-\tau^L) n_j w_j h_j + \sum_i u_i p^C b_i + a + p^C T, \\
n'_j &= n_j - \pi n_j + \sum_i \phi_{ij} u_i \qquad \forall j, \qquad (14) \\
u'_i &= \pi n_i + u_i (1 - \sum_j \phi_{ij}) \qquad \forall i. \qquad (15)
\end{aligned}
$$

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

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

where λ 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 p^C 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

$$\beta \mathbb{E}\Big[V'_{a'}\Big] = \lambda p^a. \qquad (16)$$

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

$$V_a = \lambda,$$

which holds in every period implying

$$V'_{a'} = \lambda'. \qquad (17)$$

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 the employment and unemployment of each worker type to get the envelope conditions

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

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

Eq. 18 states that the value (for the household) of having a worker employed at firm 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 π. Eq. 19 indicates that the value of having an unemployed worker of type 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:

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

where $\eta \in [0,1]$ denotes the firm's bargaining power. Solving gives the following respective equilibrium conditions for hours and wages:[33]

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

$$\begin{aligned}(1-\tau^L)h_j w_j = (1-\eta)&\left[\frac{1-\tau^L}{1+\tau^P} p_j^n \zeta h_j\right] \\ &+ \eta\left[\frac{\psi\chi h_j^{1+\frac{1}{\chi}}}{\lambda(1+\chi)} + p^C b_j + \beta\frac{\sum_i \phi_{ji}\left(V'_{n_i} - V'_{u_j}\right)}{\lambda}\right] \quad \forall j. \end{aligned} \tag{21}$$

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 (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 green firms' output and the second is a tax τ^E on fossil firms' emissions. The net price p_j^y corresponds to the gross price p_j adjusted for any subsidy receipts and emissions tax payments, meaning

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

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

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

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

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.[34] The ratio is defined as

$$\frac{\hat{y}_{n_j} - \hat{Z}_j}{\hat{y}_{n_j}},$$

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 $\hat{Z}_j$ is the flow value of unemployment, equal to the value of leisure plus unemployment benefits

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

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

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	π	0.037
Bargaining power of employer	η	0.5
Matching elasticity	γ	0.5
Discount rate	β	0.997
Frisch elasticity of labor supply	χ	1
Elasticity in the bottom consumption nest	σ^{fg}	0.75
Elasticity in the top consumption nest	σ^{C}	0.5
Labor income tax	τ^{L}	0.29
Payroll tax	τ^{P}	0.15
No-policy steady state calibration		
Cross-type matching friction for firm $j \in \{\texttt{f},\texttt{g},\texttt{z}\}$	ξ_j	0.58, 0.87, 1
Matching efficiency for firm $j \in \{\texttt{f},\texttt{g},\texttt{z}\}$	μ_j	4.18, 3.87, 3.84
Labor productivity	ζ	3.20
Disutility of work	ψ	5.93
CES share of good $r \in \{\texttt{f},\texttt{g},\texttt{z},\texttt{fg}\}$	ϱ_r	0.73, 0.27, 0.93, 0.07
Unemployment benefits for worker $i \in \{\texttt{f},\texttt{g},\texttt{z}\}$	b_i	0.25, 0.27, 0.28
Emissions factor of fossil firms	ϵ	0.0075

Note: The table lists the parameter values. The values are either based on the literature and data sources ("Direct calibration") or estimated using the search model in the no-policy steady state ("No-policy steady state calibration").

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.[35] I set π 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 γ,

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

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,[36] which translates into a monthly discount rate β of $1.0343^{-1/12} = 0.997$. The Frisch elasticity of labor supply χ 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 σ^C 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 σ^{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.[37] 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 $\tau^P = 0.15$.

4.2 Calibration using the no-policy steady state

I make five assumptions in the no-policy steady state. First, I set $\overline{u} = 5.9\%$ to mirror the average unemployment rate in the United States during 2000-2019.[38] This implies $\overline{n} = 1 - \overline{u} = 94.1\%$. Second, I distribute total employment $\overline{n}$ and total consumption C in proportion to the employment shares in 2019 in Fig. 1. The green, fossil, and neutral employment shares are 1.8%, 4.9%, and 93.3% respectively. Third, without loss of generality, I normalize prices, total consumption, and workers' time endowment to unity. Fourth, I assume that

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

[37] 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#.

[38] See the Current Population Survey of the BLS, available at https://data.bls.gov/timeseries/LNS14000000.

one third of the time endowment (i.e., eight hours per day) is spent working, meaning $h_j = 1/3$. Fifth, I assume that the shares of within-type matches correspond to the diagonal elements of Table 1. In particular, let ω_j denote the share of matches for firm j with workers of type j such that

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

I set ω_j equal to the diagonal elements of Table 1, such that $\omega_{\mathtt{f}} = 0.39, \omega_{\mathtt{g}} = 0.14$, and $\omega_{\mathtt{z}} = 0.95$. The values of ω_j correspond to the share of workers starting job j that previously had the same job $i = j$.

4.2.1 Calibrating ξ_j

To estimate ξ_j, I first rearrange Eqs. 3 and 4 and substitute them into Eq. 23 to get[39]

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

Substituting for ϕ_{jj} using Eq. 6 and then for μ_j using Eq. 5 gives

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

In the steady state, Eq. 24 links ξ_j to the variables $\{u_{\mathtt{f}}, u_{\mathtt{g}}, u_{\mathtt{z}}\}$ and to exogenous parameters. To see why υ_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 υ_j is determined exogenously by $\upsilon_j = n_j \pi / (q_j h_j)$.

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

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

[39] No empirically-based estimate exists, to my knowledge, for ξ_j. Most studies implicitly assume zero cross-type matching ($\xi_j = 0$, whereby Eq. 2 reduces to a Cobb-Douglas function of firm j's recruitment effort and the number of unemployed workers of type j) or frictionless cross-type matching ($\xi_j = 1$). Values in between are scarce. Hafstead and Williams (2018) conduct a sensitivity analysis on ξ_j, but do not take a stance on the empirical value.

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 (ξ_j and u_j) in the no-policy steady state.[40] Solving for ξ_j and u_j using both equations gives

$$\xi_j = \begin{cases} 0.58 & \text{for } j = \mathtt{f}, \\ 0.87 & \text{for } j = \mathtt{g}, \\ 1 & \text{for } j = \mathtt{z},^{41} \end{cases}$$

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

The high values of ξ_j for neutral and green firms imply that they can easily match with outside workers. This is especially the case for neutral firms, as they face no matching friction with outside workers. Fossil firms, on the other hand, face some friction due to a smaller ξ_j. While this restricts the ability of neutral and green workers to obtain fossil jobs, the overall degree of labor mobility in the model is high. Turning to the values of u_j, we see that most unemployed workers in the no-policy steady state are of the neutral type. This largely stems from the prevalence of these workers.

4.2.2 Calibrating the remaining parameters

The matching efficiency μ_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 ζ is obtained by rearranging Eq. 1 to $\zeta = y_{\mathtt{g}}/(l_{\mathtt{g}} h_{\mathtt{g}})$ and setting $y_{\mathtt{g}} = n_{\mathtt{g}}$, $l_{\mathtt{g}} = n_{\mathtt{g}} - v_{\mathtt{g}}$, and $h_{\mathtt{g}} = 1/3$.[42] I pin down the disutility of work ψ by the hour bargaining condition in Eq. 20. The CES consumption shares ϱ_r are obtained from Eqs. 12 and 11. Similarly to Hafstead and Williams (2018), unemployment benefits b_i are endogenously determined

[40] Note that μ_j is determined by ξ_j and $\{u_{\mathtt{f}}, u_{\mathtt{g}}, u_{\mathtt{z}}\}$ by Eq. 5.

[41] I restrict ξ_j to a maximum value of 1 as this represents an extreme whereby matching does not depend on a worker's employment history.

[42] I pin down ζ using $j = \mathtt{g}$. The choice of firm type is arbitrary since y_j/l_j and $1/h_j$ are identical across firm types in the no-policy benchmark.

by the wage bargaining condition in Eq. 21. I get $b_{\mathtt{f}} = 0.25, b_{\mathtt{g}} = 0.27$ and $b_{\mathtt{z}} = 0.28$.[43] The values imply replacement rates of 38%, 41%, and 42% for fossil, green, and neutral workers 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 ϵ 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,[44] while carbon dioxide emissions were 5.262 billion tons.[45] The emissions per dollar of consumption were therefore 0.0004 tCO_2. Second, I adjust this number for the fact that only fossil firms emit in my model. Consumption of the fossil good accounts for 4.9% of total consumption (that equals one) in the initial steady state, meaning the emissions factor of fossil firms is 0.0075 tCO_2 per unit of output.

5 Numerical analysis

This section presents the employment outcomes from a green subsidy and a carbon tax. Section 5.1 assumes the government finances the subsidy and recycles the carbon tax revenue in a non-distortionary manner. Section 5.2 relaxes this assumption. 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. It is set such that the 10-year subsidy expenditure in Section 5.1 equals $781 billion, which is the estimated size of the IRA tax credits in the main scenario of Bistline, Mehrotra and Wolfram

[43] In contrast to Hafstead and Williams (2018), my unemployment benefits vary across workers because of the firm-specific ξ_j. This implies different flow values of unemployment (0.58, 0.60, 0.61) and fundamental surplus ratios (0.12, 0.09, 0.08) for the fossil, green, and neutral types respectively. I examine the implications of varying the unemployment benefits in Section 5.4.

[44] 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.

[45] 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.

(2023).[46]

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 (LS) taxes to balance its budget.[47] A subsidy increases steady state employment by 0.10 percentage points. A carbon tax, in contrast, reduces it by 0.03 percentage points. A subsidy therefore outperforms a carbon tax and generates employment gains when financed in a non-distortionary manner.

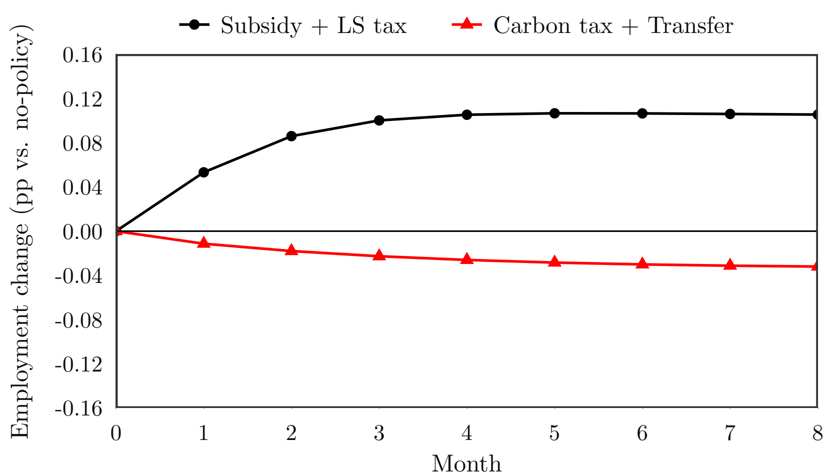

Figure 4: Employment change from a green subsidy and carbon tax with lump sum taxes and transfers

Note: The figure shows the employment change from a green subsidy financed by lump sum taxes and from a carbon tax with transfer recycling. The employment change is given in percentage points relative to the no-policy benchmark. The subsidy and carbon tax are introduced in month $t = 0$.

[46] This corresponds to a reduction in steady state emissions by 1.7% relative to the no-policy benchmark.

[47] 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.

5.1.2 Impact on each job type

In the following, I decompose the employment impact by job type. 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 the number of green jobs and decreases the number of fossil and neutral jobs.[48] Table 3 sheds light on the mechanisms.[49] A subsidy induces consumers to substitute towards the green good by making it comparatively cheaper. Green firms respond by recruiting more workers, which creates green jobs. The fossil and neutral goods, in contrast, become relatively more expensive. This induces firms producing these goods to hire fewer workers and leads to a decline in the number of fossil and neutral jobs.

Table 3: Steady state changes from a green subsidy by firm type (in percent relative to no-policy)

	Gross price p_j	Output y_j	Recruitment $\upsilon_j q_j h_j$	Employment n_j
Green	0	19.8	19.5	19.5
Fossil	30.1	-1.7	-1.9	-1.9
Neutral	30.1	0.0	-0.2	-0.2

Note: The table shows the change in steady state values, by firm type j, from a green subsidy financed by lump sum taxes. The changes are given in percent relative to the no-policy benchmark. The gross price of the green good does not change as it is the numeraire.

Table 4 decomposes the change in recruitment $\upsilon_j q_j h_j$ in the initial period and in the steady state. Green firms hire more recruiters immediately after the subsidy is introduced, while other firms hire fewer recruiters. The recruitment productivity of green firms initially decreases because the higher recruitment

[48] Green and neutral firms reach the steady state sooner because they face little cross-type matching friction. Fossil firms, in contrast, face more friction due to a lower value of ξ_j. They adjust hiring more gradually and take longer to reach the steady state in Fig. 5.

[49] Fossil employment contracts by more compared to neutral employment 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 employment share is smaller in the benchmark, which makes its employment change smaller in percentage points.

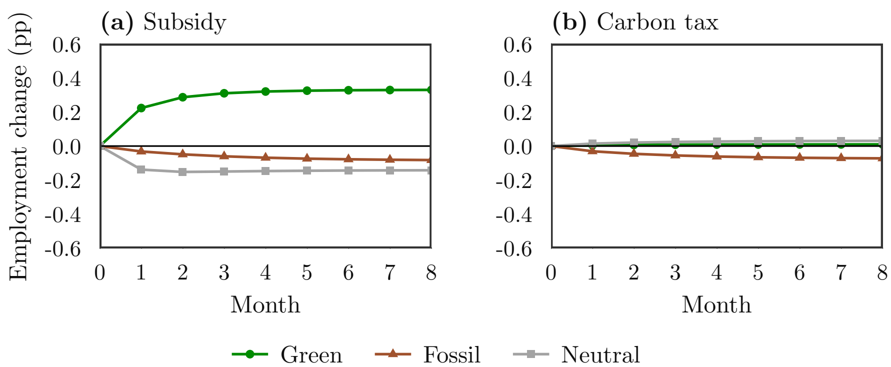

Figure 5: Employment change by job type from a green subsidy and carbon tax

Note: The figure shows the change in the number of green, fossil, and neutral jobs (in percentage points relative to the no-policy benchmark) from a green subsidy financed by lump sum taxes (Panel (a)) and a carbon tax with transfer recycling (Panel (b)). The subsidy and carbon tax are introduced in month $t = 0$.

tightens the labor market for them. The values of υ_j, q_j, and h_j converge to more similar levels across firms in the steady state.[50] The steady state is characterized by more recruiters υ_j, lower recruitment productivity q_j (because of a tighter labor market), and more hours worked h_j.

Table 4 also depicts worker-level outcomes. The subsidy benefits workers with green jobs. 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 job-finding probabilities converge to similar levels across workers.[51] The levels are higher than in the no-policy benchmark, implying that the subsidy increases wages and the likelihood of finding a job.

[50] The values are, however, not identical because the degree of friction associated with cross-type matching ξ_j varies across firms.

[51] The wage changes in Table 4 explain why the number of fossil jobs decreases by more compared to neutral jobs in Table 3. The steady state wage is slightly higher in fossil jobs compared to neutral jobs. Fossil workers face less outside competition because $\xi_{\mathtt{f}} < 1$ implies that fossil firms face frictions when matching with other types of workers. Neutral workers, in contrast, are not shielded from outside competition because $\xi_{\mathtt{z}} = 1$. The fact that $\xi_{\mathtt{f}} < \xi_{\mathtt{z}}$ means fossil workers have a stronger bargaining position and can demand a higher wage. The higher wage reduces the value of a match for fossil firms. These firms consequently recruit fewer workers, which explains why the number of fossil jobs contracts by more.

Table 4: Changes from a green subsidy by firm type, worker type, 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 $(1-\tau^L)w_i/p^C$
Green	$t=0$	345.0	-8.6	12.3	16.9	7.475
	SS	21.6	-1.9	0.2	1.9	0.448
Fossil	$t=0$	-21.0	3.5	-0.6	-3.2	-0.090
	SS	-0.2	-1.9	0.2	1.9	0.449
Neutral	$t=0$	-2.5	-1.9	0.1	1.5	0.406
	SS	1.5	-1.9	0.2	1.9	0.448

Note: The table shows the change in firm-level and worker-level outcomes, by firm type j, worker type i, and time period, from a green subsidy financed by lump sum taxes. The time periods are the first period ($t = 0$) and the steady state (SS). The changes are given in percent relative to the no-policy benchmark.

5.1.2.2 Carbon tax

Panel (b) of Fig. 5 displays the impact of a carbon tax on each job type. Two insights emerge with respect to how the carbon tax compares to the subsidy.

First, the two instruments have opposite effects on the number of neutral jobs. A subsidy decreases neutral employment 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 of neutral firms. A carbon tax, conversely, makes the neutral good relatively cheaper and increases recruitment of neutral firms (Table 5).

Second, a subsidy produces much larger green employment gains compared to a carbon tax. A subsidy, when financed in a non-distortionary manner, reduces labor costs for green firms and increases their recruitment. A carbon tax, in contrast, does not reduce labor costs 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 reduce labor market distortions for green firms by making it cheaper for them to recruit workers.

The previous paragraph touches on an important issue, namely that the

Table 5: Steady state changes from a carbon tax by firm type (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	0.53	0.58	0.58
Fossil	0.03	-1.68	-1.63	-1.63
Neutral	0.00	-0.02	0.04	0.04

Note: The table shows the change in steady state values, by firm type j, from a carbon tax with transfer recycling. The changes are given in percent relative to the no-policy benchmark. The gross price of the green good does not change as it is the numeraire.

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 considerable 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 payroll taxes are used for financing and revenue recycling. 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.

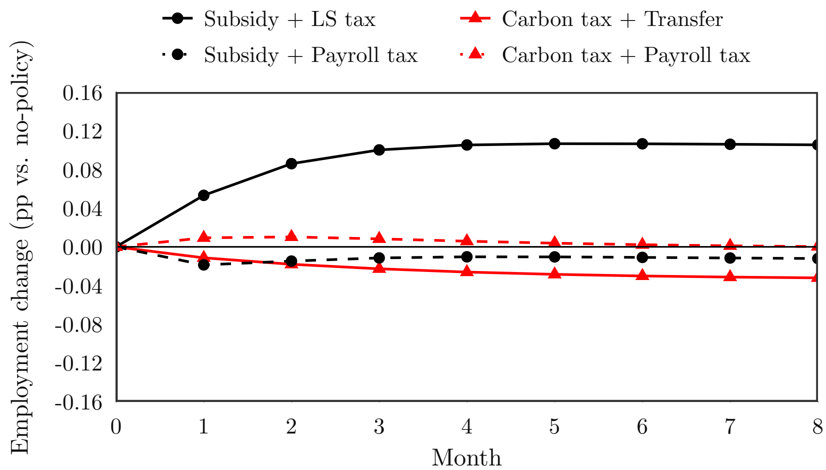

Figure 6: Employment change from a green subsidy and carbon tax by financing/recycling mechanism

Note: The figure shows the change in employment from various climate policy instruments. The policy instruments are a green subsidy financed by lump sum taxes, a green subsidy financed by payroll taxes, a carbon tax with transfer recycling, and a carbon tax with payroll tax recycling. The employment change is given in percentage points relative to the no-policy benchmark. The climate policy instruments are introduced in month $t = 0$.

Fig. 7 decomposes the employment change from a subsidy by job type and financing mechanism.[52] A subsidy increases the number of green jobs, irrespective of the financing mechanism. However, the increase is smaller when the subsidy is paid for by payroll taxes. The reason is twofold. First, higher payroll taxes increase the level of distortion for green firms 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 distortions for green firms by less because it induces a lower subsidy rate.[53] The subsidy rate is lower because each dollar in subsidy payments increases production costs for fossil firms (from the higher payroll taxes). Their output, and consequently emissions, therefore contract by more for a given subsidy level

[52] The equivalent decomposition for a carbon tax is performed in Fig. D.9 in Appendix D.

[53] The subsidy decreases from 30 to 25 cents per dollar of green output when switching from lump sum to payroll taxes.

when payroll taxes finance the subsidy. The lower subsidy rate further slows down recruitment of green firms and contributes to the smaller green job gains.[54]

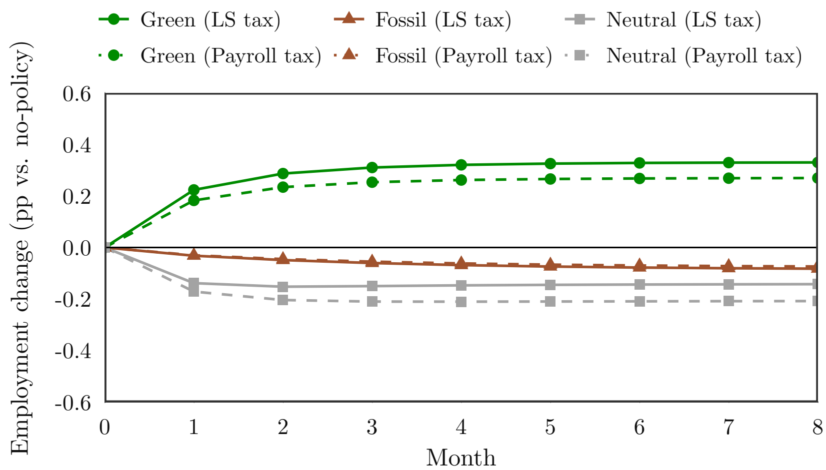

Figure 7: Employment change from a green subsidy by job type and financing mechanism

Note: The figure shows the change in employment, by job type, from a green subsidy financed by either lump sum taxes ("LS tax") or payroll taxes ("Payroll tax"). The employment change is given in percentage points relative to the no-policy benchmark. The green subsidy is introduced in month $t = 0$.

[54] While switching from lump sum to payroll taxes decreases green and neutral employment in Fig. 7, it increases fossil employment slightly. The payroll taxes decrease green recruitment which reduces the reallocation of fossil workers to green jobs. This offsets the fossil employment losses from the payroll taxes and explains why the number of fossil jobs increases.

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

		Output y_j	Recruitment $v_j q_j h_j$
Green subsidy with lump sum taxes	Green	19.8	19.5
	Fossil	-1.7	-1.9
	Neutral	0.0	-0.2
Green subsidy with payroll taxes	Green	15.9	16.0
	Fossil	-1.7	-1.7
	Neutral	-0.2	-0.2

Note: The table shows steady state changes, by firm type j, from a green subsidy financed by either lump sum taxes or payroll taxes. The changes are given in percent relative to the no-policy benchmark. Fossil output is constant since the abatement level is fixed.

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.

5.3 Preexisting distortions

Fig. 8 shows the employment impact of a subsidy given various financing mechanisms and benchmark labor tax rates. A higher level of preexisting distortions (represented by a 50% increase in τ^P and τ^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.

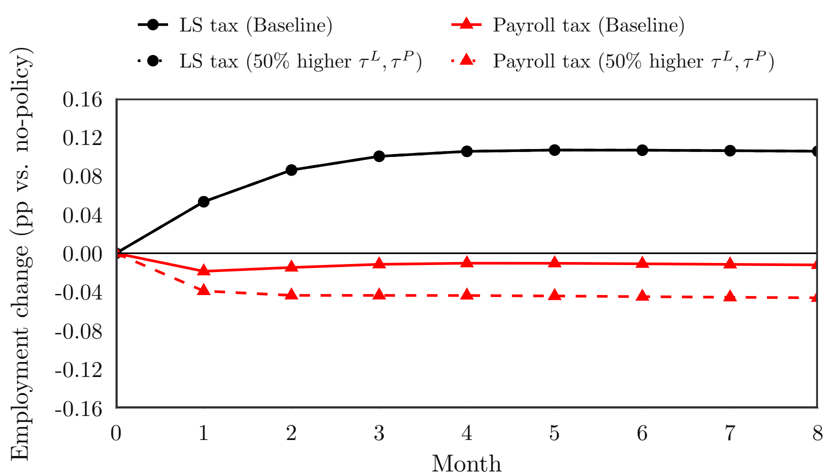

Figure 8: Employment change from a green subsidy by financing mechanism and benchmark tax rates

Note: The figure shows the employment change from a green subsidy financed by lump sum taxes ("LS tax") or payroll taxes ("Payroll tax") for various benchmark tax scenarios. The scenarios are "Baseline" (where the labor income tax τ^L equals 0.29 and the payroll tax τ^P equals 0.15 in the benchmark) and a scenario where τ^L and τ^P increase by 50% in the benchmark relative to "Baseline". The employment change is given in percentage points relative to the benchmark. The green subsidy is introduced in month $t = 0$.

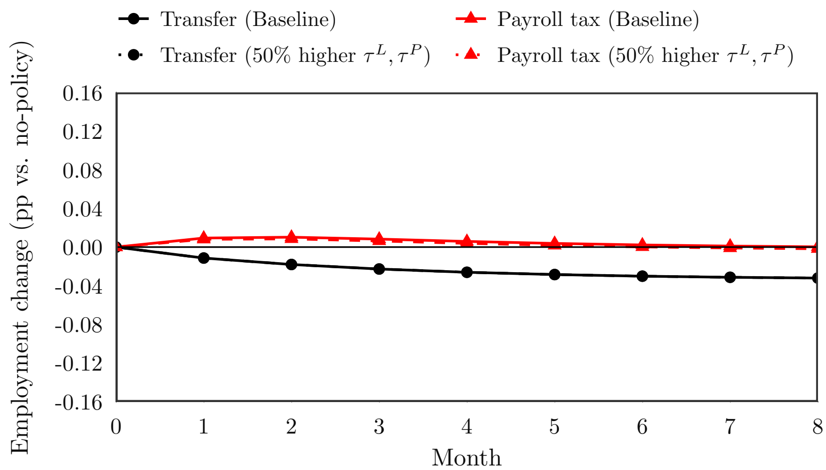

Figure 9: Employment change from a carbon tax by recycling mechanism and benchmark tax rates

Note: The figure shows the employment change from a carbon tax with transfer ("Transfer") or payroll tax ("Payroll tax") recycling for various benchmark tax scenarios. The scenarios are "Baseline" (where the labor income tax τ^L equals 0.29 and the payroll tax τ^P equals 0.15 in the benchmark) and a scenario where τ^L and τ^P increase by 50% in the benchmark relative to "Baseline". The employment change is given in percentage points relative to the benchmark. The carbon tax is introduced in month $t = 0$.

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 ψ and unemployment benefits b_i in the no-policy benchmark. Table 7 presents the results. The qualitative effects are robust. A non-distortionary subsidy always produces employment gains.[55] 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.

Looking at the subsidy outcomes in Table 7, we see that changing recruit-

[55] 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 + Transfer	Carbon tax + Payroll tax
Baseline	0.104	-0.014	-0.034	-0.001
q_j up by 50%	0.155	-0.025	-0.050	-0.002
q_j down by 50%	0.048	-0.005	-0.016	-0.001
$\eta = 0.7$	0.226	-0.050	-0.072	-0.003
$\eta = 0.3$	0.041	-0.004	-0.014	-0.001
$\gamma = 0.75$	0.052	-0.006	-0.017	-0.001
$\gamma = 0.25$	0.155	-0.024	-0.049	-0.003
$\chi = 2$	0.078	-0.009	-0.024	-0.001
$\chi = 0.5$	0.121	-0.019	-0.041	-0.002
$\sigma^{fg} = 0.9$	0.065	-0.007	-0.032	-0.001
$\sigma^{fg} = 0.6$	0.253	-0.047	-0.036	-0.002
$\sigma^{C} = 0.6$	0.166	-0.030	-0.030	-0.001
$\sigma^{C} = 0.4$	0.075	-0.008	-0.038	-0.002

Note: The table shows the employment change, by sensitivity test, from various climate policy instruments. The policy instruments are a green subsidy financed by lump sum taxes, a green subsidy financed by payroll taxes, a carbon tax with transfer recycling, and a carbon tax with payroll tax recycling. The employment change is given in percentage points relative to the no-policy benchmark.

ment productivity q_j in the benchmark has an uneven impact across financing mechanisms. A higher q_j means a unit of recruitment effort $v_j h_j$ 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 η increases the flow value of unemployment and reduces the fundamental surplus ratio.[56,57] A small fundamental sur-

[56] The relationship between η 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 η raises the flow value of unemployment because unemployment benefits b_i increase. The larger flow value of unemployment, in turn, reduces the fundamental surplus ratio.

[57] As shown in Table 9, a higher η 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.

plus ratio means that a productivity shock has a large percentage impact on profits because profits are initially small (Ljungqvist and Sargent, 2017). There 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 γ reduces the matching efficiency μ_j.[58] The lower μ_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 χ 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) and labor supply on the extensive margin rises.

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

Increasing the elasticity of substitution between the fossil-green composite and the neutral good σ^C amplifies the employment outcomes from a subsidy. A higher σ^C induces more consumption substitution from the neutral to the cheaper green good. More workers flow from neutral to green jobs in response to the substitution, which crowds out some of the reallocation of fossil workers to green jobs. 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

[58] 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 green 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 s	
	LS	Payroll	LS	Payroll	LS	Payroll
Baseline	1.74	-0.48	0.198	-0.014	0.30	0.25
q_j up by 50%	2.76	-0.69	0.175	-0.015	0.31	0.24
q_j down by 50%	0.66	-0.32	0.223	-0.014	0.30	0.25
$\eta = 0.7$	4.19	-1.17	0.148	-0.017	0.31	0.24
$\eta = 0.3$	0.51	-0.30	0.224	-0.014	0.29	0.25
$\gamma = 0.75$	2.65	-0.55	0.223	-0.014	0.30	0.25
$\gamma = 0.25$	0.84	-0.38	0.173	-0.014	0.31	0.24
$\chi = 2$	1.23	-0.39	0.293	-0.020	0.31	0.25
$\chi = 0.5$	2.09	-0.59	0.121	-0.010	0.29	0.25
$\sigma^{fg} = 0.9$	1.08	-0.28	0.120	-0.007	0.17	0.15
$\sigma^{fg} = 0.6$	4.21	-1.36	0.551	-0.050	1.01	0.57
$\sigma^{C} = 0.6$	2.71	-0.95	0.339	-0.031	0.53	0.37
$\sigma^{C} = 0.4$	1.29	-0.28	0.139	-0.008	0.21	0.18

Note: The table shows the change in various outcomes, by sensitivity test, from a green subsidy financed by either lump sum taxes ("LS") or payroll taxes ("Payroll"). The change in recruitment effort and hours is reported as the percentage change in the steady state values relative to the no-policy benchmark. The subsidy rate is given in cents per dollar of green output.

contrast, payroll taxes must increase to cover a higher distortionary subsidy, which exacerbates the employment losses.

Finally, I vary ξ_j to consider the role of frictions associated with cross-type matching. Fig. 10 shows the employment impact of a non-distortionary subsidy for different values of ξ_j. Changing the parameter has little impact on the steady state, as employment converges to the same level. The speed of convergence, however, varies. A small value of ξ_j slows down convergence and a sufficiently small value can even eliminate the employment gains in the short run. A low value of of ξ_j means firms face friction when matching with workers of a different type. The friction increases the time it takes for firms to adjust hiring and reach their steady state recruitment level. Thus, while ξ_j has little effect on the steady state, it impacts the subsidy's performance during the transition.[59] Fig. 10 in

[59] This result is analogous to that for a carbon tax in Hafstead and Williams (2018).

Appendix D shows that the same is true for a subsidy financed by payroll taxes.

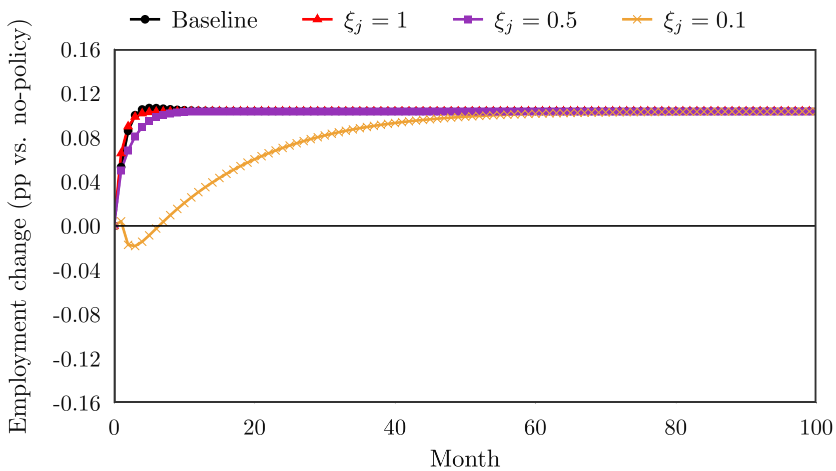

Figure 10: Employment change from a green subsidy financed by lump sum taxes by value of ξ_j

Note: The figure shows the employment change, by value of ξ_j, from a green subsidy financed by lump sum taxes. The "Baseline" scenario assumes the values of ξ_j in Table 2. The employment change is given in percentage points relative to the benchmark. The green subsidy is introduced in month $t = 0$.

Table 9: Outcomes from a non-distortionary subsidy by firm/worker type 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	0.27	0.25	0.28	0.60	0.58	0.61	0.61	0.09	0.12	0.08	0.08	0.33	-0.09	-0.14
q_j up by 50%	0.29	0.28	0.29	0.62	0.61	0.62	0.62	0.06	0.08	0.05	0.05	0.34	-0.09	-0.10
q_j down by 50%	0.21	0.17	0.23	0.54	0.50	0.56	0.56	0.18	0.24	0.16	0.16	0.32	-0.09	-0.19
$\eta = 0.7$	0.30	0.29	0.31	0.63	0.62	0.63	0.63	0.04	0.05	0.04	0.04	0.35	-0.08	-0.04
$\eta = 0.3$	0.20	0.15	0.21	0.53	0.48	0.54	0.54	0.20	0.27	0.18	0.18	0.32	-0.09	-0.20
$\gamma = 0.75$	0.27	0.25	0.28	0.60	0.58	0.61	0.61	0.09	0.12	0.08	0.08	0.32	-0.09	-0.18
$\gamma = 0.25$	0.27	0.25	0.28	0.60	0.58	0.61	0.61	0.09	0.12	0.08	0.08	0.34	-0.09	-0.10
$\chi = 2$	0.16	0.14	0.17	0.60	0.58	0.61	0.61	0.09	0.12	0.08	0.08	0.34	-0.09	-0.17
$\chi = 0.5$	0.38	0.36	0.39	0.60	0.58	0.61	0.61	0.09	0.12	0.08	0.08	0.32	-0.08	-0.12
$\sigma^{fg} = 0.9$	0.27	0.25	0.28	0.60	0.58	0.61	0.61	0.09	0.12	0.08	0.08	0.23	-0.08	-0.08
$\sigma^{fg} = 0.6$	0.27	0.25	0.28	0.60	0.58	0.61	0.61	0.09	0.12	0.08	0.08	0.82	-0.10	-0.47
$\sigma^{C} = 0.6$	0.27	0.25	0.28	0.60	0.58	0.61	0.61	0.09	0.12	0.08	0.08	0.59	-0.09	-0.33
$\sigma^{C} = 0.4$	0.27	0.25	0.28	0.60	0.58	0.61	0.61	0.09	0.12	0.08	0.08	0.22	-0.08	-0.07

Note: The table shows the change in various outcomes, by sensitivity test, from a green subsidy financed by lump sum taxes. The outcomes are reported by firm or worker type. The “mean” columns denote weighted averages, where the weights are the worker types’ benchmark unemployment rates. 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 develop a general equilibrium search model to analyze how green subsidies impact the number of green, fossil, and neutral jobs. I underpin the analysis with empirical evidence on the distribution of jobs and job transitions in the United States. The job transition estimates are used to calibrate the degree of friction associated with cross-type matching in the search model. This allows me to investigate the impact of green subsidies for a more realistic degree of labor mobility.

The empirical analysis suggests that green jobs in the United States have become more prevalent, while the number of fossil jobs has decreased. Green and fossil jobs account for a small fraction of overall employment. The majority of jobs are neutral and not directly affected by green subsidies and carbon taxes. With regard to job transitions, the data shows that fossil workers rarely move to a green job. They are instead more likely to start a neutral job. I furthermore estimate the distribution of hires by job type and use it to calibrate the degree of friction associated with cross-type matching in the search model. The level of friction is generally low, which implies a high degree of labor mobility in the model.

In the numerical analysis, 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 worse employment outcomes compared to a carbon tax. The choice of financing mechanism is therefore an important determinant of a subsidy's overall employment impact.

Finally, the preexisting level of distortion can affect the performance of green subsidies. The impact depends on the financing mechanism. A subsidy paid for by non-distortionary taxes is unaffected by the level of distortion, while a subsidy financed by labor taxes generates larger employment losses if preexisting distortions are high. Financing a subsidy with lump sum, as opposed to labor, taxes is thus especially advantageous if the labor market is already 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 Administrators and Architects	15-1199	Computer Occupations, All Other	0.86
		15-1141	Database Administrators	0.14
1108	Computer Occupations, 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
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

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
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 table lists the Census occupation codes with a one-to-many mapping to SOC. 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* ≥ 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

Note: The table lists the O*NET occupations with a *GreenShare* score of at least 0.5.

Table A.3: Green occupations in the main specification

SOC code	SOC title	Average *GreenShare*
17-2081	Environmental Engineers	1
17-2141	Mechanical Engineers	0.53
19-2040	Environmental Scientists and Geoscientists	0.57
41-3099	Sales Representatives, Services, All Other	1
47-2231	Solar Photovoltaic Installers	1
47-4041	Hazardous Materials Removal Workers	1
47-4090	Miscellaneous Construction and Related Workers	0.67
49-9081	Wind Turbine Service Technicians	1
49-909X	Other installation, maintenance, and repair workers	0.5
51-9199	Production Workers, All Other	1
53-7081	Refuse and Recyclable Material Collectors	1

Note: The table lists the occupations that are classified as green in the main specification. The occupations have by definition an average *GreenShare* score of at least 0.5.

Table A.4: Fossil occupations in the main specification

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.4: Fossil occupations in the main specification (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

Note: The table lists the occupations that are classified as fossil in the main specification.

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.[60]

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").

[60] 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†
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‡
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: The table describes how the green task shares of O*NET occupations with a many-to-one mapping to a 6-digit parent group were aggregated to the parent group. The last column details the aggregation procedure: "Zero" means that the 6-digit parent group was assigned a green task share of zero, while "Mean" implies that the 6-digit parent group was assigned the average of the O*NET occupations' green task shares.

†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, Air-conditioning, 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: The table lists the instances in which multiple NAICS codes map to a single Census code and only some of the NAICS code are dirty. The last column shows whether the Census code is ultimately classified as 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.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: The table lists the instances in which a 2-digit or 3-digit NAICS code maps to a Census code and has some 4-digit subcategories that are dirty. The second column shows the share of 4-digit subcategories that are dirty. The last column shows whether the Census code is ultimately classified as dirty.

[†]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	22131 22133	Water Supply and Irrigation Systems Steam and Air-Conditioning Supply	0670	Water, Steam, Air-conditioning, and Irrigation systems	Yes
	Systems	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	32621	Tire Manufacturing	2380	Tire Manufacturing	Yes
	Manufacturing	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	32711	Pottery, Ceramics, and Plumbing Fixture Manufacturing	2470	Pottery, Ceramics, and Plumbing Fixture Manufacturing	Yes
	Manufacturing	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: The table lists the instances in which a dirty NAICS code is indirectly mapped to a Census code through 5-digit or 6-digit subcategories. The last column shows whether the Census code is ultimately classified as dirty.

†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

Note: The table lists the sectors that are classified as dirty.

Appendix D: Figures

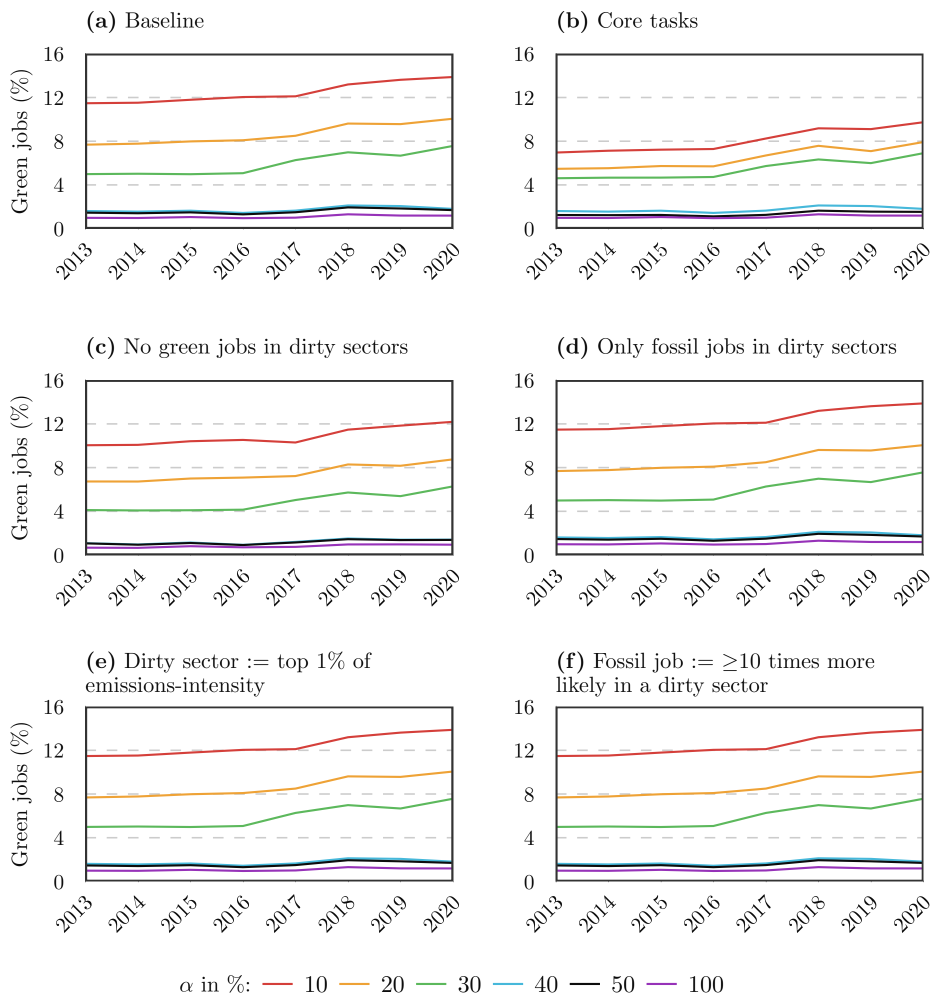

Figure D.1: Green job share over time by sensitivity test (panels) and α (lines)

Note: The figure shows the percent of green jobs in the United States during 2013-2020 for various sensitivity tests (panels) and values of α (lines). Panel (a) is the main specification, Panel (b) restricts tasks to the "core" tasks, Panel (c) restricts green jobs to those in non-dirty sectors, Panel (d) restricts fossil jobs to those in dirty sectors, Panel (e) defines dirty sectors as sectors lying in the top 1% of emissions intensity, and Panel (f) defines fossil jobs as jobs at least 10 times more likely than the average job to be found in a dirty sector. The parameter α denotes the minimum share of green tasks for an occupation to be classified as "green". Although difficult to discern from the figure, the green job share is increasing by at least 0.2 percentage points in all panels for $\alpha = 100\%$.

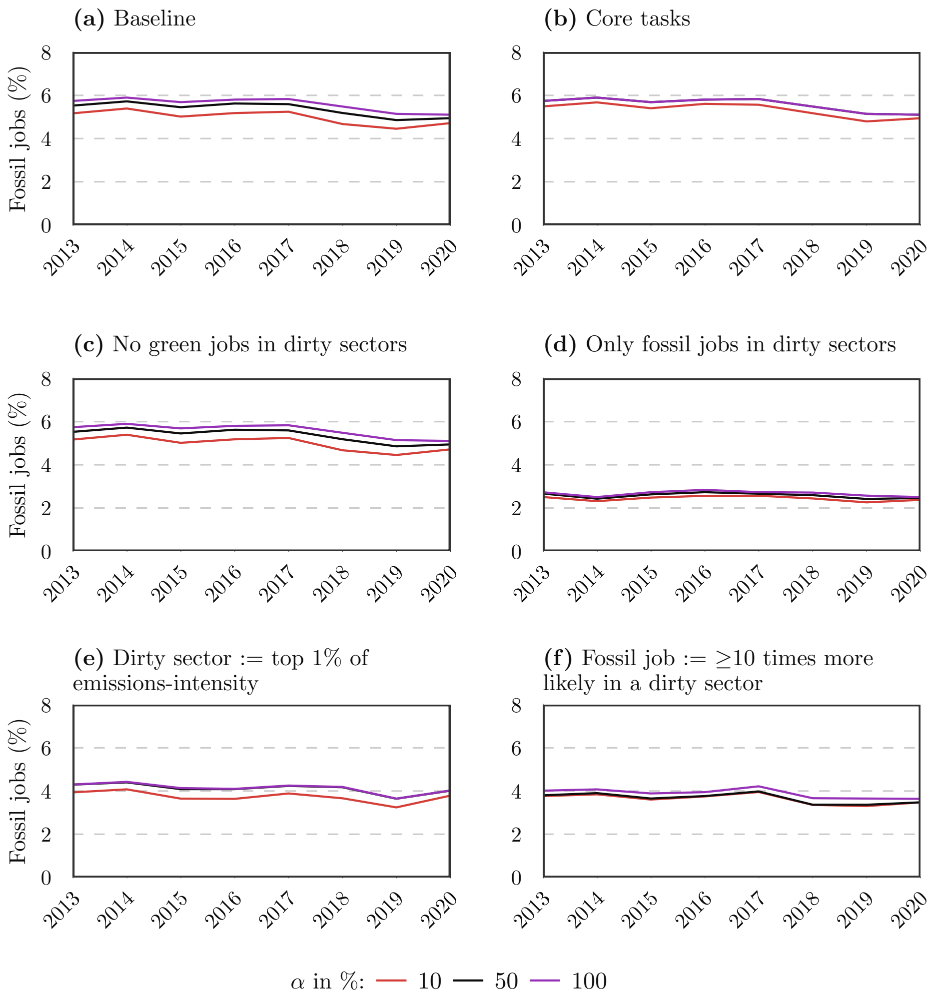

Figure D.2: Fossil job share over time by sensitivity test (panels) and α (lines)

Note: The figure shows the percent of fossil jobs in the United States during 2013-2020 for various sensitivity tests (panels) and values of α (lines). Panel (a) is the main specification, Panel (b) restricts tasks to the "core" tasks, Panel (c) restricts green jobs to those in non-dirty sectors, Panel (d) restricts fossil jobs to those in dirty sectors, Panel (e) defines dirty sectors as those lying in the top 1% of emissions intensity, and Panel (f) defines fossil jobs as those at least 10 times more likely than an average job to be found in a dirty sector. The parameter α denotes the minimum share of green tasks for an occupation to be classified as "green". Although difficult to discern from the figure, the fossil job share is decreasing by at least 0.2 percentage points in all panels for $\alpha = 100\%$.

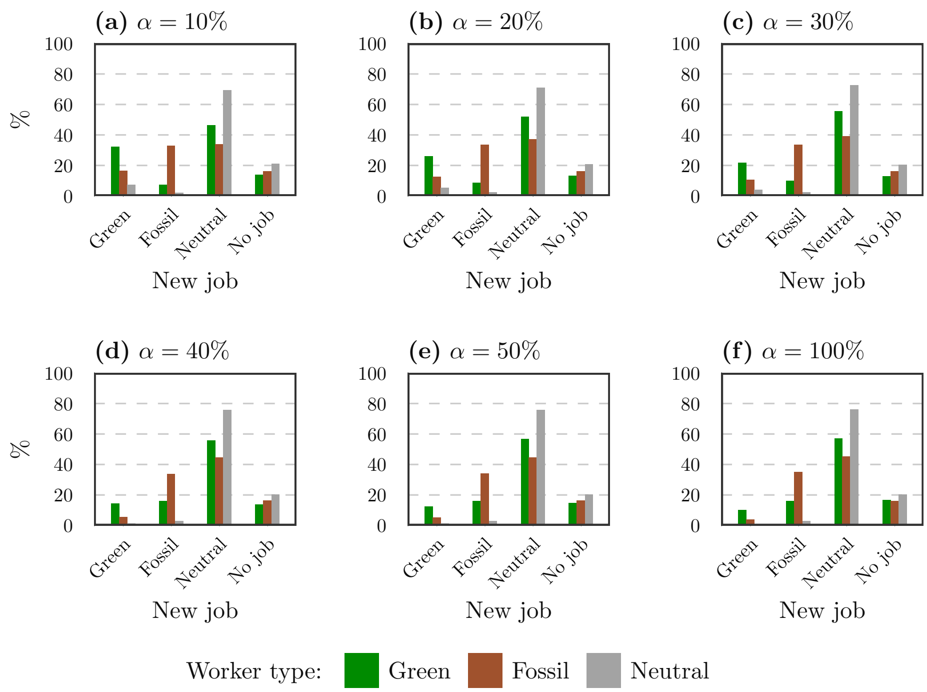

Figure D.3: Job-finding probability by α, type of job, and worker type

Note: The panels show the probability of transitioning to a green job, fossil job, neutral job, or unemployment by worker type (green, fossil, or neutral). The panels differ in terms of α (i.e., the minimum share of green tasks for an occupation to be classified as "green").

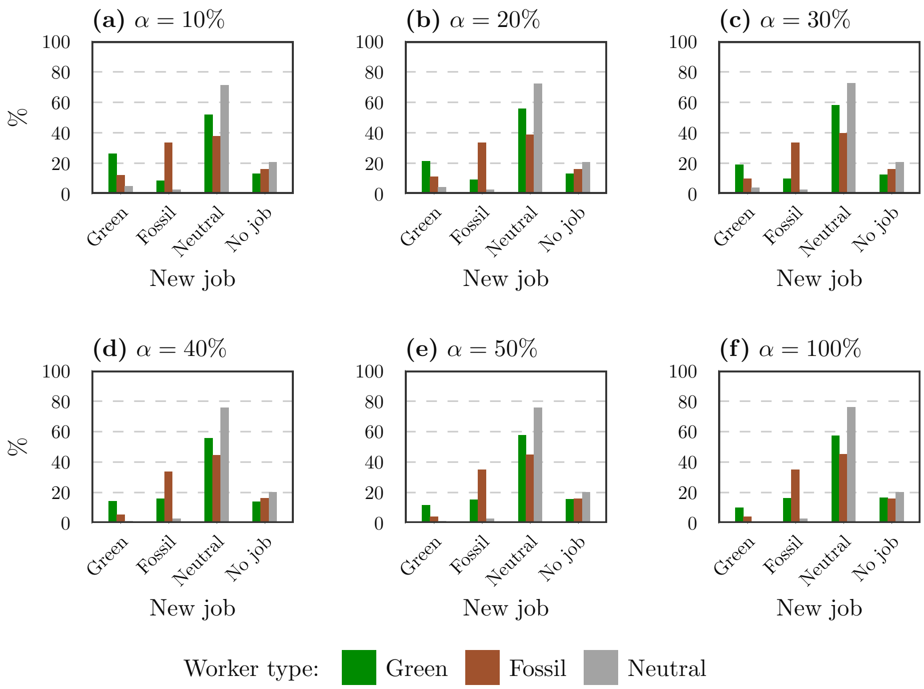

Figure D.4: Job-finding probability by α, type of job, and worker type (assuming only core tasks)

Note: The panels show the probability of transitioning to a green job, fossil job, neutral job, or unemployment by worker type (green, fossil, or neutral) assuming tasks are restricted to the "core" tasks. The panels differ in terms of α (i.e., the minimum share of green tasks for an occupation to be classified as "green").

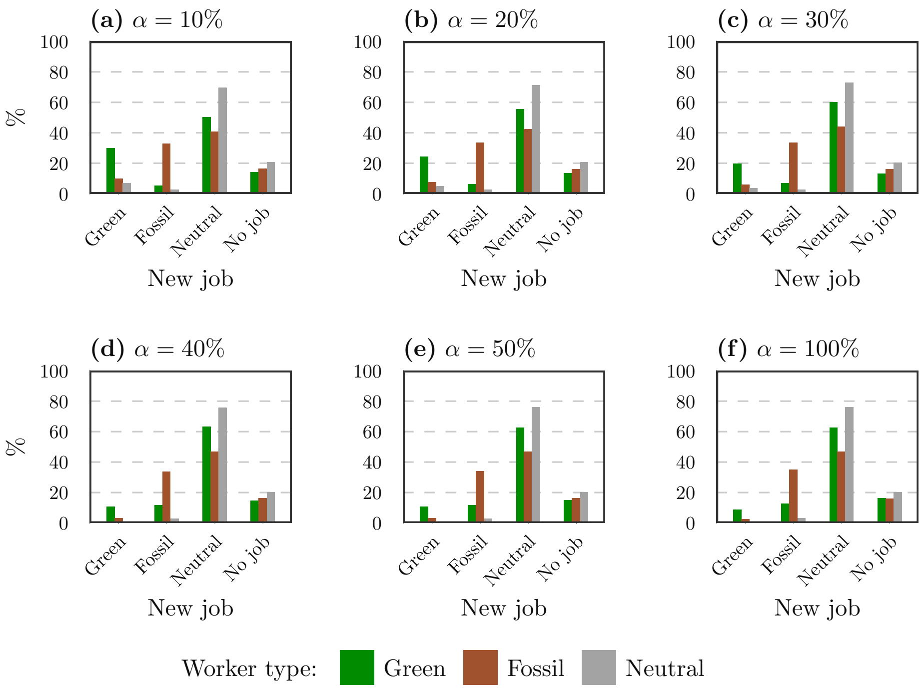

Figure D.5: Job-finding probability by α, type of job, and worker type (assuming no green jobs in dirty sectors)

Note: The panels show the probability of transitioning to a green job, fossil job, neutral job, or unemployment by worker type (green, fossil, or neutral) assuming green jobs are restricted to those in non-dirty sectors. The panels differ in terms of α (i.e., the minimum share of green tasks for an occupation to be classified as "green").

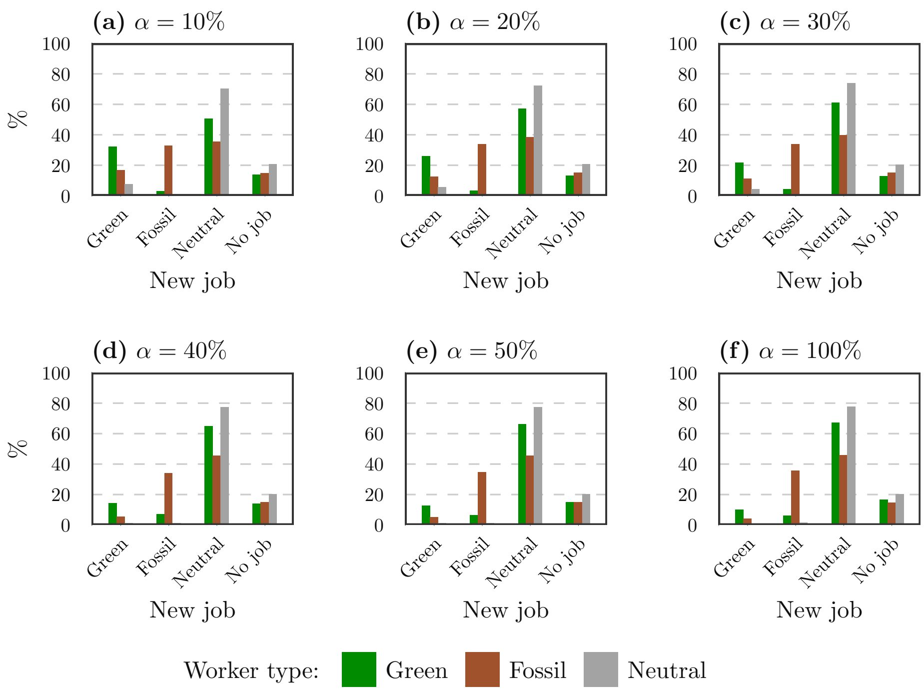

Figure D.6: Job-finding probability by α, type of job, and worker type (assuming only fossil jobs in dirty sectors)

Note: The panels show the probability of transitioning to a green job, fossil job, neutral job, or unemployment by worker type (green, fossil, or neutral) assuming fossil jobs are restricted to those in dirty sectors. The panels differ in terms of α (i.e., the minimum share of green tasks for an occupation to be classified as "green").

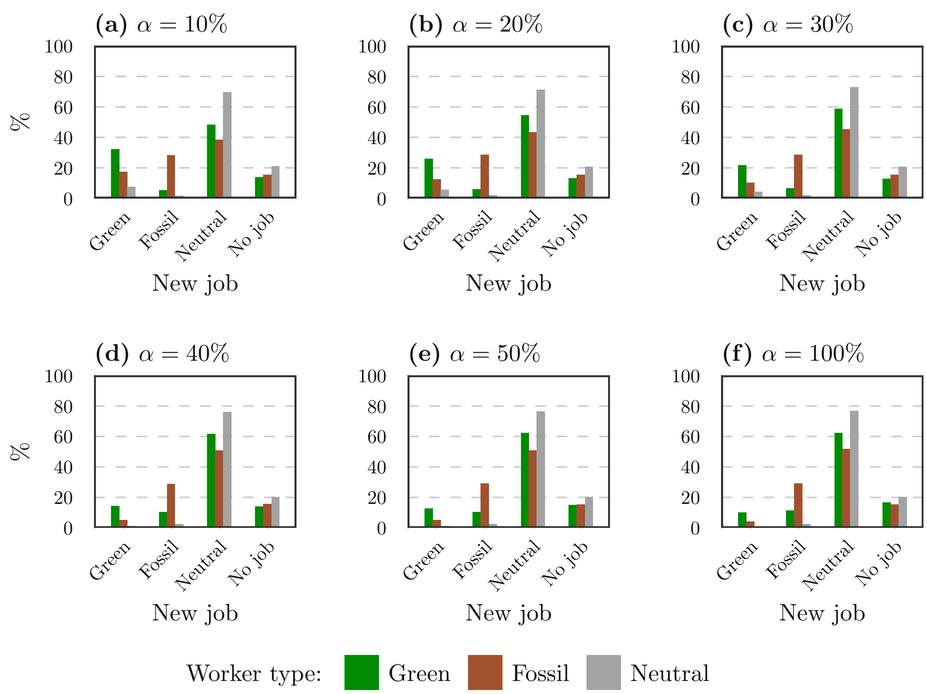

Figure D.7: Job-finding probability by α, type of job, and worker type (assuming dirty sectors lie in the top 1% of emissions-intensity)

Note: The panels show the probability of transitioning to a green job, fossil job, neutral job, or unemployment by worker type (green, fossil, or neutral) assuming dirty sectors are defined as sectors lying in the top 1% of emissions-intensity. The panels differ in terms of α (i.e., the minimum share of green tasks for an occupation to be classified as "green").

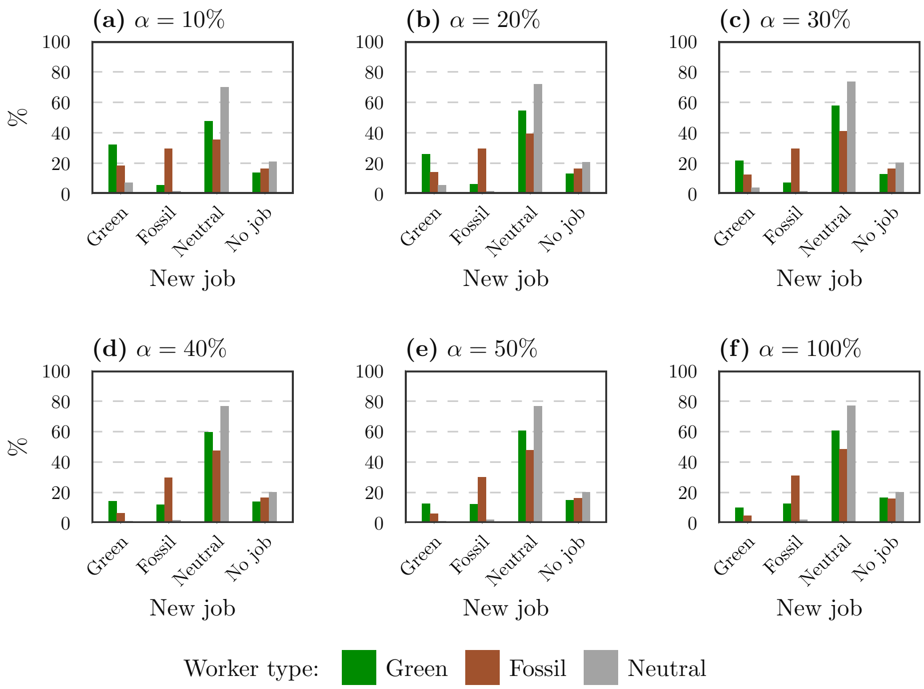

Figure D.8: Job-finding probability by α, type of job, and worker type (assuming fossil jobs are ≥ 10 more likely in a dirty sector)

Note: The panels show the probability of transitioning to a green job, fossil job, neutral job, or unemployment by worker type (green, fossil, or neutral) assuming fossil jobs are defined as jobs at least 10 times more likely than the average job to be found in a dirty sector. The panels differ in terms of α (i.e., the minimum share of green tasks for an occupation to be classified as "green").

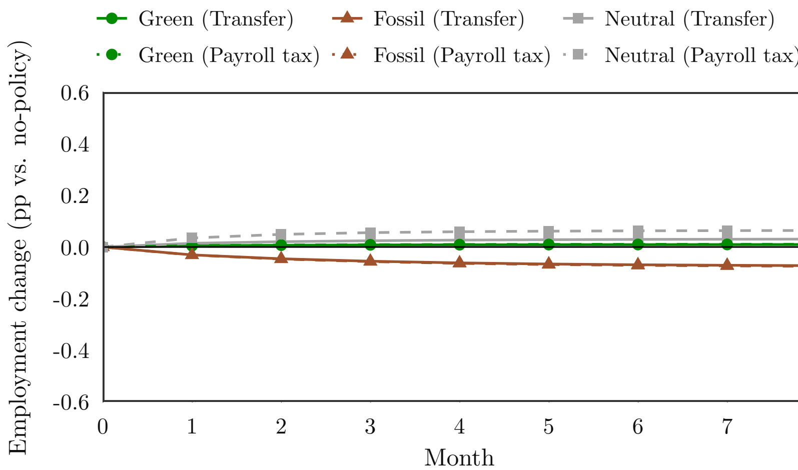

Figure D.9: Employment change from a carbon tax by job type and recycling mechanism

Note: The figure shows the change in employment, by job type, from a carbon tax with transfer ("Transfer") or payroll tax ("Payroll tax") recycling. The employment change is given in percentage points relative to the benchmark. The carbon tax is introduced in month $t = 0$.

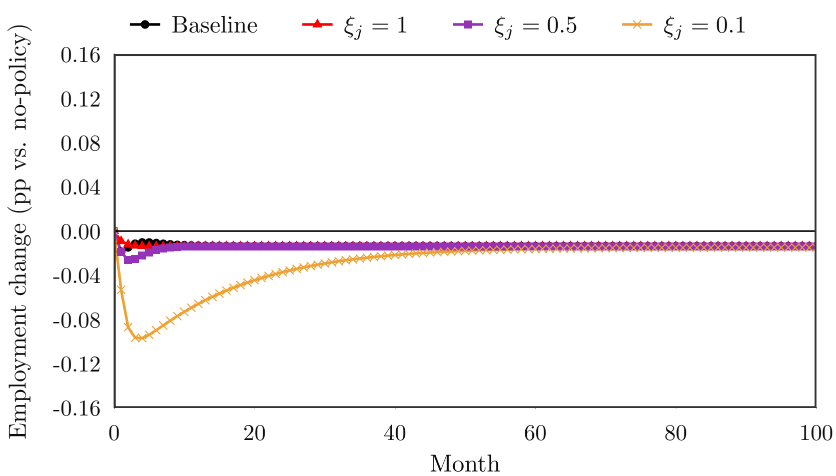

Figure D.10: Employment change from a green subsidy financed by payroll taxes by value of ξ_j

Note: The figure shows the employment change, by value of ξ_j, from a green subsidy financed by payroll taxes. The "Baseline" scenario assumes the values of ξ_j in Table 2. The employment change is given in percentage points relative to the benchmark. The green subsidy is introduced in month $t = 0$.