Labor Reallocation, Green Subsidies, and Unemployment *

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Abstract: Green subsidies are a common decarbonization tool, yet their labor market implications are not well understood. This paper examines the labor market and welfare impacts of green subsidies by combining a labor search model with evidence from U.S. microdata on worker transitions between green, fossil, and all remaining "neutral" jobs. A key insight from the microdata is that workers in fossil jobs rarely transition to green jobs and more often start neutral jobs. The results show that the impacts of green subsidies depend on the financing mechanism. While subsidies financed by payroll taxes reduce employment and welfare, subsidies financed in a non-distortionary manner increase employment. The employment gains translate into higher welfare relative to carbon pricing for low abatement levels. This suggests that appropriately funded green subsidies can serve as a cost-effective alternative to carbon pricing when emissions reductions are small.

Keywords: Green subsidies, Labor reallocation, Unemployment, Welfare

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1 Introduction

Green subsidies are prevalent, yet their labor market effects are largely unclear.[1] First, it is not known how green subsidies impact employment and welfare in the presence of search frictions that cause unemployment and hinder job transitions. Second, no study has examined whether employment outcomes from green subsidies are shaped by the tax system. Third, it is unclear how green subsidies compare to carbon pricing in terms of labor market impacts and welfare. Carbon pricing is widely advocated by economists, but can face public opposition (Dechezleprêtre et al., 2022; Douenne and Fabre, 2022). When carbon pricing cannot be used, it is valuable to know the implications of adopting green subsidies instead.

In this paper, I develop a search model to analyze the impacts of output-based green subsidies on the labor market and welfare. The model is characterized by search frictions that cause unemployment and prevent workers from transitioning between jobs. The contributions are threefold. First, I use microdata for the U.S. to estimate worker transitions between green, fossil, and all remaining "neutral" jobs. I use the estimates to quantify the frictions workers face when moving between jobs in the model. The estimates reveal that fossil workers rarely move to green jobs and more often start neutral jobs.

Second, I show that green subsidies can generate higher welfare relative to carbon pricing. This result is conditional on financing the subsidies in a non-distortionary manner and on a low abatement level. Subsidies financed by non-distortionary taxes counteract search frictions by increasing the return on recruitment. Firms take advantage of this by recruiting more workers, which creates an employment dividend in the form of lower unemployment. If abatement is low, the employment dividend translates into higher welfare compared to carbon pricing. However, the welfare advantage of a subsidy over carbon pricing disappears either at high abatement levels (when the subsidy is inefficient) or if the subsidy is financed by distortionary payroll taxes.

Third, I find that the tax system affects subsidies differently depending on the financing mechanism. Subsidies financed by payroll taxes perform worse in distortionary tax systems, while subsidies financed in a non-distortionary manner perform equally well. An implications is that non-distortionary financing is especially valuable in distortionary tax systems. In the following, I describe the model and elaborate on the contributions.

The model is similar to the framework in Hafstead and Williams (2018).[2] Unemployment in equilibrium results from endogenous recruitment and exogenous job loss. Climate

[1] By green subsidies, I mean payments or tax credits to producers of green products and services. The U.S., the EU, and China all give green subsidies. The U.S. Inflation Reduction Act provides production tax credits worth hundreds of billions of dollars to the wind power, solar power, hydrogen, carbon capture and storage, and battery value chains (Bistline, Mehrotra and Wolfram, 2023). Renewable electricity subsidies exceed €500 billion in the EU since 2015 (European Commission, 2023, 2025) and \$100 billion in China since 2020 (IEA, 2024).

[2] Hafstead and Williams (2018) build on the framework in Shimer (2010).

policy affects recruitment incentives, which changes the unemployment rate. The model differs from Hafstead and Williams (2018) in a number of ways. First, I account for empirically relevant "neutral" jobs that are not directly affected by climate policy. This allows me to study movements between three job types: green, fossil, and neutral jobs. Second, I apply my model to a different context by focusing on green subsidies. Third, I provide an empirical basis for the distribution of jobs and the frictions associated with labor reallocation.[3] In particular, I use U.S. occupational survey data to estimate the number of green, fossil, and neutral jobs as well as worker transitions between the jobs. I use the transition estimates to quantify the frictions workers face when moving between jobs that are differently exposed to climate policy in the model.

The first contribution is to provide empirical evidence on worker transitions between green, fossil, and neutral jobs in the U.S. I find that workers rarely move from fossil to green jobs. This reinforces the insight from previous studies that for workers in polluting industries can find it challenging to exploit job opportunities created from the green transition (Popp et al., 2021; Saussay et al., 2022; Colmer, Lyubich and Voorheis, 2023; Colmer et al., 2024; Curtis, O'Kane and Park, 2024). However, I also find that fossil workers frequently reallocate to neutral jobs. This result is driven by the abundance of neutral jobs and suggests that neutral jobs should not be overlooked in the context of the green transition.

The second contribution is to show that green subsidies can increase welfare relative to carbon pricing. This result is conditional, however, on a non-distortionary financing mechanism and a low abatement level. A subsidy financed in a non-distortionary manner has three effects. First, the subsidy increases the return on recruitment for green firms. This counteracts search frictions and increases green firms' recruitment. Second, the subsidy shifts demand to green goods by lowering their price. Green firms hire more workers, while firms elsewhere reduce recruitment. Third, the lump sum taxes financing the subsidy produce a negative income effect. However, because the taxes do not distort, the subsidy makes recruitment more attractive for green firms (from the first effect) without distorting other firms' recruitment. Employment thus expands. For low abatement levels, the employment gains translate into higher welfare relative to a carbon price.

A subsidy no longer increases welfare relative to a carbon price if abatement is high or if payroll taxes finance the subsidy. At high abatement levels, the subsidy induces inefficiently high green output which offsets the welfare gains from the lower unemployment. Moreover, financing a subsidy with payroll taxes increases distortions and eliminates the employment dividend. Unemployment then increases, which lowers welfare.

[3] There are three other differences with Hafstead and Williams (2018). First, I do not allow for an abatement technology. Abatement in my framework stems only from reductions in fossil firms' output. Second, I use a nested consumption structure. Third, I assume firms can face a heterogeneous level of friction when matching with workers of a different type, which implies that the frictions associated with labor reallocation are allowed to vary throughout the economy.

The third contribution is to illustrate the impact of the tax system on a subsidy's performance. The impact is heterogeneous across financing mechanisms. A subsidy financed in a non-distortionary manner is unaffected by the tax system, while a subsidy financed by payroll taxes generates lower employment and welfare in a distortionary tax system. Having access to a non-distortionary financing mechanism is thus especially valuable when the tax system is distortionary.

Related literature

The paper relates to four literature strands. The first empirically quantifies worker transitions between jobs that are unevenly affected by climate policy. An important task for these studies is to define fossil and green jobs. While fossil jobs are often tied to polluting industries, no standard definition exists for green jobs. One approach is to focus on the product associated with a job by calling, for instance, solar and wind power jobs green (Colmer, Lyubich and Voorheis, 2023) or broadening the scope to also include electric vehicle jobs (Curtis, O'Kane and Park, 2024). Another approach is to look at task content.[4] The green transition has created a need for new tasks, which 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 number of studies have adopted a task-based definition by conceptualizing green jobs on the basis of task content (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).

I use a task-based approach to identify green jobs. In particular, I define a job as green if it involves a high share of green tasks. This definition has three advantages. First, by not restricting itself to particular industries, it can capture the economy-wide set of jobs benefiting from the green transition, including jobs outside of traditionally green industries (e.g., climate scientists and installers of insulation). Second, the definition uses a narrow unit of analysis in the form of tasks. Third, it allows me to bring novel insights on green job transitions, as no study has quantified these transitions using a task-based definition of green jobs.

The second literature strand 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 Marin, Marino and Pellegrin, 2018; Yip, 2018 for carbon pricing). A challenge for these studies is that employment in counterfactual industries can be endogenous to environmental regulation due to workers moving between regulated and unregulated industries. Econometric estimates of employment changes therefore risk being biased (Hafstead and Williams, 2018). An alternative approach is

[4]Tasks are commonly used as the unit of analysis when assessing the labor market incidence of structural and technological change (Acemoglu and Autor, 2011; Autor, 2013).

to employ general equilibrium methods. Such methods are well-suited for studying labor movement across industries. They have generally been used, however, to analyze carbon pricing as opposed to green subsidies. A common result is that carbon pricing reallocates labor from fossil to green industries and leads 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). Representing unemployment using a reduced form approach, they find that the Inflation Reduction Act (IRA) generates a small increase in long run unemployment. Shimer (2013) analyzes the labor market impacts of green subsidies and pollution taxes in a theoretical framework characterized by workers spending an exogenous amount of time in unemployment if they switch industries. I complement these studies by examining green subsidies in a microfounded model with search frictions. 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 third literature strand looks at the interaction between environmental regulation and the tax system. A large body of work examines 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, 1995a,b; Parry, 1995; Bovenberg and Goulder, 1996; Goulder et al., 1999; Williams, 2002; Bento and Jacobsen, 2007; Carbone and Smith, 2008; Kaplow, 2012; Goulder, Hafstead and Williams, 2016; Barrage, 2019). Some attention has also been paid to green subsidies (e.g., Fullerton, 1997; Parry, 1998; Fullerton and Metcalf, 2001; Kaplow, 2012). I contribute to this literature by relaxing the full employment assumption. In particular, I examine how green subsidies affect involuntary unemployment given various tax systems. No study has, to my knowledge, analyzed this issue in a microfounded model of unemployment. By focusing on subsidies, my paper complements previous work on the interplay between carbon pricing, the tax system, and involuntary unemployment (Nielsen, Pedersen and Sørensen, 1995; Bovenberg and van der Ploeg, 1996; Carraro, Galeotti and Gallo, 1996; Bovenberg, 1997; Bovenberg and van der Ploeg, 1998a,b; Koskela and Schöb, 1999; Wagner, 2005; Hafstead and Williams, 2018).

Finally, my paper relates to the search literature and, in particular, to studies using search models to estimate the employment effects 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 matches. Shimer (2010) develops a one-sector matching function that takes recruitment effort and the number of unemployed workers as inputs. Hafstead and Williams (2018) extend this function to accommodate multiple firm and worker types. A key parameter in their matching function is the friction associated with matching between firms and workers of different types. I calibrate this parameter on the basis of survey data and allow it to vary by firm type to reflect differences in frictions throughout the economy.

The paper is structured as follows. Section 2 estimates the distribution of jobs and job transitions in the U.S. Section 3 describes the model. Section 4 details the calibration procedure. Section 5 presents the numerical results. Section 6 concludes.

2 Empirical analysis

This section estimates the distribution of jobs and job transitions in the U.S. Section 2.1 describes the data. Section 2.2 explains the procedure. Section 2.3 presents the estimates.

2.1 Occupational data

I obtain occupational data from the Survey of Income and Program Participation (SIPP). SIPP is a representative longitudinal survey of the U.S. population that is administered annually by the U.S. Census Bureau. The survey follows individuals over four years and asks them about their monthly occupation.[5] I make use of two panels: one for the period 2013-2016 and another for 2017-2020.[6] This gives me monthly occupations over an eight-year span.[7] The next step is to classify the occupations as green, fossil, or neutral.

2.2 Classifying the occupations

2.2.1 Green occupations

I define an occupation as green if its share of green tasks equals or exceeds a threshold α.[8] I set $\alpha = 50\%$ in the main specification and conduct sensitivity on this value. To operationalize the definition, I obtain task data from 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 U.S. Version 24.1 of the database

[5] If respondents report multiple jobs in a month, I determine their main job based on hours worked. In case of a tie, I choose the job with the highest income or, if a tie remains, the first job that month.

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

[7] I map the occupations from the Census Occupation system to the 6-digit 2010 Standard Occupational Classification (SOC) system using crosswalks from the U.S. Census Bureau, available at https://www.census.gov/topics/employment/industry-occupation/guidance/code-lists.html. 42 out of 518 occupations in the 2017-2020 panel have a one-to-many mapping. To achieve a one-to-one mapping, I choose the modal SOC code in the 2013-2016 panel (see Table A.1 in Online Appendix A).

[8] This approach is similar to Vona et al. (2018) who define an occupation as green if its green task share exceeds 10%.

contains detailed task information for 974 occupations on an 8-digit O*NET-SOC level.[9] The information includes task importance scores and a classification of tasks as green or non-green.[10,11] Following Vona, Marin and Consoli (2019), I weight tasks by their importance score and calculate a weighted green task share by occupation.[12] I then average the shares to the 6-digit occupational level used by SIPP (see Online Appendix B for the procedure). 11 occupations in SIPP (Table A.3 in Online Appendix A) have at least 50% green tasks and are labeled green.

2.2.2 Fossil occupations

I define fossil occupations as occupations disproportionately found in emissions-intensive ("dirty") industries using a two-step procedure.[13]

First, I establish a set of dirty industries. To do this, I obtain facility-level greenhouse gas emissions data for 2019 from the Environmental Protection Agency (EPA).[14] I aggregate the data to an industry-level and combine them with employment data from the Bureau of Labor Statistics (BLS) to calculate emissions-intensity by industry.[15] I call an industry dirty if it lies in the top five percent of employment-weighted emissions-intensity. Table C.4 in Online Appendix C lists the industries classified as dirty.

Second, I classify an occupation in SIPP as fossil if it is at least eight times more likely than the average occupation to be found in a dirty industry.[16] This gives 63 fossil occupations (see Table A.4 in Online Appendix A).[17]

[9] O*NET collects the task information from surveys, desk research, and expert input. The surveys are carried out by first selecting a sample of firms employing workers of a given occupation (where the selection probability is proportional to the number of employees engaged in the occupation) and then surveying a random sample of workers in these firms (U.S. Department of Labor, 2012).

[10] The importance scores are based on employee surveys and expert opinion. The scores range from 1 (not important) to 5 (very important) on a Likert scale. 24 occupations lack scores for some tasks. I assign these tasks the occupation's minimum score in line with Vona, Marin and Consoli (2019).

[11] 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 tasks of each occupation were identified from a literature review and online sources. Tasks that O*NET identified as being affected by the green economy were labeled green.

[12] 41 occupations have a weighted green task share of at least 50% (Table A.2 in Online Appendix A).

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

[14] The data are from the EPA's Greenhouse Gas Reporting Program (GHGRP), which requires large emitters to report scope one emissions. The emitters are power plants, oil and gas systems, and industry (including underground coal mines). The emissions include CO_2, CH_4, N_2O, HFC, PFC, SF_6, and NF_3.

[15] The BLS data are from the Occupational Employment and Wage Statistics program.

[16] SIPP reports the industries in which respondents work. I convert the industries in the 2013-2016 panel from version 2012 to version 2017 of the Census Industry system using a crosswalk from the U.S. Census Bureau, available at `https://www.census.gov/topics/employment/industry-occupation/guidance/code-lists.html`. I then harmonize the industry codes between SIPP and the dirty industry classification by converting the latter from NAICS to the Census Industry system (see Online Appendix C for more on this) using crosswalks from the U.S. Census Bureau, available at `https://www.census.gov/topics/employment/industry-occupation/guidance/code-lists.html`.

[17] Two occupations are both green and fossil: "17-2141 - Mechanical Engineers" and "51-9199 - Pro-

2.3 Empirical estimates

2.3.1 Distribution of jobs

I apply the classification to the jobs in SIPP and call jobs that are not green or fossil neutral. Fig. 1 shows the evolution of green and fossil jobs in the U.S. The share of fossil jobs decreased from 5.5% to 4.9% during 2013-2020, while the share of green jobs increased slightly from 1.5% to 1.7%.[18] The combined share of green and fossil jobs is less than 10% in every year. Most jobs are therefore neutral.[19]

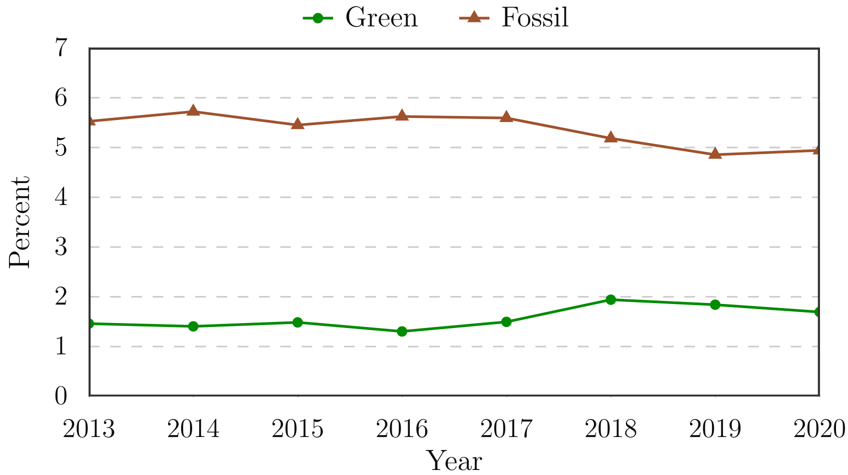

Figure 1: Green and fossil job shares over time
Note: The figure shows the percent of green and fossil jobs in the U.S. during 2013-2020.

2.3.2 Job transitions

Fig. 2 depicts job transition probabilities by worker and job types.[20] The brown bars illustrate that fossil workers are only 5% likely to start a green job and eight times more likely to transition to a neutral job.[21] The sensitivity analysis in Appendix A shows

duction Workers, All Other". I classify them as green and do sensitivity on this in Section 2.3.

[18]The green job 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). Curtis and Marinescu (2023) and Curtis, O'Kane and Park (2024) find green job shares below one percent. They focus on green jobs in a subset of industries, while my analysis spans all industries.

[19]Appendix A conducts sensitivity on these estimates. The majority of jobs are neutral in all sensitivity tests in line with the main specification. For reasonable values of α, green jobs account for a small employment share of less than 2.2% in all sensitivity tests.

[20]Some job transitions in SIPP (e.g., waiters switching restaurants) occur between jobs with the same occupation code. I cannot identify these transitions on the basis of occupation codes since the codes do not change. I identify them instead as follows. First, I assume that a change in either the industry or a job's unique identifier code reflects a job transition. Second, SIPP assigns January as the starting month for jobs continued from the previous year and I therefore assume any other starting month indicates a job transition. Third, I assume the end of an unemployment spell implies a job transition.

[21]The low transition probability from fossil to green jobs is in line with Colmer, Lyubich and Voorheis (2023) and Curtis, O'Kane and Park (2024), who find transition probabilities below one percent. With

that these findings are qualitatively robust: fossil workers rarely start green jobs and are more likely to move to neutral jobs in all specifications. These findings have two key implications. First, because fossil workers rarely start green jobs, they likely face reallocation costs. Second, neutral jobs are pertinent to the green transition since fossil workers often reallocate to them.

How much are the job transition probabilities driven by the availability of each job type? Fossil workers might rarely move to green jobs simply because these jobs are scarce and often start neutral jobs since they are numerous. To correct for differences in job availability, Fig. B.1 in Appendix B shows how the job transition probabilities would change if there were an equal number of each job type. Two key insights emerge. First, the new probability of starting a green job is lowest for fossil workers, which suggests that their lack of movement to green jobs is not only due to the scarcity of these jobs. Second, the probability of starting a neutral job decreases considerably for fossil workers, which implies that their high reallocation rate in Fig. 2 is largely driven by the abundance of neutral jobs.

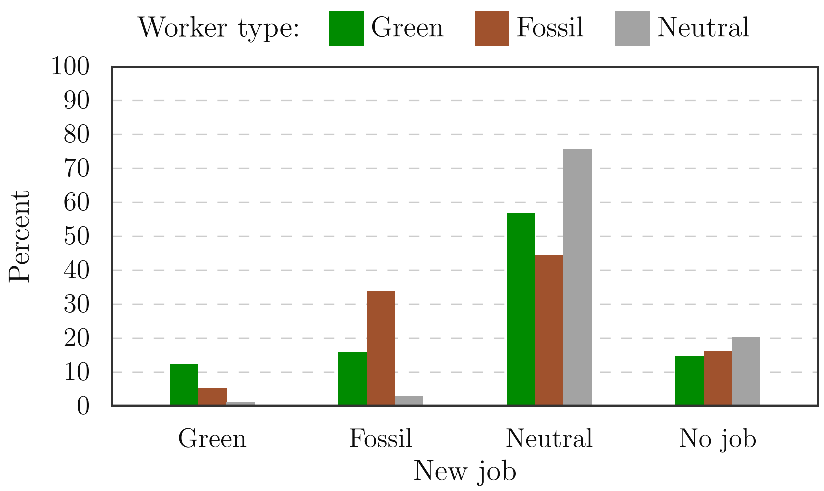

Figure 2: Job transition probabilities by worker type and job type
Note: The figure shows the transition probabilities to green jobs, fossil jobs, neutral jobs, and unemployment by worker type in the U.S. during 2013-2020.

Finally, Table 1 depicts the distribution of workers starting each job. The first numerical column shows the distribution of workers starting green jobs: 14% of workers were green (i.e., previously had a green job), 18% were fossil, and 68% were neutral. The table's diagonal elements are the share of transitions from the same job type. 14% of workers starting green jobs previously had a green job, 39% of workers starting fossil jobs previously had a fossil job, and 95% of workers starting neutral jobs previously had a neutral job. Section 4.2 uses the diagonal elements to calibrate the frictions associated

regard to transitions from fossil to neutral jobs, Colmer, Lyubich and Voorheis (2023) find a transition probability of around 50%, which is similar to my probability of 45%.

with labor reallocation in the search model. The model is described next.

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 starting green, fossil, and neutral jobs in the U.S. during 2013-2020. Some columns sum imperfectly to unity due to rounding. The employment shares of green, fossil, and neutral workers were 1.6%, 5.4%, and 93.1% respectively in 2020.

3 Search model

The model builds on Hafstead and Williams (2018) and is characterized by search frictions (Pissarides, 1985; Mortensen and Pissarides, 1994) in the labor market. The search frictions imply that firms have to invest in recruitment to match with workers. Unemployment is determined by the amount of endogenous recruitment and exogenous job loss. I assume that only unemployed workers search for jobs.[22] Climate policy affects recruitment by changing the value of a match. The model is elaborated on below.

3.1 Basic set-up

The time resolution is monthly.[23] There are three firm types: fossil firms ($j = \mathtt{f}$), green firms ($j = \mathtt{g}$), and neutral firms ($j = \mathtt{z}$). There are n_j workers employed at firm j and u_i unemployed workers that previously worked for firm i. Total employment is $\overline{n} := \sum_j n_j$ and total unemployment is $\overline{u} := \sum_i u_i$. The workforce is normalized to unity, meaning $\overline{n} + \overline{u} = 1$.

3.2 Firms

Firm j employs l_j production workers and $n_j - l_j = v_j$ recruiters. Production workers generate output, while recruiters hire workers. Workers are identical meaning firms are indifferent between assigning a new worker to production or recruitment. All workers at firm j receive wage w_j and work h_j hours.

[22] Job searchers are therefore synonymous with unemployed workers.

[23] The time subscripts are suppressed henceforth for legibility.

3.2.1 Production

Production workers use a constant-returns-to-scale technology that converts labor into output y_j according to

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

where ζ is labor productivity. Output is sold at net price p_j^y. Fossil firms generate ϵ emissions per unit of output. Green and neutral firms are emissions-free.

3.2.2 Matching

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

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

where μ_j is matching efficiency, k is an alias for j, γ is the matching elasticity, δ_{ij} equals 1 for $i = j$ and 0 otherwise, and ξ_j controls the friction associated with cross-type matching. The number of matches m_{ij} between job searcher i and firm j is increasing in the firm's recruitment effort and the number of job searchers of type i. Conversely, it is decreasing in economy-wide recruitment effort (as more effort by other firms reduces the likelihood of a match for firm j) and the total number of job searchers (as more competition makes a match less likely for job searcher i).

ξ_j ranges from 0 to 1. If $\xi_j = 0$, firm j can only recruit job searchers of its own type, meaning job searcher $i \neq j$ cannot match with firm j. If $\xi_j = 1$, matching does not depend on a job searcher's type, implying *ceteris paribus* that all job searchers are equally likely to match with firm j. For values in between, the share of cross-type matches for firm j is proportional to ξ_j, holding all else constant.

Recruitment productivity $q_j = \sum_i m_{ij}/(\upsilon_j h_j)$ equals the number of matches per unit of recruitment effort, while the job-finding probability $\phi_{ij} = m_{ij}/u_i$ for job searcher i at firm j is the ratio of the number of matches between them to the number of job searchers of type i. Using Eq. 2, the recruitment productivity and job-finding probability can be expressed in terms of labor market tightness measures θ_{ij}, θ_j, and θ:

$$q_j = \mu_j \left[\xi_j \theta^{-\gamma} + (1-\xi_j)\theta_{jj}^{-\gamma} \right], \tag{3}$$

$$\phi_{ij} = \mu_j \left[\xi_j \theta_j \theta^{-\gamma} + (1-\xi_j)\theta_{ij}^{1-\gamma} \delta_{ij} \right], \tag{4}$$

where $\theta_{ij} = \upsilon_j h_j / u_i$ is the ratio of firm j's recruitment effort to the number of job searchers of type i, $\theta_j = \upsilon_j h_j / \overline{u}$ is the ratio of firm j's recruitment effort to the total number of job searchers, and $\theta = \sum_j \upsilon_j h_j / \overline{u}$ is the ratio of total recruitment effort to the total number of job searchers.

3.2.3 Firm's problem

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

$$\overline{v}_j = \frac{v_j}{n_j}. \tag{5}$$

The firm's problem is to choose the $\overline{v}_j$ that maximizes the firm's value over time. The firm's value equals revenue minus after-tax labor costs plus expected future profits. Denoting values in the next period with an apostrophe, the Bellman equation is

$$J(n_j) = \max_{\overline{v}_j}\left[p_j^y \zeta h_j n_j \big(1-\overline{v}_j\big) - \big(1+\tau^P\big) n_j h_j w_j + \mathbb{E}\Big[p^a J(n_j')\Big]\right], \tag{6}$$

where J is the firm's value function, τ^P is a payroll tax, p^a is the price of an Arrow security, and next period employment n_j' is current employment minus layoffs at rate π plus hires:

$$n_j' = n_j - n_j\pi + n_j q_j \overline{v}_j h_j. \tag{7}$$

Denoting partial derivatives with a subscript, the first-order condition is

$$p_j^y \zeta = q_j \mathbb{E}\Big[p^a J_{n_j}'\Big], \tag{8}$$

where J_{n_j}' is the value in the next period of employing a worker today. Eq. 8 states that, in equilibrium, the value of a production worker's output equals the present value of the profits that a recruiter indirectly generates from hiring workers.

Differentiating Eq. 6 with respect to n_j gives the envelope condition. It states that the firm's match value J_{n_j} equals the value of the worker's output minus after-tax labor costs plus the present value of the worker in the next period:

$$J_{n_j} = p_j^y \zeta h_j - \big(1+\tau^P\big) h_j w_j + (1-\pi)\mathbb{E}\Big[p^a J_{n_j}'\Big]. \tag{9}$$

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.[24,25] Workers get utility from consumption and disutility from work. Consumption is separable from leisure and identical across employed and unemployed workers. Utility is

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

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

[25] The full insurance assumption, dating back to Merz (1995), is common in the search literature and simplifies the household's problem (Hall, 2009). It implies that the household maximizes the combined utility of workers by equalizing the marginal utility of consumption across workers.

where ψ is disutility from work and χ is the Frisch elasticity of labor supply. Consumption of the aggregate good C is a constant elasticity of substitution (CES) aggregate of a fossil-green composite and the neutral good (see Fig. 3 for the nesting structure). Consumption c_r of good $r \in \{\mathtt{f},\mathtt{g},\mathtt{z},\mathtt{fg}\}$ is

$$c_r = \varrho_r \left(\frac{p_{\mathtt{fg}}}{p_r}\right)^{\sigma^{fg}} c_{\mathtt{fg}} \qquad \forall r \in \{\mathtt{f},\mathtt{g}\}, \tag{10}$$

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

where $r = \mathtt{fg}$ is the fossil-green composite, ϱ_r is a share parameter, σ^{fg} and σ^C are elasticities, p_r is the gross price of good r, and p^C is the gross price of the aggregate good. The gross prices of the fossil, green, and neutral goods are complementary to the market clearing conditions such that

$$y_j \geq c_j \quad \perp p_j \quad \forall j, \tag{12}$$

where $\perp$ indicates complementarity. The gross prices $p_{\mathtt{fg}}$ and p^C are defined by

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

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

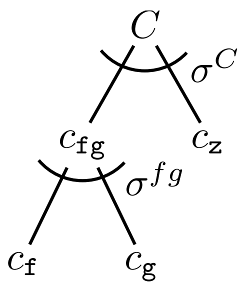

Figure 3: Consumption structure

Note: The figure shows the consumption structure. The aggregate good is created from a fossil-green composite and the neutral good.

An employed worker earns income $w_j h_j$ and faces income tax τ^L. An unemployed worker receives unemployment benefits b_i. The representative household receives a transfer T from the government and owns assets a.

The household's problem is to choose the consumption C and 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

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

subject to

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

where V is a value function. The first-order conditions imply that the marginal utility of consumption equals the marginal cost of consumption and that the present value of one unit of future assets equals the cost of this unit:

$$
\begin{aligned}
\frac{1}{C} &= \lambda p^C, \\
\beta \mathbb{E}\Big[V'_{a'}\Big] &= \lambda p^a, \qquad (16)
\end{aligned}
$$

where λ is the Lagrange multiplier for the budget constraint.

Differentiating Eq. 13 with respect to a and inserting into Eq. 16 gives the Euler equation $p^a \lambda = \beta \lambda'$. Differentiating Eq. 13 with respect to n_j and u_i gives the envelope conditions

$$
V_{n_j} = U\big(C, h_j\big) + \lambda\big(1-\tau^L\big) w_j h_j + \beta\Bigg((1-\pi)\mathbb{E}\Big[V'_{n_j}\Big] + \pi \mathbb{E}\Big[V'_{u_j}\Big]\Bigg) \qquad \forall j, \qquad (17)
$$

$$
V_{u_i} = U\big(C, 0\big) + \lambda p^C b_i + \beta\Bigg(\mathbb{E}\Big[V'_{u_i}\Big] + \sum_j \phi_{ij}\Bigg(\mathbb{E}\Big[V'_{n_j}\Big] - \mathbb{E}\Big[V'_{u_i}\Big]\Bigg)\Bigg) \qquad \forall i. \qquad (18)
$$

Eq. 17 states that the value of an employed worker for the household equals the worker's utility plus the value of after-tax labor income and the discounted expected value in the next period if the worker is employed with probability $1-\pi$ and unemployed with probability π. Eq. 18 states that the value of an unemployed worker equals 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, and the worker then joins the firm in the following period. The match surplus is the value to the firm of an additional worker plus the value to the household of a worker being hired. 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 η denotes the firm's bargaining power. Solving gives the equilibrium conditions for hours and wages.[26] Hours are chosen to maximize the match surplus (Eq. 19), while the wage is set such that each party receives a fixed share of the surplus (Eq. 20).[27]

$$(1+\tau^P)\psi h_j^{\frac{1}{\chi}} = (1-\tau^L)\lambda p_j^y \zeta \quad \forall j, \tag{19}$$

$$(1-\tau^L)h_j w_j = (1-\eta)\left[\frac{1-\tau^L}{1+\tau^P} p_j^y \zeta h_j\right] + \eta\left[\frac{\psi\chi h_j^{1+\frac{1}{\chi}}}{\lambda(1+\chi)} + p^C b_j + \beta\frac{\sum_i \phi_{ji}\left(V'_{n_i} - V'_{u_j}\right)}{\lambda}\right] \quad \forall j. \tag{20}$$

3.5 Government and climate policy

The government has two climate policy instruments. The first is an excise subsidy s on green firms' output and the second is an excise price τ^E on fossil firms' emissions. The net price p_j^y is the gross price adjusted for subsidy receipts and carbon pricing payments:

$$p_j^y = \begin{cases} p_j + s & \text{for } j = \mathtt{g}, \\ p_j - \tau^E \epsilon & \text{for } j = \mathtt{f}, \\ p_j & \text{for } j = \mathtt{z}. \end{cases} \tag{21}$$

Inserting the definition of p_j^y in Eq. 21 into Eq. 9 shows that climate policy affects a firm's match value J_{n_j}. A green subsidy increases the match value for green firms by making workers generate $p_{\mathtt{g}} + s > p_{\mathtt{g}}$ per unit of output. A carbon price, however, reduces the match value for fossil firms since they receive $\tau^E\epsilon$ dollars less per unit of output.

The government collects tax and carbon pricing revenue and returns the revenue as transfers, unemployment benefits, and subsidy payments. The budget constraint is

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

4 Calibration

The model is calibrated to the U.S. economy in 2019 using secondary sources and the business as usual (BAU) benchmark. Table 2 summarizes the calibration.

4.1 Calibration using secondary sources

The quit rate π is set equal to the average U.S. job separation rate in 2019 of 3.9%.[28] The bargaining power is split equally across firms and workers ($\eta = 0.5$), which is standard

[26] The derivations of Eqs. 19 and 20 are analogous to the one-good framework in Shimer (2010) and are therefore omitted for conciseness.

[27] The after-tax wage is a weighted average of the marginal product of labor (first square bracket in Eq. 20) and the marginal rate of substitution between consumption and leisure (second square bracket).

[28] See the Job Openings and Labor Turnover Survey of the BLS, available at `https://data.bls.gov/timeseries/JTS000000000000000TSR`.

Table 2: Calibration overview

(a) Direct calibration based on secondary sources

Parameter description	Symbol	Value	Source
Quit rate	π	0.037	BLS
Bargaining power of employer	η	0.5	Literature
Matching elasticity	γ	0.5	Literature
Discount factor	β	0.997	World Bank
Frisch elasticity of labor supply	χ	1	Literature
Elasticity in top consumption nest	σ^C	0.5	Literature
Elasticity in bottom consumption nest	σ^{fg}	0.75	Set relative to σ^C
Labor income tax	τ^L	0.29	OECD
Payroll tax	τ^P	0.15	OECD

(b) Calibration using the benchmark

Parameter description	Symbol	Value
Cross-type matching friction for firm $j \in \{\texttt{f,g,z}\}$	ξ_j	0.58, 0.87, 1
Matching efficiency for firm $j \in \{\texttt{f,g,z}\}$	μ_j	4.19, 3.87, 3.84
Labor productivity	ζ	3.20
Disutility of work	ψ	5.93
CES share of good $r \in \{\texttt{f,g,z,fg}\}$	ϱ_r	0.73, 0.27, 0.93, 0.07
Unemployment benefits for worker $i \in \{\texttt{f,g,z}\}$	b_i	0.25, 0.27, 0.28
Emissions factor of fossil firms	ϵ	0.00741

Note: Panel (a) lists the parameters that are calibrated based on the literature and data sources. Panel (b) lists the parameters that are calibrated using the benchmark.

in the literature (e.g., Mortensen and Pissarides, 1999; Ljungqvist and Sargent, 2017; Finkelstein Shapiro and Metcalf, 2023). Regarding the elasticity of matches with respect to unemployment γ, 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. I adopt a middle value of $\gamma = 0.5$ in line with Yedid-Levi (2016) and Hafstead and Williams (2018).

The average U.S. real interest rate was 3.43% in 2019,[29] which implies a monthly discount factor β of $1.0343^{-1/12} = 0.997$. The Frisch elasticity of labor supply χ is set to unity in line with Hall and Milgrom (2008). The elasticity of substitution between the green-fossil composite and the neutral good σ^C equals 0.5, which is a standard value in aggregated CES consumption structures (e.g., Landis, Fredriksson and Rausch, 2021). The elasticity between the fossil and green goods σ^{fg} is higher (0.75) to reflect the larger switch in consumption from fossil to green goods as a result of climate policy.

U.S. tax data for 2019 were obtained from the OECD.[30] The average marginal federal

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

[30] See "Table I.4. Marginal personal income tax and social security contribution rates on gross labour

and state labor income tax was 29% ($\tau^L = 0.29$), while the average marginal payroll tax, consisting of social security contributions of employers and workers, was 15% ($\tau^P = 0.15$).

4.2 Calibration using the benchmark

I make six assumptions in the benchmark. First, I set $\overline{u} = 5.9\%$ to mirror the average U.S. unemployment rate during 2000-2019.[31] This implies $\overline{n} = 1 - \overline{u} = 94.1\%$. Second, total employment $\overline{n}$ and total consumption C are distributed according to the green, fossil, and neutral employment shares of 1.8%, 4.9%, and 93.3% respectively in 2019 (see Fig. 1). Third, without loss of generality, prices, total consumption, and workers' time endowment are normalized to unity. Fourth, one third of the time endowment (i.e., eight hours per day) is spent working, meaning $h_j = 1/3$. Fifth, recruitment productivity q_j is held fixed. Silva and Toledo (2009) estimate that the cost of recruiting one worker is around 4% of a quarterly wage, which is 12% of a monthly wage. Assuming this cost is borne in terms of hours, a recruiter spends 12% of their time hiring one worker, or $0.12 \times \frac{1}{3} = 0.04$ hours. A recruiter thus hires $1/0.04 = 25$ workers per hour, meaning $q_j = 25$ in the benchmark. Sixth, the shares of within-type matches equal 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

$$\omega_j = \frac{m_{jj}}{\sum_i m_{ij}}. \tag{22}$$

I set ω_j equal to the diagonal elements of Table 1 so that $\omega_{\mathtt{f}} = 0.39, \omega_{\mathtt{g}} = 0.14$, and $\omega_{\mathtt{z}} = 0.95$. These values denote the share of workers starting job j that previously had the same job j.[32]

4.2.1 Calibrating ξ_j

To estimate ξ_j, I recall that $q_j = \sum_i m_{ij}/(\upsilon_j h_j)$ and $\phi_{ij} = m_{ij}/u_i$.[33] Rearranging and substituting into Eq. 22 gives $\omega_j = u_j \phi_{jj}/(\upsilon_j h_j q_j)$. Combining with Eqs. 3 and 4 gives

$$\omega_j = \frac{u_j \left[\xi_j \theta_j \theta^{-\gamma} + (1 - \xi_j) \theta_{jj}^{1-\gamma} \right]}{\upsilon_j h_j \left[\xi_j \theta^{-\gamma} + (1 - \xi_j) \theta_{jj}^{-\gamma} \right]} \quad \forall j. \tag{23}$$

income", available at https://stats.oecd.org/index.aspx?DataSetCode=TABLE_I4#.

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

[32] Estimating ω_j on the basis of only unemployed workers' job transitions gives the same values for the green and neutral types and a slightly lower value ($\omega_{\mathtt{f}} = 0.33$) for the fossil type.

[33] No empirical estimate exists 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 ($\xi_j = 1$). Hafstead and Williams (2018) conduct sensitivity on ξ_j, but do not take a stance on the empirical value.

Eq. 23 links ξ_j to $\{u_j\}_{j\in\{\mathtt{f},\mathtt{g},\mathtt{z}\}}$ and exogenous parameters.[34] To define u_j, I note that employment and unemployment are constant in the steady state. Eqs. 14 and 15 thus imply $u_j = \sum_i u_i\phi_{ij}/\sum_i \phi_{ji}$, which, using Eq. 4, can be rewritten as

$$u_j = \frac{\overline{u}\mu_j\left[\xi_j\theta_j\theta^{-\gamma} + (1-\xi_j)\theta_{jj}^{1-\gamma}\right]}{\sum_i \mu_i\left[\xi_i\theta_i\theta^{-\gamma} + (1-\xi_i)\theta_{ji}^{1-\gamma}\delta_{ij}\right]} \quad \forall j. \tag{24}$$

Eqs. 23 and 24 are two sets of equations for two sets of unknowns: $\{u_j\}_{j\in\{\mathtt{f},\mathtt{g},\mathtt{z}\}}$ and $\{\xi_j\}_{j\in\{\mathtt{f},\mathtt{g},\mathtt{z}\}}$.[35] Solving gives $u_{\mathtt{f}} = 0.002, u_{\mathtt{g}} = 0.001, u_{\mathtt{z}} = 0.056$, and

$$\xi_j = \begin{cases} 0.58 & \text{for } j = \mathtt{f}, \\ 0.87 & \text{for } j = \mathtt{g}, \\ 1 & \text{for } j = \mathtt{z}.^{36} \end{cases}$$

The high values of ξ_j for neutral and green firms mean these firms can easily match with outside workers. Fossil firms have a lower ξ_j and thus face more friction when matching with outside workers.

4.2.2 Calibrating the remaining parameters

The matching efficiency μ_j is pinned down by rearranging Eq. 3 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 $y_{\mathtt{g}} = n_{\mathtt{g}}$, $l_{\mathtt{g}} = n_{\mathtt{g}} - \upsilon_{\mathtt{g}}$, and $h_{\mathtt{g}} = 1/3$.[37] Disutility of work ψ is pinned down by the hour bargaining condition in Eq. 19. The CES consumption shares ϱ_r are obtained from Eqs. 10 and 11. Similarly to Hafstead and Williams (2018), unemployment benefits b_i are endogenously determined by the wage bargaining condition in Eq. 20. I get $b_{\mathtt{f}} = 0.25, b_{\mathtt{g}} = 0.27$ and $b_{\mathtt{z}} = 0.28$. 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 to Hafstead and Williams (2018). First, personal consumption expenditure in the U.S. was \$14.4 trillion in 2019,[38] while CO_2 emissions were 5.234 billion tons.[39] The emissions-intensity of

[34] υ_j is exogenously determined by Eqs. 5 and 7. Because employment in the steady state is constant, the two equations imply $\upsilon_j = n_j\pi/(q_jh_j)$.

[35] Note that μ_j is a function of ξ_j and $\{u_j\}_{j\in\{\mathtt{f},\mathtt{g},\mathtt{z}\}}$ (see Section 4.2.2).

[36] ξ_j is restricted to a maximum value of 1 as this represents an extreme whereby matching is independent of a worker's type.

[37] The choice of firm type here is arbitrary as y_j/l_j and $1/h_j$ are identical across firms in the benchmark.

[38] 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.

[39] 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.

consumption was therefore 0.000363 tCO_2/\$. Second, I adjust this number for the fact that only fossil firms emit. Fossil consumption accounts for 4.9% of total consumption (that equals one) in the benchmark, meaning the emissions factor of fossil firms is 0.00741 tCO_2 per dollar of output.

5 Labor market and welfare impacts

This section presents the labor market and welfare impacts of green subsidies and carbon pricing. Section 5.1 depicts the labor market impacts, Section 5.2 shows the welfare outcomes, and Section 5.3 conducts a sensitivity analysis. The abatement level is fixed at 7% unless stated otherwise. The level reflects the estimated abatement from the IRA tax credits in Bistline, Mehrotra and Wolfram (2023).[40]

5.1 Labor market impacts

5.1.1 Climate policy with non-distortionary taxes

Fig. 4 shows the employment change by climate policy instrument when the government balances its budget with lump sum (LS) taxes. A green subsidy generates higher employment compared to a carbon price. The subsidy increases steady state employment by 0.43 percentage points (pp), while the carbon price reduces it by 0.15 pp.

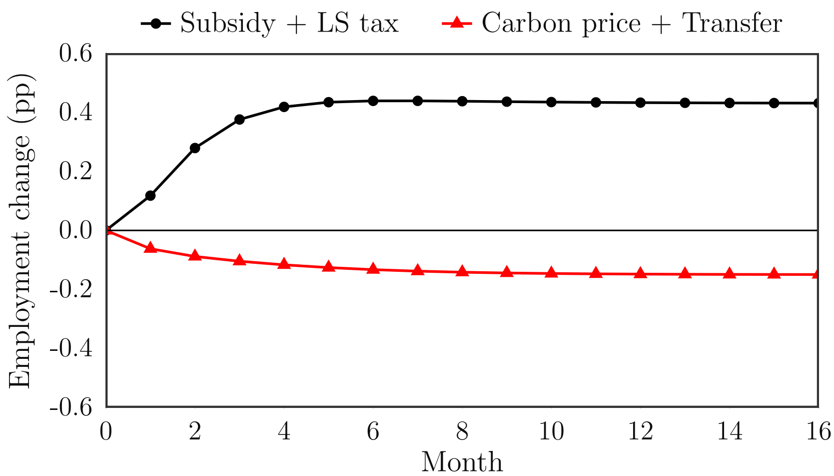

Figure 4: Employment changes from a green subsidy financed by lump sum taxes and a carbon price with transfer recycling

Note: The figure shows the employment changes (in pp relative to BAU) from a green subsidy financed by lump sum taxes and a carbon price with transfer recycling.

A green subsidy has three effects. First, it makes green goods cheaper compared to non-green goods. Table 3 shows that the price of green goods falls after the subsidy is

[40] In their main scenario, Bistline, Mehrotra and Wolfram (2023) find that the IRA tax credits induce abatement of 6% by 2030 relative to 2005. This implies abatement of 7% relative to 2019.

introduced and remains lower in the new steady state. The lower price of green goods increases demand for them. Green firms respond to the higher demand by increasing output and expanding recruitment. Fossil and neutral firms, in contrast, reduce steady state output and recruitment because they experience less demand for their goods. The switch in demand from non-green to green goods translates into more green jobs and fewer non-green jobs (Panel (a) of Fig. 5).

Second, the green subsidy counteracts search frictions by increasing the match value for green firms. The last column of Table 3 shows that the value of hiring a worker increases by 221% for green firms immediately after the subsidy is introduced. The subsidy means a green worker generates $p_{\mathrm{g}} + s > p_{\mathrm{g}}$ dollars per unit of output. Green firms take advantage of this by hiring more workers, which explains the large increase in green jobs in Panel (a) of Fig. 5.

Third, the lump sum taxes financing the green subsidy reduce household income. The taxes, however, do not distort recruitment incentives. Green firms still have a larger incentive to recruit workers because they gain more revenue per worker in production, while the incentive for non-green firms remains unchanged. The net result is a large increase in green employment that translates into higher overall employment.

Table 3: Changes in percent from a green subsidy by firm and time period

Firm	Time period	Price	Output	Recruiters	Recruiting productivity	Recruitment	Match value
Green	$t = 0$	-31	28.6	1517	-15	1788	221
	SS	-69	121.4	135	-8	119	8
Fossil	$t = 0$	-2	-1.2	-72	30	-65	-37
	SS	0	-7.0	-2	-8	-8	8
Neutral	$t = 0$	0	0.2	-23	-6	-27	-5
	SS	0	-0.3	6	-8	-1	8

Note: The table shows changes (in percent relative to BAU) from a lump sum tax-financed green subsidy by firm type and time period. The time periods are the first period ($t = 0$) and the new steady state (SS). The price of the neutral good is the numeraire.

Panel (b) of Fig. 5 decomposes the employment change from a carbon price. The carbon price increases green employment by shifting demand from fossil to green goods.[41] However, the increase is small because the carbon price does not counteract search frictions. The incentive to recruit is lower for fossil firms and unchanged for other firms. The carbon price consequently creates fewer jobs compared to the subsidy.

The analysis has so far assumed that a green subsidy can be financed in a non-distortionary manner. The following section relaxes this assumption to examine the implications of using payroll taxes to pay for the subsidy.

[41] A green subsidy and a carbon price have opposite effects on neutral employment. A green subsidy reduces it by making neutral goods relatively costlier, while a carbon price has the inverse effect.

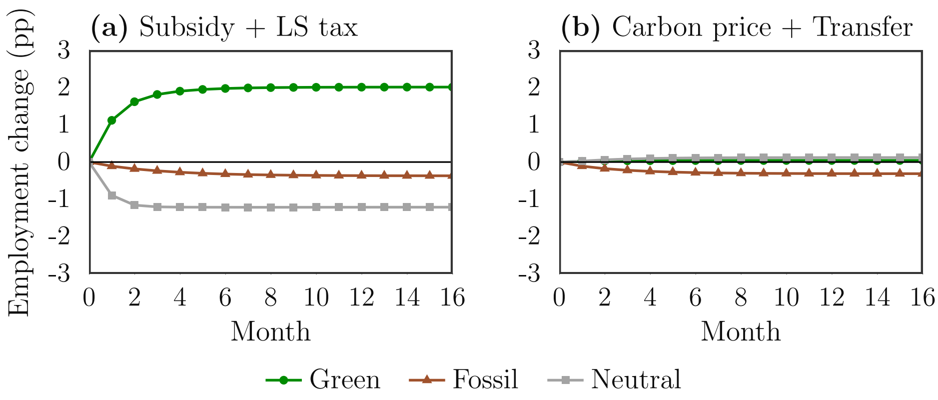

Figure 5: Employment changes from a green subsidy and carbon price by job type
Note: The figure shows the employment changes (in pp relative to BAU) from a green subsidy financed by lump sum taxes (Panel (a)) and a carbon price with transfer recycling (Panel (b)) by job type.

5.1.2 The role of the financing mechanism

Fig. 6 shows how the employment impacts depend on the financing and revenue recycling mechanisms. 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 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 price. Fig. 6 shows that while a subsidy outperforms a carbon price when financed by lump sum taxes, the inverse is true when payroll taxes are used. An implication is that subsidies are especially advantageous when lump sum taxes are available. If this is not the case, a carbon price generates more favorable employment outcomes.

Fig. 7 decomposes the employment change from a subsidy by job and financing mechanism. 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.[42] The reason is twofold. First, higher payroll taxes increase distortions for green firms by making labor more costly. This reduces green output and recruitment relative to a subsidy financed by lump sum taxes.[43] Second, a payroll tax-financed subsidy counteracts search frictions for green firms by less because it decreases the subsidy from \$0.69 to \$0.59. The subsidy is smaller since the payroll taxes reduce fossil firms' output

[42]While switching from lump sum to payroll taxes decreases green and neutral employment in Fig. 7, it slightly increases fossil employment. 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.

[43]Green output increases by 121% (81%) from a subsidy financed by lump sum (payroll) taxes.

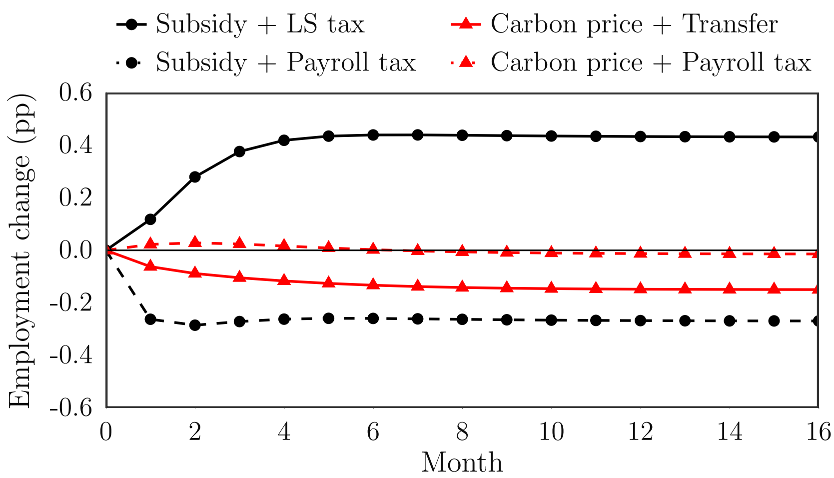

Figure 6: Employment changes from a green subsidy and carbon price by financing and recycling mechanisms

Note: The figure shows the employment changes (in pp relative to BAU) from a green subsidy financed by lump sum taxes, a green subsidy financed by payroll taxes, a carbon price with transfer recycling, and a carbon price with payroll tax recycling.

and emissions, meaning a lower subsidy rate is needed to achieve a given abatement level.

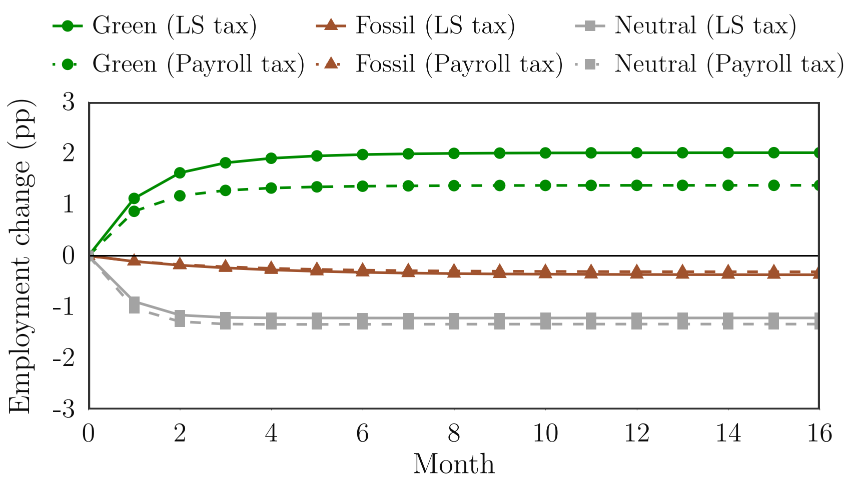

Figure 7: Employment changes from a green subsidy by job type and financing mechanism

Note: The figure shows the employment changes (in pp relative to BAU) from a green subsidy financed by lump sum or payroll taxes by job type.

5.1.3 The role of the tax system

Fig. 8 illustrates how the subsidies impact employment in different tax systems. The red lines refer to a subsidy financed by payroll taxes. This subsidy generates employment losses in the baseline tax system (solid red line). The losses grow when taxes are initially 20% higher (dashed red line). The reason is that the higher taxes dampen economic activity and erode the tax base. The smaller tax base means that the payroll taxes must increase by a larger amount to finance the subsidy. The higher payroll taxes increase labor costs, reduce recruitment, and decrease employment.[44]

A subsidy financed in a non-distortionary manner, in contrast, does not perform worse in a distortionary tax system. This subsidy is unaffected by the tax system (as shown by the overlapping black lines in Fig. 8) because its financing mechanism does not interact with preexisting distortions. An implication is that a non-distortionary financing mechanism is especially valuable in distortionary tax systems since its advantage over a payroll tax-based mechanism is higher then.

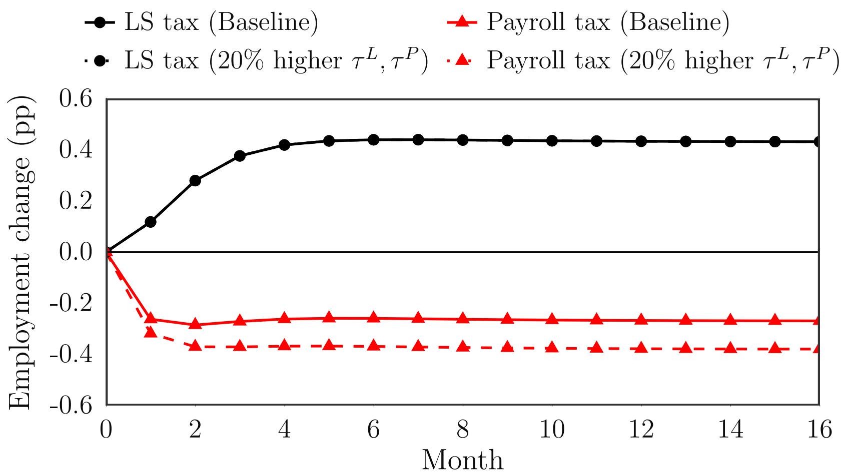

Figure 8: Employment changes from a green subsidy by financing mechanism and tax system

Note: The figure shows the employment changes (in pp relative to BAU) from a green subsidy financed by lump sum or payroll taxes assuming either baseline labor tax rates ($\tau^L = 0.29$, $\tau^P = 0.15$) in the BAU or 20% higher labor tax rates in the BAU. The black lines in the figure overlap.

5.2 Welfare impacts

Welfare corresponds to the discounted lifetime utility of the representative household. The household's utility in a given period is

$$\log(C) - \sum_j n_j \frac{\psi\chi}{1+\chi} h_j^{1+\frac{1}{\chi}}.$$

I measure welfare changes using the equivalent variation (i.e., the change in benchmark consumption, evaluated at benchmark prices, that gives the same utility as after a policy

[44]The employment losses from a payroll tax-financed subsidy grow relative to a carbon price in distortionary tax systems. This is implied by Fig. B.2 in Appendix B, which shows that the carbon price is largely unaffected by the tax system.

is implemented). I calculate the equivalent variation by fixing employment n_j and hours worked h_j at their benchmark levels. This is in line with Hafstead and Williams (2018) and is motivated by workers not controlling either variable: n_j is determined by firms and h_j results from a bargaining process. Holding n_j and h_j fixed means welfare changes stem solely from changes in consumption.[45]

Table 4 reports welfare changes by policy and tax system. For the baseline tax system, a subsidy financed by lump sum taxes increases welfare and performs better than a carbon price. Such a subsidy draws labor out of unemployment by counteracting search frictions, which increases production and welfare. A subsidy financed by payroll taxes, in contrast, reduces welfare and performs worse than a carbon price. The reason is that the employment dividend from such a subsidy is missing, since the higher payroll taxes decrease employment.

If the tax system is more distortionary, Table 4 shows that the welfare losses from a payroll tax-financed subsidy grow. In contrast, the welfare gains from the lump sum tax-financed subsidy are unchanged. This reinforces the finding from Section 5.1.3 that non-distortionary financing is especially valuable in distortionary tax systems.

Table 4: Welfare changes in percent by policy and tax system

Tax system	Subsidy + LS tax	Subsidy + Payroll tax	Carbon price + Transfer	Carbon price + Payroll tax
Baseline	0.61	-1.06	-0.40	-0.05
20% higher τ^L, τ^P	0.61	-1.29	-0.40	-0.06

Note: The table shows the welfare changes (in percent relative to BAU) from a green subsidy financed by lump sum taxes, a green subsidy financed by payroll taxes, a carbon price with transfer recycling, and a carbon price with payroll tax recycling assuming either baseline labor tax rates ($\tau^L = 0.29$, $\tau^P = 0.15$) in the BAU or 20% higher labor tax rates in the BAU.

5.3 Sensitivity analysis

5.3.1 Employment outcomes

This section looks at how the employment outcomes vary with key parameters. The analysis is carried out by recalibrating disutility of work ψ and unemployment benefits b_i in the benchmark. Table 5 shows that the qualitative results from the main specification are robust: a subsidy financed in a non-distortionary manner increases employment, a subsidy paid for by payroll taxes reduces employment, and a carbon price produces employment losses that are larger when revenue is recycled via transfers.

[45] Section 5.3.2 calculates welfare on the basis of both consumption and leisure changes.

Table 5: Employment changes in percentage points by policy and sensitivity test

	Subsidy + LS tax	Subsidy + Payroll tax	Carbon price + Transfer	Carbon price + Payroll tax
Baseline	0.43	-0.27	-0.15	-0.01
q_j up by 50%	0.62	-0.52	-0.22	-0.02
q_j down by 50%	0.21	-0.10	-0.07	-0.01
$\eta = 0.6$	0.61	-0.50	-0.22	-0.02
$\eta = 0.4$	0.29	-0.15	-0.10	-0.01
$\gamma = 0.75$	0.22	-0.12	-0.08	-0.01
$\gamma = 0.25$	0.64	-0.47	-0.22	-0.03
$\chi = 2$	0.35	-0.17	-0.11	-0.01
$\chi = 0.5$	0.47	-0.40	-0.19	-0.02
$\sigma^{fg} = 1.5$	0.11	-0.04	-0.11	-0.01
$\sigma^{fg} = 0.6$	0.91	-0.84	-0.16	-0.02
$\sigma^{C} = 0.6$	0.67	-0.55	-0.13	-0.01
$\sigma^{C} = 0.4$	0.31	-0.15	-0.17	-0.02
Flat nesting	1.45	-1.97	-0.11	-0.01
13% abatement	0.84	-1.24	-0.30	-0.05
$\xi_j = 1$	0.43	-0.27	-0.15	-0.01
$\xi_j = 0.5$	0.43	-0.27	-0.15	-0.01
$\xi_j = 0.1$	0.43	-0.27	-0.15	-0.01

Note: The table shows the employment changes (in pp relative to BAU) from a green subsidy financed by lump sum taxes, a green subsidy financed by payroll taxes, a carbon price with transfer recycling, and a carbon price with payroll tax recycling by sensitivity test.

Looking at the subsidy outcomes in Table 5, we see that changing recruitment productivity q_j in the benchmark has an uneven impact across financing mechanisms. A higher q_j means a unit of recruitment effort generates more matches. A subsidy financed by non-distortionary taxes increases recruitment effort 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, meaning a higher q_j results in fewer matches.

A higher bargaining power of firms η increases the flow value of unemployment, which reduces the fundamental surplus ratio.[46] A small fundamental surplus ratio means 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 financing mechanism, meaning recruitment and the employment gains grow. Conversely, the shock is negative for a distortionary mechanism, meaning

[46]The positive relationship between firms' bargaining power and the flow value of unemployment is consistent with Hagedorn and Manovskii (2008). They find empirical evidence that the cost of posting vacancies is low and that wages are only moderately procyclical. They argue that the former implies small accounting profits (since free entry implies that vacancy posting costs equal accounting profits) and thus a high flow value of unemployment, and that the latter implies high firm bargaining power.

employment declines by more.

A higher elasticity of matching with respect to unemployment γ reduces the matching efficiency μ_j by Eq. 3. The lower μ_j reduces the number of matches from a unit of recruitment effort. This weakens the employment gains from a subsidy with lump sum taxes. On the other hand, the number of matches from a payroll tax-financed subsidy falls by less, which curtails 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 financing mechanism, the wage change is positive, meaning hours increase. This crowds out labor supply on the extensive margin and reduces the employment gains. For the case of a distortionary financing mechanism, the wage change is negative. Hours therefore decrease and labor supply on the extensive margin rises.

A higher elasticity of substitution between the fossil and green good σ^{fg} decreases the subsidy rate from \$0.69 to \$0.23. 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 substitution of green for neutral goods. This leads to more workers moving from neutral to green jobs, which crowds out some of the reallocation from fossil to green jobs. The subsidy rate increases to \$0.83 to counterbalance the lower abatement from the crowding out effect. The higher subsidy is beneficial in the context of a non-distortionary financing mechanism, but worsens the employment losses from a distortionary mechanism.

Switching from a nested to a flat consumption structure with an elasticity of 0.75 amplifies the employment changes because the subsidy rate increases to \$0.96. The subsidy rate increases since there is less substitution between the fossil and green good. Consumers instead substitute away more from the neutral good. The smaller reduction in fossil consumption means the subsidy rate must increase by more to induce abatement, which amplifies the employment changes.

The baseline assumes an abatement level of 7%. This is a lower bound for the estimated impact of the IRA in the literature (Larsen et al., 2022; Bistline et al., 2023; Bistline, Mehrotra and Wolfram, 2023; U.S. Energy Information Administration, 2023; Voigts and Paret, 2024).[47] Adopting the upper bound of 13% amplifies the magnitude of the employment changes but does not change the signs.

Finally, I vary ξ_j to consider the role of frictions associated with cross-type matching. Fig. 9 shows the employment impact of a subsidy financed in a non-distortionary manner for different values of ξ_j. Changing ξ_j has little impact on the steady state, as employment converges to the same level. The speed of convergence, however, varies. A small value of

[47] The estimated abatement from the IRA in the literature ranges from 6%-11% relative to 2005 levels. This gives a range of 7%-13% relative to 2019 levels (using data from 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).

ξ_j slows down convergence and can even eliminate the employment gains in the short run. A low ξ_j means firms face frictions when matching with workers of a different type. The frictions increase the time it takes for firms to adjust hiring and reach their steady state recruitment level. A take-away therefore is that while ξ_j has little effect on the steady state, it impacts the subsidy's performance during the transition.[48]

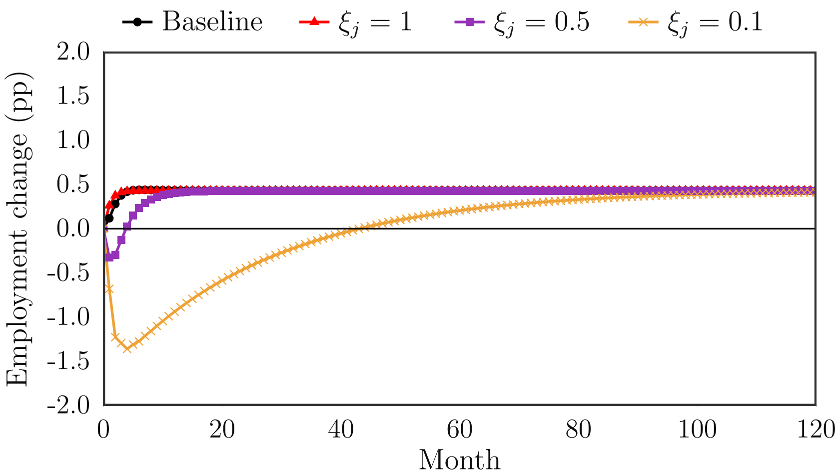

Figure 9: Employment changes from a lump sum tax-financed green subsidy by ξ_j
Note: The figure shows the employment changes (in pp relative to BAU) from a lump sum tax-financed green subsidy by ξ_j. "Baseline" assumes the values of ξ_j in Table 2.

5.3.2 Welfare outcomes

Table 6 shows welfare impacts by sensitivity test. There are two key insights. First, a subsidy financed by payroll taxes always performs worse than a carbon price. Second, a subsidy financed by lump sum taxes is generally, but not always, preferable to a carbon price. There are four instances in which the subsidy performs worse: when the abatement level is high, the elasticity of substitution σ^{fg} is low, the consumption structure is flat, or welfare includes leisure changes.[49]

To see why a subsidy performs poorly in the first instance when abatement is high, Fig. 10 depicts welfare changes by abatement level. The subsidy increases welfare at low abatement levels, but reduces welfare as abatement becomes stringent. At low abatement levels, the subsidy is small and not much consumption is shifted across goods. The welfare gains from the job creation then dominate and welfare increases. As the subsidy rate grows with the abatement level, more consumption is shifted towards the green good. An inefficient amount is shifted beyond a threshold. The inefficiency ultimately outweighs the

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

[49] In the first three instances, the subsidy rate increases to switch demand away from the fossil good. The high subsidy rate generates an inefficient amount of green production, which offsets the welfare gains from the employment creation. In the fourth instance, the employment gains from the subsidy imply less leisure, which reduces welfare.

welfare gains from the job creation and makes the subsidy perform worse than a carbon price. An important implication is that subsidies financed in a non-distortionary manner increase welfare relative to carbon pricing, but only when emissions reductions are small. Fig. B.3 in Appendix B shows that this is also true for the other three instances.[50]

Table 6: Welfare changes in percent by policy and sensitivity test

	Subsidy + LS tax	Subsidy + Payroll tax	Carbon price + Transfer	Carbon price + Payroll tax
Baseline	0.61	-1.06	-0.40	-0.05
q_j up by 50%	0.70	-1.28	-0.44	-0.06
q_j down by 50%	0.50	-0.92	-0.36	-0.04
$\eta = 0.6$	0.69	-1.26	-0.43	-0.06
$\eta = 0.4$	0.54	-0.97	-0.38	-0.04
$\gamma = 0.75$	0.49	-0.93	-0.36	-0.04
$\gamma = 0.25$	0.72	-1.24	-0.44	-0.06
$\chi = 2$	0.98	-1.07	-0.46	-0.05
$\chi = 0.5$	0.29	-1.11	-0.35	-0.05
$\sigma^{fg} = 1.5$	0.25	-0.14	-0.29	-0.03
$\sigma^{fg} = 0.6$	-0.75	-2.88	-0.43	-0.05
$\sigma^{C} = 0.6$	0.26	-2.01	-0.36	-0.04
$\sigma^{C} = 0.4$	0.58	-0.61	-0.46	-0.05
Flat nesting	-4.09	-5.34	-0.31	-0.04
13% abatement	-0.33	-3.89	-0.81	-0.17
$\xi_j = 1$	0.61	-1.07	-0.40	-0.04
$\xi_j = 0.5$	0.61	-1.06	-0.40	-0.04
$\xi_j = 0.1$	0.58	-1.09	-0.40	-0.05
Welfare with leisure changes	-0.26	-0.82	-0.21	-0.04

Note: The table shows the welfare changes (in pp relative to BAU) from a green subsidy financed by lump sum taxes, a green subsidy financed by payroll taxes, a carbon price with transfer recycling, and a carbon price with payroll tax recycling by sensitivity test.

[50] When σ^{fg} is low or the consumption structure is flat, the welfare gains from the job creation dominate at low abatement levels since little consumption is shifted. When welfare includes leisure changes, the welfare gains from the job creation outweigh the cost of less leisure at low abatement levels.

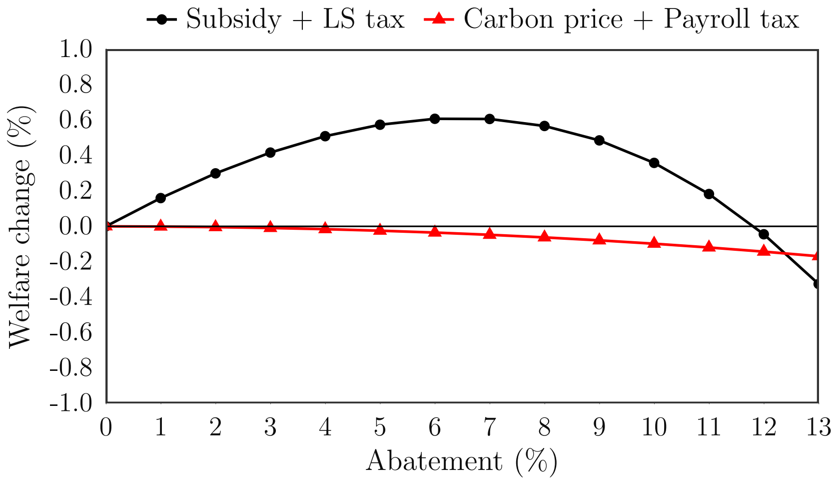

Figure 10: Welfare changes from a green subsidy with lump sum taxes and a carbon price with payroll taxes by abatement level

Note: The figure shows the welfare changes (in percent relative to BAU) from a green subsidy financed by lump sum taxes and a carbon price with payroll tax recycling by abatement level.

6 Conclusion

This paper combines empirical job transition estimates with a search model to analyze the labor market and welfare impacts of green subsidies. The analysis is carried out by comparing green subsidies to carbon pricing for various financing mechanisms and tax systems.

The main finding is that appropriately financed green subsidies can generate higher welfare compared to carbon pricing when emissions reductions are small. The higher welfare stems from the subsidies not only addressing the climate externality, but also increasing employment by counteracting search frictions. The finding that a green subsidy can be more cost-effective than a carbon price is noteworthy and implies that the standard ranking of the instruments might not hold once employment effects are taken into account.

The paper's main finding raises two questions. First, how realistic is a non-distortionary financing mechanism? Such a mechanism can indeed be viewed as a best-case scenario. However, to the extent that it is characterized by a marginal cost of public funds equal to one, a non-distortionary financing mechanism might be available in the presence of inequality aversion. In particular, Jacobs (2018) shows that income and consumption taxes can have a marginal cost of public funds equal to one when the tax revenue generates redistributional gains that offset the excess burden. This suggests that, in the presence of inequality aversion, income and consumption taxes might approximate the best-case scenario considered here.

Second, will fossil workers be able to exploit the employment opportunities from green subsidies? This paper suggests that they may find this challenging. Indeed, while the search analysis shows that green subsidies primarily create green jobs, the empirical analysis illustrates that fossil workers rarely transition to these jobs. Complementary labor market policies are therefore likely needed for fossil workers to access the jobs created from green subsidies.

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Appendix A : Sensitivity analysis on the empirical results

Distribution of jobs

The main specification assumes green jobs involve at least 50% of green tasks. Panel (a) of Fig. A.1 and Panel (a) of Fig. A.2 show how changing this threshold impacts the green and fossil job shares respectively. A restrictive threshold of $\alpha = 100\%$ gives a similar job distribution as the main specification. Lax thresholds of $\alpha \leq 30\%$ give unrealistically many green jobs. Irrespective of the threshold, however, the majority of jobs are neutral.

The remaining sensitivity tests are as follows. Panel (b) of Figs. A.1 and A.2 restricts occupations' tasks to those classified as "core" by O*NET.[51] The green task shares are thereby calculated using only the most important tasks. Panel (c) counts green jobs in dirty industries as neutral. Workers performing green tasks in industries vulnerable to climate policy are not considered green as a result. Panels (d) and (e) use stricter definitions of a fossil job. Panel (d) removes all fossil jobs in non-dirty industries (by counting these jobs as neutral). This restricts the fossil jobs to those in the most vulnerable industries. Panel (e) assumes fossil jobs are above 10 times (as opposed to 8 times) more likely than the average job to be found in a dirty industry. Panels (f)-(h) use less strict fossil job definitions. Panel (f) counts neutral jobs in dirty industries as fossil. Panel (g) assumes fossil jobs are above 6 times (as opposed to 8 times) more likely than the average job to be found in a dirty industry. Panel (h) counts overlapping green and fossil jobs as fossil. Panel (i) restricts dirty industries to industries in the top 1% (as opposed to 5%) of emissions-intensity.

In all panels, the majority of jobs are neutral and, for values of $\alpha \geq 40$, the share of green jobs is below 2.2%.

Job transition probabilities

I carry out a similar sensitivity analysis on the job transition probabilities. Fig. A.3 shows how the probabilities vary with α.[52] Fig. A.4 repeats this exercise assuming only core tasks. Fig. A.5 restricts green jobs to non-dirty industries. Figs. A.6 and A.7 use more narrow definitions of a fossil job, while Figs. A.8-A.10 use looser definitions. Fig. A.11 employs a more narrow definition of a dirty industry. In all figures, fossil workers are unlikely to start a green job and are more likely to start a neutral job, consistent with the main specification.

[51] 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 out of 5 (see https://www.onetonline.org/help/online/scales).

[52] To conserve space, I show the results for α equal to $30\%, 40\%$, and 50%. The qualitative insights hold for unrealistically lax thresholds (α equal to 10% or 20%) and for $\alpha = 100\%$. In the latter case, the job transition probabilities are largely unchanged from $\alpha = 50\%$.

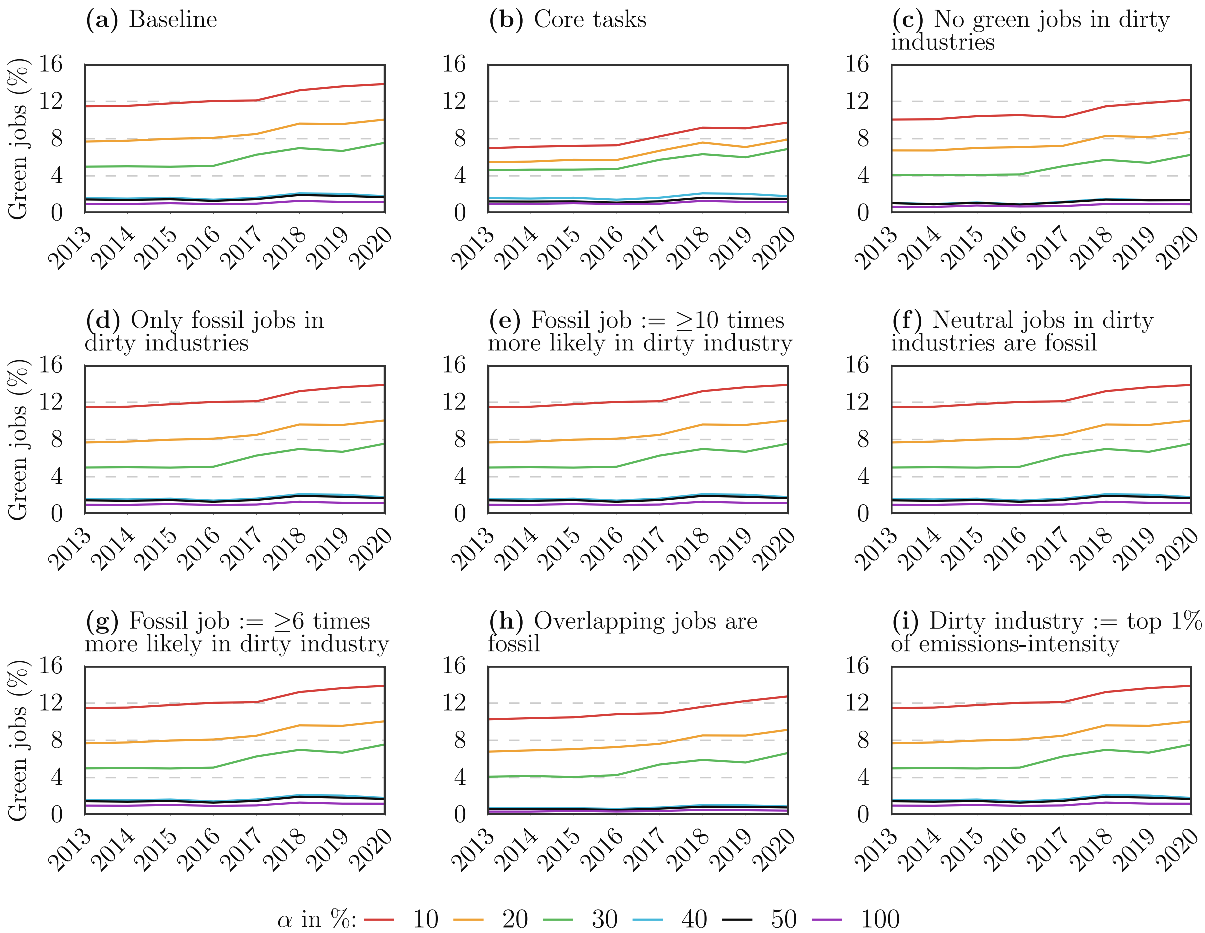

Figure A.1: Green job shares over time by sensitivity test (panels) and α (lines)
Note: The figure shows the shares of green jobs by sensitivity test (panels) and α (lines). Panel (a) is the main specification. Panel (b) uses only core tasks. Panel (c) restricts green jobs to non-dirty industries. Panel (d) restricts fossil jobs to dirty industries. Panel (e) defines fossil jobs as jobs at least 10 times more likely than the average job to be found in a dirty industry. Panel (f) counts neutral jobs in dirty industries as fossil. Panel (g) defines fossil jobs as jobs at least six times more likely than the average job to be found in a dirty industry. Panel (h) counts overlapping green and fossil jobs as fossil. Panel (i) restricts dirty industries to industries in the top 1% of emissions-intensity. α is the minimum share of green tasks in green occupations.

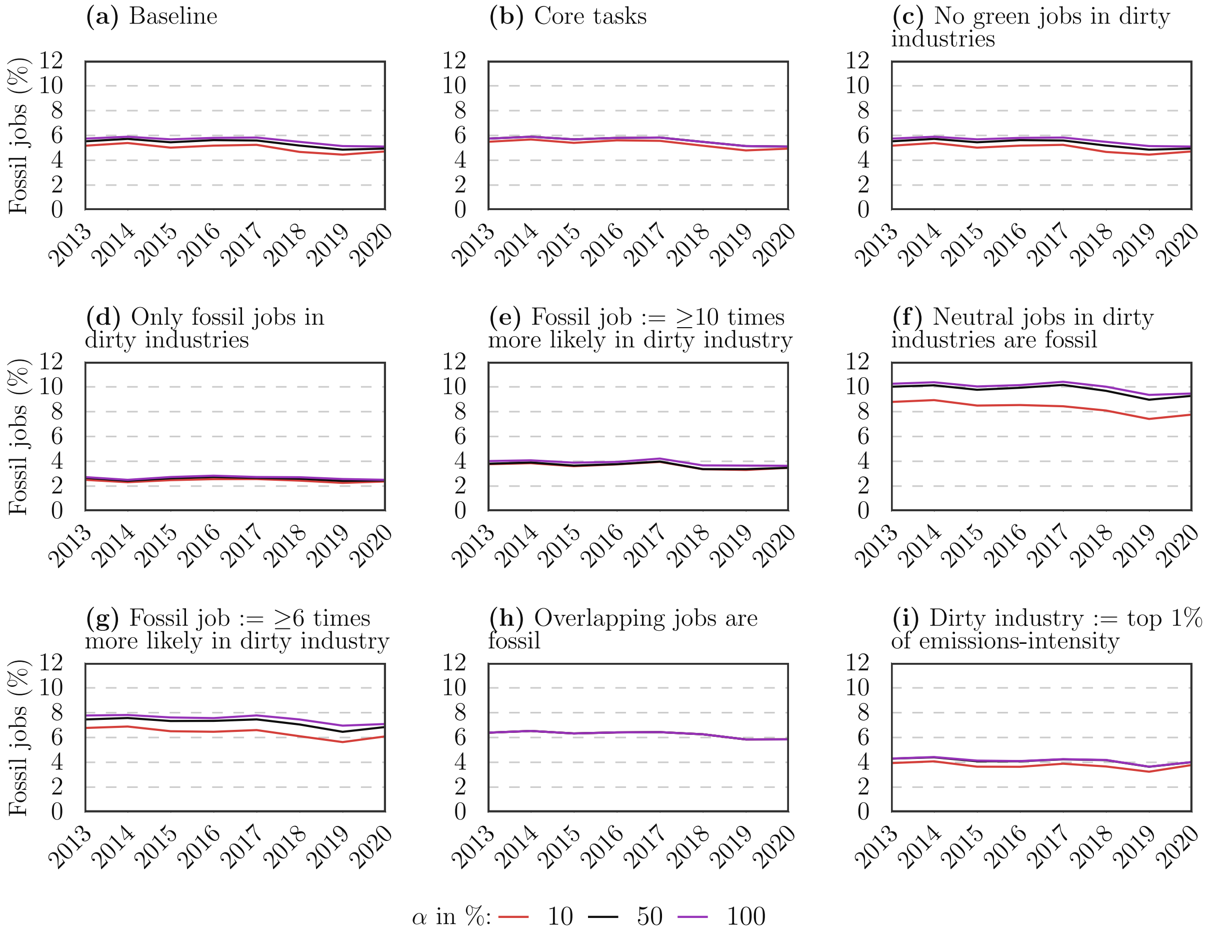

Figure A.2: Fossil job shares over time by sensitivity test (panels) and α (lines)
Note: The figure shows the shares of fossil jobs by sensitivity test (panels) and α (lines). Panel (a) is the main specification. Panel (b) uses only core tasks. Panel (c) restricts green jobs to non-dirty industries. Panel (d) restricts fossil jobs to dirty industries. Panel (e) defines fossil jobs as jobs at least 10 times more likely than the average job to be found in a dirty industry. Panel (f) counts neutral jobs in dirty industries as fossil. Panel (g) defines fossil jobs as jobs at least six times more likely than the average job to be found in a dirty industry. Panel (h) counts overlapping green and fossil jobs as fossil. Panel (i) restricts dirty industries to industries in the top 1% of emissions-intensity. α is the minimum share of green tasks in green occupations.

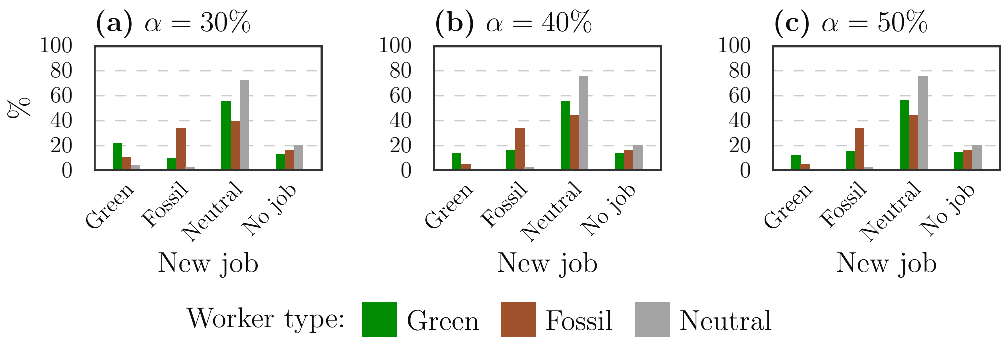

Figure A.3: Job transition probabilities by α, job type, and worker type
Note: The figure shows the job transition probabilities by α, job type, and worker type. α is the the minimum share of green tasks in green occupations.

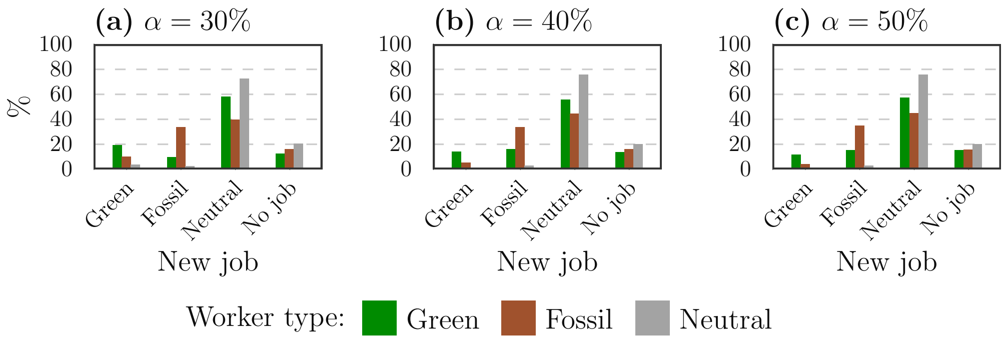

Figure A.4: Job transition probabilities by α, job type, and worker type assuming only core tasks
Note: The figure shows the job transition probabilities by α, job type, and worker type assuming tasks are restricted to core tasks. α is the the minimum share of green tasks in green occupations.

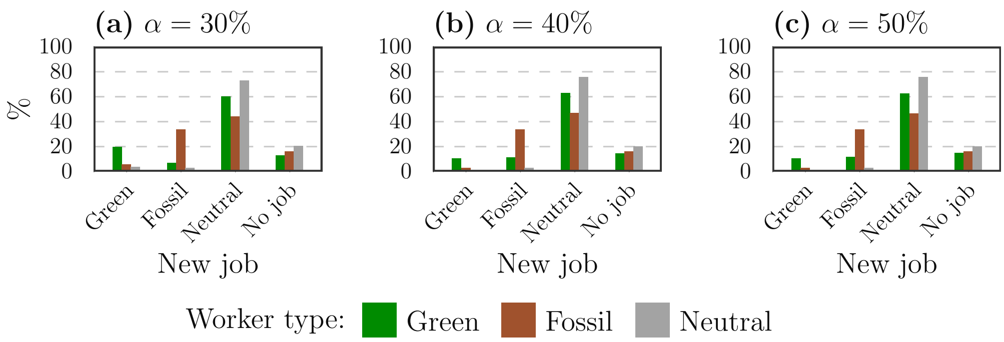

Figure A.5: Job transition probabilities by α, job type, and worker type assuming no green jobs in dirty industries
Note: The figure shows the job transition probabilities by α, job type, and worker type assuming green jobs are restricted to non-dirty industries. α is the the minimum share of green tasks in green occupations.

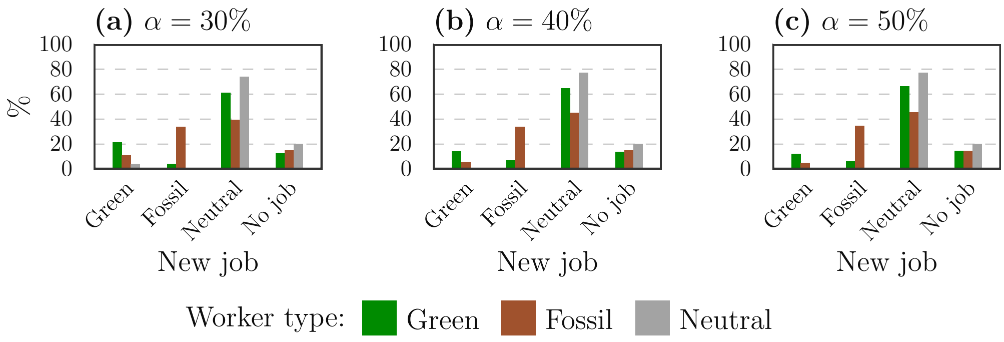

Figure A.6: Job transition probabilities by α, job type, and worker type assuming only fossil jobs in dirty industries

Note: The figure shows the job transition probabilities by α, job type, and worker type assuming fossil jobs are restricted to dirty industries. α is the the minimum share of green tasks in green occupations.

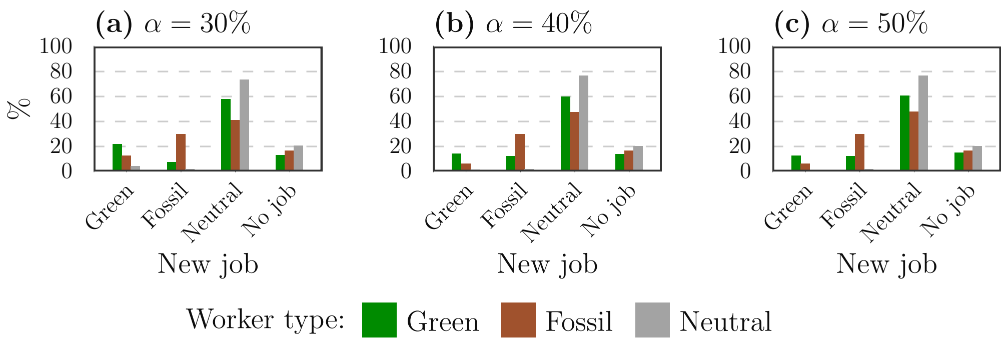

Figure A.7: Job transition probabilities by α, job type, and worker type assuming fossil jobs are ≥ 10 times more likely in a dirty industry

Note: The figure shows the job transition probabilities by α, job type, and worker type assuming fossil jobs are at least 10 times more likely than the average job to be found in a dirty industry. α is the the minimum share of green tasks in green occupations.

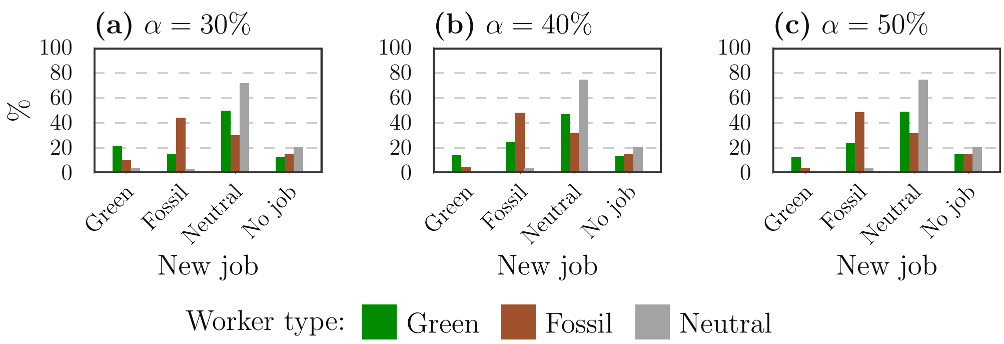

Figure A.8: Job transition probabilities by α, job type, and worker type assuming neutral jobs in dirty industries are counted as fossil

Note: The figure shows the job transition probabilities by α, job type, and worker type assuming neutral jobs in dirty industries are counted as fossil jobs. α is the the minimum share of green tasks in green occupations.

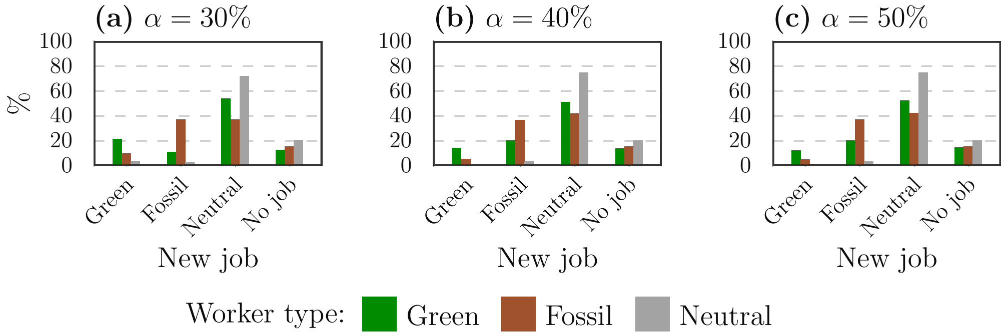

Figure A.9: Job transition probabilities by α, job type, and worker type assuming fossil jobs are ≥ 6 times more likely in a dirty industry

Note: The figure shows the job transition probabilities by α, job type, and worker type assuming fossil jobs are at least six times more likely than the average job to be found in a dirty industry. α is the the minimum share of green tasks in green occupations.

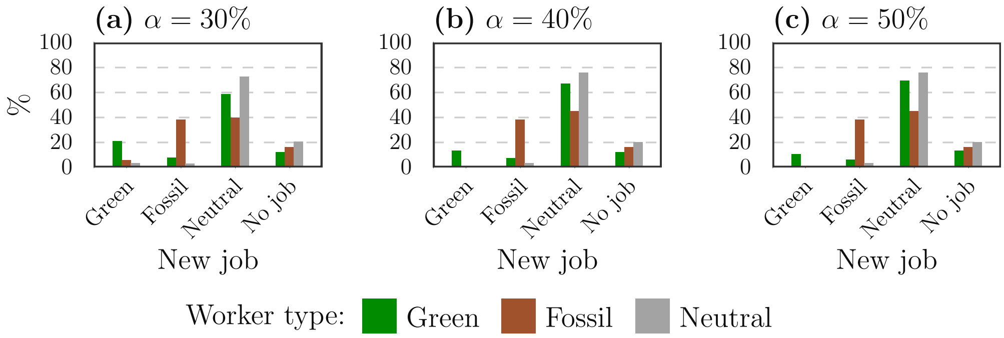

Figure A.10: Job transition probabilities by α, job type, and worker type assuming overlapping jobs are fossil

Note: The figure shows the job transition probabilities by α, job type, and worker type assuming overlapping green and fossil jobs are counted as fossil. α is the the minimum share of green tasks in green occupations.

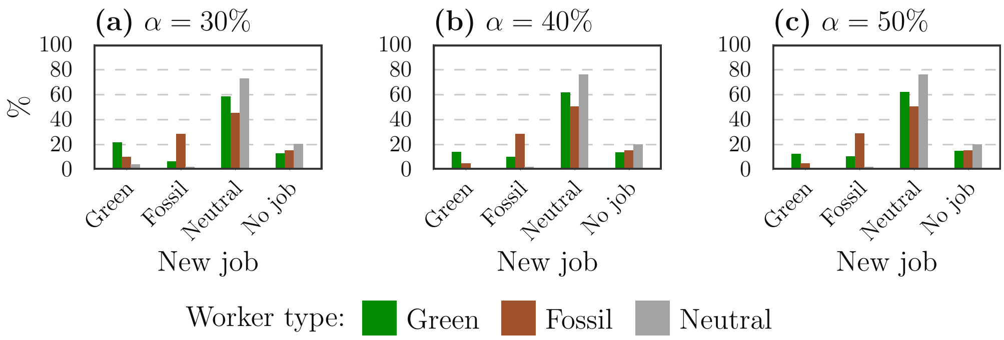

Figure A.11: Job transition probabilities by α, job type, and worker type assuming dirty industries lie in the top 1% of emissions-intensity

Note: The figure shows the job transition probabilities by α, job type, and worker type assuming dirty industries are in the top 1% of emissions-intensity. α is the the minimum share of green tasks in green occupations.

Appendix B: Additional figures

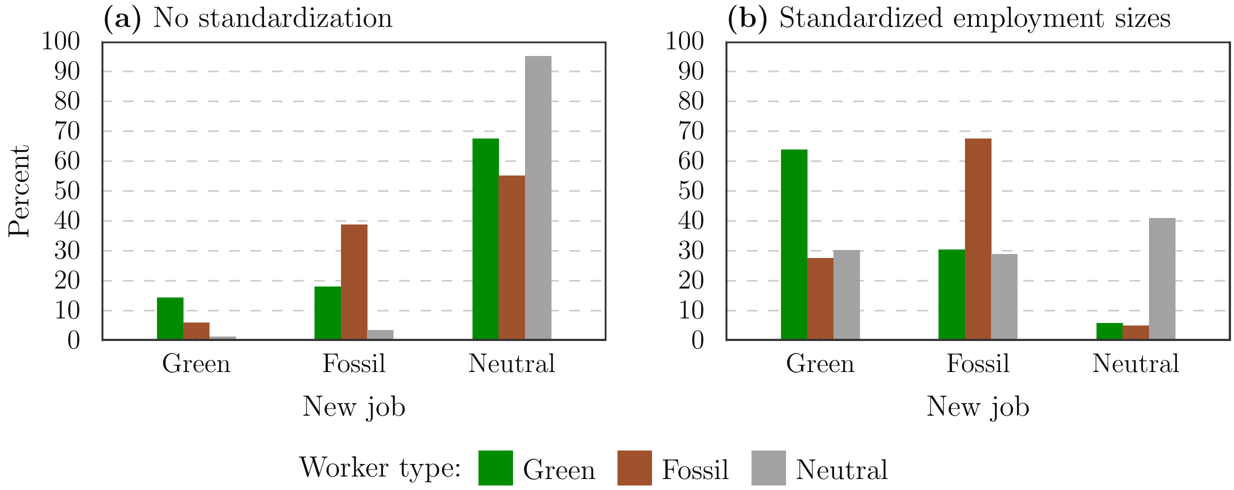

Figure B.1: Job transition probabilities by job type and worker type when employment sizes either are not standardized or are standardized

Note: The figure shows the job transition probabilities by job type and worker type. Panel (a) shows the baseline job transition probabilities. Panel (b) shows hypothetical job transition probabilities assuming identical employment shares across job types.

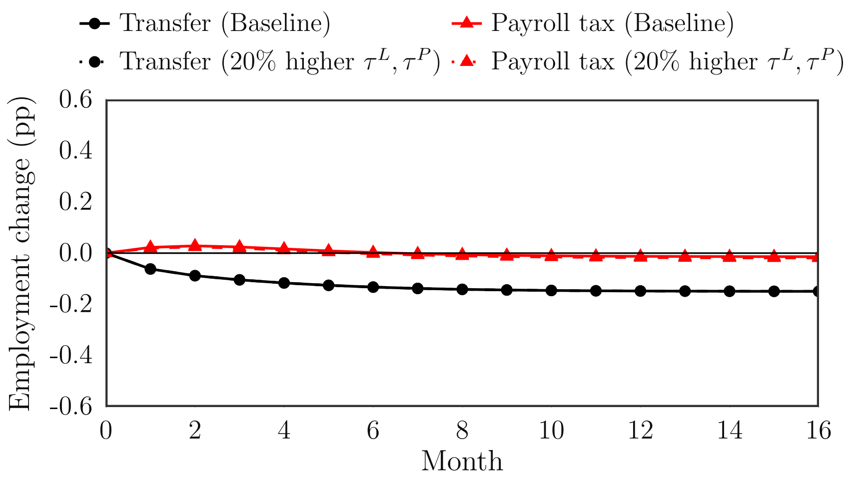

Figure B.2: Employment changes from a carbon price by recycling mechanism and tax system

Note: The figure shows the employment changes (in pp relative to BAU) from a carbon price with transfer or payroll tax recycling assuming either baseline labor tax rates ($\tau^L = 0.29, \tau^P = 0.15$) in the BAU or 20% higher labor tax rates in the BAU. The black lines in the figure overlap.

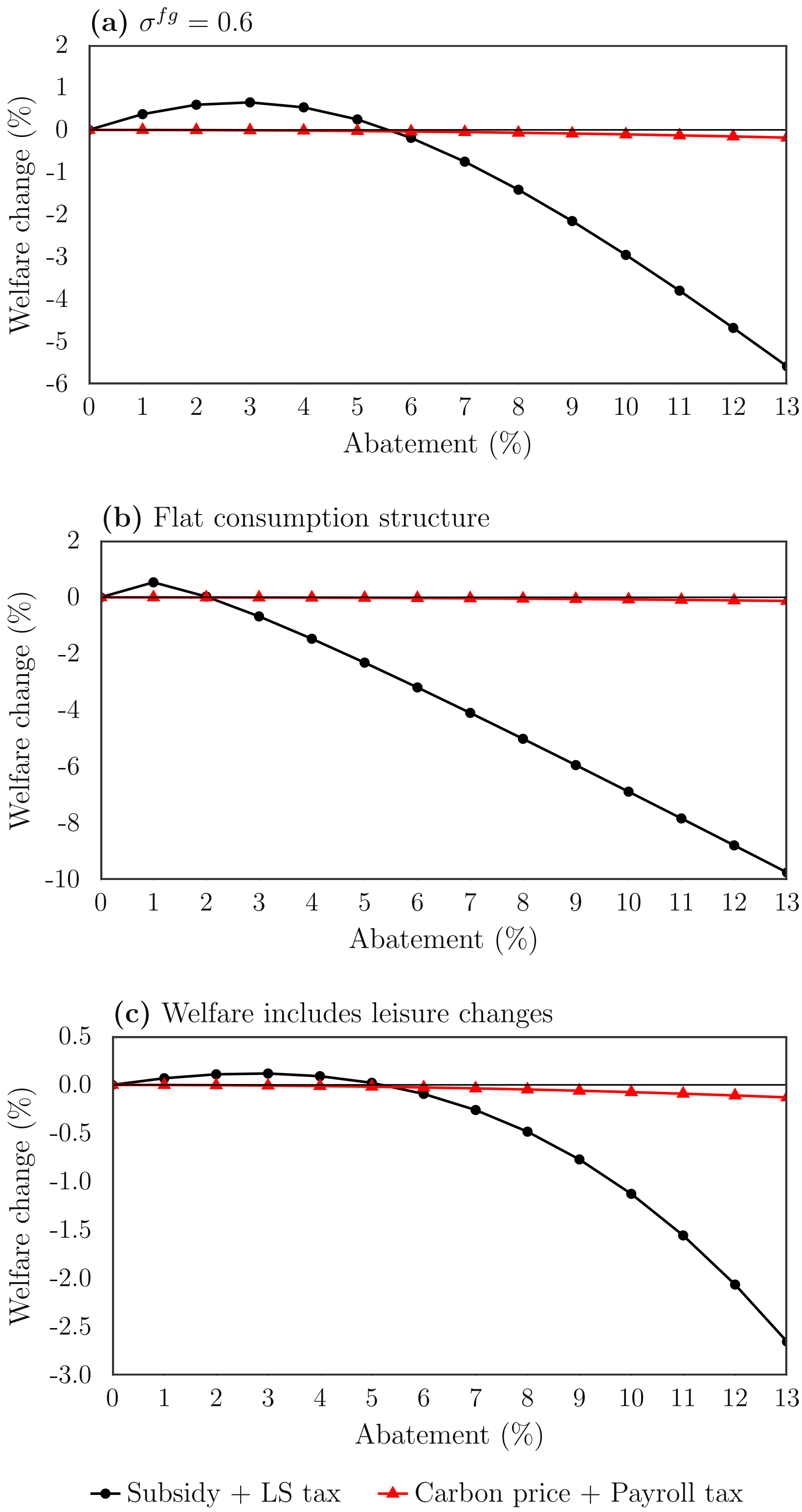

Figure B.3: Welfare changes from a green subsidy with lump sum taxes and a carbon price with payroll taxes by abatement level for various scenarios

Note: The figure shows the welfare changes (in percent relative to BAU) from a green subsidy financed by lump sum taxes and a carbon price with payroll tax recycling by abatement level and scenario. Panel (a) assumes $\sigma^{fg} = 0.6$; Panel (b) assumes a flat consumption structure; and Panel (c) assumes welfare changes include leisure changes.

Online Appendix A: Occupations

Table A.1: Census codes in the 2017-2020 SIPP panel with a one-to-many mapping to SOC

Census code	Census title	SOC code	SOC title	SOC share in 2013-2016 SIPP
0335	Entertainment and Recreation Managers	11-9199 11-9071	Managers, All Other Gaming Managers	1 0
0705	Project Management Specialists	11-9199 15-1199 13-1199	Managers, All Other Computer Occupations, All Other Business Operations Specialists, All Other	0.77 0.16 0.06
0960	Other Financial Specialists	13-2051 13-2099	Financial Analysts Financial Specialists, All Other	0.88 0.12
1022	Software Quality Assurance Analysts and Testers	15-113X 15-1199	Software Developers, Applications and Systems Software Computer Occupations, All Other	0.67 0.33
1032	Web and Digital Interface Designers	15-1199 15-1134	Computer Occupations, All Other Web Developers	0.73 0.27
1065	Database Administrators and Architects	15-1199 15-1141	Computer Occupations, All Other Database Administrators	0.86 0.14
1108	Computer Occupations, All Other	15-1199 43-9011	Computer Occupations, All Other Computer Operators	0.94 0.06
1555	Other Engineering Technologists and Technicians, Except Drafters	17-3020 55-3010	Engineering Technicians, Except Drafters Military Enlisted Tactical Operations and Air/Weapons Specialists and Crew Members	1 0
1935	Environmental Science and Geoscience Technicians	19-4090 19-4041	Miscellaneous Life, Physical, and Social Science Technicians Geological and Petroleum Technicians	0.98 0.02
2435	Librarians and Media Collections Specialists	25-90XX 25-4021	Other Education, Training, and Library Workers Librarians	0.52 0.48

Table A.1: Census codes in the 2017-2020 SIPP panel with a one-to-many mapping to SOC (continued)

Census code	Census title	SOC code	SOC title	SOC share in 2013-2016 SIPP
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
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

Table A.1: Census codes in the 2017-2020 SIPP panel with a one-to-many mapping to SOC (continued)

Census code	Census title	SOC code	SOC title	SOC share in 2013-2016 SIPP
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 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
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

Table A.1: Census codes in the 2017-2020 SIPP panel with a one-to-many mapping to SOC (continued)

Census code	Census title	SOC code	SOC title	SOC share in 2013-2016 SIPP
7905	Computer Numerically Controlled Tool Operators and Programmers	51-9199	Production Workers, All Other	0.89
		51-4010	Computer Control Programmers and Operators	0.11
7925	Forming Machine Setters, Operators, and Tenders, Metal and Plastic	51-4021	Extruding and Drawing Machine Setters, Operators, and Tenders, Metal and Plastic	0.81
		51-4022	Forging Machine Setters, Operators, and Tenders, Metal and Plastic	0.12
		51-4023	Rolling Machine Setters, Operators, and Tenders, Metal and Plastic	0.07
8025	Other Machine Tool Setters, Operators, and Tenders, Metal and Plastic	51-4032	Drilling and Boring Machine Tool Setters, Operators, and Tenders, Metal and Plastic	NA†
		51-4034	Lathe and Turning Machine Tool Setters, Operators, and Tenders, Metal and Plastic	NA†
		51-4035	Milling and Planing Machine Setters, Operators, and Tenders, Metal and Plastic	NA†
8225	Other Metal Workers and Plastic Workers	51-4199	Metal Workers and Plastic Workers, All Other	1
		51-4081	Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic	0
		51-4191	Heat Treating Equipment Setters, Operators, and Tenders, Metal and Plastic	0
		51-4192	Layout Workers, Metal and Plastic	0
		51-4193	Plating and Coating Machine Setters, Operators, and Tenders, Metal and Plastic	0
		51-4194	Tool Grinders, Filers, and Sharpeners	0

Table A.1: Census codes in the 2017-2020 SIPP panel with a one-to-many mapping to SOC (continued)

Census code	Census title	SOC code	SOC title	SOC share in 2013-2016 SIPP
8365	Textile Machine Setters, Operators, and Tenders	51-6064	Textile Winding, Twisting, and Drawing Out Machine Setters, Operators, and Tenders	0.74
		51-6063	Textile Knitting and Weaving Machine Setters, Operators, and Tenders	0.21
		51-6062	Textile Cutting Machine Setters, Operators, and Tenders	0.05
		51-6061	Textile Bleaching and Dyeing Machine Operators and Tenders	0
8465	Other Textile, Apparel, and Furnishings Workers	51-6099	Textile, Apparel, and Furnishings Workers, All Other	1
		51-6091	Extruding and Forming Machine Setters, Operators, and Tenders, Synthetic and Glass Fibers	0
		51-6092	Fabric and Apparel Patternmakers	0
8555	Other Woodworkers	51-7099	Woodworkers, All Other	1
		51-7030	Model Makers and Patternmakers, Wood	0
8990	Other Production Workers	51-9199	Production Workers, All Other	1
		51-9141	Semiconductor Processors	0
9005	Supervisors of Transportation and Material Moving Workers	53-1000	Supervisors of Transportation and Material Moving Workers	0.56
		39-1021	First-Line Supervisors of Personal Service Workers	0.44
9141	Shuttle Drivers and Chauffeurs	53-3020	Bus Drivers	0.62
		53-3041	Taxi Drivers and Chauffeurs	0.38
9265	Other Rail Transportation Workers	53-4010	Locomotive Engineers and Operators	0.64
		53-40XX	Subway, Streetcar, and Other Rail Transportation Workers	0.36
		53-4021	Railroad Brake, Signal, and Switch Operators	0
9365	Transportation Service Attendants	53-6031	Automotive and Watercraft Service Attendants	0.84
		53-60XX	Other Transportation Workers	0.16

Table A.1: Census codes in the 2017-2020 SIPP panel with a one-to-many mapping to SOC (continued)

Census code	Census title	SOC code	SOC title	SOC share in 2013-2016 SIPP
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 shows the 2018 Census codes in the 2017-2020 SIPP panel with a one-to-many mapping to SOC. To achieve a one-to-one mapping, I choose the most frequent SOC code in the 2013-2016 SIPP panel (first code in the last column).
†The SOC codes mapping to Census code "8025" - Other Machine Tool Setters, Operators, and Tenders, Metal and Plastic" 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 a weighted green task share ≥ 0.5

O*NET-SOC code	O*NET-SOC title	Total tasks	Green tasks	Weighted green task share
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

Table A.2: O*NET occupations with a weighted green task share ≥ 0.5 (continued)

O*NET-SOC code	O*NET-SOC title	Total tasks	Green tasks	Weighted green task share
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 occupations with a weighted green task share of at least 0.5.

Table A.3: Green occupations in the main specification

SOC code	SOC title	Average weighted green task share
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 classified as green in the main specification.

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

Table A.4: Fossil occupations in the main specification (continued)

SOC code	SOC title
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
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 classified as fossil in the main specification.

Online Appendix B: Aggregating the task data

I aggregate the O*NET task data from an 8-digit occupational level to a 6-digit level to align the data with SIPP. O*NET provides task data 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. If an occupation ending in ".00" has 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.[53]

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").

[53] Four 6-digit groups are special cases and exempted from the aggregation procedure (see the note at the bottom of Table B.1). 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	
53-1021.00	First-Line Supervisors of Helpers, Laborers, and Material Movers, Hand	24	0	Zero
53-1021.01	Recycling Coordinators	23	23	

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
53-6051.01	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 the green task share aggregation for occupations with a many-to-one mapping to a 6-digit parent group. "Zero" in the last column means the parent group is assigned a zero green task share. "Mean" implies that the parent group is assigned the average green task share.

†Occupation "11-9041.01" 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". Occupation "11-9041.01" is thus moved to parent group "11-9013" that contains similar occupations, while parent group "11-9041" is removed.

‡The values of the ".00" parent group are chosen because it is more important.

*The parent group is not assigned zero green tasks because occupations "19-2041.01"-"19-2041.03" have 100% green tasks and are jointly equally important as the parent group.

**The parent group is assigned zero green tasks to exclude nuclear power.

Online Appendix C: Industries

Harmonizing the industry codes

I harmonize the dirty industry 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 industries with a unique Census mapping. It is more complicated in two other instances.

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

Second, some dirty industries 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 industries. 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 industries that are indirectly mapped through subcategories. Industry "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 industries (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 industries, 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 codes are dirty. The last column shows whether the Census code is classified as dirty.
†I do not call this Census code dirty as it is typically not thought of as an industry most vulnerable to decarbonization.

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

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 when a 2- 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 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 considered most vulnerable to decarbonization.

Table C.3: Dirty NAICS industries with subcategories mapping to a Census code

Dirty NAICS code	Dirty NAICS title	NAICS code in crosswalk	NAICS title in crosswalk	Census code	Census title	Call Census code dirty?
2213	Water, Sewage and Other Systems	22131	Water Supply and Irrigation Systems	0670	Water, Steam, Air-conditioning, and Irrigation Systems	Yes
		22133	Steam and Air-Conditioning Supply			
		22132	Sewage Treatment Facilities	0680	Sewage Treatment Facilities	Yes
3132	Fabric Mills	31321	Broadwoven Fabric Mills	1480	Fabric Mills, Except Knitting Mills	Yes†
		31322	Narrow Fabric Mills and Schiffli Machine Embroidery			
		31323	Nonwoven Fabric Mills			
3141	Textile Furnishings Mills	31412	Curtain and Linen Mills	1590	Textile Product Mills, Except Carpet and Rug	No‡
		3149	Other Textile Product Mills			
3141	Textile Furnishings Mills	31411	Carpet and Rug Mills	1570	Carpet and Rug Mills	Yes‡
3132	Fabric Mills	31324	Knit Fabric Mills	1670	Knitting Fabric Mills, and Apparel Knitting Mills	No†
		3151	Apparel Knitting Mills			
3241	Petroleum and Coal Products Manufacturing	32411	Petroleum Refineries	2070	Petroleum Refining	Yes*

Table C.3: Dirty NAICS industries with subcategories mapping to a Census code (continued)

Dirty NAICS code	Dirty NAICS title	NAICS code in crosswalk	NAICS title in crosswalk	Census code	Census title	Call Census code dirty?
3241	Petroleum and Coal Products Manufacturing	32412	Asphalt Paving, Roofing, and Saturated Materials Manufacturing	2090	Miscellaneous Petroleum and Coal Products	Yes*
		32419	Miscellaneous Petroleum and Coal Products			
3262	Rubber Product Manufacturing	32621	Tire Manufacturing	2380	Tire Manufacturing	Yes
		32622	Rubber and Plastics Hoses and Belting Manufacturing	2390	Rubber Products, Except Tires, Manufacturing	Yes
		32629	Other Rubber Product Manufacturing			
3271	Clay Product and Refractory Manufacturing	32711	Pottery, Ceramics, and Plumbing Fixture Manufacturing	2470	Pottery, Ceramics, and Plumbing Fixture Manufacturing	Yes
		327120	Clay Building Material and Refractories Manufacturing	2480	Clay Building Material and Refractories Manufacturing	Yes

Table C.3: Dirty NAICS industries with subcategories mapping to a Census code (continued)

Dirty NAICS code	Dirty NAICS title	NAICS code in crosswalk	NAICS title in crosswalk	Census code	Census title	Call Census code dirty?
3364	Aerospace Product and Parts Manufacturing	336411	Aircraft Manufacturing	3580	Aircraft and Parts Manufacturing	Yes
		336412	Aircraft Engine and Engine Parts Manufacturing			
		336413	Other Aircraft Parts and Auxiliary Equipment Manufacturing			
		336414	Guided Missile and Space Vehicle Manufacturing	3590	Aerospace Products and Parts Manufacturing	Yes
		336415	Guided Missile and Space Vehicle Propulsion Unit and Propulsion Unit Parts Manufacturing			
		336419	Other Guided Missile and Space Vehicle Parts and Auxiliary Equipment Manufacturing			

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 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 industries in the main specification

Industry code	Industry 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

Table C.4: Dirty industries in the main specification (continued)

Industry code	Industry title
3180	Engine, Turbine, and Power Transmission Equipment Manufacturing
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 industries classified as dirty in the main specification.