Labor Reallocation, Green Subsidies, and Unemployment *

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Abstract: Green subsidies are a common decarbonization tool. I develop a search model to see how the subsidies affect employment and welfare. The analysis is underpinned by empirical labor market estimates for the United States. The estimates highlight the relevance of "neutral" (i.e., neither green nor fossil) jobs for the low-carbon transition: they account for most jobs and are often reallocated to by fossil workers. Inserting the empirical estimates in the search model, I find that a subsidy's financing mechanism plays an important role. A subsidy financed by payroll taxes generates more unemployment and lower welfare relative to a carbon price. However, a subsidy paid for in a non-distortionary manner counteracts search frictions and increases employment. The employment gains translate into higher welfare relative to a carbon price for low abatement levels.

Keywords: Environmental economics, Green subsidies, Labor reallocation, Unemployment, Welfare

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1 Introduction

The prevalence of green subsidies raises several questions.[1] First, how do the subsidies impact the labor market? Answering this question is important to manage potential job losses from the subsidies. However, few studies (Shimer, 2013; Bistline, Mehrotra and Wolfram, 2023) address this question in general equilibrium, and no study uses a microfounded model with search frictions. Second, how do green subsidies compare to carbon prices in terms of labor market outcomes and welfare? Carbon prices are widely advocated by economists, but can face public opposition (Dechezleprêtre et al., 2022; Douenne and Fabre, 2022). When carbon prices cannot be used, it is valuable to know the implications of adopting green subsidies instead. Third, how do green subsidies interact with the tax system? No study has investigated this issue in a general equilibrium setting with involuntary unemployment.

In this paper, I build a search model to analyze the impact of output-based green subsidies on the labor market and welfare. The model is characterized by firms investing in costly recruitment as a result of search frictions (Pissarides, 1985; Mortensen and Pissarides, 1994) in the labor market. The paper makes three contributions. First, it empirically estimates the number of green, fossil, and remaining "neutral" jobs, as well as job transitions, in the U.S. The estimates are used to provide an empirical basis for the distribution of jobs and the degree of labor mobility in the search model. A key insight from the estimates is that neutral jobs are relevant for the low-carbon transition. These jobs are the most numerous, meaning they are often transitioned to by fossil workers.

Second, using the search model, I show that green subsidies can generate higher welfare relative to a carbon price. This result is conditional on financing the subsidies in a non-distortionary manner and on a low abatement level. Subsidies financed by non-distortionary lump sum taxes counteract search frictions by increasing the return on recruitment. Firms respond 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 a carbon price. However, the welfare advantage of a subsidy over a carbon price disappears at high abatement levels when the subsidy is inefficient or if the

[1] All major economies, including the G20 and the members of the International Energy Agency, subsidize at least one of the following: renewable energy generation, clean fuel production, electric vehicle purchases, and energy efficiency improvements (IEA, 2024a). In the U.S., the Inflation Reduction Act (IRA) provides tax credits worth hundreds of billions of dollars for low-carbon electricity production and investment, carbon capture and storage, clean fuels, electric vehicle purchases, clean energy manufacturing, and private investments in energy efficiency and clean energy (Bistline, Mehrotra and Wolfram, 2023, CRFB, 2022). The EU has given more than €800 billion in renewable electricity subsidies since 2008 (European Commission, 2022) and finances low-carbon projects through the Green Deal Industrial Plan. Renewable electricity subsidies in China total more than $100 billion since 2020 (IEA, 2024b).

subsidy is financed by distortionary payroll taxes.

Third, I show that green subsidies interact differently with the tax system depending on the financing mechanism. A subsidy financed by payroll taxes reduces employment and welfare to a larger extent in the presence of preexisting tax distortions. A subsidy financed in a non-distortionary manner, however, performs equally well irrespective of the tax system. Such a subsidy is therefore especially valuable in the presence of preexisting distortions. In the following, I describe the search model and elaborate on the contributions.

The model is similar to the framework in Hafstead and Williams (2018).[2] The model represents unemployment as an equilibrium concept that results from endogenous recruitment by firms and exogenous job loss. Climate policy affects recruitment which changes the unemployment rate. My framework differs from Hafstead and Williams (2018) in a number of ways. First, I account for an empirically relevant "neutral" job type that is 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 degree of labor mobility in the model. In particular, I use survey data for the U.S. to estimate the number of green, fossil, and neutral jobs, as well as job transitions. I use the job transition estimates to calibrate the degree of friction firms face when matching with workers of a different type. This enables me to study green subsidies for a more realistic degree of labor mobility.[3]

The first contribution comes from the empirical analysis. I find that few jobs are green and most jobs are neutral in the U.S. With regard to job transitions, the data shows that workers rarely move from fossil to green jobs. This reinforces the insight from previous studies that workers in emissions-intensive industries can find it difficult to exploit job opportunities created by the green transition (Walker, 2013; Saussay et al., 2022; Colmer, Lyubich and Voorheis, 2023; Curtis, O'Kane and Park, 2023; Colmer et al., 2024). However, my results also show that many fossil workers reallocate to neutral jobs. Neutral jobs should therefore not be overlooked in the context of the green transition. While the discussion on jobs and the green transition typically revolves around enabling fossil workers to reallocate to green jobs, the abundance of neutral jobs means many displaced workers will start these jobs.

The second contribution is to show that a green subsidy can increase welfare relative to a carbon price. This result is conditional, however, on using a non-distortionary financing

[2] Hafstead and Williams (2018) model a clean and a dirty sector. They extend the one-sector model of Shimer (2010).

[3] There are three other differences with Hafstead and Williams (2018). First, I do not model an abatement activity. Abatement in my framework stems only from reductions in fossil firms' output. Second, I use a nested consumption structure. Third, I allow for a heterogeneous degree of labor mobility by relaxing the assumption that all firms face the same level of friction when matching with workers of a different type.

mechanism and on 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 makes green firms hire more workers. Second, the subsidy lowers the price of green goods which shifts demand to these goods. Green firms hire more workers, while firms elsewhere reduce recruitment. Third, the lump sum taxes financing the subsidy produce a negative income effect for consumers. However, because the taxes do not distort, the subsidy increases the return on recruitment 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 the subsidy is financed by payroll taxes. At high abatement levels, the subsidy induces inefficiently high production of 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.

The third contribution is to illustrate that the tax system impacts a subsidy differently depending on the financing mechanism. While a subsidy financed in a non-distortionary manner is unaffected by the tax system, a subsidy paid for by payroll taxes generates higher unemployment and lower welfare in the presence of other distortions. A distortionary financing mechanism such as payroll taxes is thus especially disadvantageous if the tax system is already distortionary.

Related literature

The paper relates to four literature strands. The first empirically measures the number of green jobs. A challenge for these studies is that no standard definition of a green job exists. One approach is to focus on the product associated with a job. Curtis and Marinescu (2022) and Colmer, Lyubich and Voorheis (2023) call solar and wind power jobs green, while Curtis, O'Kane and Park (2023) also count jobs related to electric vehicle production. These studies provide a rigorous characterization of green employment, but only for a subset of jobs that might benefit from the green transition. Engineers working on energy efficiency projects or environmental scientists conducting climate-related research might, for instance, be ignored. One way to also capture these jobs is to look at task content. Tasks are commonly used as the unit of analysis in the labor economics literature when assessing the incidence of structural and technological change (Acemoglu and Autor, 2011; Autor, 2013). A seminal example is Autor, Levy and Murnane (2003) who show that the impact of computerization on jobs depends on whether tasks are complements or substitutes to computers. The green transition can be analyzed through a similar task-based lens. The transition has created a need for new tasks 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 recent literature strand has adopted such a task-based approach by conceptualizing green jobs on the basis of their 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 measure the number of green jobs in the U.S. In particular, I define green jobs as jobs involving a high share of green tasks and use this definition to quantify green employment. By also measuring the number of fossil and neutral jobs, I estimate the distribution of jobs and job transitions. The job transition estimates are used to calibrate the degree of labor mobility in the search model.

The second related 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 Greenstone, 2002; Morgenstern, Pizer and Shih, 2002; Walker, 2011, 2013; 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 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 IRA generates a small increase in long run unemployment. Shimer (2013) analyzes the labor market impact 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).[4] 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 prices, 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. Search models are a well-established theory of equilibrium unemployment and have been used to investigate a range of labor market and macroeconomic issues (e.g., Hall, 2005; Shimer, 2005; Hagedorn and Manovskii, 2008; Hall and Milgrom, 2008; Ljungqvist and Sargent, 2017). They have also been applied in the context of environmental regulation (Hafstead and Williams, 2018; Aubert and Chiroleu-Assouline, 2019; Fernández Intriago, 2021; Hafstead, Williams and Chen, 2022; Finkelstein Shapiro and Metcalf, 2023). A key feature of search models is the matching function that determines the number of hires. Shimer (2010) develops a one-sector matching function of recruitment effort and the unemployment rate. Hafstead and Williams (2018) extend this function to allow for differentiated matching within and across sectors.[5] A key parameter in their matching function is the degree of 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 labor mobility throughout the economy.

[4]These studies emphasize two opposing effects of a subsidy in the presence of full employment and preexisting labor taxes: a revenue-financing effect and a tax-interaction effect (Parry, 1998). The revenue-financing effect is the welfare loss from financing a subsidy with distortionary taxes. The tax-interaction effect is the welfare gain from the subsidy increasing voluntary labor supply.

[5]Most studies use a one-sector matching function. Two exceptions are Hafstead and Williams (2018) and Yedid-Levi (2016) who employ multi-sector functions.

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

2 Estimating the distribution of jobs and job transitions

This section empirically estimates the distribution of jobs and job transitions in the U.S. Section 2.1 gives an overview of the data, while Section 2.2 describes the job classification procedure. Section 2.3 presents the estimates.

2.1 Occupation data

I obtain data on occupations over time 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.[6] I make use of two panels: one for the period 2013-2016 and another for 2017-2020.[7] This gives me monthly employment data over an eight-year span (2013-2020).[8,9]

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

2.2 Classifying jobs by type

2.2.1 Defining green jobs

I define green jobs as jobs involving a high share of green tasks. This approach offers several advantages (Vona, Marin and Consoli, 2019; Vona, 2021). First, the unit of analysis is the tasks carried out by a worker. The definition therefore centers around the characteristics of a job, as opposed to a broader unit such as an industry. Second, it captures green jobs across all industries, including jobs indirectly created by the green transition in non-energy industries. Third, it allows for a non-binary definition. This is advantageous since not all green jobs are

[6]Some respondents report multiple jobs in a month. I determine their main job based on the highest average number of 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.

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

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

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

fully green. A task-based approach allows for a proportional relationship between the degree to which an occupation is green and the share of tasks devoted to green activities.

I call an occupation green if its share of green tasks equals or exceeds a threshold α.[10] I set $\alpha = 50\%$ in the main specification and conduct sensitivity on this value in Section 2.3. The green job definition is operationalized using 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 contains detailed task information for 974 occupations on an 8-digit O*NET-SOC level.[11] The information includes task importance scores and a classification of tasks as green or non-green.[12] Following Vona, Marin and Consoli (2019), I weight tasks by their importance score and calculate a weighted green task share by 8-digit occupation.[13,14] I aggregate the shares to a 6-digit level by taking an average across the 8-digit occupations (see Appendix B for the aggregation procedure). 11 occupations on a 6-digit level have a green task share of at least 50%. I call these occupations green (see Table A.3 in Appendix A for a list of these occupations).

2.2.2 Defining fossil jobs

I define fossil jobs as jobs disproportionately found in emissions-intensive ("dirty") industries. The fossil jobs thus represent the jobs vulnerable to the green transition as a result of their industry.[15] I identify the fossil jobs using a two-step procedure.[16]

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

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

[12] O*NET classified the tasks as follows (Dierdorff et al., 2009; O*NET, 2010). Job titles relating to the green economy 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 and sorted into three occupational groups:

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

O*NET reviewed the literature and online sources (e.g., job descriptions, employment databases, and career information websites) to identify tasks for each occupation that are affected by green economy activities and technologies. These tasks were labeled green. Occupations in the first group were assigned zero green tasks since their tasks are by definition not directly affected by the green economy. Occupations in the third group were created from the green economy and thus all their tasks were labeled green.

[13] O*NET assigns the importance scores based on employee surveys and occupational experts. 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 minimum score for that occupation in line with Vona, Marin and Consoli (2019).

[14] 41 occupations have a weighted green task share of at least 50% (see Table A.2 in Appendix A).

[15] While workers in fossil jobs risk becoming displaced due to their industry, some will be able to transition to jobs with a similar task profile in non-dirty industries. Capturing the workers whose skills become less valuable from the green transition requires data on fossil tasks which does not exist.

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

First, I establish a set of dirty industries. To do this, I obtain facility-level greenhouse gas emissions data for the year 2019 from the Greenhouse Gas Reporting Program (GHGRP) of the Environmental Protection Agency.[17] I aggregate the data to an industry-level and combine them with employment data from the Occupational Employment and Wage Statistics program of the Bureau of Labor Statistics (BLS).[18] This allows me to calculate emissions intensity by industry. I call an industry dirty if it lies in the top five percent of the employment-weighted emissions intensity distribution. Table C.4 in Appendix C lists the industries classified as dirty.

Second, I define fossil jobs by taking advantage of industry-level information in SIPP. Each survey respondent reports both their occupation and industry.[19] I classify an occupation as fossil if it is at least eight times more likely than the average occupation to be found in a dirty industry.[20] This gives 63 fossil jobs (see Table A.4 in Appendix A).[21]

2.3 Estimation results

I apply the classification scheme to the jobs in SIPP and call any job that is neither green nor fossil neutral.[22] Section 2.3.1 shows the distribution of jobs. Section 2.3.2 presents job transition estimates.

2.3.1 Distribution of jobs

Fig. 1 shows the evolution of green and fossil jobs in the U.S. The share of green jobs increased slightly from 1.5% to 1.7% during 2013-2020. The 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).[23] The share of fossil jobs,

[17]The GHGRP requires large emitters to report scope one emissions on a facility-level. The emitters are power plants, oil and gas systems, and industry (including underground coal mines). The emissions are CO_2, Methane, Nitrous Oxide, HFC, PFC, SF_6, NF_3, and other greenhouse gas emissions (that account for less than 0.05% of total emissions).

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

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

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

[21]Two jobs are both green and fossil: "17-2141 - Mechanical Engineers" and "51-9199 - Production Workers, All Other". I classify them as green in line with Vona et al. (2018) and do sensitivity on this in Section 2.3.

[22]Table D.3 in Appendix D lists the most common industries by job type.

[23]The green job shares in Fig. 1 are higher than two recent studies for the U.S. Both studies use a narrower definition of green jobs. Curtis, O'Kane and Park (2023) find that jobs related to electric vehicle production,

in contrast, decreased from 5.5% to 4.9% during 2013-2020. Green and fossil jobs accounted for less than 10% of all jobs in every year. Most jobs are therefore neutral.

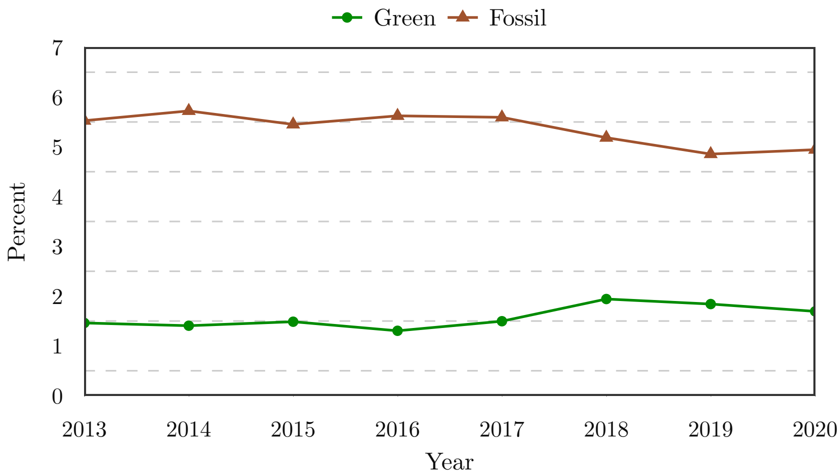

Figure 1: Green and fossil jobs over time
Note: The figure shows the percent of green and fossil jobs in the U.S. during 2013-2020.

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

While changing the green job definition affects the composition of jobs, the qualitative insights do not change. The majority of jobs are neutral, while the share of green jobs increases and the share of fossil jobs decreases by at least a small amount.

The remaining sensitivity tests are as follows. Panel (b) of Figs. D.1-D.2 restricts occupations' tasks to those classified as "core" by O*NET.[24] The green task shares are thereby calculated on the basis of the most important tasks for each occupation. 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)-(e) use stricter

solar power, and wind power accounted for 0.8% of jobs on average during 2005-2019. Curtis and Marinescu (2022) estimate that 0.2% of job postings in 2019 were solar and wind jobs.

[24] 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).

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 cases, the qualitative insights hold: the majority of jobs are neutral and the share of green (fossil) jobs increases (decreases) by at least a small amount.

2.3.2 Job transitions

Fig. 2 shows job transition probabilities by worker and job type.[25] Fossil workers have a low probability (5%) of starting a green job. They are more likely to start a neutral job, as this probability exceeds 40%.[26] The high probability highlights the relevance of neutral jobs for the green transition and suggests that many displaced workers will start neutral jobs.[27]

I conduct a similar sensitivity analysis as in Section 2.3.1. Fig. D.3 in Appendix D shows how the job transition probabilities vary with α. Fig. D.4 repeats this exercise assuming only core tasks. Fig. D.5 restricts green jobs to non-dirty industries. Figs. D.6-D.7 use more narrow definitions of a fossil job, while Figs. D.8-D.10 use looser definitions. Fig. D.11 employs a more narrow definition of a dirty industry. In all figures, fossil workers are more likely to start a neutral job compared to a green job, which corroborates the qualitative insight from the main specification.

Finally, I estimate the distribution of workers starting each job. The results are shown in Table 1. Each column contains the distribution of workers starting a given job type. 14%

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

[26] Panel (b) of Fig. E.1 in Appendix E shows that the probability of starting a neutral job is much smaller when correcting for differences in employment shares. The high likelihood of starting a neutral job in Fig. 2 is therefore driven by the abundance of neutral jobs.

[27] Appendix D provides more details on the job transitions. Table D.1 lists the most common neutral occupations that fossil workers transition to and the percentage of cases when the neutral job is in a dirty industry. Table D.2 repeats this exercise for fossil to green transitions.

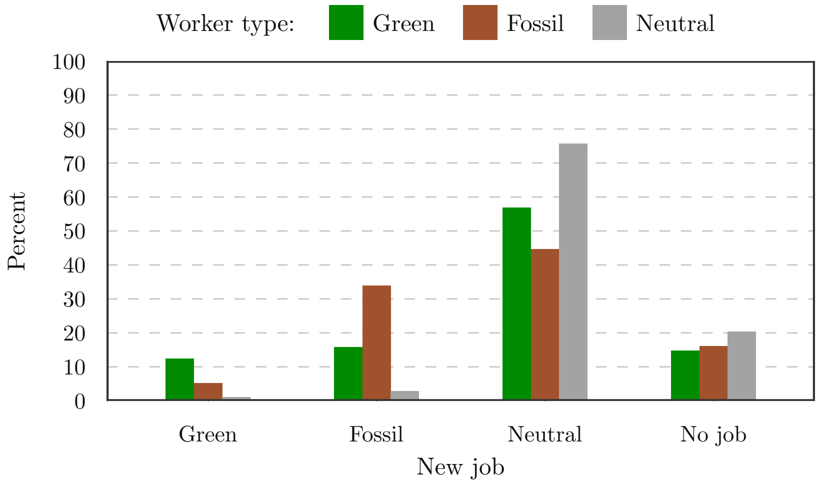

Figure 2: Job transition probability by type of worker and job

Note: The figure shows the probability of starting a green job, fossil job, neutral job, or unemployment by worker type (green, fossil, or neutral) in the U.S. during 2013-2020.

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

Table 1: Distribution of workers starting each job

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

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

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

3 Search model

I employ a search model to study the employment and welfare impact of green subsidies. The model builds on Hafstead and Williams (2018) and is characterized by search frictions in the labor market. The search frictions mean it takes time for firms to match with job searchers. Unemployment in equilibrium is determined by the amount of hiring and job loss. Hiring takes the form of an endogenous job matching process. Once a worker and firm match, they negotiate wages and hours worked according to a Nash bargaining process. The worker then joins the firm in the following period. An exogenous number of workers π lose their job at the end of each period. I assume that only unemployed workers search for jobs. Climate policies affect recruitment by changing the value of a match for firms (see Section 3.5). I elaborate on the model in the remainder of this section.

3.1 Basic set-up

The model is characterized by $t = \{0, 1, 2, ...\}$ months.[28] There are three firm types $i, j, k \in \mathcal{J} = \{\texttt{f}, \texttt{g}, \texttt{z}\}$. Fossil firms ($j = \texttt{f}$) generate emissions in production, while green firms ($j = \texttt{g}$) and neutral firms ($j = \texttt{z}$) are emissions-free.

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

3.2 Firms

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

[28] The time subscript is suppressed henceforth for legibility.

3.2.1 Production

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

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

where ζ is labor productivity. The output is sold at net price p_j^y. Fossil firms generate ϵ emissions from each unit of output. Total emissions e are given by

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

3.2.2 Matching

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

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

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

The parameter ξ_j controls the degree of friction associated with cross-type matching.[29] If $\xi_j = 0$, firm j can only recruit workers of type j, meaning there is no cross-type matching. If $\xi_j = 1$, matching does not depend on a worker's type, implying *ceteris paribus* that workers i and $j \neq i$ are equally likely to match with firm j. For values of ξ_j in between zero and one, the share of cross-type matches for firm j is proportional to ξ_j.

The degree of labor market tightness determines the ease at which workers can find a job and the amount of recruitment effort that firms must exert to hire workers. There are three measures of labor market tightness: the ratio of firm j's recruitment effort to the number of unemployed workers of type i (θ_{ij}), the ratio of firm j's recruitment effort to total

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

unemployment (θ_j), and the ratio of total recruitment effort to total unemployment (θ):

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

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

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

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

$$q_j = \mu_j \left[\xi_j \theta^{-\gamma} + (1-\xi_j)\theta_{jj}^{-\gamma}\right], \tag{5}$$
$$\phi_{ij} = \mu_j \left[\xi_j \theta_j \theta^{-\gamma} + (1-\xi_j)\theta_{ij}^{1-\gamma}\delta_{ij}\right]. \tag{6}$$

Recruitment productivity q_j is decreasing in labor market tightness: a tighter labor market, from either an increase in recruitment effort or a decrease in unemployment, means recruiters have to exert more effort to hire a given number of workers. The probability of finding a job ϕ_{ij} is increasing in labor market tightness measures θ_j and θ_{ij} since a worker i is more likely to find a job at firm j if the firm exerts more recruitment effort or if competition from other workers decreases. The probability of finding a job at firm j is, in contrast, decreasing in θ because higher recruitment effort by other firms means worker i can more easily find a job outside of firm j.

3.2.3 Firm's problem

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

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

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

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

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

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

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

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

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

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

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

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

3.3 Household

The workers own the firms and belong to a representative household. The household pools workers' income together and fully insures workers against temporary income shocks (e.g., from unemployment or wage changes).[30] The assumption of full insurance, dating back to Merz (1995), is common in the search literature and simplifies the household's problem (Hall, 2009). It implies that the household equalizes the marginal utility of consumption across workers in order to maximize their combined utility.

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

Workers get utility from consumption C and disutility from work. Consumption is separable from leisure and identical across employed and unemployed workers. Utility is

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

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

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

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

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

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

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

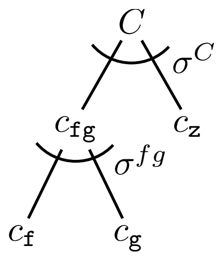

Figure 3: Consumption structure

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

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

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

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

subject to

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

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

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

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

The first-order condition with respect to consumption equates the marginal utility of consumption with the marginal cost, such that

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

where λ is the Lagrange multiplier for the budget constraint.

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

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

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

$$V_a = \lambda,$$

which holds in every period implying

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

Combining Eqs. 16 and 17 gives the Euler equation that equates the price of an Arrow security with the discounted intertemporal ratio of the marginal utility of income:

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

To obtain $V_{n_{\mathcal{J}}}$ and $V_{u_{\mathcal{J}}}$, I differentiate Eq. 13 with respect to the number of employed and unemployed workers of each type to get the envelope conditions

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

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

Eq. 18 states that the value 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. 19 indicates that the value of an unemployed worker corresponds to the worker's utility plus the value of unemployment benefits and the discounted expected value in the next period if the worker is unemployed or finds a job with probability $\sum_j \phi_{ij}$.

3.4 Wages and hours

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

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

where $\eta \in [0,1]$ denotes the firm's bargaining power. Solving gives the following respective equilibrium conditions for hours and wages:[31]

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

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

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

Eq. 21 indicates that the match surplus is split between the worker and firm according to a constant share rule. A worker's after-tax wage income equals a weighted average of

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

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

3.5 Government, climate policy, and market clearing

The government has access to two climate policy instruments. The first is 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 corresponds to the gross price p_j adjusted for any subsidy receipts and carbon pricing payments, meaning

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

A green subsidy increases the value of a match for green firms because a worker can generate $p_\mathtt{g} + s > p_\mathtt{g}$ per unit of output. A carbon price, in contrast, makes a match less valuable for fossil firms since they have to pay τ^E dollars on the ϵ emissions from each unit of output.

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

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

Finally, the market for each good clears implying

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

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

4 Calibration

I calibrate the model to the U.S. economy in 2019. Some parameter values are based on the literature and data sources (Section 4.1), while others are estimated using the search model in the business as usual benchmark (Section 4.2). Table 2 summarizes the calibration.

Table 2: Calibration overview

(a) Direct calibration

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

(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 on the basis of the business as usual benchmark.

4.1 Direct calibration

The average job separation rate in the U.S. was 3.7% in 2019.[32] I set π equal to this value. The bargaining power is split equally across firms and workers ($\eta = 0.5$) in line with 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 using survey data. I adopt a middle value of $\gamma = 0.5$, which is also the approach of Yedid-Levi (2016) and Hafstead and Williams (2018).

The average real interest rate in the U.S. was 3.43% in 2019,[33] which translates into a monthly discount factor β of $1.0343^{-1/12} = 0.997$. The Frisch elasticity of labor supply χ is equalized to unity in line with Hall and Milgrom (2008). I set the elasticity of substitution between the green-fossil composite and the neutral good σ^C to 0.5, which is a standard value in aggregated CES consumption structures (see e.g., Landis, Fredriksson and Rausch, 2021).

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

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

The elasticity between the fossil and green good σ^{fg} is set to a higher level (0.75) in order to reflect the larger switch in consumption from fossil to green goods as a result of climate policy.

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

4.2 Calibration using the benchmark

I make six assumptions in the benchmark. First, I set $\overline{u} = 5.9\%$ to mirror the average unemployment rate in the U.S. during 2000-2019.[35] This implies $\overline{n} = 1 - \overline{u} = 94.1\%$. Second, I distribute total employment $\overline{n}$ and total consumption C in proportion to the employment shares in 2019 in Fig. 1. The green, fossil, and neutral employment shares are 1.8%, 4.9%, and 93.3% respectively. Third, without loss of generality, I normalize prices, total consumption, and workers' time endowment to unity. Fourth, I assume that one third of the time endowment (i.e., eight hours per day) is spent working, meaning $h_j = 1/3$. Fifth, I fix recruitment productivity q_j. Silva and Toledo (2009) estimate that the cost of recruiting one worker is approximately 4% of a quarterly wage, which corresponds to 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 consequently hires $1/0.04 = 25$ workers per hour, meaning $q_j = 25$ in the benchmark. Sixth, I assume that the shares of within-type matches correspond to the diagonal elements of Table 1. In particular, let ω_j denote the share of matches for firm j with workers of type j such that

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

I set ω_j equal to the diagonal elements of Table 1, such that $\omega_{\mathtt{f}} = 0.39, \omega_{\mathtt{g}} = 0.14$, and $\omega_{\mathtt{z}} = 0.95$. The values of ω_j correspond to the share of workers starting job j that previously had the same job $i = j$.[36]

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

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

[36] An inconsistency between the empirical analysis and the model is that the former estimates ω_j on the basis of *all* job transitions while only unemployed workers switch jobs in the model. Estimating ω_j on the basis of only unemployed workers' job transitions gives similar values of ω_j. The values are the same for the green and neutral types and slightly lower ($\omega_{\mathtt{f}} = 0.33$ as opposed to $\omega_{\mathtt{f}} = 0.39$) for the fossil type.

4.2.1 Calibrating ξ_j

To estimate ξ_j, I first rearrange Eqs. 3 and 4 and substitute them into Eq. 23 to get[37]

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

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

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

Eq. 24 links ξ_j to $\{u_\mathtt{f}, u_\mathtt{g}, u_\mathtt{z}\}$ and exogenous parameters.[38] To define $\{u_\mathtt{f}, u_\mathtt{g}, u_\mathtt{z}\}$, I note that employment and unemployment are constant in the steady state. Eqs. 14 and 15 thus imply

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

which, using Eq. 6, can be rewritten as

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

Eqs. 24 and 25 contain two unknowns (ξ_j and u_j) in the benchmark.[39] Solving for ξ_j and u_j using both equations gives

$$\xi_j = \begin{cases} 0.58 & \text{for } j = \mathtt{f}, \\ 0.87 & \text{for } j = \mathtt{g}, \\ 1 & \text{for } j = \mathtt{z}, ^{40} \end{cases}$$

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

The high values of ξ_j for neutral and green firms mean they can easily match with outside workers. This is especially the case for neutral firms, as they face no matching friction with outside workers. Fossil firms, on the other hand, face some friction due to a smaller ξ_j. While this restricts the ability of neutral and green workers to obtain fossil jobs, the overall degree of labor mobility in the model is high. Turning to the values of u_j, most unemployed workers in the benchmark are neutral. This is due to the prevalence of neutral workers.

[37] 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 ($\xi_j = 1$). Values in between are scarce. Hafstead and Williams (2018) conduct a sensitivity analysis on ξ_j, but do not take a stance on the empirical value.

[38] υ_j is determined exogenously in the steady state by Eqs. 7 and 9. Because employment in the steady state is constant, the two equations imply that υ_j is pinned down by $\upsilon_j = n_j\pi/(q_j h_j)$.

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

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

4.2.2 Calibrating the remaining parameters

The matching efficiency μ_j is pinned down by rearranging Eq. 5 to $\mu_j = q_j/(\xi_j \theta^{-\gamma} + (1 - \xi_j)\theta_{jj}^{-\gamma})$. Labor productivity ζ is obtained by rearranging Eq. 1 to $\zeta = y_{\mathtt{g}}/(l_{\mathtt{g}} h_{\mathtt{g}})$ and setting $y_{\mathtt{g}} = n_{\mathtt{g}}$, $l_{\mathtt{g}} = n_{\mathtt{g}} - \upsilon_{\mathtt{g}}$, and $h_{\mathtt{g}} = 1/3$.[41] I pin down the disutility of work ψ by the hour bargaining condition in Eq. 20. The CES consumption shares ϱ_r are obtained from Eqs. 11 and 12. Similarly to Hafstead and Williams (2018), unemployment benefits b_i are endogenously determined by the wage bargaining condition in Eq. 21. I get $b_{\mathtt{f}} = 0.25, b_{\mathtt{g}} = 0.27$ and $b_{\mathtt{z}} = 0.28$.[42] The values imply replacement rates of 38%, 41%, and 42% for fossil, green, and neutral workers respectively. These are similar to the 41% in Hafstead and Williams (2018) and lie in between the 25% and 50% in Hall and Milgrom (2008) and Finkelstein Shapiro and Metcalf (2023) respectively.

The emissions factor ϵ is parametrized using a similar procedure as in Hafstead and Williams (2018). First, I note that total personal consumption expenditure in the U.S. was \$14.4 trillion in 2019,[43] while carbon dioxide emissions were 5.234 billion tons.[44] The emissions intensity of consumption was therefore 0.000363 tCO_2/\$. Second, I adjust this number for the fact that only fossil firms emit. Consumption of the fossil good accounts for 4.9% of total consumption (that equals one) in the initial steady state, meaning the emissions factor of fossil firms is 0.00741 tCO_2 per dollar of output.

5 Employment and welfare impacts

This section presents the labor market and welfare outcomes from a green subsidy and a carbon price. Section 5.1 depicts the labor market impacts assuming the government finances the subsidy and recycles carbon revenue in a non-distortionary manner. Section 5.2 introduces distortionary financing and recycling mechanisms. Section 5.3 changes the level of preexisting

[41] I pin down ζ using $j = \mathtt{g}$. The choice of firm type is arbitrary since y_j/l_j and $1/h_j$ are identical across firm types in the benchmark.

[42] In contrast to Hafstead and Williams (2018), my unemployment benefits vary across workers because of the firm-specific ξ_j. This implies different fundamental surplus ratios (0.12, 0.09, 0.08) for the fossil, green, and neutral types respectively. As shown by Ljungqvist and Sargent (2017), the fundamental surplus ratio determines the magnitude of the employment change from a productivity shock. A lower fundamental surplus ratio implies larger employment changes from climate policy and vice versa. The ratio is defined as $\frac{\hat{y}_{n_j} - \hat{Z}_j}{\hat{y}_{n_j}}$ where $\hat{y}_{n_j} = \frac{1-\tau^L}{1+\tau^P} p_j^y \zeta h_j$ is the after-tax marginal product of labor and $\hat{Z}_j = \frac{\psi \chi h_j^{1+\frac{1}{\chi}}}{\lambda(1+\chi)} + p^C b_j$ is the flow value of unemployment, equal to the value of leisure plus unemployment benefits. I examine the implications of varying the unemployment benefits and fundamental surplus ratios in Section 5.5.

[43] 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.

[44] 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.

distortions. Section 5.4 depicts welfare outcomes, while Section 5.5 conducts sensitivity. The abatement level is fixed throughout unless stated otherwise. It is set such that the 10-year subsidy expenditure in Section 5.1 equals $781 billion, which is the estimated size of the IRA tax credits in the main scenario of Bistline, Mehrotra and Wolfram (2023).[45]

5.1 Climate policy with lump sum taxes

5.1.1 Total employment impact

Fig. 4 shows the change in employment from a subsidy and a carbon price when the government balances its budget with lump sum (LS) taxes.[46] A subsidy increases steady state employment by 0.10 percentage points. A carbon price, in contrast, reduces it by 0.03 percentage points. A subsidy therefore generates higher employment compared to a carbon when financed in a non-distortionary manner.

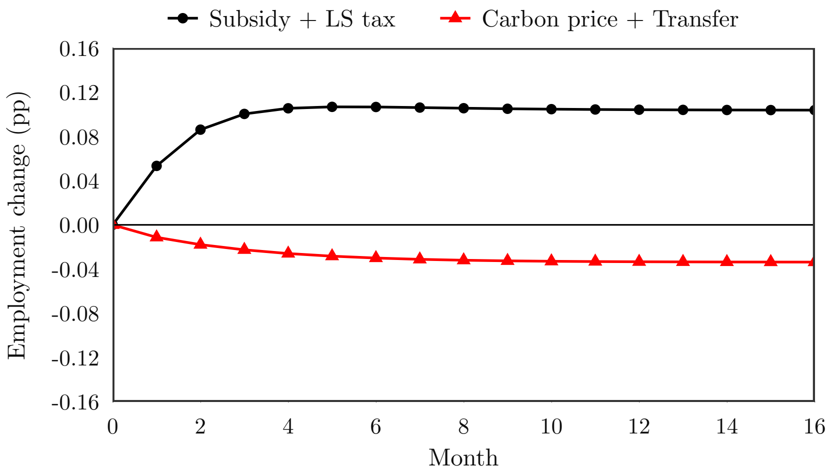

Figure 4: Employment change from a green subsidy and carbon price with lump sum taxes and transfers

Note: The figure shows the employment change from a green subsidy financed by lump sum (LS) taxes and from a carbon price with transfer recycling. The employment change is given in percentage points relative to the business as usual benchmark.

5.1.2 Impact by job type

5.1.2.1 Subsidy

To see why a green subsidy reduces unemployment, Panel (a) of Fig. 5 decomposes the employment change by job type. Two key insights emerge from the panel.

[45] This reduces steady state emissions by 1.7%. Section 5.5 examines the implications of increasing the abatement level.

[46] The lump sum taxes are negative (i.e., equivalent to a transfer) for a carbon price.

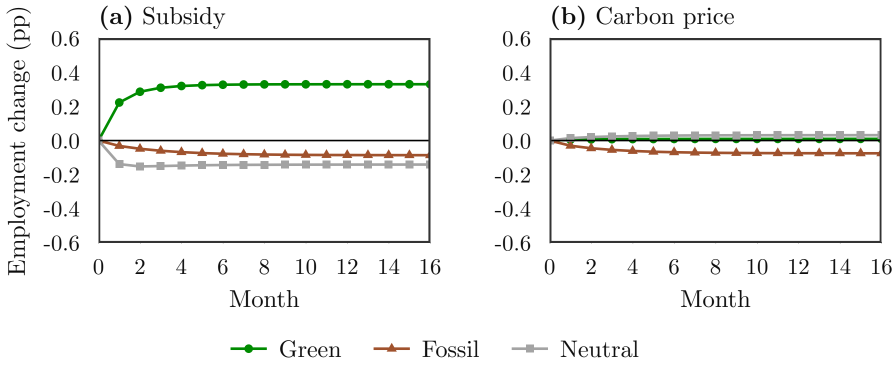

Figure 5: Employment change by job type from a green subsidy and carbon price

Note: The figure shows the change in the number of green, fossil, and neutral jobs (in percentage points relative to the benchmark) from a green subsidy financed by lump sum taxes (Panel (a)) and a carbon price with transfer recycling (Panel (b)).

First, a green subsidy increases the number of green jobs and reduces the number of other jobs. The reallocation of labor to green jobs stems from the subsidy switching demand to green goods by making them cheaper. Green firms respond by hiring workers and creating green jobs. Fossil and neutral firms, in contrast, reduce recruitment because their goods become comparatively more expensive. The number of fossil and neutral jobs therefore decline.

Table 3 shows these effects. A subsidy reduces the relative price of the green good. Green firms respond by increasing (steady state) output, hiring more recruiters, and expanding recruitment.[47] Their output and recruitment increase relative to non-green firms.[48]

Second, the green subsidy produces disproportionately large green jobs gains. The gains outweigh the job losses elsewhere in the economy, which explains why unemployment falls. The green job gains are so large because a subsidy increases the return on hiring workers for green firms without introducing additional distortions. The last column of Table 3 shows that the value of hiring a worker increases by 97% for green firms immediately after the subsidy is introduced.[49] The subsidy means a green worker generates $p_g + s$ as opposed to p_g per unit of output. Green firms take advantage of this by hiring more workers, which creates green jobs. Meanwhile, the subsidy is financed by lump sum taxes that do not distort recruitment

[47]Green firms reduce output immediately after the subsidy is introduced. The reason is that they switch workers from production to recruitment. Table 3 shows that the number of green recruiters expands by 345% immediately after the subsidy is introduced. In the steady state, the number of production workers and recruiters in green firms both increase.

[48]Table 3 shows that neutral firms hire more recruiters. Neutral recruitment contracts, however, because recruitment productivity declines from a tighter labor market (stemming from the green subsidy increasing economy-wide employment).

[49]A subsidy increases the value of a green match to an even larger extent if recruiters are more productive. A 50% increase in recruitment productivity μ_j increases the value of a match for green firms by 25 percentage points and makes these firms almost double their steady state recruitment.

decisions. The subsidy therefore increases the value of hiring workers for green firms without distorting the recruitment decisions of non-green firms. This leads to net job gains.

Table 3: Changes from a green subsidy by firm and time period (in % vs. benchmark)

Firm	Time period	Gross price p_j	Output y_j	Recruiters v_j	Recruiting productivity q_j	Recruitment $v_j q_j h_j$	Match value J_{n_j}
Green	$t = 0$	0	-4.3	345.0	-8.6	356.7	97
	SS	0	19.8	21.6	-1.9	19.5	33
Fossil	$t = 0$	15.1	-13.9	-20.9	3.5	-18.6	9
	SS	30.1	-1.7	-0.2	-1.9	-1.9	33
Neutral	$t = 0$	15.9	-13.4	-2.5	-1.9	-4.3	17
	SS	30.1	0.0	1.5	-1.9	-0.2	33

Note: The table shows the impact of a lump sum tax-financed green subsidy on various outcomes by firm and time period, where the time periods are the first period ($t = 0$) and the steady state (SS). The impacts are given in percent relative to the business as usual benchmark. The gross price of the green good does not change as it is the numeraire.

5.1.2.2 Carbon price

Panel (b) of Fig. 5 displays the impact of a carbon price on each job type.[50] A carbon price produces smaller green employment gains compared to a green subsidy. The reason is that a carbon price does not increase the value of a match. Green employment expands because demand shifts to green goods. However, because search frictions are not counteracted, the change in green employment is small. Recycling the carbon revenue in a lump sum manner does not reduce distortions, which further explains why green firms increase recruitment by only a small amount.

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

[50] A green subsidy and a carbon price have opposite effects on neutral employment in Fig. 5. A subsidy decreases neutral employment while a carbon price increases it slightly. The discrepancy stems from how the instruments affect the neutral good's price. A subsidy makes the neutral good more expensive relative to an average consumption basket, which reduces recruitment of neutral firms. A carbon price, conversely, makes the neutral good relatively cheaper (Table E.1 in Appendix E) and increases recruitment of neutral firms.

5.2 Climate policy with labor taxes

The black lines in Fig. 6 show the employment impact of a subsidy given different financing methods. The solid black line is the same as in Fig. 4 and represents a situation in which the government finances a subsidy with lump sum taxes. Employment increases in this case. The dashed black line depicts the employment change if the government instead increases payroll taxes to finance the subsidy. The job gains thereby disappear and employment 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 for financing and revenue recycling. An implication is that subsidies are especially advantageous when lump sum taxes are available. If this is not the case, Fig. 6 suggests that a carbon price generates more favorable employment outcomes.

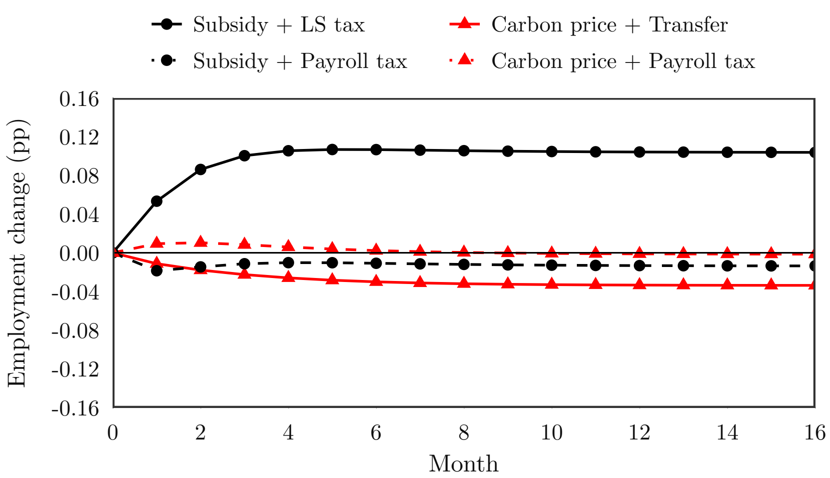

Figure 6: Employment change from a green subsidy and carbon price by financing or recycling mechanism

Note: The figure shows the change in employment 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. The employment change is given in percentage points relative to the business as usual benchmark.

Fig. 7 decomposes the employment change from a subsidy by job and financing mechanism.[51] A subsidy increases the number of green jobs, irrespective of the financing mechanism. However, the increase is smaller when the subsidy is paid for by payroll taxes. The reason is twofold. First, higher payroll taxes increase distortions for green firms by making labor more costly. This reduces green output and recruitment relative to a subsidy financed by lump

[51] Fig. E.2 in Appendix E performs an analogous decomposition for a carbon price.

sum taxes.[52] Second, a payroll tax-financed subsidy counteracts search frictions for green firms by less because it induces a lower subsidy rate.[53] The subsidy rate is lower because each dollar in subsidy payments increases production costs for fossil firms (from the higher payroll taxes). Their output, and consequently emissions, therefore contract by more for a given subsidy level. The lower subsidy rate further slows down recruitment of green firms and contributes to the smaller green job gains.[54]

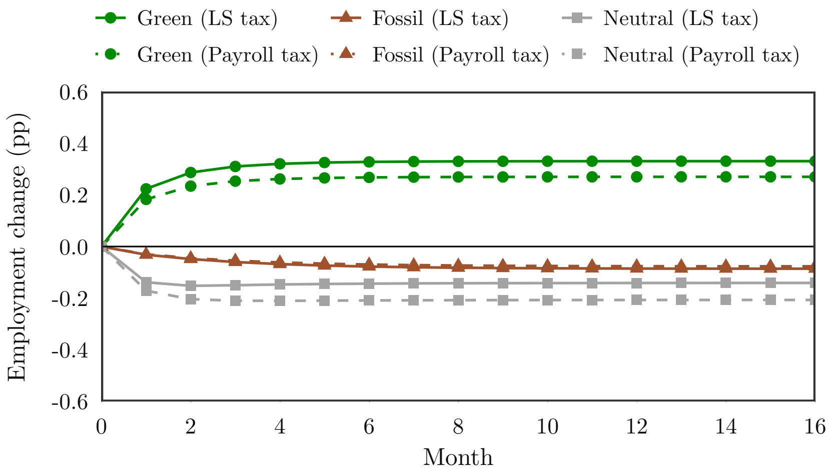

Figure 7: Employment change from a green subsidy by job type and financing mechanism
Note: The figure shows the change in employment, by job type, from a green subsidy financed by either lump sum taxes ("LS tax") or payroll taxes. The employment change is given in percentage points relative to the business as usual benchmark.

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

5.3 Preexisting distortions

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

[52]The output of green firms increases by 20% from a subsidy financed by lump sum taxes, but only by 16% from a subsidy financed by payroll taxes.

[53]The subsidy decreases from \$0.30 to \$0.25 cents per dollar of green output when switching from lump sum to payroll taxes.

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

increase in the labor income tax τ^L and payroll tax τ^P in the benchmark) has heterogeneous effects across financing mechanisms. Employment is lower if the subsidy is financed by payroll taxes but unchanged if lump sum taxes are used. Financing a subsidy with payroll taxes is therefore less attractive if the labor market is already distorted. This is also true relative to a carbon price. Fig. 9 shows that the carbon price is less affected by the level of preexisting distortions. The employment losses from a payroll tax-financed subsidy therefore grow relative to a carbon price when the labor market is initially more distorted.

A subsidy financed by payroll taxes performs worse in the presence of high preexisting distortions because the distortions dampen economic activity and erode the tax base. To finance a given subsidy level, payroll taxes thereby need to increase by a larger amount. The higher payroll taxes increase labor costs, reduce recruitment, and decrease employment.

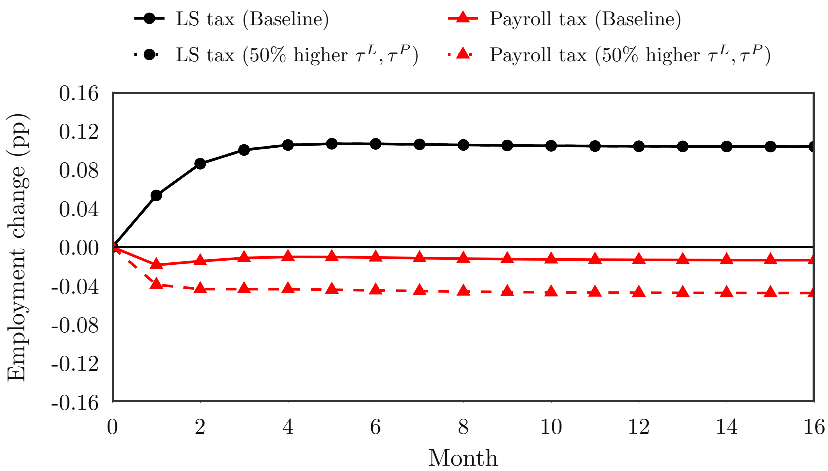

Figure 8: Employment change from a green subsidy by financing mechanism and benchmark tax rates

Note: The figure shows the employment change from a green subsidy financed by lump sum taxes ("LS tax") or payroll taxes in two scenarios: "Baseline" (where the labor income tax τ^L equals 0.29 and the payroll tax τ^P equals 0.15 in the benchmark) and a scenario where τ^L and τ^P are 50% higher in the benchmark. The employment change is given in percentage points relative to the business as usual benchmark. The black lines overlap in the figure.

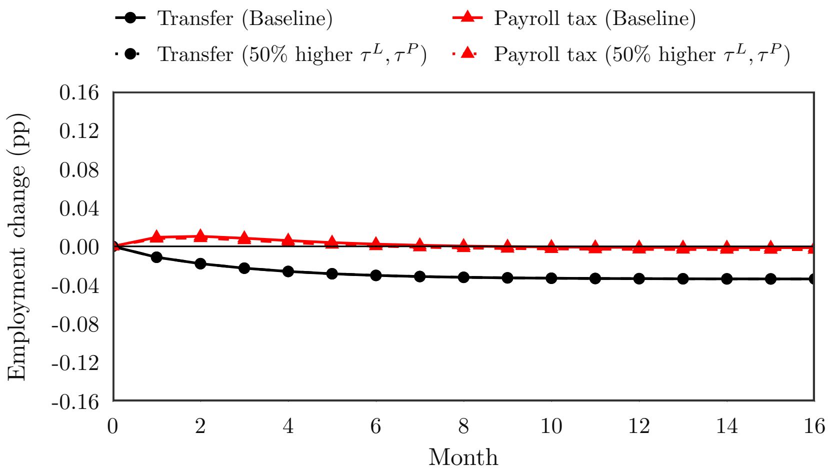

Figure 9: Employment change from a carbon price by recycling mechanism and benchmark tax rates

Note: The figure shows the employment change from a carbon price with transfer or payroll tax recycling in two scenarios: "Baseline" (where the labor income tax τ^L equals 0.29 and the payroll tax τ^P equals 0.15 in the benchmark) and a scenario where τ^L and τ^P are 50% higher in the benchmark. The employment change is given in percentage points relative to the business as usual benchmark. The black lines overlap in the figure.

5.4 Welfare

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. The equivalent variation is the change in benchmark consumption, evaluated at benchmark prices, that gives the same utility as after a policy is implemented. When calculating the equivalent variation, I fix 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.[55]

Table 4 reports the welfare change by policy instrument for different levels of preexisting distortions. For the baseline level of distortions, a subsidy financed by lump sum taxes increases welfare by 0.26% and performs better than a carbon price. The reason is that the

[55]The qualitative results are similar if leisure is included in the welfare calculations (see Table E.2 in Appendix E). The only difference is that the initial distortion level now impacts a lump sum tax-financed subsidy. In particular, a higher distortion level makes the subsidy perform *better*. The reason is that disutility from work ψ is lower in the benchmark when preexisting distortions are high.

subsidy counteracts search frictions and draws labor out of unemployment (Section 5.1). The higher employment increases production and welfare.

The welfare gains disappear if a subsidy is financed by payroll taxes. A subsidy then generates welfare losses that exceed those from a carbon price with payroll tax recycling. If payroll taxes finance the subsidy, the subsidy no longer increases employment (Section 5.2) because the higher match value for green firms is offset by the increase in economy-wide distortions. A subsidy consequently performs more poorly in this case.

Increasing the initial distortion level in Table 4 does not affect the welfare gains from the lump sum tax-financed subsidy. However, the losses are larger from a subsidy financed by payroll taxes since the distortions from the payroll taxes grow. Having access to a non-distortionary financing mechanism like lump sum taxes is therefore especially valuable if the labor market is initially distorted.

Table 4: Welfare change in % by policy instrument and initial distortion level

Initial distortion level	Subsidy + LS tax	Subsidy + Payroll tax	Carbon price + Transfer	Carbon price + Payroll tax
Baseline	0.26	-0.06	-0.09	-0.00
50% higher τ^L, τ^P	0.26	-0.15	-0.09	-0.01

Note: The table shows welfare changes by initial distortion level 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. The initial distortion levels are "Baseline" (where the labor income tax τ^L equals 0.29 and the payroll tax τ^P equals 0.15 in the benchmark) and a scenario where τ^L and τ^P are 50% higher in the benchmark. The welfare changes are given in percent relative to the business as usual benchmark.

5.5 Sensitivity analysis

5.5.1 Employment outcomes

This section looks at how the employment outcomes vary with key parameters. The analysis is carried out by recalibrating the disutility of work ψ and unemployment benefits b_i in the benchmark. Table 5 presents the results. The qualitative effects are robust. A subsidy with a non-distortionary financing mechanism always produces employment gains. Using a distortionary financing mechanism, in contrast, increases unemployment. A carbon price always produces employment losses. The losses are smaller when the revenue is recycled via lower payroll taxes.

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

Table 5: Employment change by policy instrument and parameter (in percentage points relative to the benchmark)

	Subsidy + LS tax	Subsidy + Payroll tax	Carbon price + Transfer	Carbon price + Payroll tax
Baseline	0.104	-0.014	-0.034	-0.001
q_j up by 50%	0.155	-0.025	-0.05	-0.002
q_j down by 50%	0.048	-0.005	-0.016	-0.001
$\eta = 0.7$	0.226	-0.050	-0.072	-0.003
$\eta = 0.3$	0.041	-0.004	-0.014	-0.001
$\gamma = 0.75$	0.052	-0.006	-0.017	-0.001
$\gamma = 0.25$	0.155	-0.024	-0.050	-0.003
$\chi = 2$	0.078	-0.009	-0.024	-0.001
$\chi = 0.5$	0.121	-0.019	-0.041	-0.002
$\sigma^{fg} = 1.5$	0.026	-0.002	-0.025	-0.001
$\sigma^{fg} = 0.6$	0.253	-0.047	-0.036	-0.002
$\sigma^{C} = 0.6$	0.166	-0.030	-0.030	-0.001
$\sigma^{C} = 0.4$	0.075	-0.008	-0.038	-0.002
Flat nesting	0.689	-0.193	-0.026	-0.001
13% abatement	0.840	-1.252	-0.301	-0.046
$\xi_j = 1$	0.104	-0.014	-0.033	-0.001
$\xi_j = 0.5$	0.104	-0.014	-0.033	-0.001
$\xi_j = 0.1$	0.104	-0.014	-0.033	-0.001

Note: The table shows the employment change, by sensitivity test, 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. The employment change is given in percentage points relative to the business as usual benchmark.

taxes increases recruitment effort (see Table 6) and therefore generates more matches when q_j is high. The opposite occurs if a subsidy is financed by payroll taxes. Recruitment effort then decreases (Table 6), meaning a higher q_j result in fewer matches and more unemployment.

A higher bargaining power of firms η increases the flow value of unemployment and reduces the fundamental surplus ratio.[56,57] A small fundamental surplus ratio means that a productivity shock has a large percentage impact on profits because profits are initially small (Ljungqvist and Sargent, 2017). There is consequently a strong incentive to adjust recruitment in response to a productivity shock. The shock is positive in the context of a non-distortionary financing mechanism, meaning recruitment and the employment gains grow. Conversely, the shock is negative for a distortionary mechanism, meaning employment declines by more.

A higher elasticity of matching with respect to unemployment γ reduces the matching

[56] The relationship between η and the flow value of unemployment in my analysis is similar to Hagedorn and Manovskii (2008). They find empirical evidence of small profits and only moderately procyclical wages. They argue that the latter indicates a high bargaining power of firms, which, together with small profits, imply that the flow value of unemployment is high. The same relationship is evident in my benchmark calibration. A higher value of η raises the flow value of unemployment because unemployment benefits b_i increase. The larger flow value of unemployment, in turn, reduces the fundamental surplus ratio.

[57] As shown in Table E.3 in Appendix E, a higher η increases the average flow value of unemployment in the benchmark from 0.61 to 0.63, and reduces the average fundamental surplus ratio in the benchmark from 0.08 to 0.04.

efficiency μ_j.[58] The lower μ_j reduces the number of matches from a unit of recruitment effort. This weakens the employment gains from a subsidy with lump sum taxes. On the other hand, the number of matches from a payroll tax-financed subsidy falls by less, which reduces the employment losses from such a subsidy.

Increasing the labor supply elasticity χ makes workers react more on the intensive margin to wage changes. For the case of a non-distortionary financing mechanism, the wage change is positive, meaning hours increase (Table 6). 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 (Table 6) and labor supply on the extensive margin rises.

A higher elasticity of substitution between the fossil and green good σ^{fg} decreases the required subsidy rate (Table 6). This weakens the magnitude of the employment effects.

Table 6: Subsidy rate and change in recruitment effort and hours from a green subsidy by financing mechanism and parameter value

	% change in recruitment effort $\frac{\sum_j v_j h_j n_j}{\sum_j n_j}$		% change in hours $\frac{\sum_j h_j n_j}{\sum_j n_j}$		Subsidy s	
	LS	Payroll	LS	Payroll	LS	Payroll
Baseline	1.74	-0.48	0.198	-0.014	0.30	0.25
q_j up by 50%	2.76	-0.69	0.175	-0.015	0.31	0.24
q_j down by 50%	0.66	-0.32	0.223	-0.014	0.30	0.25
$\eta = 0.7$	4.19	-1.17	0.148	-0.017	0.31	0.24
$\eta = 0.3$	0.51	-0.30	0.224	-0.014	0.29	0.25
$\gamma = 0.75$	2.65	-0.55	0.223	-0.014	0.30	0.25
$\gamma = 0.25$	0.84	-0.38	0.173	-0.014	0.31	0.24
$\chi = 2$	1.23	-0.39	0.293	-0.020	0.31	0.25
$\chi = 0.5$	2.09	-0.59	0.121	-0.010	0.29	0.25
$\sigma^{fg} = 1.5$	0.43	-0.10	0.047	-0.002	0.06	0.06
$\sigma^{fg} = 0.6$	4.21	-1.36	0.551	-0.050	1.01	0.57
$\sigma^{C} = 0.6$	2.71	-0.95	0.339	-0.031	0.53	0.37
$\sigma^{C} = 0.4$	1.29	-0.28	0.139	-0.008	0.21	0.18
Flat nesting	9.72	-4.80	2.355	-0.194	4.67	1.08
13% abatement	12.03	-21.93	3.298	-0.934	8.16	3.55
$\xi_j = 1$	1.74	-0.48	0.198	-0.014	0.30	0.25
$\xi_j = 0.5$	1.74	-0.48	0.198	-0.014	0.30	0.25
$\xi_j = 0.1$	1.74	-0.48	0.198	-0.014	0.30	0.25

Note: The table shows the change in various outcomes, by sensitivity test, from a green subsidy financed by either lump sum taxes ("LS") or payroll taxes ("Payroll"). The change in recruitment effort and hours is reported as the percentage change in the steady state values relative to the business as usual benchmark. The subsidy rate is given in dollars per dollar of green output.

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

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. A higher subsidy is required to counterbalance the lower abatement from the crowding out effect (Table 6). The higher subsidy is beneficial in the context of a non-distortionary financing mechanism, but worsens the employment losses if a distortionary mechanism is used.

Switching from a nested to a flat consumption structure with an elasticity of 0.75 amplifies the employment changes because of a higher subsidy rate (Table 6). 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 a given abatement level, which amplifies the employment changes.

The baseline assumes an abatement target of 1.7%. This is lower compared to estimated emissions reductions from the IRA (Larsen et al., 2022; Bistline et al., 2023; Bistline, Mehrotra and Wolfram, 2023; Voigts and Paret, 2024) that range from 7%-13% of 2019 emissions by 2030.[59] I adopt the upper bound of this range by setting the emissions reduction target to 13%. This amplifies the magnitude of the employment changes but leaves the signs unchanged.

Finally, I vary ξ_j to consider the role of frictions associated with cross-type matching. Fig. 10 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 ξ_j slows down convergence and a sufficiently small value can even eliminate the employment gains in the short run. A low value of ξ_j means firms face friction when matching with workers of a different type. The friction increases the time it takes for firms to adjust hiring and reach their steady state recruitment level. Thus, while ξ_j has little effect on the steady state, it impacts the subsidy's performance during the transition.[60] Fig. 10 in Appendix E shows that the same is true for a subsidy financed by payroll taxes.

[59] The emissions reduction estimates in the literature are given relative to 2005 levels. I express the estimates relative to 2019 levels by converting them using historical emissions 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`.

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

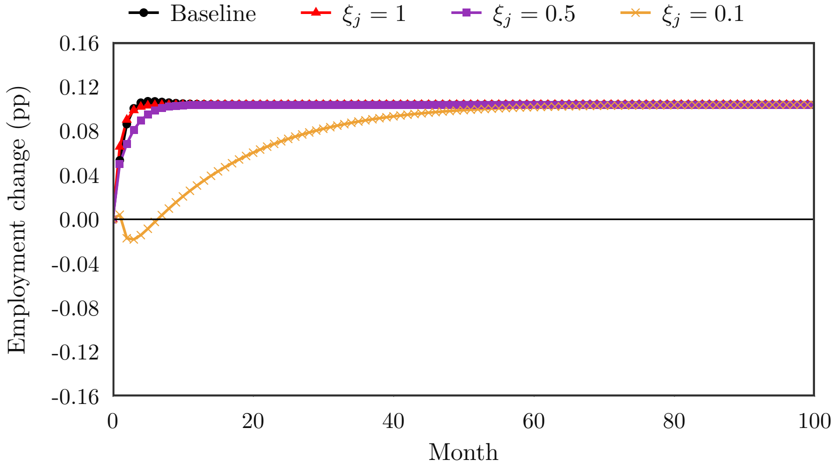

Figure 10: Employment change from a lump sum tax-financed green subsidy by ξ_j

Note: The figure shows the employment change from a lump sum tax-financed green subsidy by value of ξ_j. "Baseline" assumes the values of ξ_j in Table 2. The employment change is given in percentage points relative to the business as usual benchmark.

5.5.2 Welfare outcomes

This section looks at how welfare outcomes change with the calibration. Table 7 shows that the qualitative insights from the baseline specification are generally robust. A subsidy financed by payroll taxes always generates welfare losses that exceed those from a carbon price with payroll tax recycling. A subsidy financed by lump sum taxes increases welfare and outperforms a carbon price in most cases. The only exception is when the abatement target increases to 13%. The subsidy results in welfare *losses* then and no longer outperforms a carbon price with payroll tax recycling.

To explain the welfare losses, Fig. 11 depicts the welfare change by policy instrument and abatement target. A subsidy financed in a non-distortionary manner increases welfare at low abatement levels. The welfare gains shrink as abatement grows and ultimately disappear. Welfare losses arise because the subsidy induces too much consumption of the green good. At low abatement levels, the welfare gain from the job creation dominates. However, as the subsidy rate grows in tandem with the abatement level, too much consumption is shifted which is inefficient.[61] The inefficiency ultimately outweighs the employment gain and makes the subsidy perform worse than a carbon price. A take-away therefore is that subsidies

[61] A higher elasticity of substitution between the green and fossil goods reduces the welfare losses at high abatement levels. For instance, the welfare change is positive (+0.41%) for an abatement target of 13% if $\sigma^{fg} = 1.5$. A higher σ^{fg} makes it easier to shift consumption from fossil to green goods. This is beneficial when the subsidy is inefficiently high since the subsidy can be lowered to achieve a given abatement target. The subsidy rate decreases from \$8.16 to \$0.61 when σ^{fg} increases to 1.5.

financed in a non-distortionary manner increase welfare relative to carbon pricing, but only for low abatement levels.

Table 7: Welfare change in % by policy instrument and parameter

	Subsidy + LS tax	Subsidy + Payroll tax	Carbon price + Transfer	Carbon price + Payroll tax
Baseline	0.257	-0.058	-0.090	-0.003
q_j up by 50%	0.287	-0.070	-0.098	-0.004
q_j down by 50%	0.226	-0.049	-0.081	-0.003
$\eta = 0.7$	0.323	-0.095	-0.108	-0.005
$\eta = 0.3$	0.223	-0.048	-0.081	-0.003
$\gamma = 0.75$	0.225	-0.050	-0.081	-0.002
$\gamma = 0.25$	0.289	-0.069	-0.099	-0.005
$\chi = 2$	0.325	-0.059	-0.105	-0.003
$\chi = 0.5$	0.199	-0.059	-0.077	-0.003
$\sigma^{fg} = 1.5$	0.067	-0.008	-0.066	-0.002
$\sigma^{fg} = 0.6$	0.541	-0.201	-0.097	-0.003
$\sigma^{C} = 0.6$	0.382	-0.127	-0.080	-0.003
$\sigma^{C} = 0.4$	0.192	-0.032	-0.102	-0.004
Flat nesting	0.220	-0.787	-0.069	-0.003
13% abatement	-0.325	-3.897	-0.809	-0.169
$\xi_j = 1$	0.257	-0.058	-0.090	-0.002
$\xi_j = 0.5$	0.257	-0.058	-0.090	-0.002
$\xi_j = 0.1$	0.256	-0.062	-0.090	-0.003

Note: The table shows the welfare change, by sensitivity test, 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. The welfare change is given in percent relative to the business as usual benchmark.

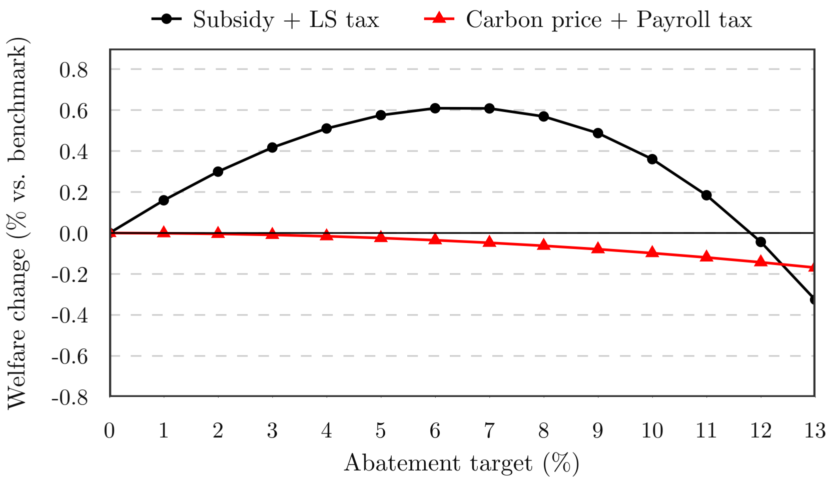

Figure 11: Welfare change from a green subsidy with lump sum taxes and a carbon price with payroll taxes by abatement target

Note: The figure shows the welfare change from a green subsidy financed by lump sum taxes and from a carbon price with payroll tax recycling for various abatement targets. The welfare change is given in percent relative to the business as usual benchmark.

6 Conclusion

This paper examines the impact of green subsidies on the labor market and welfare. Using a search model, I compare green subsidies to carbon prices for different ways of financing the subsidies and for various tax systems. The analysis is underpinned by empirical labor market estimates of the distribution of jobs and job transitions in the U.S.

The empirical analysis indicates that green jobs account for a small share of U.S. employment. The majority of jobs are neutral and not directly affected by green subsidies and carbon pricing. With regard to job transitions, the data shows that fossil workers rarely move to a green job. They are instead more likely to start a neutral job. This finding is driven by the abundance of neutral jobs and suggests that neutral jobs should not be overlooked in the context of the low-carbon transition.

The numerical analysis highlights an important benefit of green subsidies when financed in a non-distortionary manner, namely that they increase employment by counteracting search frictions. The employment gains translate into higher welfare relative to a carbon price, conditional on a low abatement level. As abatement becomes stringent, the subsidies induce an inefficiently high level of green production. This offsets the welfare gains from the higher employment and makes the subsidies generate lower welfare compared to a carbon price.

In the event that a non-distortionary financing mechanism is unavailable and replaced by payroll taxes, green subsidies perform worse. The subsidies then increase unemployment and reduce welfare relative to a carbon price. The performance of green subsidies is therefore closely tied to the financing mechanism. The choice of financing mechanism is especially consequential in a distortionary tax system. While a non-distortionary mechanism is unaffected by the tax system, a distortionary mechanism performs worse in the presence of preexisting distortions. Having access to a non-distortionary mechanism is therefore especially valuable if labor taxes are initially high.

While this paper focuses on the short run impact of green subsidies, extending the horizon to the long run, by introducing physical and human capital accumulation, would be a valuable avenue for future research. Moreover, to complement the empirical analysis, shifting the focus from a national to a local context could shed light on the degree to which job transition patterns are heterogeneous on a within-country level.

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Appendix A: Occupations

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

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

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

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

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

Census code	Census title	SOC code	SOC title	SOC share in SIPP
6950	Other Extraction Workers	47-50XX	Other Extraction Workers	0.53
		47-5040	Mining Machine Operators	0.47
		47-5081	Helpers–Extraction Workers	0
7640	Other Installation, Maintenance, and Repair Workers	49-909X	Other Installation, Maintenance, and Repair Workers	1
		49-9097	Signal and Track Switch Repairers	0
7905	Computer Numerically Controlled Tool Operators and Programmers	51-9199	Production Workers, All Other	0.89
		51-4010	Computer Control Programmers and Operators	0.11
7925	Forming Machine Setters, Operators, and Tenders, Metal and Plastic	51-4021	Extruding and Drawing Machine Setters, Operators, and Tenders, Metal and Plastic	0.81
		51-4022	Forging Machine Setters, Operators, and Tenders, Metal and Plastic	0.12
		51-4023	Rolling Machine Setters, Operators, and Tenders, Metal and Plastic	0.07
8025	Other Machine Tool Setters, Operators, and Tenders, Metal and Plastic	51-4032	Drilling and Boring Machine Tool Setters, Operators, and Tenders, Metal and Plastic	NA†
		51-4034	Lathe and Turning Machine Tool Setters, Operators, and Tenders, Metal and Plastic	NA†
		51-4035	Milling and Planing Machine Setters, Operators, and Tenders, Metal and Plastic	NA†
8225	Other Metal Workers and Plastic Workers	51-4199	Metal Workers and Plastic Workers, All Other	1
		51-4081	Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic	0
		51-4191	Heat Treating Equipment Setters, Operators, and Tenders, Metal and Plastic	0
		51-4192	Layout Workers, Metal and Plastic	0
		51-4193	Plating and Coating Machine Setters, Operators, and Tenders, Metal and Plastic	0
		51-4194	Tool Grinders, Filers, and Sharpeners	0
8365	Textile Machine Setters, Operators, and Tenders	51-6064	Textile Winding, Twisting, and Drawing Out Machine Setters, Operators, and Tenders	0.74
		51-6063	Textile Knitting and Weaving Machine Setters, Operators, and Tenders	0.21
		51-6062	Textile Cutting Machine Setters, Operators, and Tenders	0.05
		51-6061	Textile Bleaching and Dyeing Machine Operators and Tenders	0

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

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

Note: The table lists the Census occupation codes with a one-to-many mapping to SOC. The last column shows the distribution of SOC codes in the 2013-2016 SIPP panel. To acheive a one-to-one mapping, I choose the most frequent SOC code (i.e., the SOC code with the highest share in the last column).
†The SOC codes mapping to Census code "8025" are not present in the 2013-2016 SIPP panel. I therefore map this Census code to the first SOC category "51-4032 - Drilling and Boring Machine Tool Setters, Operators, and Tenders, Metal and Plastic".

Table A.2: O*NET occupations with a weighted green task share of at least 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
17-2081.00	Environmental Engineers	28	28	1
17-2081.01	Water/Wastewater Engineers	27	27	1
17-2141.01	Fuel Cell Engineers	26	26	1
17-2199.03	Energy Engineers	21	21	1
17-2199.10	Wind Energy Engineers	16	16	1
17-2199.11	Solar Energy Systems Engineers	13	13	1
17-3025.00	Environmental Engineering Technicians	26	26	1
19-1013.00	Soil and Plant Scientists	27	17	0.62
19-1031.01	Soil and Water Conservationists	33	33	1
19-2041.01	Climate Change Analysts	14	14	1
19-2041.02	Environmental Restoration Planners	22	22	1
19-2041.03	Industrial Ecologists	38	38	1
19-3011.01	Environmental Economists	19	19	1
19-4091.00	Environmental Science and Protection Technicians, Including Health	26	26	1
41-3099.01	Energy Brokers	16	16	1
41-4011.07	Solar Sales Representatives and Assessors	13	13	1
47-1011.03	Solar Energy Installation Managers	15	15	1
47-2231.00	Solar Photovoltaic Installers	26	26	1
47-4041.00	Hazardous Materials Removal Workers	21	21	1
47-4099.02	Solar Thermal Installers and Technicians	21	21	1
47-4099.03	Weatherization Installers and Technicians	18	18	1
49-9081.00	Wind Turbine Service Technicians	13	13	1
49-9099.01	Geothermal Technicians	24	24	1
51-8099.01	Biofuels Processing Technicians	19	19	1
51-8099.03	Biomass Plant Technicians	16	16	1
51-8099.04	Hydroelectric Plant Technicians	21	21	1
51-9199.01	Recycling and Reclamation Workers	18	18	1
53-1021.01	Recycling Coordinators	23	23	1
53-7081.00	Refuse and Recyclable Material Collectors	16	16	1

Note: The table lists the O*NET occupations with a weighted green task share of at least 0.5, where the weights are task importance scores.

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 that are classified as green in the main specification. The occupations have by definition an average weighted green task share of at least 0.5.

Table A.4: Fossil occupations in the main specification

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

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

SOC code	SOC title
51-9051	Furnace, Kiln, Oven, Drier, and Kettle Operators and Tenders
51-9061	Inspectors, Testers, Sorters, Samplers, and Weighers
51-9111	Packaging and Filling Machine Operators and Tenders
51-9191	Adhesive Bonding Machine Operators and Tenders
51-9195	Molders, Shapers, and Casters, Except Metal and Plastic
51-9196	Paper Goods Machine Setters, Operators, and Tenders
51-9197	Tire Builders
51-9198	Helpers–Production Workers
53-5011	Sailors and Marine Oilers
53-6031	Automotive and Watercraft Service Attendants
53-7021	Crane and Tower Operators
53-7051	Industrial Truck and Tractor Operators
53-7070	Pumping Station Operators
53-7199	Material Moving Workers, All Other

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

Appendix B: Aggregating the O*NET task data

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

I use a procedure based on Vona, Marin and Consoli (2019) to account for weight differences across occupations. The procedure is as follows. If an occupation corresponding to the parent group (i.e., ending in ".00") has zero or relatively few green tasks, I assign a green task share of zero to the parent group. In all other cases, I average the green task shares across the occupations in the parent group.[62]

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").

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

**The parent group was assigned zero green tasks to avoid calling occupations in the nuclear power industry green (Bowen and Kuralbayeva, 2015).

Appendix C: Crosswalking from NAICS to the Census Industry system

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 ultimately 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-digit 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 in which a 2-digit or 3-digit NAICS code maps to a Census code and has some 4-digit subcategories that are dirty. The second column shows the share of 4-digit subcategories that are dirty. The last column shows whether the Census code is ultimately classified as dirty.

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

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

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

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

Note: The table lists the instances in which a dirty NAICS code is indirectly mapped to a Census code through 5-digit or 6-digit subcategories. The last column shows whether the Census code is ultimately classified as dirty.

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

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

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

Table C.4: Dirty Census industries in the main specification

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

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

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

Note: The table lists the industries that are classified as dirty in the main specification.

Appendix D: Empirical diagnostics and sensitivity tests

Table D.1: Most common neutral jobs that fossil workers transition to and percentage of cases when the neutral job is in a dirty industry

SOC code of neutral job	SOC title of neutral job	% of fossil → neutral transitions involving the neutral job	% of cases when the neutral job is in a a dirty industry
11-9199	Managers, All Other	7.3	51
53-7062	Laborers and Freight, Stock, and Material Movers, Hand	6.8	28
37-201X	Janitors and Building Cleaners	2.8	21
49-9071	Maintenance and Repair Workers, General	2.2	34
17-2199	Engineers, All Other	2.1	50
53-3030	Driver/Sales Workers and Truck Drivers	2.0	26
41-1011	First-Line Supervisors of Retail Sales Workers	1.8	10
53-7064	Packers and Packagers, Hand	1.8	40
43-5081	Stock Clerks and Order Fillers	1.8	27
47-2061	Construction Laborers	1.7	0
41-2010	Cashiers	1.6	32
51-4120	Welding, Soldering, and Brazing Workers	1.4	32
41-2031	Retail Salespersons	1.4	3
45-2090	Miscellaneous Agricultural Workers	1.2	0
51-4041	Machinists	1.2	28
49-1011	First-Line Supervisors of Mechanics, Installers, and Repairers	1.1	32
51-2020	Electrical, Electronics, and Electromechanical Assemblers	1.1	66
47-2111	Electricians	1.1	37
43-4051	Customer Service Representatives	1.0	19

Note: The table lists the neutral jobs that fossil workers most often transition to. The third column shows the percentage of fossil to neutral transitions that involve a given neutral job. The last column shows the percentage of cases when the new neutral job is located in a dirty industry.

Table D.2: All green jobs that fossil workers transition to and percentage of cases when the green job is in a dirty industry

SOC code of green job	SOC title of green job	% of fossil → green transitions involving the green job	% of cases when the green job is in a dirty industry
51-9199	Production Workers, All Other	70.0	43
17-2141	Mechanical Engineers	18.1	56
49-909X	Other Installation, Maintenance, and Repair Workers	4.2	23
41-3099	Sales Representatives, Services, All Other	3.6	0
53-7081	Refuse and Recyclable Material Collectors	1.2	20
47-4041	Hazardous Materials Removal Workers	0.9	0
19-2040	Environmental Scientists and Geoscientists	0.9	0
47-4090	Miscellaneous Construction and Related Workers	0.6	0
17-2081	Environmental Engineers	0.6	0

Note: The table lists the green jobs that fossil workers transition to. The third column shows the percentage of fossil to green transitions that involve a given green job. The last column shows the percentage of cases when the new green job is located in a dirty industry.

Table D.3: Most common industries by job type

(a) Green jobs

Industry code	Industry title	Share
3570	Motor vehicles and motor vehicle equipment manufacturing	6.0%
7290	Architectural, engineering, and related services	5.1%
7690	Services to buildings and dwellings (except cleaning during construction and immediately after construction)	4.3%
7790	Waste management and remediation services	4.1%
0770	Construction (the cleaning of buildings and dwellings incidental during construction and immediately after construction)	4.0%
1990	Printing and related support activities	3.7%
7380	Computer systems design and related services	3.4%
3291	Machinery manufacturing, n.e.c. or not specified	2.5%
7390	Management, scientific, and technical consulting services	2.4%
3960	Medical equipment and supplies manufacturing	1.9%

(b) Fossil jobs

Industry code	Industry title	Share
3570	Motor vehicles and motor vehicle equipment manufacturing	8.9%
1180	Animal slaughtering and processing	3.6%
0770	Construction (the cleaning of buildings and dwellings is incidental during construction and immediately after construction)	3.1%
2290	Industrial and miscellaneous chemicals	2.8%
3580	Aircraft and parts manufacturing	2.6%
3291	Machinery manufacturing, n.e.c. or not specified	2.6%
2370	Plastics product manufacturing	2.6%
0490	Support activities for mining	2.5%
3390	Electronic component and product manufacturing, n.e.c.	2.5%
3960	Medical equipment and supplies manufacturing	2.2%

(c) Neutral jobs

Industry code	Industry title	Share
7860	Elementary and secondary schools	6.9%
8680	Restaurants and other food services	6.1%
0770	Construction (the cleaning of buildings and dwellings is incidental during construction and immediately after construction)	5.6%
8190,8191,8192[†]	Hospitals	4.4%
7870	Colleges, universities, and professional schools, including junior colleges	3.8%
7380	Computer systems design and related services	2.0%
9470	Justice, public order, and safety activities	1.9%
4970,4971,4972[†]	Grocery stores	1.8%
7070,7071,7072[†]	Real estate	1.6%
6990,6991,6992[†]	Insurance carriers and related activities	1.5%

Note: The table lists the ten most common industries by job type. The last column contains the share of jobs (of a given type) in an industry. For instance, 6.0% of green jobs are found in Industry code "3570".
[†]These are instances of one-to-many mappings from the 2012 Census Industry system (used by the 2013-2016 SIPP panel) to the 2017 Census Industry system (used by the 2017-2020 panel). The codes ending in "0" are version 2012, while those ending in "1" or "2" are version 2017. The industry titles in the table correspond to the "0" codes.

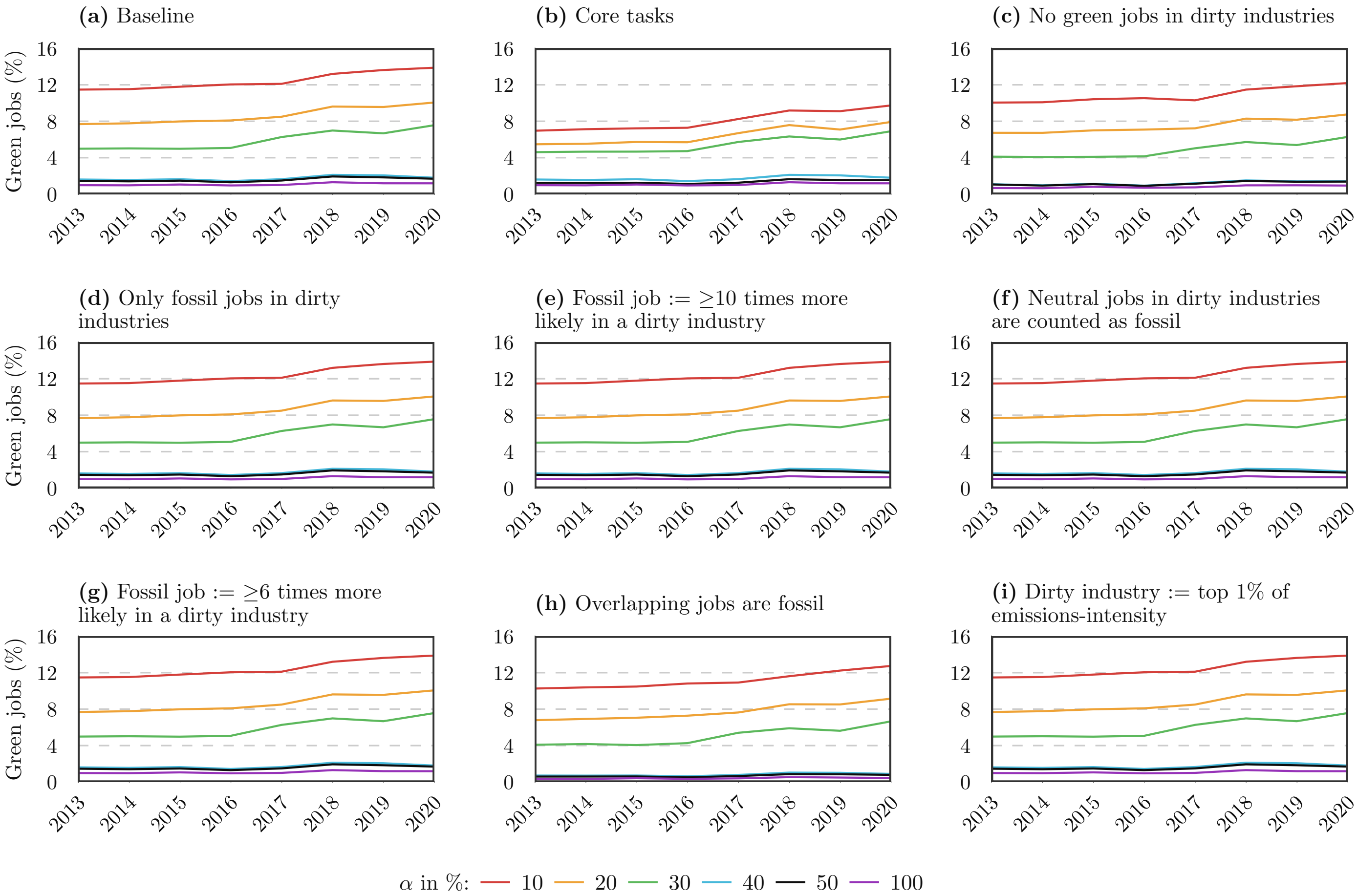

Figure D.1: Green job share over time by sensitivity test (panels) and α (lines)

Note: The figure shows the share of green jobs in the U.S. during 2013-2020 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 6 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) defines dirty industries as industries lying in the top 1% of emissions intensity. α is the minimum share of green tasks for an occupation to be classified as green. The green job share increases by at least 0.1 percentage points for all panels and α.

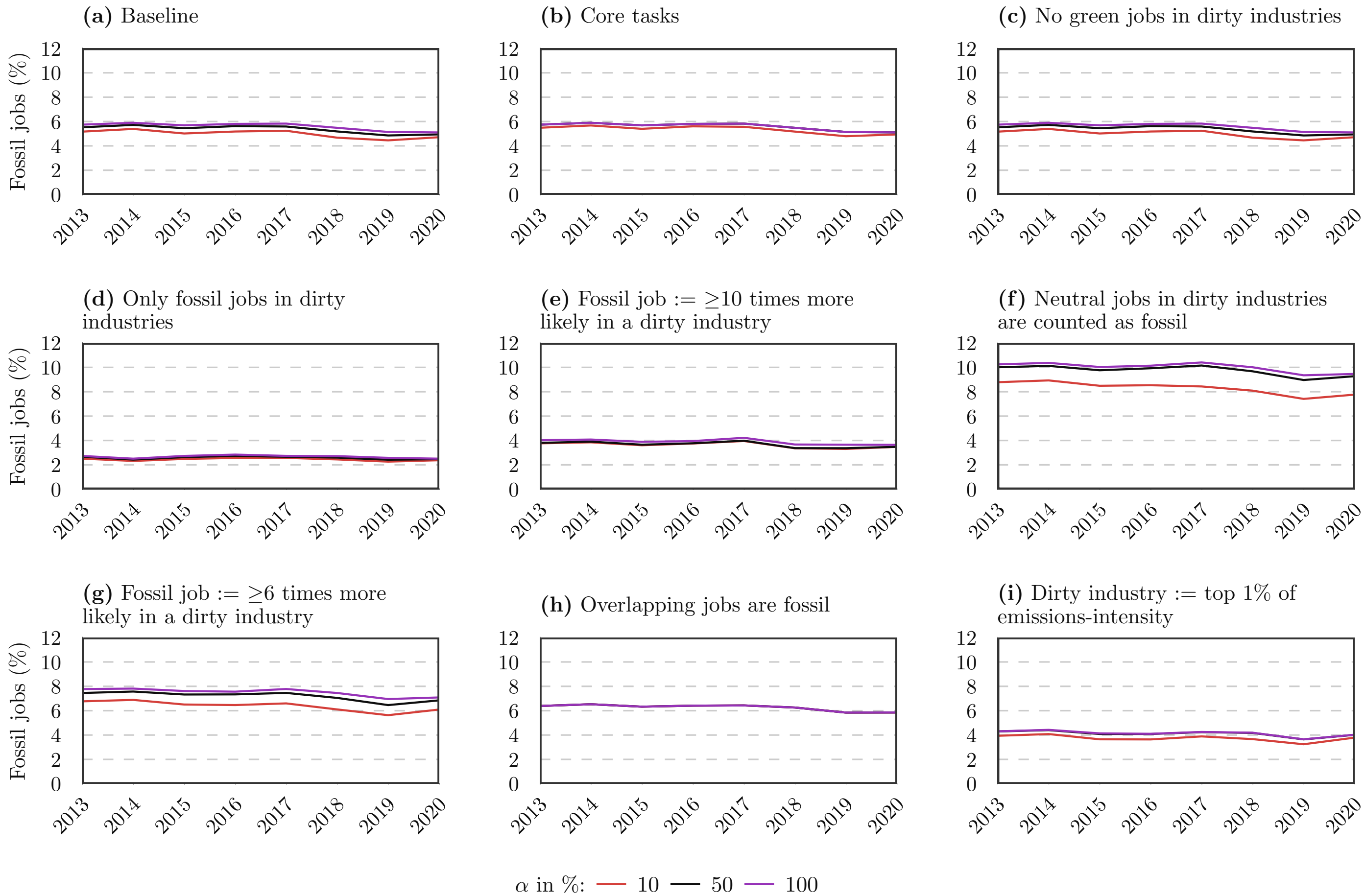

Figure D.2: Fossil job share over time by sensitivity test (panels) and α (lines)

Note: The figure shows the share of fossil jobs in the U.S. during 2013-2020 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 6 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) defines dirty industries as industries lying in the top 1% of emissions intensity. α is the minimum share of green tasks for an occupation to be classified as green. The fossil job share decreases by at least 0.2 percentage points for all panels and α.

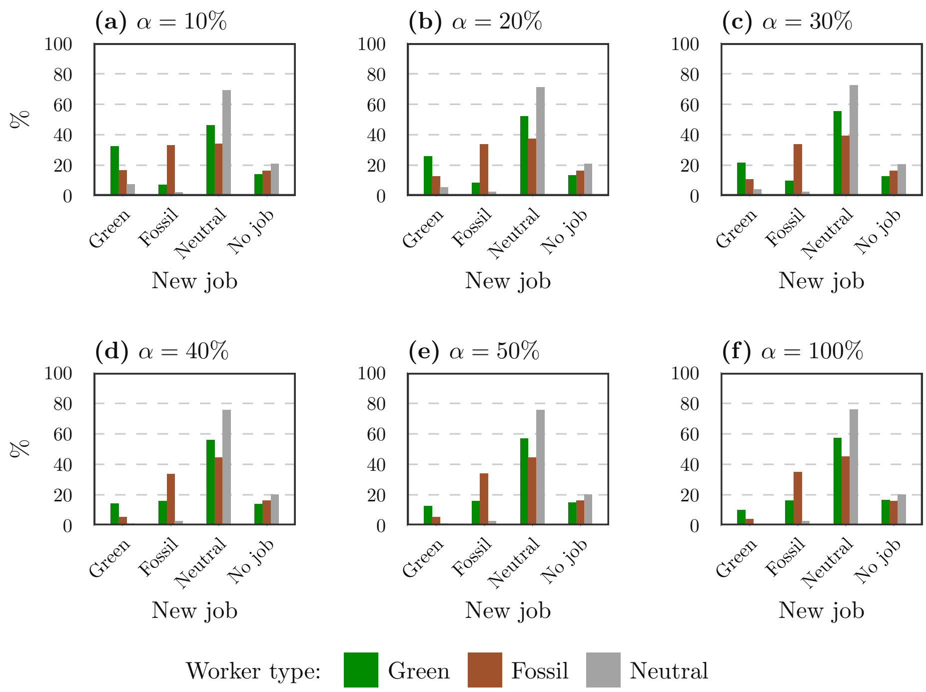

Figure D.3: Job-finding probability by α, type of job, and worker type

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

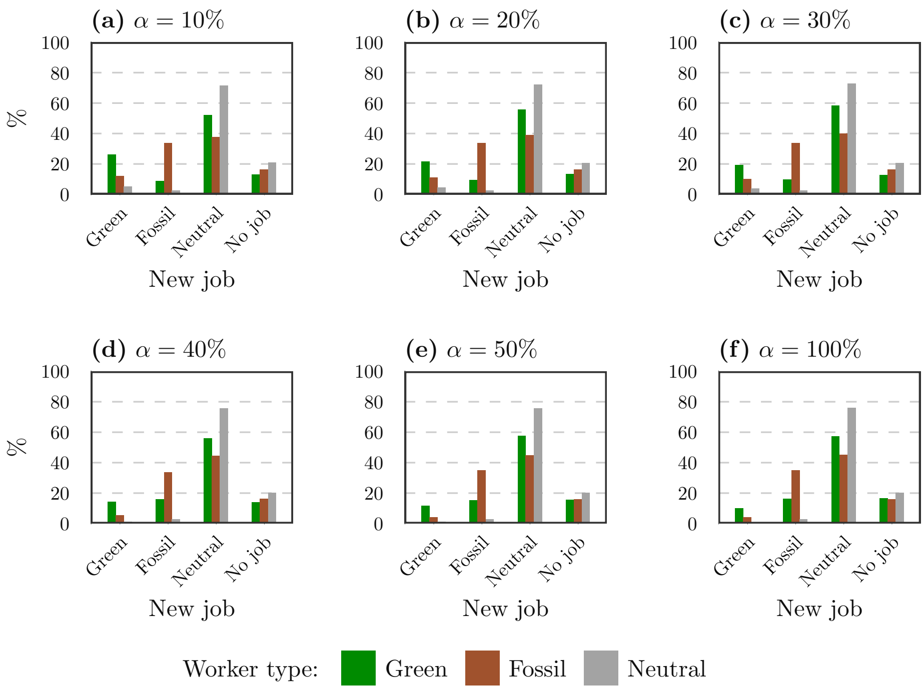

Figure D.4: Job-finding probability by α, type of job, and worker type (assuming only core tasks)

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

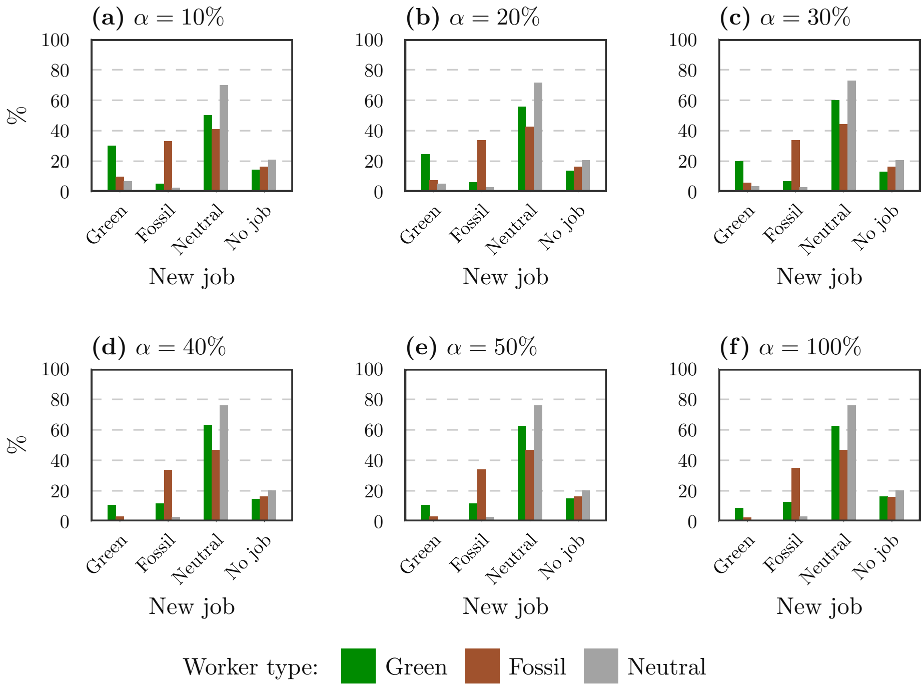

Figure D.5: Job-finding probability by α, type of job, and worker type (assuming no green jobs in dirty industries)

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

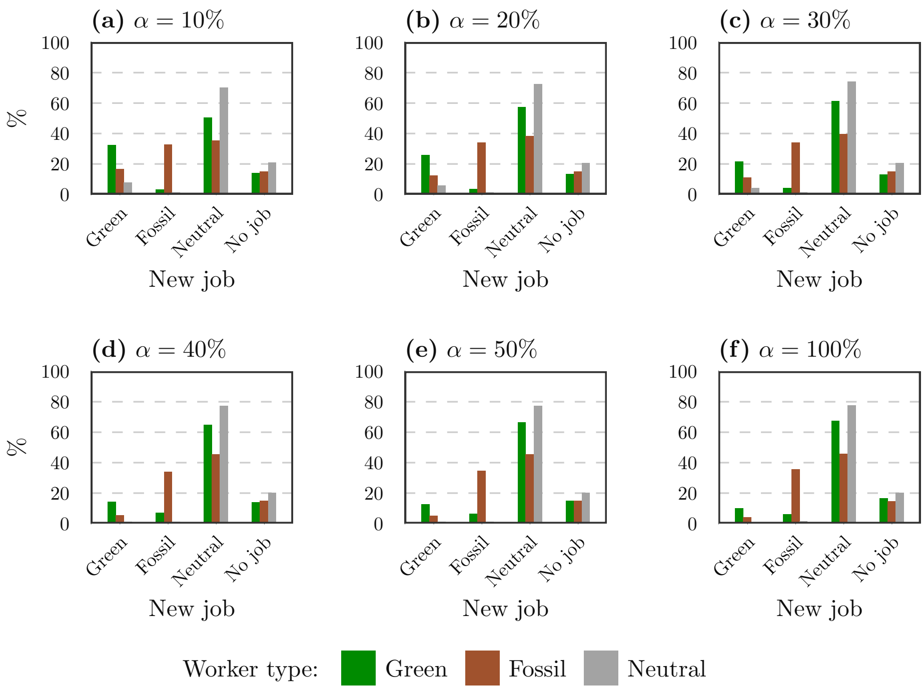

Figure D.6: Job-finding probability by α, type of job, and worker type (assuming only fossil jobs in dirty industries)

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

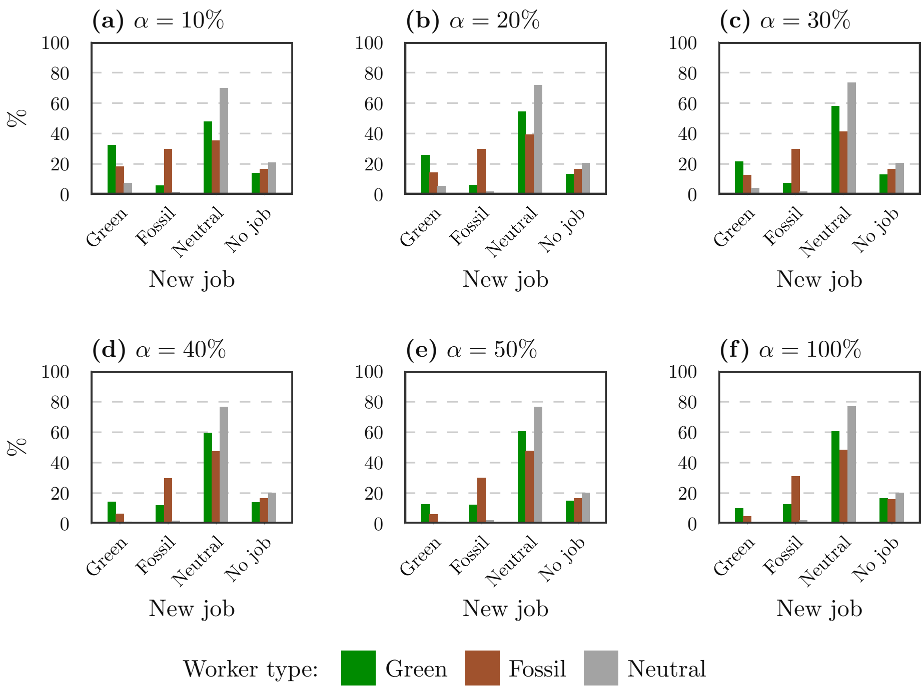

Figure D.7: Job-finding probability by α, type of job, and worker type (assuming fossil jobs are ≥ 10 more likely in a dirty industry)

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

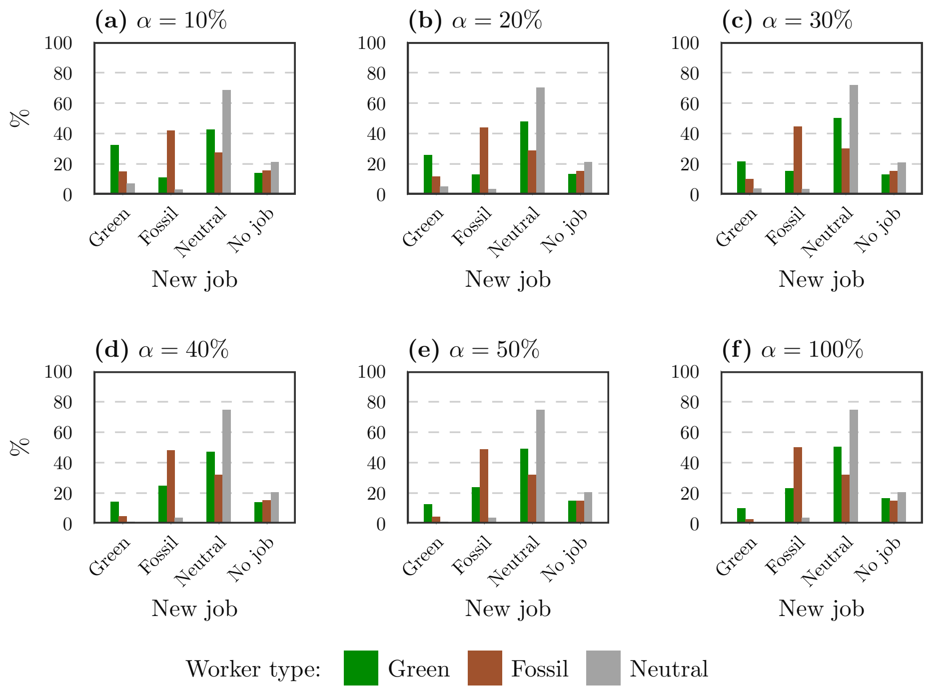

Figure D.8: Job-finding probability by α, type of job, and worker type (assuming neutral jobs in dirty industries are counted as fossil)

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

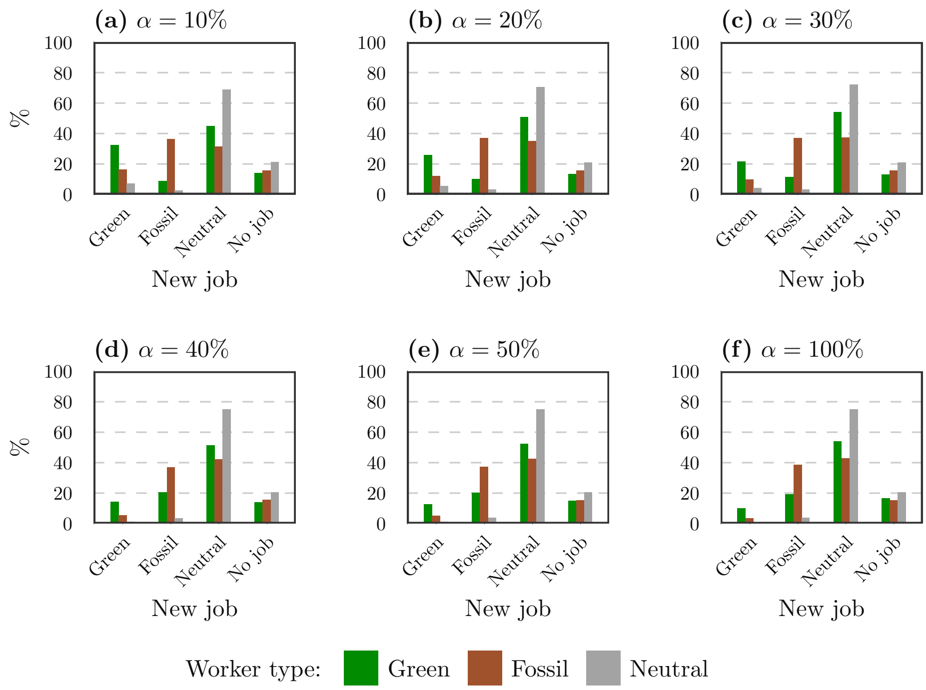

Figure D.9: Job-finding probability by α, type of job, and worker type (assuming fossil jobs are ≥ 6 more likely in a dirty industry)

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

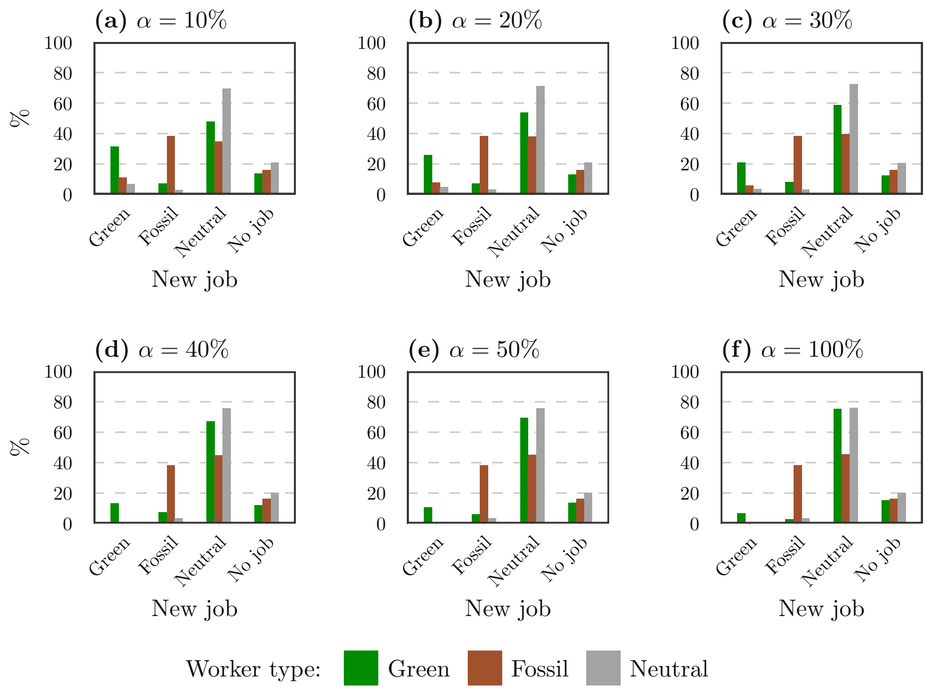

Figure D.10: Job-finding probability by α, type of job, and worker type (assuming overlapping jobs are fossil)

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

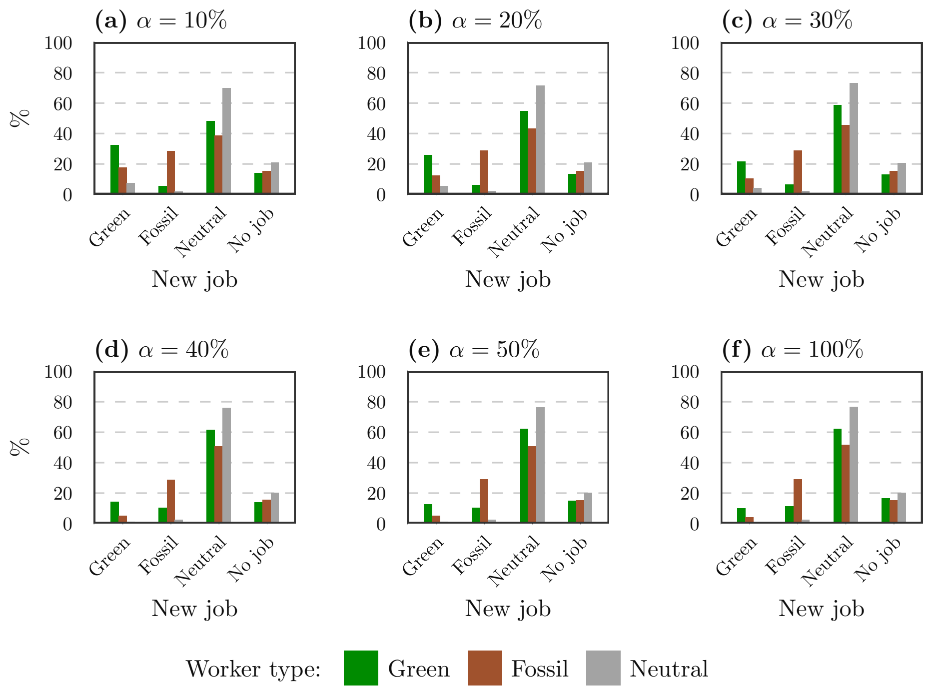

Figure D.11: Job-finding probability by α, type of job, and worker type (assuming dirty industries lie in the top 1% of emissions-intensity)

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

Appendix E: Additional figures and tables

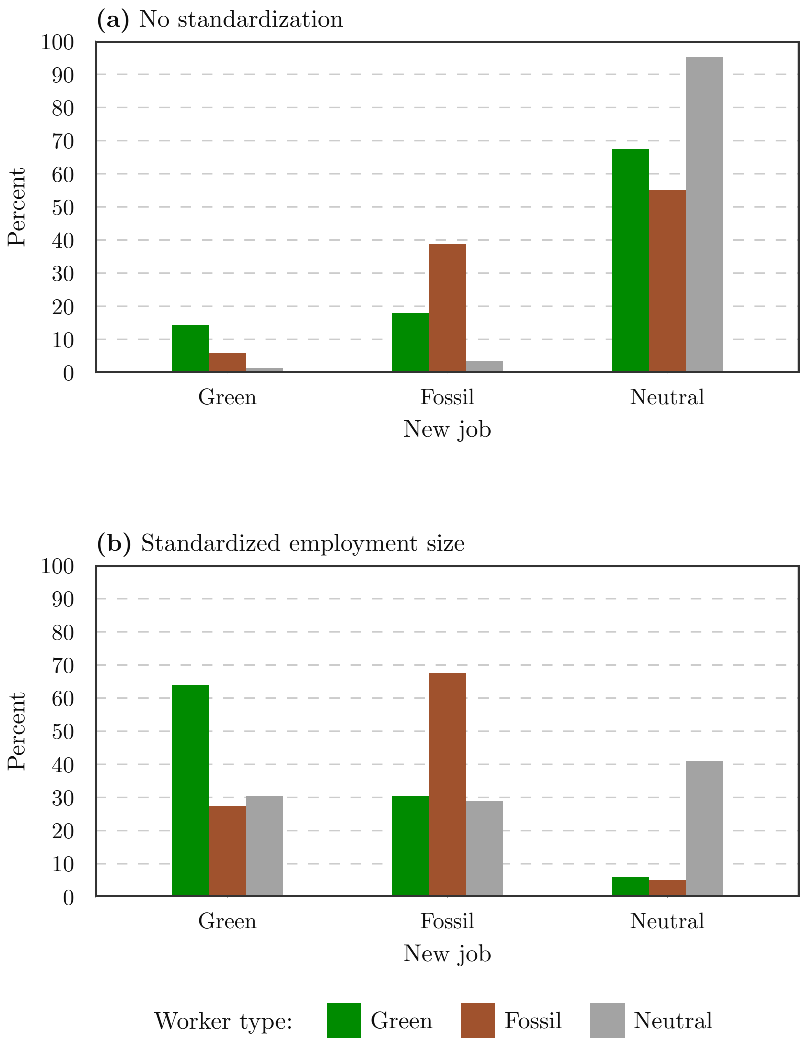

Figure E.1: Job finding probability by worker type and job type given that the employment sizes are not standardized (Panel (a)) or standardized (Panel (b)) across job types

Note: The figure shows the probability of transitioning to a green, fossil, or neutral job by worker type (green, fossil, or neutral) in the U.S. during 2013-2020. Panel (a) shows the raw job finding probabilities, while Panel (b) standardizes them to correct for employment size differences in 2019. Panel (b) therefore shows hypothetical job finding probabilities assuming identical employment shares across job types.

Table E.1: Changes from a carbon price by firm and time period (in % vs. benchmark)

Firm	Time period	Gross price p_j	Output y_j	Recruiters v_j	Recruiting productivity q_j	Recruitment $v_j q_j h_j$	Match value J_{n_j}
Green	$t = 0$	0	0.3	7.4	0.0	7.6	1
	SS	0	0.5	0.0	0.6	0.6	-1
Fossil	$t = 0$	1.7	-0.9	-21.0	5.2	-17.8	-9
	SS	3.0	-1.7	-2.2	0.6	-1.6	-1
Neutral	$t = 0$	-0.2	0.1	0.0	0.5	0.4	-1
	SS	0.0	0.0	-0.5	0.6	0.0	-1

Note: The table shows the impact of a carbon price with transfer recycling on various outcomes by firm and time period, where the time periods are the first period ($t = 0$) and the steady state (SS). The impacts are given in percent relative to the business as usual benchmark. The gross price of the green good does not change as it is the numeraire.

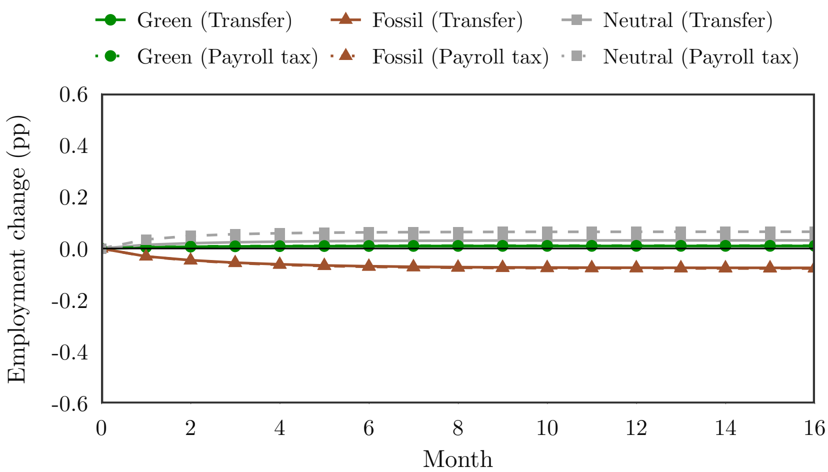

Figure E.2: Employment change from a carbon price by job type and recycling mechanism

Note: The figure shows the change in employment, by job type, from a carbon price with transfer ("Transfer") or payroll tax recycling. The employment change is given in percentage points relative to the business as usual benchmark.

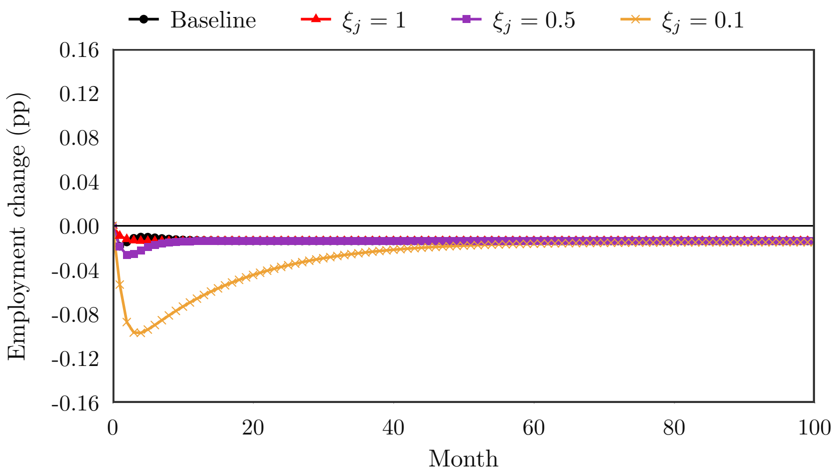

Figure E.3: Employment change from a payroll tax-financed green subsidy by ξ_j

Note: The figure shows the employment change from a payroll tax-financed green subsidy by value of ξ_j. The "Baseline" scenario assumes the values of ξ_j in Table 2. The employment change is given in percentage points relative to the business as usual benchmark.

Table E.2: Welfare change in % when accounting for disutility of work by policy instrument and initial distortion level

Initial distortion level	Subsidy + LS tax	Subsidy + Payroll tax	Carbon price + Transfer	Carbon price + Payroll tax
Baseline	0.10	-0.04	-0.04	-0.00
50% higher τ^L, τ^P	0.14	-0.11	-0.06	-0.01

Note: The table shows welfare changes by initial distortion level 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. The welfare changes reflect changes in both consumption and leisure, and are given in percent relative to the business as usual benchmark. The initial distortion levels are "Baseline" (where the labor income tax τ^L equals 0.29 and the payroll tax τ^P equals 0.15 in the benchmark) and a scenario where τ^L and τ^P are 50% higher in the benchmark.

Table E.3: Outcomes from a lump sum tax-financed subsidy by firm/worker type and sensitivity test

	Benchmark unemployment benefits			Benchmark flow value of unemployment				Benchmark fundamental surplus ratio				Employment change (pp)		
	`g`	`f`	`z`	`g`	`f`	`z`	mean	`g`	`f`	`z`	mean	`g`	`f`	`z`
Baseline	0.27	0.25	0.28	0.6	0.58	0.61	0.61	0.09	0.12	0.08	0.08	0.33	-0.09	-0.14
q_j up by 50%	0.29	0.28	0.29	0.62	0.61	0.62	0.62	0.06	0.08	0.05	0.05	0.34	-0.09	-0.10
q_j down by 50%	0.21	0.17	0.23	0.54	0.50	0.56	0.56	0.18	0.24	0.16	0.16	0.32	-0.09	-0.19
$\eta = 0.7$	0.30	0.29	0.31	0.63	0.62	0.63	0.63	0.04	0.05	0.04	0.04	0.35	-0.08	-0.04
$\eta = 0.3$	0.27	0.25	0.28	0.60	0.58	0.61	0.61	0.09	0.12	0.08	0.08	0.32	-0.09	-0.18
$\gamma = 0.75$	0.27	0.25	0.28	0.60	0.58	0.61	0.61	0.09	0.12	0.08	0.08	0.32	-0.09	-0.18
$\gamma = 0.25$	0.27	0.25	0.28	0.60	0.58	0.61	0.61	0.09	0.12	0.08	0.08	0.34	-0.09	-0.10
$\chi = 2$	0.16	0.14	0.17	0.60	0.58	0.61	0.61	0.09	0.12	0.08	0.08	0.34	-0.09	-0.17
$\chi = 0.5$	0.38	0.36	0.39	0.60	0.58	0.61	0.61	0.09	0.12	0.08	0.08	0.32	-0.08	-0.12
$\sigma^{fg} = 1.5$	0.27	0.25	0.28	0.60	0.58	0.61	0.61	0.09	0.12	0.08	0.08	0.14	-0.08	-0.03
$\sigma^{fg} = 0.6$	0.27	0.25	0.28	0.60	0.58	0.61	0.61	0.09	0.12	0.08	0.08	0.82	-0.10	-0.47
$\sigma^{C} = 0.6$	0.27	0.25	0.28	0.60	0.58	0.61	0.61	0.09	0.12	0.08	0.08	0.59	-0.09	-0.33
$\sigma^{C} = 0.4$	0.27	0.25	0.28	0.60	0.58	0.61	0.61	0.09	0.12	0.08	0.08	0.22	-0.08	-0.07
Flat nesting	0.27	0.25	0.28	0.60	0.58	0.61	0.61	0.09	0.12	0.08	0.08	4.29	-0.18	-3.42
13% abatement	0.27	0.25	0.28	0.60	0.58	0.61	0.61	0.09	0.12	0.08	0.08	5.82	-0.73	-4.26
$\xi_j = 1$	0.28	0.28	0.28	0.61	0.61	0.61	0.61	0.08	0.08	0.08	0.08	0.33	-0.09	-0.14
$\xi_j = 0.5$	0.28	0.28	0.28	0.61	0.61	0.61	0.61	0.08	0.08	0.08	0.08	0.33	-0.09	-0.14
$\xi_j = 0.1$	0.28	0.28	0.28	0.61	0.61	0.61	0.61	0.08	0.08	0.08	0.08	0.33	-0.09	-0.14

Note: The table shows the change in various outcomes, by sensitivity test, from a green subsidy financed by lump sum taxes. The outcomes are reported by firm or worker type. The "mean" columns denote weighted averages, where the weights are benchmark unemployment rates. "Employment change" refers to the change in steady state employment relative to the business as usual benchmark.