Unemployment, Labor Mobility, and Climate Policy

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Abstract: We develop a computable general equilibrium model of the US economy to study the unemployment effects of climate policy and the importance of cross-industry labor mobility. We consider two specifications of mobility costs: either perfect mobility with no moving costs, as is assumed in much previous work, or a model where workers face moving costs. The effect of a $45 per ton carbon tax on aggregate unemployment is small and similar across the two labor mobility assumptions (0.2 percentage points). The effect on unemployment in fossil fuel sectors is much larger under the immobility assumption—for example, a 13-percentage-point increase in the coal sector unemployment rate—suggesting that models omitting labor mobility frictions may greatly underpredict sectoral unemployment effects. Returning carbon tax revenue through labor tax cuts can dampen or even reverse negative impacts on unemployment, while command-and-control policies yield less efficient outcomes.

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THE DESIGN OF CLIMATE POLICY has important implications for how it affects carbon emissions and economic outcomes, such as employment. Many studies have modeled the effect of environmental policies on economies using computable general equilibrium (CGE) models. While CGE models are valuable in learning about both

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the economy-wide and sector-specific effects of policies, most CGE models allow for neither involuntary unemployment nor for cross-sector labor market immobility. By definition, these are equilibrium models, and that usually means that all markets, including the labor market, clear. While economists have typically focused on efficiency and cost-effectiveness impacts of policy, there is a great interest among policymakers and among the general public on unemployment effects. Much of public opinion comes from the presumed impact that it has on jobs and unemployment, like the impact of protecting the northern spotted owl on logging jobs or the impact of the Clean Power Plan on coal jobs.[1] Studying these effects is impossible using only models that impose the assumptions of full employment in and perfect mobility across all sectors.

Previous studies have used general equilibrium models or econometrics to calculate the effects of environmental policies on unemployment. Hafstead and Williams (2018), Aubert and Chiroleu-Assouline (2019), and Fernández Intriago (2019) use analytical general equilibrium models to study unemployment effects of climate policy. Some CGE models of environmental policy do allow for unemployment in various ways, but many of these have been limited to analysis of countries other than the United States (Böhringer et al. 2003; André et al. 2005; O'Ryan et al. 2005). To our knowledge, Hafstead et al. (2022) is the only other study that develops a CGE model of the US economy allowing for involuntary unemployment to study climate or environmental policy.

The purpose of this study is to develop a CGE model of the US economy that explicitly allows for involuntary unemployment and cross-sectoral mobility frictions and use it to study the effect of climate policy on jobs as well as on overall economic efficiency. Like a standard full-employment CGE model, this model includes a specification of various sectors of the economy, including fossil-fuel sectors that are expected to be more exposed to effects of climate policy. The model includes a detailed calibration of each sector's production process and responsiveness to price changes. We allow for involuntary labor unemployment with a search-and-matching model, à la Pissarides (2000). We then compare a specification with perfect cross-sectoral labor mobility to one where workers face moving costs when changing sectors. We compare the unemployment effects of a carbon tax to the effects of a command-and-control clean electricity standard (CES) policy, and we study the effects on unemployment when the carbon tax revenue is returned through tax cuts.

Relative to most CGE models of domestic environmental policy, this study furthers our understanding of the employment effects of policy by explicitly modeling involuntary unemployment in multiple disaggregated industries. Simply using a full-employment CGE model and studying voluntary changes in employment, as some other CGE models do, will be misleading. Relative to Hafstead et al. (2022) and other CGE models of environmental policy that do include involuntary unemployment, we extend the literature by considering the effect of assumptions about cross-sectoral labor mobility. One extreme

1. See Carattini et al. (2018) for a review of drivers of public resistance to climate policy.

assumption is perfect labor mobility across sectors, an assumption imposed by most previous studies. In contrast to this assumption, we incorporate sectoral switching costs for workers, à la Artuç et al. (2010) or Hafstead and Williams (2019). We then compare the typical perfectly mobile labor market model to one with moving frictions. Hafstead et al. (2022) argue that sectoral unemployment effects might be large but aggregate unemployment effects are small since workers are able to reallocate. We investigate this claim when workers face moving frictions.

Some empirical studies find evidence of interindustry labor reallocation costs.[2] Industry reallocation frictions are determined by several factors. Workers may face training costs, they may incur moving costs, or they may have a distaste for other types of work. Firms may be more likely to hire workers with industry-specific knowledge, or there may be industry-specific information networks. We do not attempt to identify which mechanisms lead to immobility but, rather, to assess the impact of these mobility costs. While the primary motivation of our analysis is quantifying the effects of climate policy, our results shed light on a much broader set of policies and how assumptions about labor mobility affect outcomes.

We find that the effect of climate policy on sectoral unemployment depends on the assumption made about labor mobility. Under the assumption of perfect labor mobility, a $45 per ton carbon tax with revenue returned lump sum increases the aggregate unemployment rate by just 0.17 percentage points, and the increase under the assumption of costly moving is only 0.01 percentage points larger (0.18 percentage points). However, this small aggregate effect on unemployment masks large increases in unemployment in the most vulnerable sectors, and it masks substantial differences between the two labor mobility assumptions. Under the assumption of costly moving, the unemployment rate increases by 9 percentage points in the gas extraction sector, 2.4 percentage points in the oil extraction sector, and by 13 percentage points in the coal mining sector. This could mean that unemployment effects might be concentrated in regions that have high shares of labor employed in a regulated sector. The effect of carbon policy on emissions reductions is not sensitive to the assumption over labor mobility, but the effect on output quantity and prices is. Output in the vulnerable sectors decreases somewhat more under mobile labor than it does under immobile labor. The price of carbon-intensive goods increases more under the costly mobility assumption than under the free mobility assumption. The carbon tax can lead to an increase of labor employed in other sectors, including non-fossil-fuel electricity generation.

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2. Walker (2013) finds that the Clean Air Act induced substantial mobility costs for affected workers—earnings losses for workers in regulated sectors average 20% postregulation, and almost all of these losses are driven by workers forced to find a new job. Vona et al. (2018) explore this point by identifying the types of skills that are in demand for both "green" and "brown" jobs and by estimating the effect that environmental regulation has on the demand for green skills. To the extent that acquiring green skills is costly, this contributes to intersectoral labor mobility frictions.

We also find that policy design matters. For a carbon tax, the choice over how to recycle tax revenues can affect unemployment. When the tax revenues are returned via a uniform cut in the labor tax, the aggregate unemployment rate stays the same at the baseline 5%. While this policy decreases the aggregate employment losses compared to returning the revenues lump sum, the difference in unemployment in the fossil fuel sectors is very small. When revenues are returned with a labor tax cut targeted just at the fossil-fuel and energy-intensive sectors, some sectors experience significantly smaller unemployment effects compared to the lump-sum return policy. However, for the heavily affected sectors of coal and natural gas, the employment boosts are much smaller. Finally, a command-and-control policy that requires a specified proportion of electricity to be generated from non-fossil-fuel sources generates comparable unemployment rates for small changes but much higher unemployment rates as reductions in emissions increase.

1. LITERATURE REVIEW

Computable general equilibrium (CGE) models are simulations of the economy widely used to model the effects of government policy. CGE models are often used to examine the effects of environmental regulation.[3] Most CGE models assume full employment in labor markets, and therefore the only source of changes in employment in the model is consumers choosing more leisure or workers being reallocated across sectors. However, three basic structural frameworks have been used in CGE models to incorporate involuntary unemployment.[4] They are the efficiency wage model of Shapiro and Stiglitz (1984), collective wage bargaining (McDonald and Solow 1981), which is likely less significant in the United States than in other countries, or the search-and-matching model developed by Mortensen and Pissarides (1994), which is our approach. An alternative to these three specifications of involuntary unemployment is to use a less structural relationship between wages and unemployment: a wage curve. Blanchflower and Oswald (2005) find consistent evidence across countries that the elasticity of the wage with respect to the unemployment rate is about −0.1.

CGE models differ in their assumptions about cross-sectoral labor mobility.[5] Most CGE models assume perfect mobility, implying that there is a single economy-wide wage rate equalized across all sectors. It is more likely that there is some friction between industries, whether it be industry-specific human capital or even network problems in finding jobs in new industries.

3. Carbone and Rivers (2017), for example, use several CGE models to determine the effect of environmental regulations on domestic competitiveness in international trade markets.

4. For a thorough discussion of these three methods, see Boeters and Savard (2013).

5. Empirical evidence for immobility between industries in labor markets is found in Neal (1995) and Walker (2013).

A growing literature uses general equilibrium models to study the impact of environmental regulations on the labor market, in particular on unemployment.[6] Hazilla and Kopp (1990) use a full-employment CGE model and report a 1% reduction in employment from Clean Air and Clean Water acts. Bernstein et al. (2017) is a more recent full-employment CGE model that reports the effects of environmental regulations on employment; in their case, they find that the manufacturing sector could lose 440,000 jobs in 2025 due to the Clean Power Plan. Other papers use relatively simple, for example, two-sector, general equilibrium models to study this issue (e.g., Hafstead and Williams 2018; Aubert and Chiroleu-Assouline 2019). An advantage of this simplicity is that often analytical closed-form solutions can be found and interpreted, rather than relying solely on a CGE "black box" for results.

The papers closest to ours are those that use CGE models that allow for involuntary unemployment and frictions in mobility between sectors to calculate the effects of environmental policy.[7] Fernández Intriago (2019) uses a general equilibrium model to analyze the effects of climate policy and how workers reallocate. The paper differentiates high- and low-skilled workers to drive mobility frictions. The paper most like ours is Hafstead and Williams (2019), which also develops a CGE model (based on the CGE model in Goulder et al. [2016] and the unemployment modeling in Hafstead and Williams [2018]) of the US economy allowing for involuntary unemployment and slow adjustments between sectors. They compare policies that phase in at different rates to show the distributional effects of adjustment in the short run.

The contributions of our study relative to this literature are the following. First, we focus on the United States, allowing for a more detailed description of the domestic economy though not focusing on other economies. Hafstead et al. (2022) and Balistreri (2002) also study the United States, though Balistreri (2002) focuses on measures of aggregate unemployment to demonstrate a new unemployment model. Second, we consider the effect of labor mobility to a greater extent than any of the previous literature. Babiker and Eckaus (2007) and Balistreri (2002) allow some form

6. Bergman (2005) and Jorgenson et al. (2013) provide overviews of the use of CGE models in environmental economics.

7. These papers are summarized in table A1. Most of these papers are looking at specific countries other than the United States or are using a world-wide CGE model. In almost all of the papers, labor is modeled as homogeneous and perfectly mobile across sectors (though immobile across regions in multiregion models). Only O'Ryan et al. (2005) and Küster et al. (2007) model heterogeneous labor (two types: skilled and unskilled), and only Babiker and Eckaus (2007) model rigidities in sectoral labor mobility. The most common specifications of unemployment are either a reduced-form wage curve (as in Böhringer et al. 2003, 2008; and André et al. 2005) or a type of wage rigidity based on sticky wages (Babiker and Rutherford 2005) or a wage floor (Babiker and Eckaus 2007). Balistreri (2002) and Hafstead and Williams (2018) both base unemployment on a search-and-matching model, though Balistreri (2002) develops a way of modeling this process as a negative externality of unemployment in labor markets.

of labor immobility, but mobility is not the focus of these papers. Hafstead and Williams (2018) model immobility, but only in the context of their two-sector model. Third, we model alternative forms of revenue recycling and their impacts on efficiency and unemployment, including lump-sum transfers and cuts in the labor tax rate, and we compare a carbon tax to a command-and-control quantity policy.

2. MODEL DESCRIPTION

Our model consists of $I = 12$ industries (or sectors) each modeled by a representative firm, indexed by i, producing output Y_i. There are also $J = 8$ labor markets indexed by j. Since our purpose is to model intersectoral labor mobility, the definition of each labor market is based on the definition of the industries, though the labor markets are not identical to the industries. There are fewer labor markets than industries ($J < I$) due to computational constraints.[8] Because we focus on climate policy's effects on employment, the industries most vulnerable to climate policy each have their own industry-specific labor markets. These are the three fossil-fuel producers—natural gas, coal, and oil—two electricity sectors—fossil-fuel and non-fossil-fuel—and manufacturing industries. Each of these six industries has its own labor market; we combine the remaining six industries into two labor markets: agriculture, mining, and construction are in a single labor market, and transportation, consumer services, and government services are in a single labor market.[9] The wage, unemployment rates, and vacancy rates are determined in relation to the market that they characterize and are unique to each market. All representative firms within a single labor market pay the same wage and observe the same unemployment rate.

There are $J = 8$ representative households in the model, one for each of the eight labor markets. We categorize households by the labor market they are in at the initial equilibrium and denote the households by the subscript k. The total labor force within each representative household is a continuum of fixed size. Within representative household k, a fraction of the labor force n_k is employed and the remaining fraction u_k is unemployed. After a policy change brings about a new equilibrium, the unemployment rate

8. The fossil-fuel and electricity markets only comprise a small share of overall labor allocations, but they are important to include because they are of interest to this study. This requires us to solve for the labor distribution to a high degree of accuracy, which requires more iterations. Including a labor market for each industry did not allow for a stable solution.

9. We choose this aggregation of the six non-carbon-intensive industries because agriculture, mining, and construction use relatively more capital than the other service industries. While computational constraints prevent us from running all policy simulations without aggregating any labor markets, we do simulate the base case results presented below under a model with our largest industry, consumer services, in its own labor market and agriculture, mining, construction, transportation, and government services aggregated in another single labor market. These results are presented in fig. A1 and compared to the base-case results.

within a labor market can change. Furthermore, some fraction of the labor force that was initially in labor market *k* may move to another labor market to seek employment there, and of that fraction some may succeed and be employed while others may be unemployed. We will present simulation results on the effect of policy on unemployment in specific industries, for example, coal mining. Since workers can switch between industries and between labor markets, when we say "unemployment in the coal mining industry," we more precisely mean the unemployment rate among workers who end up in the coal mining industry and labor market after the policy change, though some of them may have started in another industry in the initial equilibrium.

We consider two assumptions about intersectoral labor mobility. Under the first assumption, workers are frictionally mobile across labor markets, resulting in a vector of labor-market-specific wages. Workers know the prevailing wage and unemployment rate in each labor market as well as the cost of moving between markets and then choose how to allocate labor across all markets. Under the second assumption, the moving costs are set to zero so that workers are perfectly mobile, resulting in a single economy-wide wage and unemployment rate.

Labor markets are defined based on industries, since our interest is in interindustry labor mobility. Other papers have alternatively modeled labor markets based on geography, for example, commuting zones (Acemogulu and Restrepo 2000) or other definitions. As we described in the introductory section, intersectoral mobility costs may arise for many reasons, including geographical moving costs (e.g., to move from the coal sector to the agriculture sector might require that you move across the country). Our model is neither able to nor trying to disentangle or identify these different sources of intersectoral mobility frictions (our calibrated mobility costs include these frictions), but rather we seek to learn how incorporating these frictions into a CGE model will affect the impacts of climate policy on workers.

Our model is static. The results that we present below are comparative statics, comparing the equilibrium under a given policy to the initial pre-policy equilibrium. We do not model the transition between equilibria. However, part of our model relies on and is adapted from two labor market models that are dynamic—a search-and-matching unemployment model and a sectoral mobility model. In the sections below, we detail how we incorporate these dynamic models into our static model. Basically, for each of the dynamic components, we only solve for the steady state, and we plug that into our overall static CGE model. In the subsection below, we describe households' decisions and the labor market, which clarifies this point.

2.1. Households and the Labor Market

The representative household *k* maximizes a quasilinear utility function over consumption and labor supplied. Households purchase final goods for consumption using income from capital and labor as well as government transfers. We index a household with *k* and a good with *i*. The household's utility function is

$$U_k = C_k - \xi \frac{(n_k)^{1+\frac{1}{\psi}}}{1+\frac{1}{\psi}} L_k.$$

The consumption variable, C_k is a Cobb-Douglas composite of consumption over all I available goods c_k^i, where baseline expenditure shares are denoted by the parameter ϑ_k^i: $C_k \equiv \prod_{i=1}^{I} c_k^{i\,\vartheta_k^i}$. (Each good c_k^i is also composite of foreign and domestic goods, which is described in the section below on foreign trade.) The employment rate (i.e., the fraction of the fixed labor force represented by household k that is employed) is n_k, and the intensive margin of labor supplied by those working is L_k. The disutility of working is determined by a constant ξ and the Frisch elasticity of the extensive margin of labor supply ψ. The household's budget constraint is

$$P_k^C C_k \leq P_k^L \left(1 - T_k^L\right) n_k L_k + P^K \left(1 - T_k^K\right) K_k + \Pi_k + TR_k.$$

The price index of total consumption P_k^C is calculated using the consumption parameters and the prices P_i of each good i, including any sales tax, T_i^S: $P_k^C \equiv \prod_{i=1}^{I} ([(1 + T_i^s)P_i]/\vartheta_j^i)^{\vartheta_j^i}$. Income for the household is on the right-hand side of the budget constraint inequality. It is the sum of net-of-tax returns to capital and labor, profits from firm ownership Π_k, as well as a lump-sum government transfer TR_k. The term P_k^L is the wage that the worker in labor market k receives, and T_k^L is the income tax rate on wages. Both of these are defined based on the labor market k that a household works in. If a worker changes labor markets, then they receive the wage in that sector and the tax rate, so a reduced income tax rate does not follow the worker. The term L_k is the intensive margin of labor supplied to labor market k among those employed. Likewise, P^K is the price on capital, T_k^K is the tax rate on capital, and K_k is a constant allocation of capital that the household owns.

2.1.1. *Labor Market: Search-and-Matching and Unemployment*

The next two subsections describe how we incorporate the two dynamic models—the search-and-matching unemployment model and the labor mobility model—into our static CGE model. We discuss time periods within these dynamic models, but all the results that we present in our simulations are just from the steady state. We do not explicitly model or simulate the transition; instead, we solve for the steady state of these dynamic models and substitute that in to our overall CGE model.

The dynamic processes of search-and-matching and mobility have two simultaneous steps. In the first step, workers emerge from the matching process (described in this subsection) and are either employed or searching for work (unemployed) in a labor market. In the second step (described in the following subsection), workers decide to stay in the same labor market or move to a new one depending on the expected wages, unemployment rates, and moving costs. The employment rate for household k, n_k, is determined by the search-and-matching process and the share of labor, L_k, is determined by the labor mobility process.

We incorporate unemployment into our model using a standard flow model of search and matching, dating to the canonical Diamond-Mortensen-Pissarides labor search models (see Diamond 1982; Mortensen and Pissarides 1994). Workers exist in two states: employed and unemployed. Unemployed workers search for vacancies posted by firms. The matching function, which describes how unemployed workers match to vacancies, is:

$$m_j = D u_j^{\gamma} v_j^{1-\gamma}.$$

The variables are indexed by j to indicate that they differ across labor markets. The unemployment rate is u_j, the vacancy rate is v_j, and m_j is the number of matches made in labor market j. The coefficient D is a scaling parameter representing matching efficiency, and the exponent γ is the elasticity of the matching function. All unemployed workers in each labor market j search for work. The filling rate on vacancies for the firm, q_j, the job-finding rate for unemployed workers, f_j, and the labor market tightness θ_j are:

$$q_j = \frac{m_j}{v_j},$$

$$f_j = \frac{m_j}{u_j},$$

$$\theta_j \equiv \frac{f_j}{q_j} = \frac{v_j}{u_j}.$$

$$u_j = \frac{x}{(x + f_j)}. \quad (1)$$

The labor market tightness θ_j is the ratio of the job-finding rate to the filling rate and, due to the structure of the matching function, is equal to the ratio of the vacancy and unemployment rates. There is an exogenous job separation rate x identical for all sectors; this fraction of all employed workers loses their jobs each period.[10] Using the job finding rate and the exogenous separation rate, we solve for the steady-state unemployment rate defined in equation (1).

Within the dynamic search-and-matching model, the representative household in labor market j optimizes the following value function:[11]

10. Though this separation rate is exogenous, the labor mobility model described below also includes an endogenous decision by workers in each period to seek employment in a new sector. In the main specification, the exogenous separation rate x is homogeneous across markets, though in a sensitivity analysis we allow it to be heterogeneous.

11. We index this problem by the labor market j, though it identically could be indexed by household k, since within this dynamic model each household is matched to a single labor market.

$$V_j\left(n_j, L_j; \theta_j\right) = \max_{c_j}\left\{C_j - \xi \frac{\left(n_j\right)^{1+\frac{1}{\psi}}}{1+\frac{1}{\psi}} L_j + \beta E\left[V\left(n_j', L_j'; \theta_j'\right)\right]\right\}$$

$$\text{s.t.}$$

$$n_j' = (1-x)n_j + f_j\left(1-n_j\right)$$

and such that the income budget constraint described earlier holds in each period. The constraint here is the evolution of the labor supplied in market *j*. Solving the household's problem gives the following Euler equation, which summarizes the value of an additional worker to the household:

$$V_{j,n_j} = \frac{P_j^L}{P_j^C}\left(1 - T_j^L\right)L_j - \xi\left(n_j\right)^{\frac{1}{\psi}}L_j + \beta\left(1 - x - f_j\right)\beta E\left[V_{j,n'}\right]. \tag{2}$$

2.1.2. Labor Market: Cross-sectoral Mobility Frictions

In addition to allowing for involuntary unemployment, we also allow for workers to move across sectors and face moving frictions, as in Artuç et al. (2010) and Hafstead and Williams (2019). While several papers in the labor literature discuss mobility frictions across skill levels and geography, relatively few discuss mobility between industries. To add this feature to our model, we turn to the trade literature. Trade policy and climate policy both target industries based on their output, so careful consideration is given to relationships between sectors. We follow the model from Artuç et al. (2008, 2010), which explicitly models transition costs in moving between sectors, as described below.[12] The model was designed to capture the effects on workers in industries experiencing a demand shock, so it fits well with our research question. Additionally, the model can be numerically solved for a steady-state distribution of workers among sectors, and their paper estimates the parameters needed to calibrate the model using data from the United States.

Again, although the overall CGE model is static, we will be using the steady state from this dynamic model of mobility. The model in Artuç et al. (2008, 2010) does not include unemployment, so we include it in the following way. The steady state of the search-and-matching model described in the previous subsection yields a wage and unemployment rate for each labor market, which are plugged into the mobility model. The expected wage in market *j* given the employment rate and tax rate is $n_j P_j^L(1 - T_j^L)$. That is, the employment rate n_j is the probability of being employed, and $P_j^L(1 - T_j^L)$ is the net-of-tax wage conditional on being employed, where T_j^L is the tax rate on labor income. These values are used as inputs in the mobility model. Additionally, the

12. By contrast, Hafstead and Williams (2019) incorporate transition frictions into the matching function itself. Either specification generates mobility frictions, though our framework allows for those frictions to be heterogeneous across sectors.

mobility model parameters are estimated on an annual basis, so one period (year) in this section is equivalent to 12 periods (months) in the unemployment model.

The cost of moving between labor markets has two components. The first component is C_{jh}, a common moving cost for all workers moving from labor market j to h. We allow this cost to differ for different pairs of labor markets, as in Artuç et al. (2010), rather than imposing a constant cost across all markets C as in Artuç et al. (2008) or Hafstead and Williams (2019). The second component is an idiosyncratic benefit that a worker receives at the end of a period for working in labor market j and denoted by ϵ_j. This benefit is distributed across all workers and is independently distributed across workers and time periods. We assume ϵ_j takes the form of an extreme-value distribution as in Artuç et al. Adding in the constant cost of moving, the total cost of moving from market j to market h is $C_{jh} + \epsilon_j - \epsilon_h$.

We now move to setting up a value function describing the labor-switching choice for the worker. First, we assume that a maximized utility function, $q_j(L_j)$ across labor markets exists for the worker that considers the wages from all labor markets and moving costs.

$$q_j\left(L_j\right) = n_j P_j^L\left(1 - T_j^L\right) + \zeta_j + \bar{\beta} EQ\left(L_j'\right) + \max_h\left\{\epsilon_h + \bar{\epsilon}_{jh}\right\}, \tag{3}$$

$$\bar{\epsilon}_{jh} \equiv \bar{\beta} E\left[Q_h'(L_h) - Q_j'\left(L_j\right)\right] - C_{jh}. \tag{4}$$

The first term in equation (3) is the wage from a particular sector j, and the second term is a constant utility differential that we use to match the baseline equilibrium. The third term is the future value of staying in labor market j.[13] The fourth term is the value of moving to a new labor market. This is the sum of the ϵ_h value of being in labor market h and the premium in future values from that labor market over the current labor market. The difference in future values is given by equation (4). This is the discounted value of moving from the current labor market j to h, denoted by the first term, minus the moving cost. Suppose that the current labor market j yields the best option for the worker. Then the difference in value functions is zero, and the moving cost is $C_{jj} = 0$. Equation (4) collapses to zero, and equation (3) is only the value of current and future employment in labor market j plus the idiosyncratic benefit of staying there. If instead, another labor market h is the best option, then the worker receives the current and future benefits of the current labor market, plus the additional future benefits of being in the new labor market and idiosyncratic benefit of that new labor market minus the moving cost.

13. The discount factor in the mobility model is $\bar{\beta} = \beta^{12}$, which reflects the fact that the mobility model is calibrated to annual time periods rather than months, like the matching model. This is because Artuç et al. (2010) use annual data. However, we only solve this model in steady state, so the month-to-month unemployment rate will equal the annual unemployment rate.

To turn this into a Bellman equation that yields aggregate variables, we take the average across all workers with respect to the vector $\epsilon = \{\epsilon_1, \ldots, \epsilon_j, \ldots, \epsilon_J\}$. We denote this by the uppercase $q_j(L_j)$ for the average for each labor market:

$$Q_j(L_j) = n_j P_j^L (1 - T_j^L) + \zeta_j + \beta E Q(L_j') + \Omega(\bar{\epsilon}_j) \\ \bar{\epsilon}_j = \{\bar{\epsilon}_{j1}, \ldots, \bar{\epsilon}_{jh}, \ldots, \bar{\epsilon}_{jJ}\}. \tag{5}$$

The only difference from equation (3) is the final term, which is the "option value" for the worker. This is the average of $\max_h\{\epsilon_h + \bar{\epsilon}_{hj}\}$ from equation (3), and it is the value of the option of moving to a new labor market if the prospects are better there. This allows workers to consider wage differentials, future values of staying in the same labor market, and the future possibility of switching when deciding where to move. Artuç et al. (2008) shows that using the extreme-value distribution for the idiosyncratic benefit the option value can be modeled as:

$$\Omega(\bar{\epsilon}_j) = -\nu \ln(l_{ii}). \tag{6}$$

We take the parameters ν and C_{jh} from estimates in the literature. The transition of workers from one labor market to another is then described by l_{jh}, which is the share of the labor force in j that moves to h. This creates entries in a transition matrix describing how labor flows between markets. The parameter ν comes from extreme-value distribution of $\bar{\epsilon}_{jh}$ and is estimated along with the moving costs. So, the mobility friction comes from two parts: the common cost of moving labor markets captured by C_{jh} and the variance in preferences among workers for different labor markets captured by ν. The share of workers who move from j to h is also computed from Artuç et al. (2008) as:

$$l_{jh} = \frac{\exp(\bar{\epsilon}_{jh}/\nu)}{\sum_{k=1}^{J} \exp(\bar{\epsilon}_{jk}/\nu)}, \tag{7}$$

$$L_j' = \sum_{h=1}^{J} l_{hj} L_h. \tag{8}$$

The transition shares found in equation (7) can then be used to compute next-period labor markets in equation (8) by multiplying across transition shares from all other labor markets h into labor market j. Just like with the search-and-matching model, we use only the steady state of this mobility model in our static CGE model. However, with the search-and-matching model, a steady state can be directly calculated within the dynamic model, though with the mobility model we are only able to numerically approximate the steady state. Once we solve for the steady-state transition matrix, we need to multiply this matrix by our initial labor distribution several times to determine the new steady-state distribution of labor. We choose to use eight periods, reflecting the finding in the annual model of Artuç et al. (2010) that it takes eight years to achieve a 95% convergence in response to a trade shock. In practice, this number is arbitrary since our results are virtually identical if we use larger numbers.

To generate the perfectly mobile case, moving costs ν and C_{ij} are set to zero, so the model collapses to a single labor market with free movement and identical preferences for all workers across labor markets. The parameters on moving costs are taken from Artuç et al. (2010), which estimates the model for workers in the United States using data from the Current Population Survey (CPS). These are quite high, four to five times the annual wages for most industries. We show the parameter value choices for the common cost matrix entries C_{jh} and the extreme-value distribution parameter ν in the appendix (available online).

2.2. Production

Production is undertaken by I different firms, each representing an industry aggregate (we will interchangeably refer to these representative firms as industries or sectors). Technology for firm i is modeled using a nested constant elasticity of substitution (CES) production function that exhibits constant returns to scale, as shown in equation (9).

$$F_i^s(X) = \Gamma_i^s \left[\sum_h \alpha_{i,h}^s X_{i,h}^{\rho_i^s} \right]^{\frac{1}{\rho_i^s}}. \tag{9}$$

The elasticity parameter ρ_i^s, the share parameters $\alpha_{i,h}^s$, and the shift parameter Γ_i^s can potentially differ across industries i and across stages s of the nested production process.[14] The stage s can be either the final good, value added, intermediate goods, energy, materials, or electricity {Final, VA, I, E, M, Elec}. The term $X_{i,h}$ is a quantity of an input h into the production of firm i, which differs across the different nests, described below.

Figure 1 shows a diagram of the nesting structure for production. In the first nest, output from industry i, Y_i, is produced by combining the value-added composite VA_i and an intermediate goods composite A_i:

$$Y_i = F_i^{\mathrm{Final}}(\mathrm{VA}_i, A_i). \tag{10}$$

Capital and labor are combined into the value-added composite.

$$\mathrm{VA}_i = F_i^{\mathrm{VA}}(K_i, L_i). \tag{11}$$

In turn, the intermediate composite is made with two other types of composites: an energy composite E_i and a materials composite M_i, each of which is composed of demands from energy and material industries, respectively. We divide all the sectors in our data into either energy sectors or materials. The number of energy sectors in the economy is denoted by $\bar{e}$ and the number of material sectors is $\bar{m}$, and they are listed in figure 1. In addition to the division of energy goods, we subdivide electricity into "renewable" and

14. The substitution elasticity is $\sigma_i^s = 1/(1 - \rho_i^s)$.

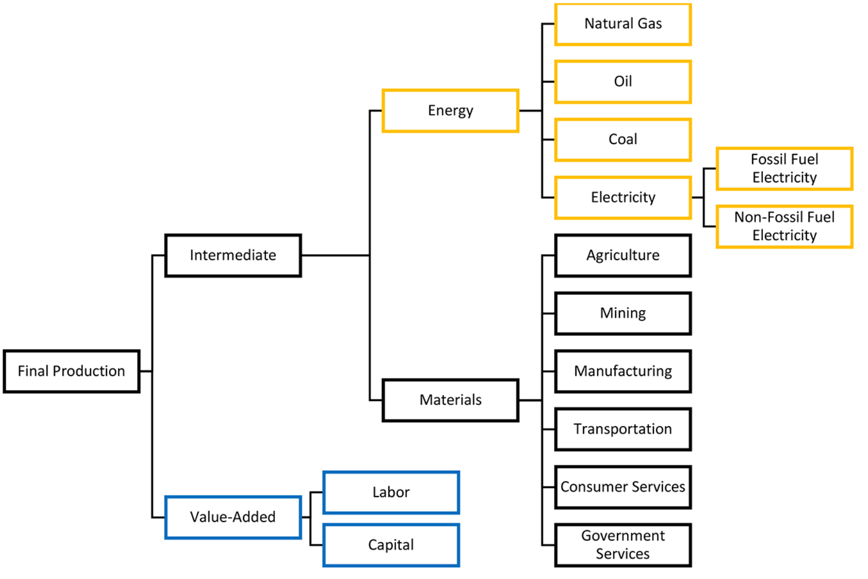

Figure 1. Nested production structure. This figure presents the nested production structure of the CGE model used in this study.

"nonrenewable," where the renewable electricity sector does not use fossil fuels. The inputs to the energy composite E_i are the energy inputs e_{i1}, .., $e_{i\bar{e}}$, and the input to the materials composite M_i are the inputs $m_{i1}, \ldots, m_{i\bar{m}}$. For the electricity sector, the inputs are the quantities of renewable and nonrenewable electricity inputs, denoted by Z_i and NZ_i, respectively. (All other sectors just use the composite electricity input, Elec_i^d.)

$$A_i = F_i^I(E_i, M_i), \tag{12}$$

$$E_i = F_i^E(e_{i1}, \ldots, e_{i\bar{e}}), \tag{13}$$

$$M_i = F_i^M(m_{i1}, \ldots, m_{i\bar{m}}), \tag{14}$$

$$\mathrm{Elec}_i = F_i^{\mathrm{Elec}}(Z_i, NZ_i). \tag{15}$$

Models differ on how they structure the different nested inputs to final production. The biggest difference typically relates to how the model treats the value-added components of labor and capital. Some models, such as Hafstead and Williams (2018), combine labor with all other inputs in the top nest of production. Our model is more comparable to other models on the energy and environment such as MIT's Economic Projection and Policy Analysis (EPPA) model or EPA's Applied Dynamic Analysis of the Global Economy (ADAGE) model, which create a value-added nest combining labor and capital before combining with other energy and material inputs.

Producers observe commodity prices P_i^c, wages P_i^L,, and capital rents P_i^K. They then use these prices to determine their cost-minimizing factor demands. Factor prices can be industry-specific, both because labor and capital tax rates can be industry specific (though in the base case, all labor tax rates are identical across industries) and because, for wages, labor is industry specific in the case of labor immobility.

The producer's problem is solved backwards (or up the nesting tree). First, the producer chooses how much nonrenewable and renewable electricity to use in production. Then each firm decides the cost-minimizing inputs of energy goods (i.e., what ratio between energy goods produces one unit of the energy composite most cheaply), which includes the electricity composite. The firm then makes the same decision for material goods and the material composite. After this step, the minimum costs of one unit of the energy and one unit of material composite have been determined. So, the fuel costs to firm (and the incidence of a carbon price) are completely included in the decision by the firms.

2.2.1. Production: Search-and-Matching and Unemployment

Within the dynamic search-and-matching model described earlier, we must specify the firm's decision each period (though we only use the steady-state outcomes from that dynamic model in our CGE model). The firm's problem can be expressed as a dynamic optimization problem using a value function. The firm's problem is a dynamic problem within the search model since the firm decided each period how many vacancies to post and advertise.

In the search-and-matching model, the value function for firm i is:

$$\begin{aligned} J_i(n_iL_i;\theta_i) = \max_{v_{i,t}} \Big\{ & P_i F_i^{\text{Final}}\left(VA_i^d(K_i, n_iL_i), A_i\right) - P_i^L n_i L_i - g v_i L_i \\ & - P^K K_i - P^A A_i + \beta E\left[J_i\left(n_i' L_i'; \theta_i'\right)\right] \Big\} \end{aligned}$$

$$\text{s.t.}$$

$$n_i' = (1 - x)n_i + q_i v_i.$$

The value function J_i is a summation of current and future values of the firm, where the future value of the firm is discounted by β. Labor market tightness θ_i is taken as an exogenous state variable by the firm, just as it is by the representative household. The term $P_i^L n_i L_i$ is the cost of labor, where n_i is the employment rate among workers in industry i, and L_i is the labor supplied per worker; $g v_i L_i$ is the cost of vacancies to the firm. As in the search-and-matching literature, this cost of vacancies can be interpreted as recruitment costs or other job search costs on behalf of the firm. The firm buys services as an input to post a vacancy in their labor market. The parameter g is the cost of a vacancy per unit of labor the firm uses multiplied by the output price of services. So we multiply by the amount of labor supplied per worker allocated to each firm, L_i. The first constraint is the evolution of the labor supply n_i in the labor market.

The firm treats q_i, the job-filling rate, as exogenous, while the household treats f_i, the job-finding rate, as exogenous.

First-order conditions give the optimal choices for the firm. The first is the vacancy creation equation.

$$\beta E\left[J_{i,n_i'}\right] = \frac{g}{q_i} L_i. \tag{16}$$

The second is the marginal value of an additional worker to the firm. While the labor supply is determined in two parts: unemployment and mobility, the firm only makes one decision over total labor utilized.

$$J_{i,n_i} = \frac{\partial F_i}{\partial VA_i}\frac{\partial VA_i}{\partial n_i L_i} L_i P_i - P_i^L L_i + (1-x)\frac{g}{q_i} L_i. \tag{17}$$

One final issue is with how we are defining firms and labor markets. Since some labor markets encompass multiple representative firms, firms in the same labor market use the same labor pool and value function. This changes the subscript i to j for the variables in equation (17). In the perfectly mobile case, workers can move to any industry at no cost and the subscripts could be eliminated. Thus, all our labor market variables P_i^L, L_i, or q_i, are defined by the labor market the firm is attached to. This also implies that the marginal product of labor $[(\partial F_i/\partial VA_i)(\partial VA_i/\partial n_i L_i)]P_i$ is equalized across the firms in the same labor market. So when we change these variables to j we are referring to the marginal product of labor from an arbitrary firm within that labor market.

The value functions and first-order conditions within the search-and-matching model for the firms and households (described earlier) determine an equilibrium in the labor markets. Equilibria are determined by firms and households engaging in Nash bargaining over the total surplus from the match. The total surplus is equal to the value of an additional worker to the firm plus the value of an additional worker to the household. So, market wages are a result of the following problem:

$$\max_{V_{j,n},J_{i,n}} \left(V_{j,n}\right)^b \left(J_{j,n}\right)^{1-b}$$

s.t.

$$S_j = V_{j,n} + J_{j,n}.$$

In this problem, b is the bargaining power for the household, and $1-b$ is the bargaining power for the firm. The term S_j is the total surplus resulting from the match that the firm and worker bargain over. Solving the problem and substituting in equations (2) and (17) gives the following wage equation:

$$P_j^L = \frac{b\left(\frac{\partial F_j}{\partial VA_j}\frac{\partial VA_j}{\partial n_j L_j} P_j + f_j \frac{g}{q_j}\right) + (1-b)\xi\left(n_j\right)^{\frac{1}{\psi}}}{b + (1-b)\frac{1-T_j^L}{P_j^c}}. \tag{18}$$

2.3. Carbon Emissions

Carbon emissions are a by-product of production of the three fossil-fuel industries: coal mining, natural gas, and crude oil. The level of carbon emissions for each of these industries is a multiple of their output. A tax T_i^{Carbon} is levied per unit of carbon dioxide created by the industry. The "carbon coefficient" CC_i equals the tons of carbon produced when an agent consumes one unit of fossil fuel X_i. The total carbon tax revenue for each industry i is:

$$\text{CTaxRev}_i = T_i^{\text{Carbon}} \times \text{CC}_i \times X_i. \tag{19}$$

Note that if a sector i does not produce a polluting fuel, its carbon coefficient is zero; this is true for all industries i other than the three fossil-fuel industries. This is a fully upstream implementation, so all other firms that use these fuels as inputs take the tax into account in their cost-minimization problems. The tax is collected at the point of sale, so all producers' input prices, and prices of final goods are modified to take account of the carbon tax (however, fossil fuels are not consumed as final goods). As described below, we will consider three different options for returning the carbon tax revenues: lump sum, through a uniform labor tax cut, and through a labor tax cut targeted just at sectors heavily affected by the carbon tax. The other policy that we model is a clean electricity standard, which we model by taxing the fossil-fuel electricity sector and using the revenues to provide a subsidy to the non-fossil-fuel electricity sector. So, that policy is revenue neutral.

2.4. Foreign Sector

The foreign sector is modeled in the same way as the domestic economy with two primary differences. First, reflecting the fact that the US economy is roughly 25% of the world economy by GDP, the foreign sector is three times bigger than the domestic sector in our model. Second, the foreign labor market is assumed to be perfectly mobile, even when we run simulations with imperfect mobility between sectors for the domestic economy. Capital is perfectly mobile across borders. We use the Armington assumption that firms and customers differentiate imports from domestic goods. We operationalize this by assuming that goods are a CES composite of domestic goods and imports and take trade elasticities from the literature. This works the same way as equation (8), except that the two inputs are foreign and domestic goods rather than goods from different industries. Each agent chooses optimal quantities of foreign and domestic goods given their prices and creates a composite that feeds into other decisions. This means that intermediate inputs for firms are composites of foreign and domestic goods or services. We denote the share of domestic goods in a composite i as d_i, which we use to specify equilibrium conditions. We do not include any tariffs or other border frictions in this model.

The United States exhibits a $400 billion trade deficit with the rest of the world, but deficits and surpluses are concentrated in certain industries. For example, the crude oil industry exhibits a trade deficit of $85 billion, and industries like services exhibit a trade surplus. In addition to calibrating our model to trade data, we need to balance international trade through income accounts. Since labor cannot be traded with the rest of the world, the balance of payments is ensured through factor payments on capital. While there is an outflow of income through the current account, there is an inflow of income through the capital account. This satisfies the macroeconomic closure rule that the sum of all expenditures must equal the sum of all income.

2.5. Government

A single government, composed of state, local, and federal entities, has a balanced-budget condition imposed to close the model. The government has four functions: collecting taxes, transferring income, producing a public good, and imposing environmental regulation. The government levies input taxes on capital and labor and sales taxes on final production, in addition to the carbon tax. The public good is produced using the same nested CES production function structure as the private industries. However, this final good is not bought by the household, and it is nonrival and nonexcludable. Final government revenue is the sum of taxes collected on emissions, final goods, and factor income. The government's revenue G is:

$$G = \sum_{i=1}^{I}\left\{\left(\mathrm{CC}_i \times T_i^{\mathrm{Carbon}} \times X_i\right) + T_i^S \sum_{j=1}^{J} c_j^i\right\} + \sum_{j=1}^{J}\left\{\left(T_j^L \times L_j \times P_j^L\right) + \left(T_j^K \times K_j \times P_j^K\right)\right\}. \tag{20}$$

The government spends its revenue two ways. Some of it is returned to consumers in a lump sum transfer, giving TR_j to household j. The rest is used to purchase goods from different industries, where government consumption of good i is g_i. So, the government's expenditure function is:

$$G = \sum_{j=1}^{J}\mathrm{TR}_j + \sum_{i=1}^{I} P_i \times g_i. \tag{21}$$

The fraction spent on government expenditure is exogenously set to match ratios of government spending to lump-sum transfers. When we return carbon tax revenues to households in a lump-sum return, it is through this transfer amount. Government spending g_i is determined by a Cobb-Douglas demand function calibrated to match government demands in the Bureau of Economic Analysis tables. Transfers to households TR_j are based on income shares for households in the baseline.

2.6. Equilibrium

Equilibrium in the economy is determined through household utility maximization, cost-minimized production by the firm, a balanced government budget, and clearing in the matching, goods, and factor markets. To find the equilibrium we employ an algorithm that first starts by making a guess at a solution vector for several variables in our model. These variables are government expenditures for the home and foreign economy, the global price of capital, and the marginal products of labor for the foreign economy and each of the labor markets in our home economy. First, we use the marginal product of labor and global price of capital to solve for the optimal inputs of intermediate goods and capital using equations (9)–(15). We then use the steady-state version of equation (16) combined with equation (17) to get the following condition:

$$\left(\frac{1}{\beta} - 1 + x\right)\left(\frac{g}{q_j}\right) = \frac{\partial F_j}{\partial \mathrm{VA}_j}\frac{\partial \mathrm{VA}_j}{\partial n_j L_j} P_j - P_j^L.$$

This equation still has two unknown variables, the employment rate which determines q_j and the wage P_j^L. Using the equilibrium wage expression in equation (18), we can solve for the equilibrium employment rate, n_j and then use that to find the unemployment rate and resulting wage. We can now move to the mobility portion of the model. We first make a guess for the value functions in equation (4) and use equation (7) to find the transition shares. The transition shares are then used in equation (6) to find the option value and then that is substituted into the steady-state version of equation (5) to evaluate the value functions. We then use this as the next guess and repeat until the value functions converge. This gives us the transition matrix, which is then multiplied by the baseline vector of labor market shares several times to calculate a steady-state vector of labor market shares. We then use the product of labor shares, unemployment rate, and total labor allocation to derive the labor supplied to the foreign economy and each of our home economy's labor markets.

After finding the labor market variables, we use the labor supply, unemployment rates, and posted wages along with the price of capital, allocation of capital, and government transfers (from the government expenditures the algorithm has called off) to calculate income for the household. After finding income, we use commodity prices to find final demands for the consumer and government. Using final demands, we can then use the input-output matrix determined in the production step to calculate total production and total demand for labor and capital. Using total demands for labor and capital, we also calculate government revenues using equations (20) and (21). We then subtract each labor market's supply of labor from labor demand in that market, the global supply of capital from the global demand for capital, and the total government revenues from total expenditures in each country. The result is a vector of excess demands that is then fed back into the algorithm to provide another guess of prices. The algorithm then runs until the excess demands are each within a tolerance of zero.[15] Appendix A.I describes the calibration method and data sources.

15. Code is written in the open-source programming language Julia, and it is available upon request.

3. SIMULATION RESULTS

We simulate four policy scenarios. For all simulations we assume that all labor markets start at a 5% unemployment rate, which is close to the natural rate of unemployment implied by most literature. We use a range of carbon tax rates from $15 to $75 per metric ton of CO_2. Unless otherwise stated, counterfactual results of a single tax rate are set at $45 per ton, which was the midpoint of our range. All policies are revenue neutral in the sense that all collections are returned to the household in either a transfer or a tax swap.

The first policy modeled is a carbon tax where revenues are returned in a lump-sum fashion to all households. Revenues are returned in shares to each representative household determined by employment shares and transfers.

The second policy modeled is a carbon tax where revenues are returned as a cut to the labor tax rate. The labor tax rate is reduced equally across all sectors.

The third policy returns revenues in a way intended to offset the deleterious effects of the policy on the targeted industries. It returns the carbon tax revenues as a cut in the labor tax rate just for the fossil-fuel extraction sectors and fossil-fuel electricity and manufacturing, which are sectors likely heavily affected by the carbon tax. The labor tax rate is cut identically across these five sectors from its initial value to ensure revenue neutrality. While this specific policy has not been proposed to our knowledge, it is intended to represent various policies that combine climate policy with targeted subsidies to carbon-intensive industries.[16]

The fourth and last policy is a command-and-control clean electricity standard (CES), which mandates a reduction in fossil-fuel electricity output and an increase in non-fossil-fuel electricity output such that a specified percentage of total electricity output is generated by non-fossil-fuel (clean) electricity. We do not differentiate renewable fuels such as solar and wind from other non-fossil-fuel generation technology such as nuclear. We separate the non-fossil-fuel and fossil-fuel electricity production based on the fuel mix in generation reported by the Energy Information Agency (EIA).

The carbon tax policy is similar to other models of such policies, in that we assume a "production" tax for carbon fuels. The tax is levied on the eventual output of carbon for a fuel at the point of purchase of the fuel. Other possible points of taxation are extraction taxes (when it is mined out of the earth) and consumption taxes, which is a tax on all final goods based on the amount of carbon used to produce it. The production tax makes the most use of our model construction by fully incorporating the carbon use throughout the entire economy. Our CES policy setup comes from the model set up by Goulder et al. (2016).

16. For example, in 2021 President Biden created the White House Interagency Working Group on Coal and Power Plant Communities and Economic Revitalization to affect employment in those sectors.

These four policy scenarios are each simulated under both assumptions about labor mobility (costly mobility and perfectly free mobility), resulting in eight sets of results. We present the following outcomes for each of these eight combinations, all presented as relative to the no-policy baseline: the change in total emissions, the change in aggregate unemployment, and the change in the unemployment rate for specific targeted sectors. In the free mobility model, the unemployment rate is an economy-wide rate, identical across sectors. In the costly mobility model, workers can move between labor markets, and each labor market can have its own unemployment rate. The sectoral unemployment rate is defined based on the population of workers in that sector or labor market after the policy change (which can be different than the population of workers in that sector in the initial equilibrium).

3.1. Lump-Sum Revenue Return

Results from the carbon tax with lump-sum revenue return are summarized in figure 2. Our model predicts reductions in emissions that are comparable with previous studies. The reduction in total emissions is shown in the upper left panel of figure 2, for various levels of the carbon tax rate. A $45 per ton carbon tax leads to a 30% reduction in carbon emissions. This magnitude is comparable to that of Resources for the Future's "tax calculator," based on the Goulder-Hafstead E3 (energy-environment-emissions) CGE model. Their model predicts a 20% reduction from a $45 tax in the short run, increasing to 33% reduction after a few years (Goulder and Hafstead 2013, 2017).[17] Similarly, under a $45 per ton carbon tax, we find a GDP loss of 0.55% in the perfectly mobile model (not reported in fig. 2). This is consistent with the E3 CGE model's prediction of a 0.29% GDP loss in the first year, which increases to 0.72% after 10 years. In comparison to a multiple model study Energy Modeling Forum 26 (EMF-26), our model reports larger emissions reductions from smaller carbon taxes and similar GDP effects. To achieve a reduction of about 30%, carbon prices ranged from $26 to $164 with an average of $78. Our model results are in the lower end of this range at $45. Additionally, the median of model results on GDP is a 0.19% decrease in response to a 16.5% emissions decrease (Böhringer et al. 2012). For the lump-sum return case, our model reports a 0.17% GDP decrease in response to a 15% decrease in emissions (see table 2). Neither our model nor the E3 model include damages from carbon emissions or productivity increases from abatement, so these GDP effects only account for the costs of climate policy and not its benefits.

For the perfectly mobile assumption, we use an economy-wide unemployment rate for all sectors, so changes in unemployment rates are the same for all industries. For the costly mobility assumption, we also choose an initial unemployment rate of 5% for all industries. When we shock the system with a carbon tax, a different unemployment rate is calculated for each labor market.

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17. See http://www.rff.org/blog/2017/introducing-e3-carbon-tax-calculator-estimating-future-co2-emissions-and-revenues.

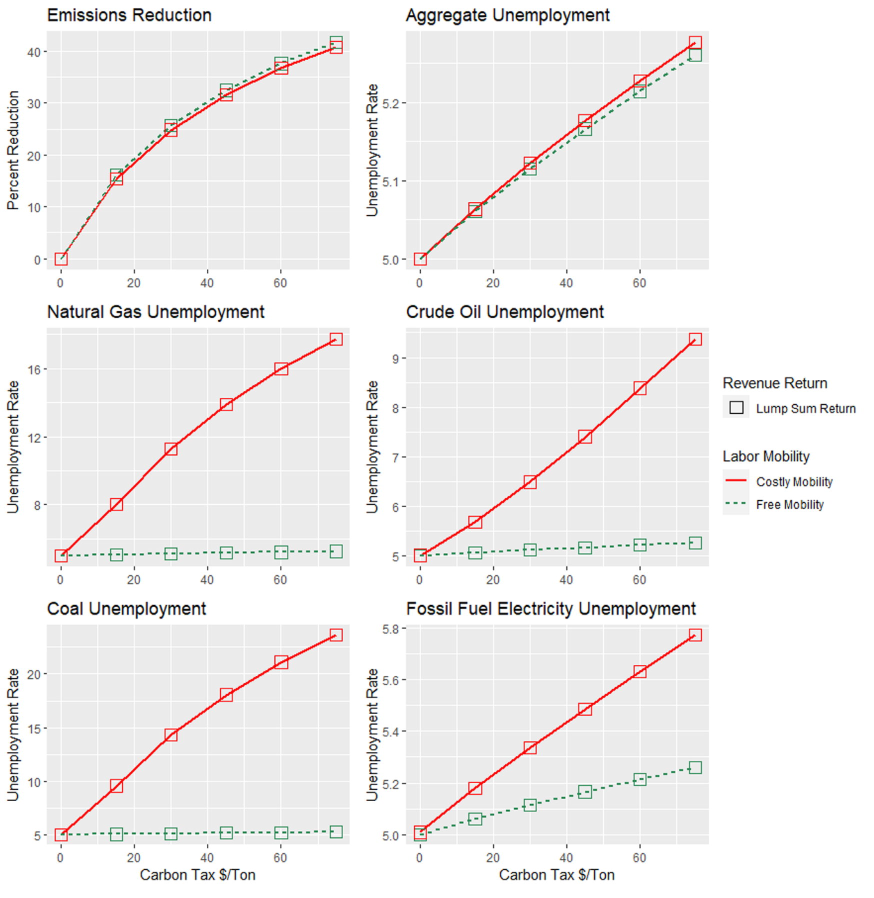

Figure 2. Results, carbon tax, lump-sum revenue return. These graphs present results under a carbon tax of varying levels (*x*-axis) with lump-sum revenue return. In the top row from left to right, the first panel shows the emissions reduction (%). The second panel shows the aggregate unemployment rate from the base level (5%). In the second row, the first panel shows the unemployment rate in the natural gas sector, and the second panel shows the unemployment rate for crude oil. The bottom row shows the unemployment rate in the coal sector in the first panel and the unemployment rate of the fossil-fuel electricity sector in the second panel. In each panel, we show results under the costly labor mobility assumption (*solid lines*) and under the perfectly mobile labor assumption (*broken lines*).

The change in the aggregate unemployment rate is shown for both the perfect mobility and costly mobility cases in figure 2, top right panel. The two curves are nearly identical to each other. The costly mobility model predicts a slightly higher unemployment rate; under a $45 carbon tax, the unemployment rate increases from 5% to 5.17% under perfectly free mobility and to 5.18% under costly mobility.

Although the aggregate unemployment rates are nearly identical between the two cases, the industry-level unemployment rates are very different from each other. Unemployment rates for the oil, gas, coal mining, and fossil electricity sectors are much higher in the costly mobility model. The left panel in the second row shows the unemployment rate for natural gas and the bottom left panel shows the unemployment rate for the coal sector. These two sectors have the highest tax burdens because they contain the most carbon per dollar of output, and so they also have the highest change in unemployment. At a $45 per ton carbon tax, the unemployment rate in the coal sector climbs to 18%, and the unemployment rate in the natural gas sector climbs to 14%, under the costly mobility assumption. The crude oil sector has the smallest spike in unemployment of the fossil-fuel extraction sectors. Under the costly mobility assumption, a $45 per ton carbon tax increases the crude oil unemployment rate to just under 7.4%. Finally, the unemployment rate for the fossil-fuel electricity sector is just 5.5% under the costly mobility assumption for a $45 per ton carbon tax. In the perfectly mobile case, the unemployment rate is the same across all sectors at 5.17%. Taken together, this figure shows that the labor mobility assumption has a modest effect on overall unemployment but can have significant effects on sectoral unemployment.[18]

Effects in other industries can differ between the two labor mobility assumptions as well. Table 1 presents a summary of results for a $45 per ton carbon tax with lump-sum revenue return, across all the sectors in the model. It presents the change in output prices, labor demand, and total output. The changes in output prices are dampened in the costly mobility model, since industries can substitute toward cheaper labor that faces costs to move from their industry. While almost all industries see a reduction in output, the energy industries are hit much worse. The change in all aggregate variables (bottom row) are virtually identical under the two mobility assumptions.

The electricity sector is of special interest, because of its heavy use of fossil-fuel inputs. The substitution toward non-fossil-fuel electricity shows up in the labor market. Table 1 shows that labor quantity increases in the non-fossil-fuel electricity sector, the only sector of the economy that sees an increase. Labor demand decreases for the fossil-fuel electricity sector, though the decrease is smaller in magnitude than the increase to the non-fossil-fuel sector. Figure 3 shows changes in labor quantity in the two electricity sectors in response to a carbon tax of varying levels, for the two labor mobility assumptions. For non-fossil-fuel electricity production, labor demands increase across all carbon tax amounts, and for the fossil-fuel electricity sector, labor demands decrease across all carbon tax amounts. The gains in the non-fossil-fuel electricity sector

18. The large sectoral difference does not translate to a large aggregate difference, since those four sectors are small relative to the aggregate economy (accounting for less than 2% of total labor demand).

Table 1. Sectoral Results, $45 per Ton Carbon Tax, Lump-Sum Revenue Return (%)

	Output Price		Labor Demand		Total Output	
Industry	Mobile	Immobile	Mobile	Immobile	Mobile	Immobile
Natural gas	15.6	12.8	−40.8	−23.4	−45.3	−43.7
Oil	5.1	3.7	−24.4	−12.5	−26.8	−22.5
Coal	.5	−8.9	−47.7	−30.9	−48.2	−46.6
Fossil-fuel electricity	16.2	15.2	−5.8	−3.3	−13.2	−12.0
Non-fossil-fuel electricity	−.1	1.4	10.2	4.4	9.6	7.0
Agriculture	.2	.3	−.5	−.8	−1.2	−1.2
Mining	−.1	.1	−.8	−1.0	−1.3	−1.3
Construction	.0	.1	.8	.5	.3	.2
Manufacturing	1.1	1.0	−1.8	−1.3	−2.9	−2.5
Transportation	.1	.2	.7	.4	.1	.0
Consumer services	−.2	.0	.6	.4	.1	.0
Government services	.6	.7	.2	.0	−.6	−.7
Aggregate	.4	.5	−.2	−.2	−1.2	−1.1

Note. This table provides changes in output price (relative to the numeraire), output quantity, and labor quantity for each industry in response to a $35 carbon tax with lump-sum revenue return, for both the perfectly mobile and costly mobility labor assumptions. The change in total production in each industry is inclusive of both intermediate and final demands; it is not a measure of GDP.

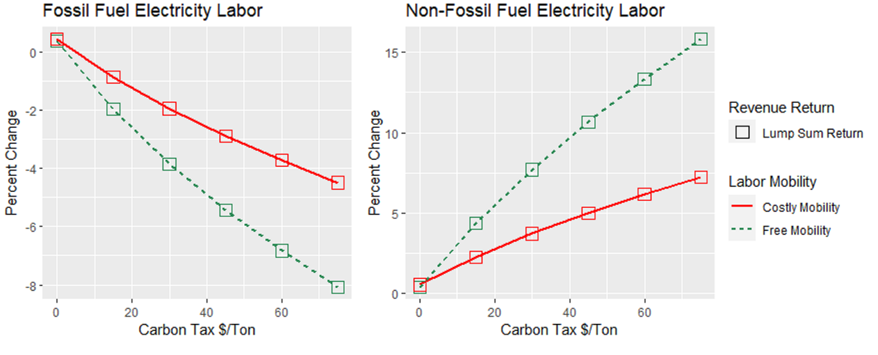

Figure 3. Labor quantity changes in electricity sectors, carbon tax, lump-sum revenue return. These graphs present the change in the quantity of labor for just the fossil-fuel and non-fossil-fuel electricity sectors (*y*-axis) resulting from differing levels of a carbon tax (*x*-axis) where revenues are returned lump sum. In each panel, we show results under the costly labor mobility assumption (*solid lines*) and under the perfectly mobile labor assumption (*broken lines*).

are twice as large under the mobile labor assumption, and the losses in the fossil-fuel sector are 75% larger in magnitude.

3.2. Uniform Labor Tax Cut

Results for the carbon tax coupled with a uniform labor tax cut are summarized in figure 4. The top left panel shows that the change in aggregate emissions resulting from a tax is virtually independent of the labor mobility assumption and of the choice of revenue return.

Aggregate unemployment rates are lower when revenues are returned through a labor tax cut, as shown in the top right panel of figure 4. This policy yields virtually no change in unemployment from the baseline, and this conclusion does not change based on the mobility assumption. For a $45 per ton carbon tax, returning revenues through an aggregate tax cut results in virtually no change in the unemployment rate from the baseline 5% under either mobility assumption.

Looking at the fossil-fuel extraction industries in figure 4, unemployment rates are slightly lower when revenue is returned through an aggregate tax cut. Natural gas and coal extraction industries have relatively small decreases in unemployment, and crude oil and fossil-fuel electricity have larger decreases in unemployment compared to the lump-sum return case. In general, unemployment rates are substantially smaller under the aggregate tax cut compared to the lump-sum revenue return for industries that saw low unemployment rates under the lump-sum case. The lowest unemployment rate is in the non-fossil-fuel electricity industry.

Figure 5 focuses on the two electricity sectors and presents their labor demand changes. Labor demands increase for the non-fossil-fuel sector and decrease for the fossil-fuel sector. However, when comparing to the lump-sum return policy, not much is different. The only discernible difference is that employment losses in the fossil-fuel electricity sector are smaller under the costly mobility assumption. Thus, while an aggregate tax cut may cushion the employment shock for the fossil-fuel sector under costly mobility, it does not seem to be effective at encouraging workers to move to the non-fossil-fuel sector under free mobility.

The policy implications are that a trade-off exists between the taxed and nontaxed industries. Although a few other sectors have employment gains compared to the lump-sum case, such as fossil-fuel electricity and manufacturing, the losses in the taxed industries do not differ very much between the two revenue return scenarios. The reason they do not differ much is likely that the tax cut ends up being rather small. Labor tax income makes up a large share of the government budget, so the tax cut is less than 2 percentage points. So when coal mining is experiencing unemployment rates of close to 20%, a small labor tax cut does not do much to offset it.

3.3. Targeted Labor Tax Cut

Our third revenue return scenario is a targeted tax cut, where only the most-affected industries receive a labor tax cut. The industries that receive a labor tax cut are natural

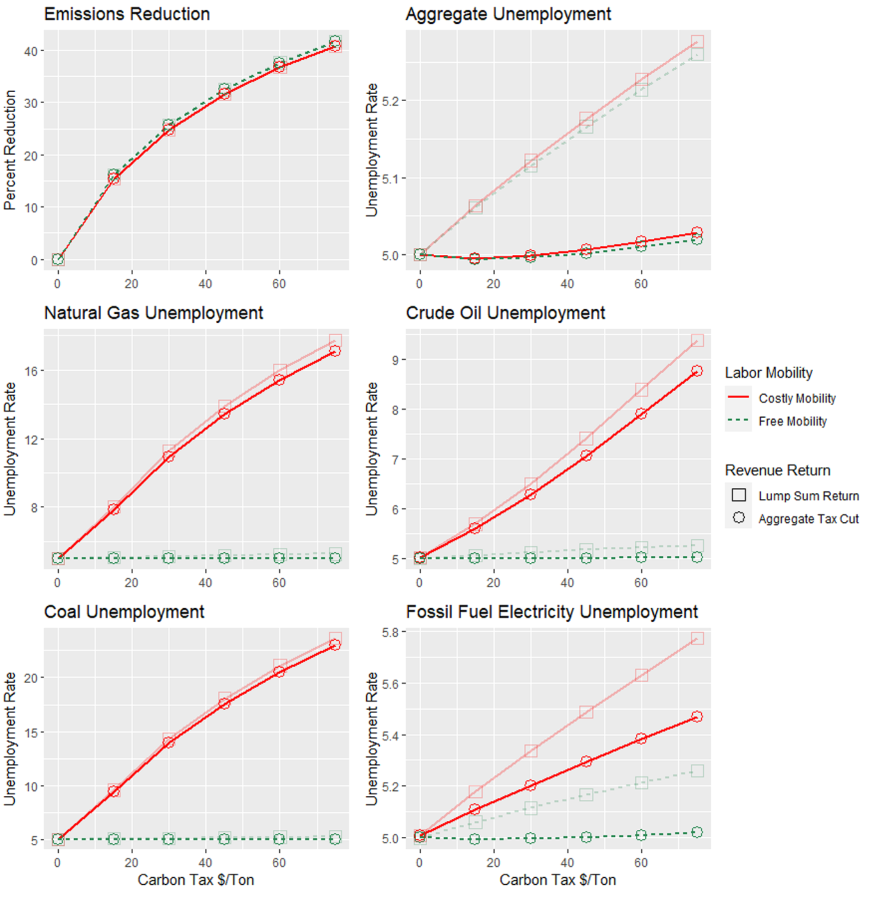

Figure 4. Results, carbon tax, revenue return through uniform labor tax cut. These graphs present results under a carbon tax of varying levels (x-axis) with revenues returned through an aggregate labor tax cut. In the top row from left to right, the first panel shows the emissions reduction (%). The second panel shows the aggregate unemployment rate from the base level (5%). In the second row, the first panel shows the unemployment rate in the natural gas sector, and the second panel shows the unemployment rate for crude oil. The bottom row shows the unemployment rate in the coal sector in the first panel and the unemployment rate of fossil-fuel electricity sector in the second panel. In each panel, we show results under the costly labor mobility assumption (*solid lines*) and under the perfectly mobile labor assumption (*broken lines*). The faded curves with the circles replicate the results under the lump-sum revenue return (fig. 2) for comparison.

gas, crude oil, coal, fossil-fuel electricity, and manufacturing. While fossil-fuel industries experience a large output demand shock from the tax, fossil-fuel electricity and manufacturing are the biggest users of energy so they experience a large input supply shock. Targeting only the fossil-fuel extraction sectors gives a large subsidy to labor

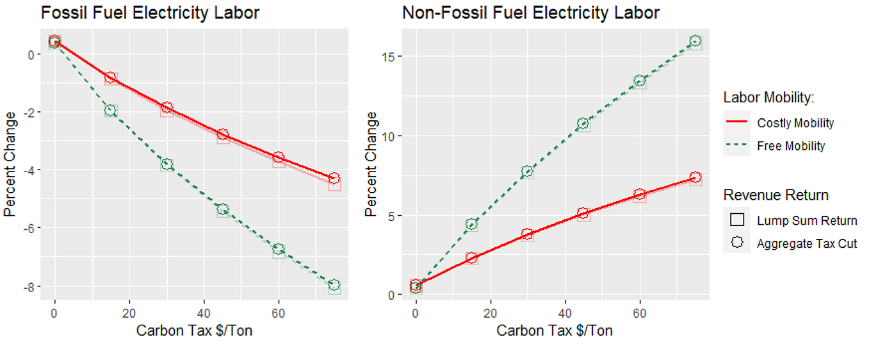

Figure 5. Labor quantity changes in electricity sectors, carbon tax, revenue return through uniform labor tax cut. These graphs present the change in the quantity of labor for just the fossil-fuel and non-fossil-fuel electricity sectors (*y*-axis) resulting from differing levels of a carbon tax (*x*-axis) where revenues are returned through an aggregate labor tax cut. In each panel, we show results under the costly labor mobility assumption (*solid lines*) and under the perfectly mobile labor assumption (*broken lines*). The faded curves with the circles replicate the results under the lump-sum revenue return (fig. 3) for comparison.

since the sectors are so small. To avoid this, we include fossil-fuel electricity and manufacturing to have a broader base for the tax cut. Aggregate results are summarized in figure 6. The top left panel shows emissions reductions, which are the same as previous policies. The top right panel shows the change in the aggregate unemployment rate. For both cases the unemployment rate is near the aggregate tax cut policy. However, aggregate unemployment rates are slightly lower in the mobile labor case.

The targeted tax cut reduces unemployment rates in the energy sectors relative to the other revenue return policies, especially in the oil and fossil-fuel electricity sectors. In the oil industry, the unemployment rate rises to 6.5% for a $45 per ton carbon tax, compared to 7.4% under the lump-sum revenue return policy. For the coal industry, the unemployment rate rises to 16.8%, which is lower than previous policies but still a smaller relative reduction than oil. Reductions in labor demands confirm this; under the lump-sum case, total labor demand in the fossil-fuel industry fell by 16.7%, compared to the targeted tax rate return, which reduced total fossil-fuel labor demand by 15.5%. Additionally, the trade-off among sectors exits for this policy as well. Under the costly mobility assumption, the large consumer services sector employment increases by 0.4% under the aggregate tax cut policy; however, labor demands decrease by 0.8% under the targeted tax scenario.

The targeted labor tax cut can alleviate the sector-specific labor market impact of the carbon tax more so than the uniform labor tax cut can. The reduction in aggregate unemployment is roughly the same across the two revenue return scenarios. There appears to be only a minimal trade-off to targeting the policy in this way.

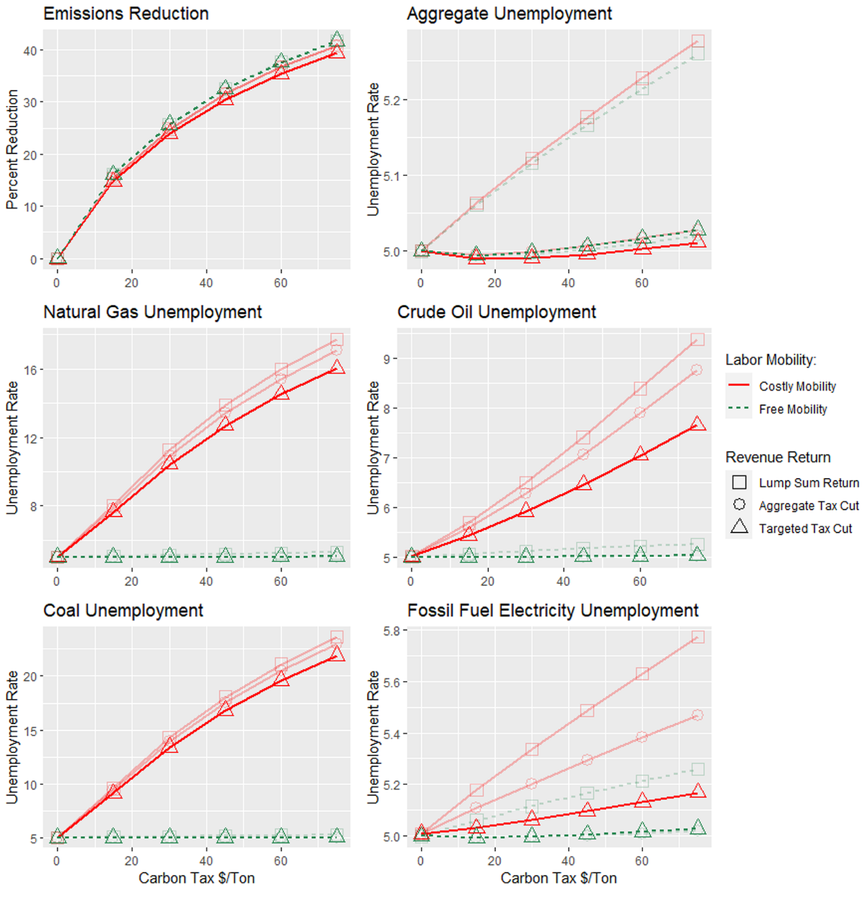

Figure 6. Results, carbon tax, revenue return through targeted labor tax cut. These graphs present results under a carbon tax of varying levels (*x*-axis) with revenues returned through a targeted tax cut (labor tax rates are cut only in the most-affected industries). In the top row from left to right, the first panel shows the emissions reduction (%). The second panel shows the aggregate unemployment rate from the base level (5%). In the second row, the first panel shows the unemployment rate in the natural gas sector, and the second panel shows the unemployment rate for crude oil. The bottom row shows the unemployment rate in the coal sector in the first panel and the unemployment rate of fossil-fuel electricity sector in the second panel. In each panel, we show results under the costly labor mobility assumption (*solid lines*) and under the perfectly mobile labor assumption (*broken lines*). The faded curves with the circles and triangles replicate the results under the previous revenue return assumptions (figs. 2 and 4) for comparison.

3.4. Clean Electricity Standard

The last policy we consider is a clean electricity standard (CES), where the fossil-fuel electricity sector is required to reduce production and the non-fossil-fuel electricity sector is required to increase production. We simulate this policy by introducing a tax on the fossil-fuel electricity sector and a subsidy to the non-fossil-fuel electricity sector to meet the specified goal. The results are presented in figure 7. The top left panel plots total emissions reductions against the required percentage of clean electricity, where the emissions reduction is on the vertical axis and the clean (non-fossil-fuel) electricity requirement is on the horizontal axis. Since there is no carbon tax to compare to in the CES policy, we use total abatement as a comparison across policies. For all remaining panels in figure 7, total abatement is on the horizontal axis. We compare a carbon tax achieving a given emissions reduction to the CES that achieves that same emissions reduction, and in figure 7 we compare the CES only to the carbon tax with lump-sum revenue return. We consider a range of clean electricity standards from 40% to 80%, with 30% being the baseline non-fossil-fuel electricity share, yielding emissions reductions from about 5% to 25%.

The remaining panels of figure 7 show the effects on aggregate and sectoral unemployment. For emissions reductions of about 15% (arising from a CES of about 60%) or less, the unemployment rates are about the same; in fact, CES unemployment is slightly lower in the free mobility assumption for total emissions reductions less than 10%. However, as the standard is set higher, aggregate unemployment climbs higher under the CES than under the carbon tax. This is also true for the fossil fuels that feed into electricity. The center left panel and bottom left panel show natural gas and coal unemployment rates, respectively. The natural gas industry experiences about the same unemployment rates across all CES standards, but the coal industry unemployment rate is much higher than the lump-sum policy. Under the costly labor mobility assumption, the fossil-fuel electricity sector has the highest unemployment rates, much higher than the unemployment rates under the carbon tax. Part of this response is due to the way the fossil-fuel electricity sector shuts down. When the carbon tax is levied, the fossil-fuel electricity sector begins switching to natural gas. Under a CES policy, the entire fossil-fuel electricity sector simply begins scaling all production back. Since the standard is implemented through a tax on output, the fossil-fuel electricity sector has no incentive to change its input mix.

The labor mobility assumption also has implications for the transition to a non-fossil-fuel electricity supply. Under the free mobility assumption, labor demanded falls by about half in the fossil-fuel electricity and more than doubles in the non-fossil-fuel electricity sector. In the immobile labor model, labor demand does not fall by as much in the fossil-fuel electricity sector and does not rise by as much in the non-fossil-fuel sector (see table A7; tables A1–A9 are available online). In the costly mobility case, the fossil-fuel electricity sector substitutes toward labor trapped in their industry, and the non-fossil-fuel electricity substitutes toward capital since it cannot hire the workers

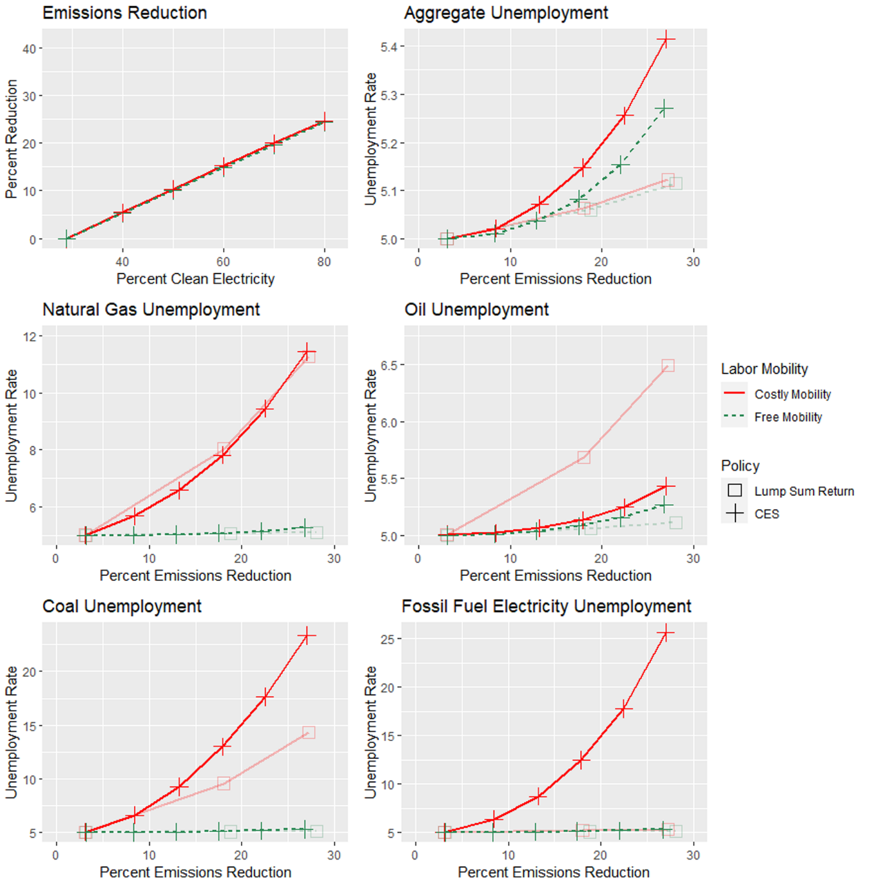

Figure 7. Results, clean electricity standard. These graphs present results under a command-and-control policy of varying levels (*x*-axis). The left panel in the top row shows the percentage reduction in emissions with the required clean electricity standard. The top right panel shows the aggregate unemployment rate from the base level (5%). The center left panel shows the unemployment rate for natural gas extraction and the center right panel shows the unemployment rate in the oil sector. The bottom left and right panels show the unemployment rates for the coal mining and fossil-fuel electricity sectors. In each panel, we show results under the costly labor mobility assumption (*solid line*) and under the perfectly mobile labor assumption (*broken lines*). The faded curves with the squares replicate the results under the carbon tax with lump-sum revenue return (fig. 2) for comparison.

necessary to expand. Though our model does not consider dynamic effects like the differences between investment and operation, analyses drawing conclusions about "green jobs" created by CES policies should consider whether labor or capital is more mobile between industries. If capital is more mobile (as is the case here), then other models could be overstating the employment gains in the non-fossil-fuel electricity sector.

Overall, low CES standards have comparable employment effects to equivalent carbon taxes, but high CES standards cause larger frictions in the labor market. This difference is due to the CES policy not taking advantage of lower marginal cost options for reducing emissions in other sectors such as oil. The center right panel shows that oil unemployment in the costly mobility model is lower than an economy-wide carbon tax over the entire range of emissions reductions. While output from the natural gas and coal sectors falls, oil output stays virtually the same. This provides a justification for coupling a CES with policies in the other sectors to achieve emissions reductions comparable to an economy-wide carbon tax.[19]

3.5. Employment and Output Effects across Policies

Finally, we compare the four policies directly to each other and examine their impacts on the overall economy. We do this by solving the eight policy simulations (four policies times two labor mobility assumptions for each policy) so that the policy results in a 15% aggregate reduction in emissions.[20] In table 2, we present the tax rate needed to achieve that reduction (except for the CES), the decrease in GDP (total final demands), and the level of the unemployment rate for each policy simulation. Because our model does not include any damages from pollution or benefits from pollution reductions, these reported changes in GDP represent only the costs of policy and not the benefits. In fact, a well-designed climate policy will reduce or eliminate the preexisting distortions from the market failure caused by pollution. These reductions should be the same across all rows in table 2 since all rows simulate the same aggregate pollution reduction.

Across all policies, the costly mobility assumption requires a slightly higher carbon tax to obtain the same emissions reduction. Since the costly mobility assumption makes aggregate labor supply more inelastic, a higher tax rate is required to generate the same change in quantity, which relates directly to emissions. Comparing GDP across the policies shows that the CES policy yields the largest drop in GDP, and the uniform labor tax cuts yield smaller drops in GDP than lump-sum revenue return. This result is in line with earlier analysis. To obtain a 15% reduction in emissions, a CES policy would need to require 75% non-fossil-fuel generation in the electricity mix. Though in our model the CES is implemented through a tax and subsidy to different electricity sectors, the higher distortion from this policy reflects the standard inefficiencies from command-and-control policies relative to uniform price policies.

19. See table A7 for the sectoral results for a command-and-control policy mandating a 60% clean electricity standard.

20. For all policies, we solve the model over a range of carbon taxes or CES standards. We then find the two closest points of emissions reductions and find the corresponding objective variable (unemployment, GDP, or tax amount) using the linear interpolation function in R and present the result for an estimated 15% reduction.

Table 2. Change in GDP (excluding pollution damages) and Aggregate Unemployment across Policies, 15% Emissions Reduction

	Tax Rate ($/ton)		Decrease in GDP (%)		Unemployment (%)	
	Free Mobility	Costly Mobility	Free Mobility	Costly Mobility	Free Mobility	Costly Mobility
Carbon tax with lump-sum return	24.23	23.30	−.17	−.17	5.07	5.08
Carbon tax with uniform labor tax cut	24.30	23.35	−.12	−.11	5.01	5.01
Carbon tax with targeted labor tax cut	24.69	23.35	−.12	−.04	5.01	5.00
Clean electricity standard	…	…	−.34	−.38	5.10	5.16

Note. This table presents the decrease in GDP (aggregate final demand) and the level of aggregate unemployment due to a 15% reduction in emissions across the four different policies. For the three carbon tax policies, we also present the tax rate that must be levied to yield a 15% emissions reduction. The model does not include pollution damages, so the reported changes in GDP do not reflect any potential productivity improvements from reducing pollution.

The lower distortion from returning carbon tax revenue via labor tax cuts rather than through lump-sum transfers reflects the revenue recycling effect from the double dividend literature.

Table 2 also presents the effects on aggregate unemployment. The CES policy has the highest unemployment rates. The targeted and uniform tax cut policies are similar across both labor mobility assumptions, except that the costly mobility assumption gives a slightly smaller unemployment rate under the targeted tax cut. Again, the recycling of revenue through tax cuts can reduce inefficiencies in the economy, and in this model that is reflected both through the effect on GDP and the effect on aggregate unemployment.

3.6. Sensitivity Analysis

We conduct sensitivity analyses by varying several parameter values to determine their effects on our conclusions. Three parameters we identify as especially important are moving costs, the wage-bargaining parameter, and the exogenous separation rate. We also explore sensitivity to the choice of aggregation of labor markets.

Our main results (fig. 2) indicate that moving costs do not have much effect on aggregate unemployment rates, but they do strongly impact sectoral unemployment rates. To explore this further, we vary the value of the moving cost parameters C_{ij} in figure 8, and we plot the unemployment rate for several sectors as a function of the moving cost parameter. Both parameters have an influence on moving costs, so changing all the C_{ij} common cost parameters would only change one part of the moving costs. To account for

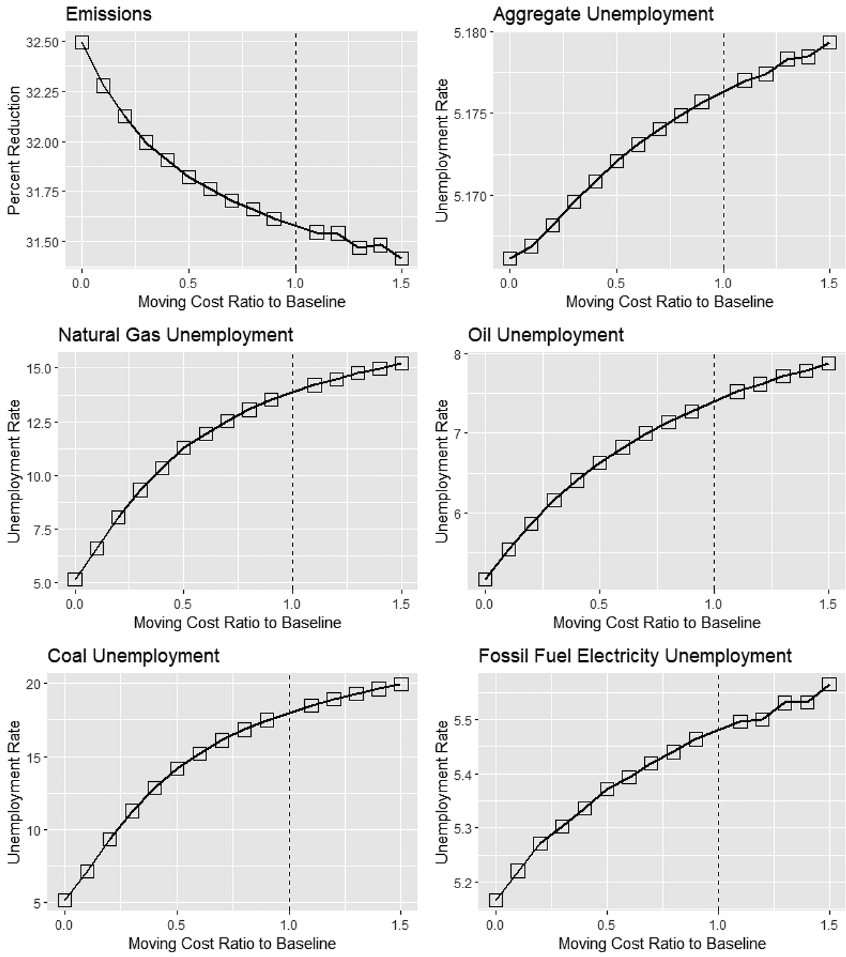

Figure 8. Effect of moving costs on industry unemployment rates. This graph shows how emissions and unemployment rates change under different moving costs. All points are simulated in response to a \$45/ton carbon tax. The vertical axis shows either the reduction in emissions or the unemployment rate and the horizontal axis is the ratio of the moving costs to those assumed in the baseline. The broken vertical line at 1 is the result from running the simulation at the baseline moving costs.

this, we scale all parameters up and down by the same amount. We then plot the results of the analysis on the *y*-axis and the scalar we multiply the costs by on the *x*-axis. Moving from left to right on the graph costs increase from zero to 50% higher than in our baseline calibration. The broken vertical line at 1 shows our baseline calibration.

Moving costs have the expected effect of increasing unemployment rates in affected sectors. Even small moving costs can generate substantially higher unemployment rates, as is shown in figure 8. When moving is free (costs are zero), sectoral unemployment rates are equal to the aggregate unemployment rate of about 5%. As moving costs increase from zero, unemployment rates in the affected sectors increase rapidly and then begin to plateau. Coal and natural gas sectors exhibit the highest unemployment rates. Increasing from no moving costs to costs 50% lower than the baseline moving costs results in unemployment rates for coal and natural gas that are 9.3 and 6.1 percentage points higher, respectively. Increasing costs from 50% lower than the baseline to 50% higher than the baseline results in unemployment rates for coal and natural gas that are 5.9 and 4.1 percentage points higher, respectively. So a change in moving costs has a much greater impact when moving costs are much lower than our calibrated values.

The second parameter that we examine is the wage-bargaining parameter. For our baseline calibration, we use a very low bargaining parameter (0.05) based on empirical justifications from Hagedorn and Manovskii (2008), meaning that the workers extract only a small fraction of the surplus from an employment match. However, this parameter has important implications for the response of unemployment rates to a change in wages. We choose three higher values for this parameter to show the sensitivity of our results: 0.25, 0.5, and 0.75. Figure 9 presents the same six outcomes across its panels as the previous simulations, under a lump-sum revenue return of the carbon tax, but it shows the results for the baseline bargaining parameter plus these three higher values. The first panel shows almost no effect on emissions. The second panel shows that the wage-bargaining parameter can have a huge effect on aggregate unemployment, even without any carbon tax. For instance, under no carbon tax, the unemployment rate ranges from about 5% in the baseline to higher than 10% when the bargaining parameter is 0.75. This difference is because we vary only the wage-bargaining parameter and no other parameters, so that the baseline equilibrium labor market differs. (An alternative strategy would be to vary both the wage-bargaining parameter and other labor market parameters so that baseline unemployment stays fixed.) The response of aggregate unemployment to the carbon tax (the slope of each line in the second panel) is about the same for each parameter value. Within the four affected sectors, however, a higher bargaining parameter leads to substantially smaller changes in the unemployment rate (i.e., the slopes of the curves are higher for lower bargaining parameters).

The third parameter we change is the separation rate. In this scenario, we use different separation rates for each labor market in the model. Using data from the Bureau of Labor Statistics Job Openings and Labor Turnover Survey for 2019, we find that separation rates are generally higher for the mining industry than the rest of the sectors in the economy. Just like with the bargaining parameter, we do not alter any other parameters, so changing the separation rate will change the initial baseline unemployment rate. Using the equation for the steady-state unemployment rate, the separation rate is positively related to the unemployment rate. The results of simulating

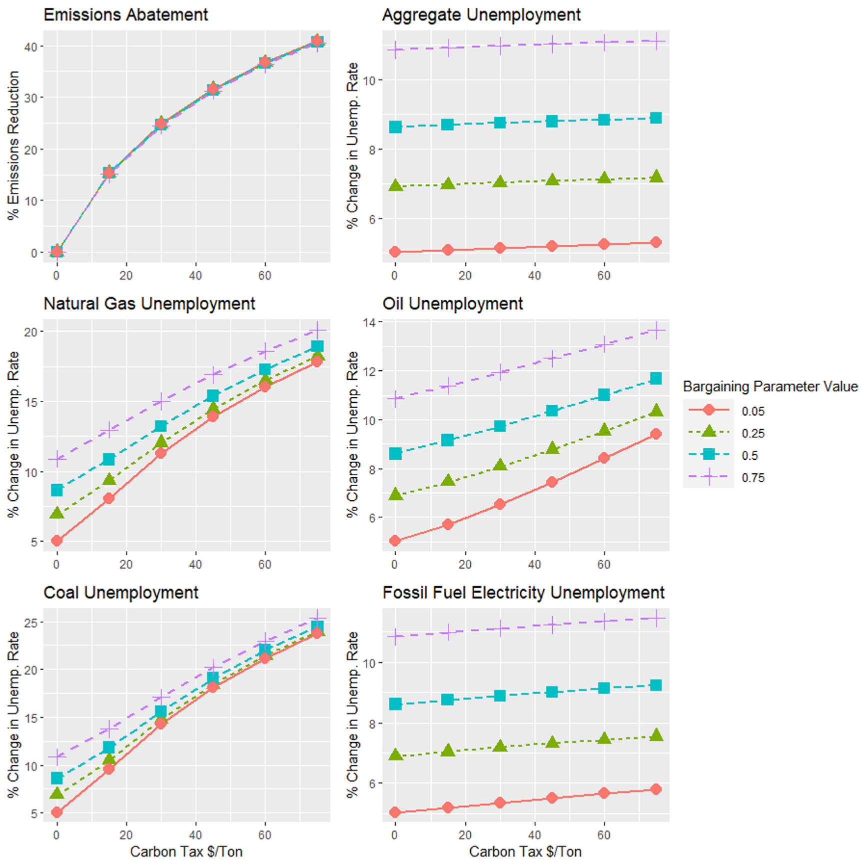

Figure 9. Effect of bargaining parameter. These graphs present results under a carbon tax of varying levels (x-axis) with lump-sum revenue return. On the top from left to right, the first panel shows the emissions reduction (%). The second panel shows the aggregate unemployment rate. The remaining panels show the sectoral unemployment rates in the natural gas, oil, coal, and fossil electricity sectors. In each panel, we show results under four different values of the wage bargaining parameter, including the baseline value of 0.05. The solid line with circles shows our base case, and the broken lines with triangles, squares, and crosses show the cases with bargaining parameter at 0.25, 0.5, and 0.75, respectively.

an economy-wide carbon tax with lump-sum revenue return are presented in figure 10. Emissions reductions are slightly larger under heterogeneous rates at higher tax levels. The aggregate unemployment rate is very similar, and it evolves over the range of carbon taxes in almost the same way. The aggregate unemployment rate is lower in the baseline and stays below the homogeneous separation rate simulations over the range of carbon tax levels. This is also true of the fossil-fuel extraction industries, but the

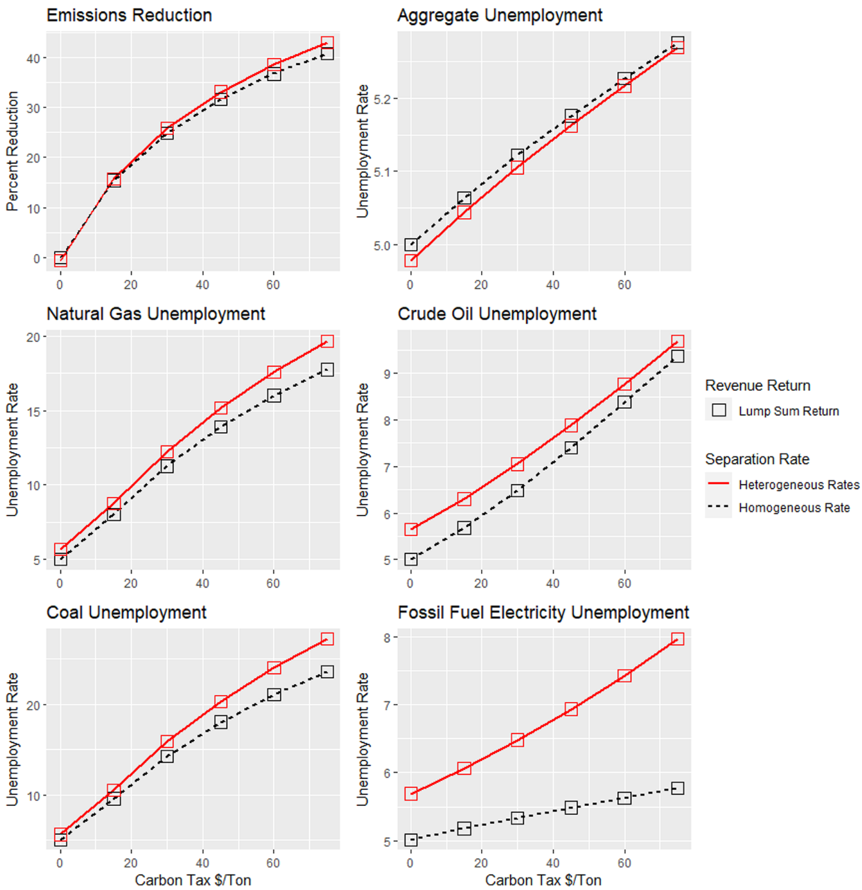

Figure 10. Effect of heterogeneous separation rate. These graphs present results under a carbon tax of varying levels (*x*-axis) with lump-sum revenue return. On the top from left to right, the first panel shows the emissions reduction (%). The second panel shows the aggregate unemployment rate. The remaining panels show the sectoral unemployment rates in the natural gas, oil, coal, and fossil electricity sectors. In each panel, we show results under two assumptions about separation rates. The homogeneous separation rate assumes the same separation rate for all industries, which is the same as the previous results and is represented by a broken line. The heterogeneous separation rate assumes that industries have different separation rates calibrated to data from the Bureau of Labor Statistics and is represented by a solid line.

pattern reverses. Sectoral unemployment rates are higher using heterogeneous separation rates, owing to the fact that separation rates in the fossil-fuel extraction industries are higher than the overall economy. The one large difference is for the fossil-fuel electricity sector, which shows a much larger initial unemployment rate due to a higher separation rate, but the unemployment rate also increases at a faster rate as the carbon tax level increases.

Finally, we consider the effect of our choice of the aggregation of labor markets. Our base-case labor market aggregation separates out the fossil-fuel, electric power, and manufacturing industries, and aggregates the remaining six industries into two groups. We check whether this choice of aggregation has an effect by choosing an alternate aggregation, where we keep our six energy-intensive industries separated, and separate our largest industry, consumer services, into its own labor market. This requires moving government services and transportation into the labor market with agriculture, mining, and transportation. We then run the model under the carbon tax with lump-sum return to the household and find that the results are virtually identical. Plots analogous to those in figure 2 are presented in figure A1 (available online).

Additional sensitivity analyses over substitution elasticity parameters are presented in appendix section A.II and table A8.

4. CONCLUSION

We develop a computable general equilibrium model of US climate policy that allows for involuntary unemployment through a search-and-matching model of the labor market. We compare the effects of climate policy under alternate assumptions about cross-sectoral labor mobility: either perfectly free mobility (commonly used in the literature), or a more realistic specification of costly mobility. We consider the effect of a carbon tax on labor market outcomes including the unemployment rate. Labor mobility does not have a substantive effect on emissions abatement or aggregate unemployment, but it can have a large effect on sectoral labor market outcomes. The increase in the aggregate unemployment rate under costly labor mobility is just 0.01 percentage points larger than the increase in the unemployment rate when labor is perfectly mobile. Unemployment in fossil-fuel industries is higher when labor mobility is costly—increasing by 9 percentage points, 2.4 percentage points, and 13 percentage points for the natural gas, oil, and coal sectors, respectively. These are large compared to just 0.2 percentage points when labor is modeled as perfectly mobile. When carbon tax revenues are returned as a labor tax cut rather than lump sum, the unemployment rate can decrease for some industries or overall.

As with any CGE model, the results depend on several modeling assumptions made, including calibration of the elasticities and other parameters. While we have performed several sensitivity analyses, there is potential for even more investigation of the effect of these assumptions on the outcomes. The primary result is that the effect on aggregate outcomes does not depend much on labor mobility, though sectoral outcomes do. Under our calibration, the mobility costs are quite large relative to earnings. However, even these large mobility costs are not enough to generate substantial differences in our aggregate variables. Our model is only evaluated in steady state, so we can study neither transition periods nor policies that change over time, like a carbon tax that increases over time. The model could include even more sectoral disaggregation, or we could include geographical disaggregation.

Our study's policy implications are important. Models that omit unemployment entirely are unreliable for gauging the effects of policy on unemployment, though full-employment models have been used to make predictions about unemployment effects. But even models that explicitly include equilibrium unemployment often make the extreme assumption that labor is perfectly mobile across sectors—an assumption unlikely to be relevant for policies that affect workers in fossil-fuel-extracting industries. By showing the importance of costly labor mobility for sectoral labor market outcomes, we demonstrate that a focus only on aggregate effects may mask large changes in specific affected sectors. Policymakers concerned with distributional impacts of climate policy can take this finding into account when determining policy options.

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