# Carbon Taxation, Green Jobs, and Sectoral Human Capital

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#### Abstract

Environmental regulations such as carbon taxation and air quality standards can lead to notable improvements in health outcomes and ambient air quality. However, these types of policies may have significant impacts on the labor market, in particular for workers in energy-intensive industries, especially if these workers have acquired specific human capital in those industries.

This paper focuses on the general equilibrium consequences of environmental regulation on the labor market. Specifically, I examine costly reallocation of workers between sectors, the welfare effects of involuntary unemployment, and the heterogeneous effects of this policy on different types of workers. To this end, I develop a two-sector search model with sectoral human capital accumulation to explore the effects on the labor market of implementing a per unit of energy use carbon tax in the US. I separate the economy into a high-intensive sector ('dirty') and a low-intensive sector ('clean'). I calibrate the model using 2014 U.S. manufacturing data. I find that a carbon tax increases total unemployment by 0.06 percentage points, decreases the dirty employment rate by 2.1 percent, and increases the clean employment rate by 1.04 percent. Firms in the dirty sector adjust by decreasing the demand for high-skilled workers and increasing the number of vacancies in the low-skilled market.

#### JEL Classification Numbers: E24, H23, J64, Q52, Q58

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# 1 Introduction

Greenhouse gas emissions in the United States are a rising concern because of their negative impact on human health and on the environment. Carbon-emitting fuels, such as coal, oil, and natural gas, provided 79 percent of the U.S. energy used in the past decade. Curbing the use of carbon through either a carbon tax or a capand-trade program is believed by many researchers to be the most efficient approach for reducing greenhouse gas emissions. <sup>1</sup> Researchers also generally agree that these types of environmental policies mitigate other negative externalities such as elevated human mortality due to particulate matter air pollution.<sup>2</sup>

At the same time, the "jobs versus the environment" discussion, has been and still is, a central part of the political debate regarding environmental regulations. In a June 2017 speech, president Donald Trump said, "Compliance with the terms of the Paris accord could cost America as much as 2.7 million jobs in 2025." Understanding the effects on the labor market is crucial to assess the true policy impact on the economy.

Furthermore, there is a growing consensus from experts, both policymakers and academics, that given global climate change, federal governments should take action. In particular, the Climate Leadership Council (CLC) recently proposed that the U.S. federal government should impose a carbon tax and that the revenue from that tax should be returned uniformly to all individuals as a lump-sum transfer, a carbon dividend.<sup>3</sup> So understanding the effects that such a policy could have on the economy

<sup>&</sup>lt;sup>1</sup>E.g., Baumol & Oates (1988)

<sup>&</sup>lt;sup>2</sup>E.g., Levy et al. (2009); Tagaris et al. (2009); Fann et al. (2012)

 $<sup>^{3}</sup>$ The CLC's proposal has received the endorsement from more than 3500 economists, including

and, in particular, on the labor markets, is crucial.

In this paper, I investigate the effects on the U.S. labor market of implementing a per unit of energy use carbon tax. In particular, I propose a theoretical framework to help us understand the costly reallocation of workers from newly regulated sectors to the unregulated ones, the welfare effects of involuntary unemployment, and the heterogeneous effects of this policy on different types of workers.

There have been multiple attempts to understand and quantify the costs that agents in the labor market face as a result of environmental policies.<sup>4</sup> At the same time, the majority of those existing studies use either a difference-in-differences approach, in which firms in the unregulated sector serve as controls; or partial equilibrium models that focus on the regulated sector, hence neglecting the cost of the inflow of new workers into unemployment or the unregulated sector. Given these research designs, it is difficult to measure precisely the overall economic effect of these regulations on the aggregate labor market. Furthermore, with these settings, it is more challenging to run counterfactuals to understand the impact of policies that have not been adopted yet.

To be able to correctly quantify and understand the effects of environmental policies on the labor market requires a general equilibrium model that allows for interaction between sectors. This paper aims to focus on the likely costs generated by environmental policies such as sectoral reallocations and unemployment, to quantify

<sup>27</sup> economics Nobel laureates, all the 4 former Fed Chairs, and 15 former Chairs of the Council of Economic Advisers.

<sup>&</sup>lt;sup>4</sup>E.g., Berman & Bui (2001), Morgenstern *et al.* (2002), Greenstone (2002), Christoph *et al.* (2012), Walker (2013), Curtis (2014), Kuminoff *et al.* (2015), Hafstead & Williams-III (2016), inter alia.

them and to analyze potential policies designed to alleviate the costs. This is consistent with Walker (2011), who points out that the appropriate measure of regulatory costs to the workforce should not be characterized by number of job lost but by the transitional costs associated with reallocating production or workers.

Additionally, to understand the potential effects, it is essential to consider a stylized fact in the labor economics literature: that policies affecting a particular sector or occupation which generate involuntary separations are time-consuming and associated with substantial transitional costs.<sup>5</sup> These costs are amplified if workers lose their sector-specific skills and tenure, and are forced to switch to another sector, resulting in significant and persistent earnings losses. These losses are even higher for those who experience unemployment spells.<sup>6</sup> Furthermore, most of the unemployment experienced following a sectoral shock can be accounted for by workers who decided to continue searching in the same sector.<sup>7</sup>

Moreover, the displacement literature has studied whether unemployed workers often suffer significant and permanent human capital losses, and if unemployment spells persist, it generates that workers detach from the labor market. For example, Ortego-Marti (2016) finds that the percentage wage loss for an additional month of unemployment is 1.22 percent.

Furthermore, in the case of previous environmental policy, the 1990 Clean Air Act Amendment, Walker (2013) finds that industry-specific human capital plays a vital role as a barrier to job mobility. In particular, the earnings losses for workers

<sup>&</sup>lt;sup>5</sup>E.g., Jacobson *et al.* (1993); von Wachter *et al.* (2011).

<sup>&</sup>lt;sup>6</sup>E.g., Kambourov & Manovskii (2008).

<sup>&</sup>lt;sup>7</sup>E.g., Murphy & Topel (1987); Loungani & Rogerson (1989).

who stay within the same industry are significantly smaller than for workers who change industries. These earnings losses also reflect losses due to non-employment between jobs that may also be higher for workers who switch industries.

In a recent study, Hafstead & Williams (2018) use an equilibrium search and matching model to study the effects of environmental policies on the labor market. They find that a carbon tax causes a substantial shift in employment between sectors, but the net impact on the labor market is small, even in the transitions. Their model provides a framework for understanding the labor market effects of environmental policy on the total number of jobs created and destroyed. Nevertheless, their model does not take into account heterogeneity and sectoral human capital accumulation which are crucial for measuring the costs of reallocation, the duration of unemployment spells, and distributional effects for individuals with and without specific human capital.

To overcome such gaps in the literature, I build a two-sector general equilibrium model to study the mechanisms through which environmental policies affect the labor market in both the regulated and unregulated sectors. My discrete time model builds upon Pilossoph (2014) by adding sectoral human capital accumulation and erosion to her framework as in Ljungqvist & Sargent (1998).

The model economy consists of two sectors (or islands), each with many workers and firms. Following Diamond (1982), Mortensen (1982), and Pissarides (1985) (DMP), workers and firms in each sector face search and matching frictions resulting in equilibrium unemployment. At the same time, the labor mobility between sectors is similar to the mobility between islands in Lucas & Prescott (1974). A key difference relative to the standard island models that have a continuum of markets where sectoral shocks do not have aggregate implications, is that I have a discrete number of islands. In particular, I have a two-island model, which implies that there are important effects of sectoral shocks. Lastly, the worker's sectoral choice problem is a discrete choice, so to describe worker flows as in Pilossoph (2014), I follow Kline (2008), Kennan & Walker (2011) and Artuc *et al.* (2007) in taking advantage of Type I Extreme Value Distribution assumptions on error term in order to derive expressions for choice probabilities.

The model economy is divided into two sectors, energy intensive (or "dirty") and non-energy intensive (or "clean"). Following Ljungqvist & Sargent (1998), I allow for learning-by-doing such that workers become more productive in their sector while on-the-job. Longer employment spells are associated with a higher probability of becoming high-skill-productive workers. When there high-skill workers lose their jobs and become unemployed, they face the risk of losing their sectoral specific human capital during the unemployment spell. Similar to learning-by-doing, I assume unlearning-by-not-doing, and the longer the unemployment spell, the higher the probability of unlearning.<sup>8</sup> Human capital levels within a sector segment labor markets implying that market tightness, and therefore job-finding and job-filling rates, vary by sector and sectoral human capital.<sup>9</sup> <sup>10</sup>

<sup>&</sup>lt;sup>8</sup>In this paper, high-skilled, higher productivity and higher human capital are synonyms.

<sup>&</sup>lt;sup>9</sup> I follow Nakajima (2012) assuming that labor markets are segmented. In his paper, he pointed out the difference in the average duration of unemployment across different income groups, and the overall average job-finding rate is declining in the unemployment spell are consistent with the assumption that workers with different productivity search in different markets and thus face different job-finding rates.

<sup>&</sup>lt;sup>10</sup>Davis et al. (2013) find significant heterogeneity in vacancy-filling rates across sectors.

Workers are ex-ante identical, but become ex-post heterogeneous as they can either accumulate sectoral human capital on-the-job or lose sectoral human capital off-the-job. The heterogeneity amplifies the effects of environmental policies through costly and endogenous shifts in their skills and sectoral composition. For simplicity, workers' sectoral human capital only takes two values, high or low.

A calibrated version of my model can be used to investigate the welfare effects of a carbon tax on workers in the newly regulated sector. The model could also be used to analyze if unemployed workers in the unregulated sectors become worse off because of the incoming sectoral switchers. In this paper, I calibrate the model to 2014 U.S. manufacturing data. After imposing a carbon tax equivalent to the social cost of carbon, I study how the model economy adjusts to a new steady state.

In particular, I measure how steady-state employment, unemployment, and wages change in both sectors, and both levels of human capital, after the introduction of the tax.

I find that under my benchmark calibration the total production decreases 3.64 percent change, increases total unemployment by 0.06 percentage points, reduces the employment rate in the dirty sector by 2.42 percent, increases the employment rate by 1.04 percent. Also, I find that there occurred substitution out from high-skilled workers towards low-skilled ones. At the same time, I find that firms in both sectors reduce the demand for energy as it becomes a more expensive input.

Also, I find that the model is sensitive to the degree of substitution between the production of the clean sector and the production of the dirty sector as inputs of an aggregate consumption good. Lastly, I perform a policy experiments to fully explore the interactions between the labor market and a carbon tax. I explore the effect of three alternative options on the usage of revenue obtained from the carbon tax. I find that it is less distortionary to rebate it lump-sum to all workers relative to rebate it to unemployed workers.

I organize the rest of the paper as follows. Section 2 presents the related literature to this paper. In section 3, I develop the two-sector search and matching model, which allows me to evaluate the effects of environmental regulations on the labor market. In section 4, the calibration strategy is presented. I discuss the baseline results in section 5. In section 6, I present a Sensitivity Analysis and Policy Experiments. Lastly, section 7 discusses the primary conclusions.

## 2 Related Literature

#### 2.1 Labor Markets and Environmental Regulations

Smith (2015) recognizes that most of the research on the employment effects of environmental regulations comes from reduced form studies. The author describes the results of past regulations on particular industries at a certain point in time reflecting the specific conditions that product and labor market were facing. This implies that at best, we can measure the outcomes. However, this type of models make it impossible to describe what will happen under new regulations, such as the carbon tax, and new economic conditions, which can only be done through a structural model.

Some recent reduced form study examples that study the relationship between labor markets and environmental regulations are: Berman & Bui (2001), who find no evidence that local air quality regulation substantially reduced employment, even when allowing for induced plant exit and dissuaded plant entry. Morgenstern *et al.* (2002), combines a unique plant-level data set with industry-level demand information, and finds that increased environmental spending generally does not cause a significant change in employment. An additional 1 million dollars in spending induced by the regulation generates a net decrease of just 1.5 jobs. Greenstone (2002) finds that during the first 15 years of the Clean Air Act, 590,000 jobs were lost in heavily regulated industries. Also, Walker (2011) finds that employment of polluting sectors in newly regulated counties decreases 15%, and Walker (2013) finds that newly regulated plants experienced, in aggregate, more than 5.4 billion in forgone earnings for the years after the change in policy. Kahn & Mansur (2013) finds adverse effects on employment in counties that have air quality worse than the National Ambient Air Quality Standards, in particular, for electricity-intensive industries, having a reduction of jobs equivalent to what would happen after an increase of 33 percent of the electricity prices. Curtis (2014) argues that the unemployed and inexperienced workers in this sector are further affected as the job opportunities in the sector are decreased and wages are reduced. Sheriff *et al.* (2015) finds that the 1990 ozone regulation reduced power plant employment without significantly affecting energy generation. Yip (2018) obtains non-employment effects on high-educated and an increase of unemployment and reallocation for low-educated in Canada.

As an alternative to reduced form analyses to study the effects of environmental regulation on the labor market, Kuminoff *et al.* (2015) uses a partial equilibrium model of residential sorting with full-employment that incorporates welfare effects of job layoffs and finds that an average worker's annual earnings would decline by \$5,553 if they lose their job during a healthy economy state.<sup>11</sup>

Also, there have been some critical efforts from the computable general equilibrium (CGE) literature to study the relationship between employment and environmental regulation, but primarily these studies rely on a full-employment assumption.<sup>12</sup> These studies abstract from frictional labor markets and unemployment, which is an important reallocation cost for workers.

<sup>&</sup>lt;sup>11</sup>Smith (2015) is the introductory article of the symposium on Unemployment, Environmental Regulation, and Benefit-Cost Analysis as a result of the October 2012 workshop sponsored by the U.S. Environmental Protection Agency (EPA). Kuminoff *et al.* (2015); Bartik (2015); Rogerson (2015) are research papers that were presented at the conference and are part of the symposium.

<sup>&</sup>lt;sup>12</sup>E.g., Bovenberg & van der Ploeg (1996, 1998)

# 2.2 Theoretical Framework: Sectoral Reallocation and Search Frictions

Several general equilibrium models have been developed to understand frictional sectoral labor mobility. Here, I discuss how my model relates to existing literature. As I mentioned in section 1, my model builds upon Pilossoph (2014). As in her work, my model relates to Lucas & Prescott (1974) in the way we model sectors as islands.

Alvarez & Shimer (2011) extended the Lucas-Prescott model, including specific skills to incorporate a cost for workers switching industries. In that paper, they show that specific skills may lead to significant rest unemployment, which is similar to my model.<sup>13</sup> Carrillo-Tudela & Visschers (2013) extend Alvarez & Shimer (2011) by including aggregate shocks finding that rest unemployment is the most significant share of total unemployment during the business cycle and frictional labor markets within the islands. They segment islands by human capital and match quality, and not by industry or occupation. Wiczer (2015) builds upon Carrillo-Tudela & Visschers (2013) but their papers differ in the way the shocks are modeled and the way the islands are segmented. He includes occupation-specific shocks and occupations segment islands.

Rogerson (2005) also extends Lucas & Prescott (1974) by introducing an overlapping generation model with sector-specific human capital, and finds that workers from the sector affected by an idiosyncratic shock leave the labor market (nonemployment) and the increase of workers in the unaffected sector comes from new

<sup>&</sup>lt;sup>13</sup>Alvarez & Shimer (2011) define rest unemployment as the unemployment caused by workers waiting for local labor market conditions to improve, rather than moving to other markets.

entrants to the economy.

There is another related literature that uses models of sectoral reallocations with search frictions without islands. Phelan & Trejos (2000) builds on Mortensen & Pissarides (1994), and finds that a single permanent change in the fundamentals that determine the sectoral composition can generate a downturn. Tapp (2011) extends Pissarides (2000a), and finds that after the persistent change in prices that differently affect a particular sector there is significant adjustment cost to the economy through the complexity of transferring skills between sectors.

Cosar (2013), using a two-sector search model with a small open economy, overlapping generations, and sector-specific human capital finds that in order to match the slow sectoral responses to trade liberalization search frictions alone are not enough, he finds that sector-specific human capital is the most critical impediment to a smoother transition.

#### 2.3 Search Models and Environmental Regulation

Using general equilibrium search models to understand the effects of environmental regulation on the labor market is a relatively recent approach in the literature. As I mentioned in section 1, Hafstead & Williams (2018) use an equilibrium search and matching model based on Shimer (2010), to study the effects of environmental policies on the labor market. They find that a carbon tax causes a substantial shift in employment between sectors, but the net impact on the labor market is small, even in the transitions.<sup>14</sup>

<sup>&</sup>lt;sup>14</sup>Hafstead *et al.* (2018), using the model developed in Hafstead & Williams (2018), compare the results of a model with full-employment assumption relative to one that assumes search frictions.

Shimer (2013) extends Lucas & Prescott (1974); he shows that even considering moving sectors is time-consuming, the optimal tax on the dirty good depends primarily on the marginal rate of substitution between private consumption of the dirty good and pollution.

Sun & Yip (2019) extend Pissarides (2000a) to theoretically understand the effects of an environmental tax and they find the conditions on the primitives under which the tax generates higher unemployment.

Pautrel (2018) introduces health status and pollution to Shi & Wen (1997). He demonstrates that assuming full-employment leads to an overestimation of the positive impact of environmental taxation on health.

Aubert & Chiroleu-Assouline (2017) takes into account the heterogeneity of workers similar to my model. But they differ in several important aspects. First, they do not allow for sectoral human capital accumulation (types are fixed). Second, only low-skilled workers are exposed to unemployment. Third, they do not explicitly model sector, so it is impossible to study reallocation. Lastly, their setting is static.

To my knowledge, the model I present here is the first to take into account human capital accumulation, search frictions, and sectoral reallocation in the context of environmental regulation. Accounting for all of these factors may be crucial for measuring the costs of reallocation, the duration of unemployment spells, and distributional effects for individuals with and without specific human capital.<sup>15</sup>

<sup>&</sup>lt;sup>15</sup>Kuralbayeva (2018) develops a model that introduces frictions as in Pissarides (2000b) to the migration model from Satchi & Temple (2009) to understand the effects of environmental regulation on migration and unemployment. This paper differs from the rest in the sense that it is intended to study developing countries with informal sectors.

## 3 The Model

#### 3.1 Environment

Time is discrete, infinite and indexed by  $t \ge 0$ . Throughout, I omit time subscripts unless needed for clarity.

There are two sectors (islands) indexed by  $s \in \{c, d\}$  where d stands for dirty sector and c for the clean one. Three types of agents populate this economy: A continuum and ex-ante homogeneous risk-neutral agents of measure 1; a large measure of risk-neutral profit-maximizing firms, and a government. Workers and firms discount future payoffs at a common rate  $\beta$ .

A firm can be either matched with a worker or vacant and posting vacancies. Each firm consists of a single worker production unit. Matched firms in each sector produce a sector-specific good using labor and energy as inputs, and the d firms differ from c firms in their energy intensity needed to produce. Also, their output and profits depend on the incumbent worker's sectoral human capital and aggregate sectoral productivity  $A_s$ .

Workers can be either employed or unemployed.<sup>16</sup> Also, all workers are heterogeneous in their skills because of unlearning-by-not-doing during unemployment and learning-by-doing during employment. Within the sector, a high-skilled worker is more productive than an otherwise identical low-skilled worker.

All new entrants to a sector start as low-skilled unemployed workers. Once they find a job, they begin as low-skilled workers, and each period they can become high-

 $<sup>^{16}{\</sup>rm I}$  abstract from labor force participation decisions. So in this context, I assume that all non-employed workers are searching.

skilled with probability  $\phi_s^{lh} \in (0, 1]$ . <sup>17</sup> On the contrary, the employed high-skilled workers who lose their jobs become high-skilled unemployed workers, and each period they can become low-skilled with probability  $\phi_s^{hl} \in (0, 1)$ .

Employed workers' wages depend on their human capital, and all unemployed workers receive a benefit b.

Furthermore, there exists a constant return to scale technology that uses the goods that each sector produces as inputs and combines them to create the consumption good.

Lastly, the government charges taxes to wages of employed workers to pay the unemployment benefits. The benchmark calibration assumes that the per unit of energy tax  $\tau_e$  is equal to zero, but in section 4.2.3, I performed experiments where the revenue is giving back as a lump-sum transfer to all the workers, employed and unemployed  $\Omega$ .

#### **3.2** Segmented Labor Markets in each Sector

As in any labor market with search frictions, à la DMP, firms and workers have to spend resources before job creation, and production takes place. Which implies that filled jobs produce rents in equilibrium.

For each sector s, let  $\lambda_s$  denote the labor force size. The labor force will consist of high-skilled employed workers  $n_s^h$ , low-skilled employed workers  $n_s^l$ , high-skilled unemployed workers  $u_s^h$ , and low-skilled unemployed workers  $u_s^l$ . Thus, the total

<sup>&</sup>lt;sup>17</sup>This assumption is similar to Kambourov & Manovskii (2009); Auray *et al.* (2017), where worker can only be skilled in one sector at a time and workers aren't allow to exert effort to increase their skills.

labor force size on sector s will be given by:

$$\lambda_s = n_s^h + n_s^l + u_s^h + u_s^l$$
, where  $\sum_s \lambda_s = 1$ 

In sector s, there are two pools, one for high skill h and another for low-skilled workers l. Implying the existence of four well-behaved matching functions, one for each pool, that determines the number of workers and the number of vacancies searching in each of them.

The matching function in the pool for workers of type i in sector s is given by the Cobb-Douglas specification:

$$m_{s}^{i}(v_{s}^{i}, u_{s}^{i}) = \mu_{s}(v_{s}^{i})^{1-\gamma}(u_{s}^{i})^{\gamma}$$
(1)

where  $m_s^i$  is the measure of new matches of type *i* in sector *s*;  $u_s^i$  is the measure of unemployed workers searching;  $v_s^i$  is the measure of posted vacancies;  $\mu_s$  is the matching effectiveness in sector *s*, and  $\gamma$  is the elasticity of the matching function with respect to unemployment.

For convenience, I introduce the vacancies to unemployed workers ratio as a separate variable, denoted by  $\theta_s^i = \frac{v_s^i}{u_s^i}$ . This term is also known as the labor market tightness. Thus, in this framework, there are four market tightness measures, one for each pool. By homogeneity of the matching function, the job finding and job filling probabilities are a function of the tightness.

To calculate the probability of filling a vacant job I divide the number of matches produced by the matching function by the number of job vacancies searching in the pool  $\frac{m_s^i}{v_s^i}$ . Expressed in as a function of  $\theta_s^i$ :

$$q(\theta_s^i) = \mu_s \frac{1}{(\theta_s^i)^{\gamma}} \tag{2}$$

Equivalently, I calculate the job finding probability by dividing the number of matches produced by the matching function by the number of unemployed workers searching. Given the structure of the matching function, it is equivalent to the product of  $\theta_s^i$  and  $q(\theta_s^i)$ :

$$p(\theta_s^i) = \theta_s^i q(\theta_s^i) = \mu_s(\theta_s^i)^{1-\gamma}$$
(3)

Following Pilossoph (2014), taking from the Discrete Choice Literature <sup>18</sup>, all workers are assumed to draw a vector of sector-specific idiosyncratic taste shocks  $\epsilon_n \sim Gumbel(-\rho\nu, \rho)$  every period. The shocks are independently and identically distributed over time and across sectors. Also, as Pilossoph (2014), I interpret these taste shocks as anything that might keep workers in a sector that is unrelated to wages or the ease of finding a job.

After realizing their tastes, low-skilled unemployed workers can move to the other sector. This assumption ensures both that there are always some workers who will find it beneficial to change sectors, and that labor mobility is bi-directional, even in the absence of the Carbon Tax.

 $<sup>^{18}</sup>$ See Kline (2008), Kennan & Walker (2011) and Artuc *et al.* (2007)

#### 3.3 Final Goods Market

I assume there is a consumption good that is a composite of the goods produced in each sector. This aggregate good Y can be used as a utility index to calculate welfare measures.<sup>19</sup> Y is produced combining  $Y_c$  and  $Y_d$  as inputs using a CES technology:

$$Y = (aY_{c}^{\chi} + (1-a)Y_{d}^{\chi})^{\frac{1}{\chi}}$$

Throughout the paper, I will normalize the price of the aggregate output (consumption good) to 1. a and 1 - a reflect the share parameter for the sector d and sector c respectively. This implies that the final good is the numeraire and can be used for, consumption, and to purchase energy at exogenous price  $p_e$ .

Since the markets for inputs are perfectly competitive, their prices are:

$$p_c = \alpha (\alpha Y_c^{\chi} + (1 - \alpha) Y_d^{\chi})^{\frac{1 - \chi}{\chi}} Y_c^{\chi - 1}$$

$$\tag{4}$$

$$p_d = (1 - \alpha)(\alpha Y_c^{\chi} + (1 - \alpha)Y_d^{\chi})^{\frac{1 - \chi}{\chi}} Y_d^{\chi - 1}$$

$$\tag{5}$$

#### 3.4 Sectoral Production of Intermediate Goods

In each sector, firms matched with a worker of type  $i \in \{l, h\}$  in sector  $s \in \{c, d\}$ , uses carbon-emitting energy  $e_s^i$ , and the worker's human capital to produce an intermediate good.

<sup>&</sup>lt;sup>19</sup>It is important to mention that I am abstracting from benefits of reducing pollution.

$$f_s^i(e) = \psi_s^i A_s(e)^{\alpha_s} \tag{6}$$

where  $\psi^i_s$  reflects the skills of the worker:

$$\psi_s^i = \begin{cases} 1 & \text{if } i = l \\ \psi_s > 1 & \text{if } i = h \end{cases}$$

$$\tag{7}$$

Firms differ between sectors in their usage intensity of carbon-emitting energy. The firms in sector d produce using a larger fraction of energy compared to the firms in sector c.  $(\alpha_d > \alpha_c)$ .

The firms buys energy  $e_s^i$  at the exogenous price  $p_e$  and pays workers real wage  $w_s^i$ .<sup>20</sup> At the beginning, I set the per unit Carbon Tax  $\tau_e$  to zero. The firm matches with a worker with probability  $q(\theta_s^i)$  defined in section 3.2. This model of production with an exogenous energy price is consistent with the assumption that the country behaves as a small open economy concerning energy.

The country imports energy at a price  $p_e$  in exchange for the final good with zero trade balance in every period. This, of course, assumes that the energy price would not respond to changes in demand caused by the climate policy.

Also, I abstract from the capital decision in the model as my main focus is to understand the effect in the labor market. It can be incorporated similar to Pissarides (2000b).

<sup>&</sup>lt;sup>20</sup> While the final goods market is competitive, the labor markets within each island are subject to standard search frictions; therefore, the determination of wages is through Nash Bargaining

So, the total output in sector  $Y_s$ , that is used as an input on the production of the market good Y is given by:<sup>21</sup>

$$Y_{s} = n_{s}^{h} f_{s}^{h}(e_{s}^{h}) + n_{s}^{l} f_{s}^{l}(e_{s}^{l})$$
(8)

#### 3.5 Firm's Optimization

A vacant firm's value equation  $V_s^i$ , in sector  $s \in \{c, d\}$  searching for a worker of type  $i \in \{l, h\}$ , represents the present-discounted value of expected profit from a vacant job in sector s searching for type i:

$$V_s^i(\Lambda) = -\kappa_s^i + \beta q(\theta_s^i) \mathbb{E}_{\Lambda'}[J_s^i(\Lambda')] + \beta (1 - q(\theta_s^i)) \mathbb{E}_{\Lambda'}[V_s^i(\Lambda')]$$
(9)

where  $\Lambda = \{n_s^h, n_s^l, u_s^h, u_s^l \forall s\}$  represents the state of the economy,  $\kappa_s^i$  is the unit cost of posting a job vacancy. With the job filling probability  $q(\theta_s^i)$ , the firm matches with a worker of type *i* and starts production in the next period, and with the complementary probability, the firms continue recruiting. Notice that in equilibrium  $V_s^i = 0$ , as free entry is assumed. From the latter assumption, the cost of posting a vacancy is equalized to the expected value of filling the vacancy:

$$\frac{\kappa_s}{q(\theta_s^i)} = \beta \mathbb{E}_{\Lambda'}[J_s^i(\Lambda')] \tag{10}$$

This equation is typically referred to in the literature as the job creation condition.

<sup>&</sup>lt;sup>21</sup>Which is consistent with an aggregate Cobb-Douglas technology by firm type. Lets define E = ne. So  $F_s^i(E,n) = \psi_s^i A_s(E)^{\alpha_s}(n)^{1-\alpha_s}$ , and  $\frac{F_s^i(E,n)}{n} = \psi_s^i A_s(e)^{\alpha_s} = f_s^i(e)$  which implies  $F_s^i(E,n) = nf_s^i(e)$ 

The dynamic problem of the firm in sector s, matched with a worker of type l, is to choose the optimal demand for energy to maximize their profits. The Bellman equation is given by:

$$J_{s}^{l}(\Lambda) = \max_{e_{s}^{l}} \left\{ p_{s} \psi_{s}^{l} A_{s}(e_{s}^{l})^{\alpha_{s}} - w_{s}^{l} - (p_{e} + \tau^{e}) e_{s}^{l} + \beta \mathbb{E}_{\Lambda'} [\delta_{s} V_{s}^{l}(\Lambda') + (1 - \delta_{s})(\phi_{s}^{lh} J_{s}^{h}(\Lambda') + (1 - \phi_{s}^{lh}) J_{s}^{l}(\Lambda'))] \right\}$$
(11)

The equation can be divided in two terms: the first, is the firm's current profit, where the  $p_s$  denotes the price of the good,  $A_s(e_s^l)^{\alpha_s}$  the output,  $w_s^l$  is the wage paid to the worker,  $p_e$  the price of energy, and  $\tau_e$  the carbon tax. The second term is the expected value of the next period, which consists of the following terms: First, the separation probability  $\delta_s$  times the value of being vacant, denoting that the match between a firm and a worker breaks and the firm becomes vacant. Second, with probability  $1 - \delta$ , a firm stays producing, in which case with probability  $\phi_s^{lh}$  the incumbent worker becomes high-skilled transforming the whole match in high type next period, and with  $1 - \phi_s^{lh}$  the firm stays filled with the low-skilled worker.

Similarly, for the firm that has already matched with a high-skilled worker h in sector s, the problem is given by:

$$J_{s}^{h}(\Lambda) = \max_{e_{h}^{h}} \left\{ p_{s} \psi_{s}^{h} A_{s}(e_{s}^{h})^{\alpha_{s}} - w_{s}^{h} - (p_{e} + \tau^{e}) e_{s}^{h} + \beta \mathbb{E}_{\Lambda'} [\delta_{s} V_{s}^{h}(\Lambda') + (1 - \delta_{s}) J_{s}^{h}(\Lambda')] \right\}$$
(12)

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Where  $\phi_s > 1$  is the parameter that reflects the higher productivity of being matched with a high-skilled worker, and which is the most relevant difference relative to the first term of equation 11. Similar pieces give the expected value: the value of becoming unmatched next period is the product of the separation probability  $\delta_s$  and the value of being vacant. And with probability  $1 - \delta_s$ , firms stay in the same match because their incumbent worker has the highest level of human capital.

Firms take their price  $p_s$ , the prices of energy  $p_e$ , wages  $w_s^i$  and tax  $\tau^e$  as given, so they buy as much energy as is necessary to maximize the value of the match. The first order condition of maximizing firm's problem  $J_s^i$  with respect to  $e_s^i$ :

$$p_s \alpha_s \psi_s^i A_s (e_s^i)^{\alpha_s - 1} = (p_e + \tau^e) \tag{13}$$

Which implies that the marginal product of energy is equal to the marginal cost of energy, yielding the following energy demand:

$$e_s^i = \left(\frac{p_s \alpha_s \psi_s^i A_s}{p_e + \tau^e}\right)^{\frac{1}{1 - \alpha_s}} \tag{14}$$

#### 3.6 Worker's Problem

Turning to the decisions of the workers, let  $U_s^l$ ,  $U_s^h$ ,  $W_s^l$  and  $W_s^h$  represent the value functions for each type of worker. First, the value function for a low-skilled unemployed worker in sector s is given by:

$$U_{s}^{l}(\Lambda) = b + \Omega + \beta p(\theta_{s}^{l}) \mathbb{E}_{\Lambda',\epsilon'} [W_{s}^{l}(\Lambda') + \epsilon'_{s,i}] + \beta (1 - p(\theta_{s}^{l})) \mathbb{E}_{\Lambda',\epsilon'} [\max \left\{ U_{s}^{l}(\Lambda') + \epsilon'_{s,i}, U_{s-}^{l}(\Lambda') + \epsilon'_{s-,i} \right\}]$$
(15)

where  $\epsilon'_{s,i}$  represents worker's *i* taste draw for the next period in sector s.<sup>22</sup> During this period the worker receives *b* unemployment benefits and  $\Omega$  lump-sum transfer. During the next period, with probability  $p(\theta_s^l)$ , she finds a job in sector *s* and receives  $W_s^n$ , while with  $1 - p(\theta_s^l)$  she stays unemployed and can choose in what sector to search next period.

On the other hand, an unemployed worker with h human capital in pool s:

$$U_{s}^{h}(\Lambda) = b + \Omega + \beta p(\theta_{s}^{h}) \mathbb{E}_{\Lambda',\epsilon'} [W_{s}^{h}(\Lambda') + \epsilon'_{s,i}] + \beta (1 - p(\theta_{s}^{h})) \phi_{s}^{hl} \mathbb{E}_{\Lambda',\epsilon'} [\max \left\{ U_{s}^{l}(\Lambda') + \epsilon'_{s,i}, U_{s-}^{l}(\Lambda') + \epsilon'_{s-,i} \right\}]$$
(16)  
+  $\beta (1 - p(\theta_{s}^{h})) (1 - \phi_{s}^{hl}) \mathbb{E}_{\Lambda',\epsilon'} [U_{s}^{h}(\Lambda') + \epsilon'_{s,i}]$ 

Equivalent to the low-skill workers, a h unemployed worker in sector s receives the unemployment benefit b and  $\Omega$  lump-sum transfer in the current period.<sup>23</sup> The next period, with probability  $p(\theta_s^h)$  she finds a job, and with  $1 - p(\theta_s^h)$  she stays unemployed, and with probability  $\phi_s^{hl}$  her human capital erodes and she becomes low-skilled unemployed worker next period and can choose in what sector to search, while with  $1 - \phi_s^{hl}$  she remains searching as an unemployed high-skilled worker.

 $<sup>^{22}</sup>$ In the next equations, using the discrete choice theory it becomes evident that the values do not depend on *i*.

 $<sup>^{23}</sup>$  In this version of the model, I do not differentiate unemployment benefit by worker type. In the U.S., the unemployment benefits depend on a percentage of your earnings over a recent 52-week period. For which I plan to differentiate them in future versions.

Now, the value function of an employed worker of type l in sector s is given by:

$$W_{s}^{l}(\Lambda) = (1 - \tau_{w})w_{s}^{l} + \Omega + \beta \delta_{s} \mathbb{E}_{\Lambda',\epsilon'} \left[ \max\left\{ U_{s}^{l}(\Lambda') + \epsilon'_{s,i}, U_{s-}^{l}(\Lambda') + \epsilon'_{s-,i} \right\} \right] + \beta (1 - \delta_{s})(\phi_{s}^{lh} \mathbb{E}_{\Lambda',\epsilon'} [W_{s}^{h}(\Lambda') + \epsilon'_{s,i}] + (1 - \phi_{s}^{lh}) \mathbb{E}_{\Lambda',\epsilon'} [W_{s}^{l}(\Lambda') + \epsilon'_{s,i}])$$

$$(17)$$

where, during the current period the workers receives a wage and pays the appropriate wage tax  $(1 - \tau_w)w_s^l$ , and the lump-sum transfer  $\Omega$ . Next period, with probability  $\delta_s$  she loses her job and becomes unemployed, with probability  $1 - \delta_s$  she stays employed, with probability  $\phi_s^{lh}$  becomes high-skilled and, with probability  $1 - \phi_s^{lh}$  stays in the same job.

Lastly, the value equation of a high-skilled employed worker in sector s is given by:

$$W_{s}^{h}(\Lambda) = (1 - \tau_{w})w_{s}^{h} + \Omega + \beta \delta_{s} \mathbb{E}_{\Lambda',\epsilon'} [U_{s}^{h}(\Lambda') + \epsilon'_{s,i}] + \beta (1 - \delta_{s}) \mathbb{E}_{\Lambda',\epsilon'} [W_{s}^{h}(\Lambda') + \epsilon'_{s,i}]$$
(18)

Again, the worker receives a wage  $w_s^l$ , paying a proportional tax  $\tau_w$ , and the lump-sum transfer  $\Omega$  in the current period. With probability  $\delta_s$ , the worker loses her job and becomes unemployed next period, while with  $1 - \delta_s$  probability, she maintains her job. In general, if a worker either stays or become low-skilled, she has to choose whether to stay unemployed in sector s or move to the other sector s-. The probability that a low-skilled worker facing reallocation chooses to move from sto s- is given by:

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$$\pi_{mov_s} = Pr\left(U_{s-}^l(\Lambda') + \epsilon'_{s-,i} > U_s^l(\Lambda') + \epsilon'_{s,i}\right) = 1 - \pi_{stays}$$

which following McFadden (1977) reduces to:

$$\pi_{mov_s} = \frac{1}{1 + exp\left(\frac{U_s^l(\Lambda') - U_{s-}^l(\Lambda')}{\rho}\right)}$$
(19)

These probabilities arise from the assumption that  $\epsilon_{is}$  come from a Gumbel distribution, which implies that it comes from the standard Logit probabilities. The move probabilities suggest that, on average, workers move in response to differences in sectoral payoffs. Furthermore, we can write the value of a low-skilled unemployed worker as a function of these move probabilities:<sup>24</sup>

$$U_{s}^{l}(\Lambda) = b + \Omega + \beta p(\theta_{s}^{l}) \mathbb{E}_{\Lambda'}[W_{s}^{l}(\Lambda')] + \beta (1 - p(\theta_{s}^{l})) \mathbb{E}_{\Lambda'}[U_{s}^{l}(\Lambda')]$$

$$+ \beta \rho (1 - p(\theta_{s}^{l})) \mathbb{E}_{\Lambda'}[log(\pi_{stau}^{-1})]$$

$$(20)$$

Where the expected value of tomorrow changes a little bit. It includes the value of finding a low-skilled job in s, the value of staying low-skilled unemployed in sector s, and the option value of remaining in sector s. Similarly, I can rewrite the rest of the value functions of the workers integrating out the idiosyncratic taste shocks, and even rewrite it as a function of the moving probabilities as in 20. See Appendix B for the alternative expressions.

<sup>&</sup>lt;sup>24</sup>See Appendix A for derivation.

#### 3.7 Wage Determination

To determine the wages, I assume that a worker and firm split the joint surplus of the match according to Nash bargaining. This bargaining is different for high-skilled and low-skilled matches as their outside options differ.

For matches between high-skilled workers and firms, I assume that firms cannot differentiate between high-skilled workers that come from unemployment and those that gain productivity on-the-job, as they have the same productivity level. Hence, once in the bargaining process, the only outside option they have is  $U_s^h$ . Implying that once they become high-skilled, they can not go back to the previous job as a low-skilled worker.

For workers of type *i*, the only credible threat of not agreeing is unemployment, and for firms it is to remain vacant.<sup>25</sup> The surplus of a job filled with a worker in sector  $s \in \{d, c\}^{26}$  is then given by:

$$S_{s}^{i}(\Lambda) = \frac{W_{s}^{i} - U_{s}^{i}}{1 - \tau_{w}} + J_{s}^{i}$$
(21)

The wage paid each period to a worker in an i-type match in sector s is assumed to be set to split the weighted product of both the worker's and firm's net gains from the match:

$$w_s^i = \arg \max_w [W_s^i - U_s^i]^{\eta} [J_s^i]^{1-\eta}$$
(22)

Where  $\eta$  is the worker's bargaining power with  $\eta \in (0, 1)$  so that both sides have <sup>25</sup>Agreement requires that  $W_s^i(\Lambda) \ge U_s^i(\Lambda)$  and  $J_s^i(\Lambda) \ge V_s^i(\Lambda)$ <sup>26</sup>Free-entry imply that  $V_s^i(\Lambda) = 0$ .

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an incentive to produce. Taking first order conditions for the maximization problem imply:

$$W_s^i - U_s^i = \eta (1 - \tau_w) S_s^i \text{ and } J_s^i = (1 - \eta) S_s^i$$
 (23)

#### 3.8 Worker Flows

The measure of employed or unemployed workers of type i in sector s, in general, consists of the sum of new workers arriving, plus the ones staying minus the ones leaving.

In particular, the number of low-skilled l unemployed workers in sector s in the next period are given by the sum of the low-skilled unemployed workers that did not find a job and decide to stay in sector s, the previously low-skilled employed workers that lost their job, and the high-skilled unemployed workers that received a negative skill shock:

$$u_{s}^{\prime l} = \pi_{stay_{s}} [(1 - p(\theta_{s}^{l}))u_{s}^{l} + \delta_{s}n_{s}^{l} + \phi_{s}^{hl}(1 - p(\theta_{s}^{h}))u_{s}^{h}] + \pi_{mov_{s-}} [(1 - p(\theta_{s-}^{l})u_{s-}^{l} + \delta_{s-}n_{s-}^{l} + \phi_{s-}^{hl}(1 - p(\theta_{s}^{h}))u_{s-}^{h}]$$

$$(24)$$

The measure of high-skilled unemployed workers in s in the next period is determined by the measure of high-skilled employed workers that lost their jobs and by the measure of high-skill unemployed workers who neither find a job or lose their productivity.

$$u_s^{\prime h} = (1 - p(\theta_s^h))(1 - \phi_s^{hl})u_s^h + \delta_s n_s^h$$
(25)

The measure of low-skilled workers in s in the next period consists of two measures, the employed workers with low-skilled that neither lose their job nor become productive plus the low-skilled unemployed workers that find a job.

$$n_s'^l = (1 - \delta_s)(1 - \phi_s^{lh})n_s^l + p(\theta_s^l)u_t^l$$
(26)

Lastly, the measure of high-skilled workers in *s* in the next period is the sum of three measures of workers from last period: first, the previously high-skilled employed workers that did not lose their job; second, the high-skilled unemployed workers that found a job; and, finally the low-skilled workers who became high-skilled.

$$n_s^{\prime h} = (1 - \delta_s) n_s^h + (1 - \delta_s) \phi_s^{lh} n_s^l + p(\theta_d^h) u_s^h$$
(27)

#### **3.9** Government

I assume that the government runs a balanced budget such that the revenues from the taxes (wage tax, and carbon tax) are equal to the value of the unemployment benefits b and lump-sum transfer (or tax) to all workers  $\Omega$ :

$$\sum_{s} \tau^{e} (e_{s}^{l} n_{s}^{l} + e_{s}^{h} n_{s}^{h}) + \sum_{i} \sum_{s} \tau_{w} w_{s}^{i} n_{s}^{i} = b(u_{c}^{l} + u_{d}^{l} + u_{c}^{h} + u_{d}^{h}) + \Omega$$
(28)

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#### 3.10 Steady State Equilibrium

**Definition:** Letting the final consumption good be the numeraire of this economy, given a set of constant exogenous parameters,  $\{A_s, p_e, \delta_s, \beta, b, \psi_s, \kappa_s^i, \eta, \gamma, \mu_s, \phi_s^{lh}, \phi_s^{hl}, \alpha_s, \alpha\}_{s=\{c,d\}}$  a steady state equilibrium is the set of values  $\{U_s^l, U_s^h, W_s^l, W_s^h, J_s^l, J_s^h\}_{s=\{c,d\}}$ , moving probabilities  $\{\pi_{mov_s}, \pi_{stay_i}\}$  transition probabilities, wages  $\{w_s^p, w_s^n\}_{s=\{c,d\}}$ , prices  $\{p_s\}_{s=\{c,d\}}$ , energy policies  $\{e_s^p, e_s^n\}_{s=\{c,d\}}$ , taxes  $\tau^e$ ,  $\Omega$  and  $\tau_w$ , and allocations  $\{n_s^l, n_s^h, u_s^l, u_s^h, \theta_s^l, \theta_s^h\}_{s=\{c,d\}}$  such that, in both sectors:

1. Vacant firms post vacancies optimally, and producing firms choose the optimal level of energy:

$$e_s^i = \left(\frac{p_s \alpha_s \psi_s^i A_s}{p_e + \tau^e}\right)^{\frac{1}{1 - \alpha_s}}$$

2. The free entry condition holds for both sectors and both human capital levels,  $V_s^i = 0$ , which implies:

$$\frac{\kappa_s^l}{\beta q_s(\theta_s^l)} = \frac{p_s A_s(e_s^l)^{\alpha_s} - w_s^l - (p_e + \tau_e)e_s^l + (1 - \delta)\phi_s^{lh} \frac{\kappa_s^h}{q_s(\theta_s^h)}}{1 - \beta(1 - \delta_s)(1 - \phi_s^{lh})}$$

$$\frac{\kappa_s^h}{\beta q_s(\theta_s^h)} = \frac{p_s \psi_s A_s(e_s^l)^{\alpha_s} - w_s^h - (p_e + \tau_e)e_s^l}{1 - \beta(1 - \delta_s)}$$

3. Unemployed workers decide where to search to maximize utility so that move probabilities satisfy:

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$$\pi_{mov_s} = \frac{1}{1 + exp\left(\frac{U_s^l - U_{s-}^l}{\rho}\right)}$$

4. Workers and firms split the surplus that maximize the generalized Nash Product, implying the following wages:

$$w_{s}^{l} = \eta (p_{s}\psi_{s}^{l}A_{s}(e_{s}^{l})^{\alpha_{s}} - (p_{e} + \tau_{e})e_{s}^{l}) + \eta \kappa_{s}^{l}\theta_{s}^{l} + \frac{(1-\eta)}{1-\tau_{w}} (b + \beta(1-p(\theta_{s}^{l}) - \delta_{s})\rho \log(\pi_{stay}^{-1}) - \beta(1-\delta_{s})\phi_{s}^{lh}((difU_{s})))$$

And for high-skilled workers, the wage is:

$$\begin{split} w_{s}^{h} = & \eta(p_{s}\psi_{s}^{h}A_{s}(e_{s}^{h})^{\alpha_{s}} - (p_{e} + \tau_{e})e_{s}^{h}) + \eta\kappa_{s}^{h}\theta_{s}^{h} \\ & + \frac{(1-\eta)}{1-\tau_{w}} \left(b + \beta\phi_{s}^{hl}(1-p(\theta_{s}^{h}))\rho\log(\pi_{stay}^{-1}) - \beta\phi_{s}^{hl}(1-p(\theta_{s}^{h}))(difU_{s})\right) \end{split}$$

where  $difU_s$  is defined as:

$$difU_{s} = \frac{\frac{\eta(1-\tau_{w})\kappa_{s}^{h}\theta_{s}^{h}}{1-\eta} - \frac{\eta(1-\tau_{w})\kappa_{s}^{l}\theta_{s}^{l}}{1-\eta} - \beta((1-p(\theta_{c}^{h}))*\phi_{s}^{hl} - p(\theta_{c}^{l}))\rho\log(\pi_{stay}^{-1})}{1-\beta(1-(1-p(\theta_{c}^{h}))*\phi_{s}^{hl})}$$

5. The intermediate goods market clears in both sectors:

$$Y_c = \frac{\alpha Y}{p_c^{1-\chi}} = n_c^l A_c(e_c)^{\alpha_c} + n_c^h \psi_c A_c(e_c)^{\alpha_c}$$

$$Y_{d} = \frac{(1-\alpha)Y}{p_{d}^{1-\chi}} = n_{d}^{l}A_{d}(e_{d})^{\alpha_{d}} + n_{d}^{h}\psi_{d}A_{d}(e_{d})^{\alpha_{d}}$$

- 6. Government maintains a budget balance following Equation 30.
- There is a stationary labor distribution of workers over employment states.
   (Inflows = Outflows)

# 4 Quantitative Strategy

In this section, I first describe the data that I am using, and then calibrate the parameters of the model using aggregate data on U.S. Manufacturing Industries. I divide the calibration of parameters into two steps. In the first step, I calibrate a group of parameters directly from the data series and previous literature. In the second step, I use a method of moments to calibrate the remaining parameters jointly. In the next section, I will present the baseline results of the calibration, the model fit, and I use the calibrated model to measure the effect of implementing a carbon tax in the U.S. on the unemployment, vacancies, and worker's transition rates.

#### 4.1 Data

I combine different data sources that I link through the North American Industry Classification System (NAICS) codes to obtain enough information to calibrate the parameters of the model. I use the Manufacturing Energy Consumption Survey (MECS) to be able to separate all manufacturing industries by their energy intensity, obtained their size and energy consumption. I use the Quarterly Census of Employment and Wages (QCEW) and Current Population Survey (CPS) to collect relevant data on aggregate employment. And lastly, I use the Panel Study of Income Dynamics (PSID), to capture heterogeneity between high-skilled and low-skilled workers.

To divide the manufacturing industries into two sectors, I follow the U.S. Energy Information Administration, and I separate them into energy-intensive manufacturing industries and non-energy-intensive manufacturing industries. In particular, the energy-intensive manufacturing group of industries is Paper Manufacturing (NAICS 322), Petroleum and Coal Products Manufacturing (NAICS 324), Chemical Manufacturing (NAICS 325), Primary Metal Manufacturing (NAICS 331), Nonmetallic Mineral Products Manufacturing (NAICS 327), and Wood Products Manufacturing (NAICS 321). The rest of the manufacturing industries are grouped to form the non-energy intensive ones. In table 1, I present the industries by sector.

	Clean	Dirty		
Code	Industry	Code	Industry	
NAICS 311	$\operatorname{Food}^n$	NAICS 321	Wood product <sup><math>d</math></sup>	
NAICS 312	Beverage and to bacco $\operatorname{product}^n$	NAICS 322	$Paper^n$	
NAICS 313	Textile mills <sup><math>n</math></sup>	NAICS $324$	Petroleum and coal products <sup><math>n</math></sup>	
NAICS $314$	Textile product $\operatorname{mills}^n$	NAICS 325	$\mathbf{Chemical}^n$	
NAICS 315	$Apparel^n$	NAICS 327	Nonmetallic mineral $\operatorname{product}^d$	
NAICS 316	Leather and allied $\operatorname{product}^n$	NAICS 331	Primary $metal^d$	
NAICS 323	$\operatorname{Printing}^n$			
NAICS 326	Plastics and rubber $products^n$			
NAICS 332	Fabricated metal $\operatorname{product}^d$			
NAICS 333	$Machinery^d$			
NAICS 334	Computer and electronic product <sup><math>d</math></sup>			
NAICS 335	Electrical equipment and $appliance^d$			
NAICS 336	Transportation $equipment^d$			
NAICS 337	Furniture and related $\operatorname{product}^d$			
NAICS 339	$Miscellaneous^d$			

 Table 1: Manufacturing Industries by Sector

Source: U.S. Energy Information Administration (EIA). Notes: EIA groups these industries as energy-intensive and non-energy-intensive. The subscripts d and n reflect if they are part of the sub-categories durable and non-durable goods.

It is worth to mention that I abstract from non-fossil sources of energy such as nuclear power and renewable energy. In the calibration, I only take into account the amount of carbon-emitting fuels. Throughout the paper, energy-intensive is equivalent to the dirty sector, and non-energy-intensive to the clean one as all the energy used is carbon-based, so producing using more energy generates higher carbon emissions. This assumption seems like a reasonable abstraction because fossil fuels have provided more than 80 percent of total U.S. energy consumption for more than 100 years. In 2016, fossil fuels accounted for 81 percent of total U.S. energy consumption.

#### 4.1.1 Manufacturing Energy Consumption Survey (MECS)

Using the 2014 MECS conducted by the EIA, I imputed the manufacturing value added from the energy consumption per value added ratio and the energy consumption values reported in MECS. <sup>27</sup> The value added in total manufacturing is 2, 401 billion dollars. From this, approximately 32 percent (\$762 billion) can be attributed to the dirty sector and 68 percent (\$1,627 billion) the clean one. Also from the MECS, I found that the total expenditure for purchased energy from all manufacturing industries in 2014 was \$149 billion. The dirty sector expenditure was \$110,530 (74 percent), and the clean sector expenditure was \$38,582 (26 percent) in millions.<sup>28</sup> Furthermore, the total consumption of energy in 2014 for the U.S. manufacturing industries was 14,875 trillion btu. Of this, the clean sector consumed 19.1 percent (2,850 trillion btu) and the dirty sector 80.8 percent (12,025 trillions btu). Lastly, the average price paid by all manufacturing industries weighted by their consumption share was 10.04 dollars per million btu. Table 2 presents the sample statistics:

<sup>&</sup>lt;sup>27</sup>MECS value added slightly differs from the one reported 2014 Annual Survey of Manufactures (ASM). The MECS and ASM are different samples selected from (roughly) the same frame (i.e., list of establishments). The ASM sample size is 3 to 4 times greater than the MECS. The MECS is optimized to get at energy variables, the ASM for economics.

<sup>&</sup>lt;sup>28</sup>Shares over value added are used to identify some of the parameters in the next subsection.

Sector	Value Added (VA)		Purchase Energy Expenditure (E)		Share $- F/VA$
Sector	Billion Dollars	Percentage	Billion Dollars	Percentage	- Share $-$ E/ VA
Clean	1,627	68%	38	26%	0.024
Dirty	762	32%	110	74%	0.145
Manufacturing	2,401	100%	149	100%	0.062
0 001135		a			

Table 2: Sample Statistics from MECS, 2014

Source: 2014 Manufacturing Energy Consumption Survey (MECS).

# 4.1.2 Quarterly Census of Employment and Wages (QCEW) and Current Population Survey (CPS)

Using the NAICS codes, I connect to the QCEW to obtain the total employment by sector. The 2014 annual average manufacturing employment is 12, 156, 536 workers. Of this, approximately 20 percent (2, 430, 927 workers) is attributed to the dirty sector and 80 percent (9, 725, 609 workers) the clean one. Furthermore, the total annual wages on average in the dirty sector are 70, 278 dollars and in the clean one are 62, 975 dollars, implying that dirty sector pays 14.9 percent more than the clean one.

I use the CPS to obtain the unemployment rate by sector. I identify each industry using the NAICS codes, and then I weighted over the size of each industry. The total annual average manufacturing unemployment rate in 2014 was 4.9 percent. For the dirty sector it was 3.8 percent and for the clean sector 5 percent.

Table 3 presents the sample statistics for both QCEW and CPS:
Sector	Annual Average Employment <sup>*</sup>		Total Annual Wages <sup>*</sup>		$Unemployment^+$
	Level	Percentage	Level	Relative $(D/C)$	Rate
Clean	9,725,609	80%	$61,\!150$	1.149	0.050
Dirty	$2,\!430,\!927$	20%	$70,\!278$		0.038
Manufacturing	$12,\!156,\!536$	100%	$62,\!975$		0.049
~	4.0	or 0			<b>C</b> 1

Table 3: Sample Statistics from QCEW and CPS, 2014

Source: \*Quarterly Census of Employment and Wages (QCEW). +Current Population Survey (CPS).

#### 4.1.3 Panel Study of Income Dynamics (PSID)

I use the PSID to be able to capture the heterogeneity among workers. This data set provides me with additional information to be able to identify the parameters that differ across high-skilled and low-skilled workers in each sector.

In particular, I use sectoral tenure as a proxy for sector-specific human capital. I exploit the longitudinal structure of the data to obtain years of experience in each specific industry. I take 7 years as the threshold to separate workers by low-skilled and high-skilled. This is consistent with Auray *et al.* (2017), who also using the PSID, finds that it takes, on average, seven years to start earning the same as the average manufacturing worker.<sup>29</sup> I study workers who are employed in any manufacturing industry in 2015 and use their history of previous years to construct their tenure.

Even though the sample size is small (955 workers), I find that the relative values are close to the ones of QCEW. For workers in the PSID, the clean sector represents 74 percent, and from it, 71 percent are low-skilled and 29 percent are high skilled. The dirty sector represents the 26 percent remaining, from which 67 percent are

<sup>&</sup>lt;sup>29</sup>Instead of using the average worker, I could have considered the median worker, I decide for the former as it is a must common statistic. But, it raises the concerned because of the skewness of the wages.

low-skilled and 33 percent are high-skilled. The average hourly wages in the dirty sector are 34.20 dollars and in the cleans sector are 29.67 dollars, implying that workers in the dirty sector earn 15.2 percent higher wages than in the clean sector. Which, is in close to the 14.9 from the QCEW. Furthermore, the average hourly wage from high-skilled worker in the clean sector is 36.6 percent higher than for a low-skilled worker. Similarly, for the dirty sector, the average hourly wage from high-skilled worker is 86.3 percent higher than for the low-skilled worker. Using the same data set, Ortego-Marti (2015) finds that on average, an additional month of unemployment lowers future wages by 1.22 percent. Table 4 presents the sample statistics:

Sector	Workers		Av.Hourly Wages		
Sector	Level	Percentage	Level	Relative $(D/C)$	Relative $(H/L)$
Clean	706	100(74)%	29.67	1.1526	
$Low-Skilled^*$	502	71(53)%	26.72		1.366
High-Skilled <sup>*</sup>	204	29(21)%	36.65		
Dirty	249	100(26)%	34.20		
$Low-Skilled^*$	167	67(17)%	26.63		1.863
$\operatorname{High-Skilled}^*$	82	33(9)%	49.61		
Manufacturing	955	100%	30.85		

Table 4: Sample Statistics from PSID, 2015

Source: Panel Study of Income Dynamics(PSID. \*Low-Skilled is defined as worker with less than 7 years of experience in an industry, and complementary, High-Skilled if experience is more than 7 years.

### 4.2 Calibration

#### 4.2.1 Direct Calibration

**Discount Factor** ( $\beta$ ): I choose a monthly discount factor of  $\beta = 0.996$  which corresponds to average annualized interest rate of 4 percent.

Matching Function Elasticity ( $\gamma$ ): I set  $\gamma = 0.5$  for both sectors following Petrongolo & Pissarides (2001).

Nash Bargaining ( $\eta$ ): In an economy without wage taxes, Hosios (1990) prove that if the Nash bargaining and the matching elasticity are equal, it guarantees efficiency of the equilibrium outcomes. I set  $\eta = 0.5$  following what is usual in the literature, but knowingly that the Hosios condition is not satisfied with taxes.

Probability of skill acquisition during employment  $(\phi_s^{lh})$ : As I discuss in the previous subsection, Auray *et al.* (2017) find that the time it takes for a manufacturing worker to earn the same as the average worker is around 7 years, which means 84 months. So, I set the probability of skill acquisition during employment in both sectors to  $\phi_s^{lh} = 0.012$ , which implies that it takes, on average, those 7 years for a newcomer to a sector to become "experienced" in that sector.

Probability of skill depreciation during unemployment  $(\phi_s^{hl})$ : I use the estimate from Ortego-Marti (2015), who finds that each additional month unemployed lowers future wages by 1.22 percent. I calculate how many months it takes the skills of a worker to depreciate in order to gain the initial wage which is around 26.5 months for the clean sector and 52 months for the dirty one. So, I set the probabilities of skill depreciation during unemployment equal to  $\phi_c^{hl} = 0.037$  and  $\phi_c^{hl} = 0.019$  respectively, reflecting the average time it takes worker's skills to depreciate.

Unemployment Benefit(b): I set the value of the unemployment benefit to 0.2 as the OECD (1996) computes the average replacement rates across countries, i.e., the ratio of benefits to average wages, and concludes that, whereas typical European replacement rates can be up to 0.70, replacement rates are at most 0.20 in the U.S.

Cost of opening vacancies ( $\kappa$ ): Following Pilossoph (2014), I normalized the cost of opening vacancies  $\kappa = 1$  as I have the same normalization issue as in Shimer (2005): doubling  $\kappa$  and multiplying the sectoral match efficiency parameters by  $2^{1-\gamma}$  doubles sectoral job-filling probabilities, but does not affect the sectoral job-finding probabilities.

Clean Sectoral Productivity and Gap  $(A_c)$ : I normalized the clean sectoral productivity  $A_c = 1$ , so the productivity I obtain for the dirty sector is going to be relative to the clean one.

Energy Production Elasticities  $(\alpha_d, \alpha_c)$ : I calculated the energy share of value added in each sector,  $(P_e E_s)/Y_s$  (where P is the price of fossil fuel,  $E_s$  the demand of energy and  $Y_s$  the value added in sector s). Setting  $\alpha_d = 0.145$  and  $\alpha_c = 0.024$ .

Final good parameters  $(a, \sigma)$ : First, for simplicity, I assume that the final good is aggregated following a CES technology where  $\chi = 0.5$ , implying an elasticity  $\sigma = 2$ . This number is the same that Pilossoph (2014) uses in her analysis. In section ?? I run sensitivity analysis of  $\chi$ .

Labor tax ( $\tau_w$ ): The labor tax is  $\tau_w = 0.25$  which is approximately the average marginal income tax rate on labor, combining federal and state income taxes.

Table 5 summarizes the direct calibration parameters.

Definition		Value	Source
β	Discount factor	0.996	Annual Interest Rate r=0.04
$\gamma$	Matching Elasticity	0.500	Petrongolo & Pissarides (2001)
$A_c$	Clean Productivity	1.000	Normalization
$\phi^{lh}_s$	Probability of skill acquisition	0.012	Av. time: 84 months
$\phi_c^{hl}$	Clean Probability of skill depreciation	0.037	Av. time: 26.5 months
$\phi_d^{hl}$	Dirty Probability of skill depreciation	0.019	Av. time: 52 months
$\eta$	Nash Bargaining	0.500	Hosios $(1990)$
b	Unemployment Benefit	0.200	OECD
$\kappa$	Cost of opening a vacancy	1.000	Normalization
$\alpha_c$	Clean Energy Elasticity	0.024	MECS
$\alpha_d$	Dirty Energy Elasticity	0.145	MECS
$\alpha$	Clean Value Added Share	0.680	MECS
$\chi$	Final Good Substitution Parameter	0.5	Fix

Table 5: Direct Calibration

#### 4.2.2 A Method of Moments

I jointly calibrate the remaining six parameters  $\{A_d, p_e, \psi_d, \psi_c, a, \delta_c, \delta_d, \rho\}$  using the general method of moments. The moment conditions used to calibrate the parameters are as follows:

To pin down the sectoral separation rates and the variance of the taste shock,  $\delta_c$ ,  $\delta_d$ , and  $\rho$ , I use the clean share of manufacturing employment which is 73 percent, the unemployment rate in the clean sector of 5 percent, and the unemployment rate in the dirty sector of 3.8 percent. The model analog to these moments are:

For the share of clean employment:

$$m_1 = \frac{n_c^l + n_c^h}{n_c^l + n_c^l + n_d^l + n_d^h}$$

For the unemployment rate in the clean sector:

$$m_2 = \frac{u_c^l + u_c^h}{u_c^l + u_c^l + n_c^l + n_c^h}$$

For the unemployment rate in the dirty sector:

$$m_3 = \frac{u_d^l + u_d^h}{u_d^l + u_d^h + n_d^l + n_d^h}$$

Next, I use the difference in wages to identify  $A_d$ ,  $\psi_c$ ,  $\psi_d$ . The model should be able to reproduce three facts: average dirty workers earn on average 15 percent more than clean workers, high-skilled workers in the clean sector earn on average 36 percent more than low-skilled workers, and finally, high-skilled workers in the dirty sector earn on average 86 percent more than low-skilled workers. The model analog to these moments are:

For the relative average wage between the dirty sector and the clean sector:

$$m_{4} = \frac{\frac{w_{d}^{l}n_{d}^{l} + w_{d}^{h}n_{d}^{h}}{n_{d}^{l} + n_{d}^{h}}}{\frac{w_{c}^{l}n_{c}^{l} + w_{c}^{h}n_{c}^{h}}{n_{c}^{l} + n_{c}^{h}}}$$

For the relative average wage between high- and low-skilled in sector c:

$$m_5 = \frac{w_c^h}{w_c^l}$$

For the relative average wage between high- and low-skilled in sector c:

$$m_6 = \frac{w_d^h}{w_d^l}$$

The price of energy  $p_e$  is determined from the ratio of energy consumption in the clean sector over the dirty sector that is equal to 0.237. Where the model analog is given by the following equation:

$$m_7 = \frac{n_c^l e_c^l + n_c^h e_c^h}{n_d^l e_d^l + n_d^h e_d^h}$$

Lastly, to identify the clean share parameter a in the aggregate production function. I use the share of value added that is equal to 0.68. Where the model analog is given by the following equation:

$$m_7 = \frac{p_c Y_c}{Y}$$

So, I minimize the distance, using the Nelder-Mead simplex algorithm, between the moments implied by the model and the empirical counterparts:

$$\sum_{i=1}^{6} (m_i^{data} - m_i)^2$$

#### 4.2.3 Carbon Tax

In the computational experiment, I analyze a carbon tax of \$27 dollars per metric ton of  $CO_2$ . This value is an average of the social cost of carbon for 2015 calculated by the EPA using discount rates of 3 and 5 percent, as I assume a discount rate of

4 percent.<sup>30</sup> Additionally, as they reported the value in 2007 U.S. dollars, I correct by inflation to convert it to 2014 dollars.

I follow Fried *et al.* (2018) strategy to calibrate the size of the tax in the model. I calculate the empirical value of the tax as a fraction of the price of a fossil energy composite of coal, coke, natural gas, and, residual and distillate oil in 2014 from MECS. To do so, I follow two steps: first, I calculate the price of this energy composite, by averaging over the price of each type of energy in 2014 and weighting by the relative consumption. Second, I calculate the carbon emitted from the energy composite by averaging over the carbon intensity of each type of energy in 2014, and weighting by the relative consumption. This process implies that a \$27 per ton carbon tax equals 32 percent of my composite fossil energy price.

 $<sup>^{30}</sup>$  The social cost of carbon in 2015 for 3 percent is \$31 and 5 percent is \$11 in 2007 dollars per metric ton of CO<sub>2</sub>.

## 5 Baseline Results

In this section, I discuss the baseline calibration parameters resulting from the estimation, the goodness of fit, and the results from the baseline simulations for different levels of the carbon tax.

### 5.1 Calibrated Parameters

Using the method of moments described on the previous section, I calibrate the following six parameters  $\{A_d, p_e, \psi_d, \psi_c, a, \delta_c, \delta_d, \rho\}$ . The results of my calibration are shown in Table 6.

	Definition	Value
$A_d$	Dirty Productivity	1.2021
$p_e$	Energy Price	0.0009
$\psi_c$	Clean Productivity Gap	0.3388
$\psi_d$	Dirty Productivity Gap	0.7283
a	Share Parameter	0.6840
$\delta_c$	Clean Exogenous separation	0.0300
$\delta_d$	Dirty Exogenous separation	0.0237
$\rho$	Variance of taste shocks	0.1612

Table 6: Calibrated Parameters

From Table 6 it can be observed that the estimated productivity for the dirty sector is 20.2 percent higher than for the clean sector. The model needs this productivity difference to reconcile the fact that the dirty sector pays on average 15 percent higher wages than the clean one. To reflect the significant wage differences between high-skilled and low-skilled workers in each sector, the values of the gap parameters are estimated to be 0.33 and 0.72, with the gap being larger in the dirty sector than

in the clean one. To explain the lower unemployment rate of the dirty sector, the model's exogenous separation rates are estimated at 0.03 and 0.02 for the dirty and clean sector, respectively. Note that these estimates are close to the one reported by the BLS for total manufacturing of 0.033 for the year 2014.

Also, to match the relative size of the sectors in the data, the model relies on the variance of the taste shocks and the share parameter. While the first parameter generates movement from one sector to the other independently of labor market outcomes, the second establishes the relative importance of the clean sector in the production of the final good.

Finally, the values of prices of energy required to match the relative demands of energy, and to be consistent with the size of the sectors is low. This can be explained by their joint calibration, as it helps match other moments that are conflicted. Compared to the literature, for example, Fried *et al.* (2018) calibrate a price of 0.0025, which is nearly 3 times larger than the one calibrated in this work.

### 5.2 Model Fit

In this section, I compare the fit of the simulated moments from my calibrated model to the corresponding moments in the data. I report the values of the data moments and the model generated ones in Table 7. In general, the model does reasonably well in matching the moments from the data. Nevertheless, two moments are hard to replicate with the model simulation. These are the proportion of clean employment, and the wage gap between the dirty and the clean sector. This is intuitive since, in the model, the main driver of the wage differential is the difference in productivity. Hence, in the long run, workers should reallocate to the more productive sector, yet this is not in line with the higher proportion of employment in the clean sector that we observe in the data. Thus, the model will need additional frictions to reconcile both facts.

Moments	Data	Model
Unemployment Rate, Clean	0.05	0.05
Unemployment Rate, Dirty	0.04	0.04
Proportion of Clean Employment	0.73	0.68
(Clean Wage High)/(Clean Wage Low)	1.36	1.35
(Dirty Wage High)/(Dirty Wage Low)	1.86	1.87
(Average Wage Dirty)/(Average Wage Clean)	1.15	1.07
(Clean Energy) / (Dirty Energy)	0.24	0.29
(Clean Value Added) / (Total Value Added)	0.68	0.65

Table 7: Results from the Method of Moments

### 5.3 After-Tax Steady State Results

As described in the previous section, the benchmark calibration helps the steady state of the model to reproduce stylized facts from the U.S. manufacturing industry. In this section, I use the model to simulate the effects of introducing a per-unitof-energy-used carbon tax, on unemployment, total and by sector, employment by sector and by human capital, wages and energy consumption.

Specifically, the policy scenario that I am considering is to impose a 27 dollars per metric ton that represents the social cost of carbon as described in the previous section. I assume the government uses the revenue from the tax on unproductive expenditure. In section 6.2, I relax this assumption and explore alternative ways to rebate the revenue. Also, I maintained all parameters constant to the baseline calibration.

Imposing a carbon tax distorts the optimal decisions of agents in this economy.<sup>31</sup> In particular, it generates an increase in the production cost of all firms affecting the demand for energy and labor. Even though the cost increases for both sectors, given that the dirty sector is more intensive in energy, its relative cost increases, while it decreases for the clean sector. As a result, the clean sector becomes relatively more attractive.

#### 5.3.1 Production

After imposing a carbon tax of 27 dollars per metric ton, total production of the economy decreases by 3.64 percent, which follows from a decrease of the dirty sector's production of 10.75 percent, while the clean sector's production stays nearly the same, increasing only 0.45 percent.

The significant decrease of the dirty sector's output is driven by two forces working in the same direction. On the one hand, the carbon tax decreases the demand for energy creating a reduction in the production per worker. On the other hand, there is a decrease in the number of workers as they become relatively less productive in the dirty sector than they were before the policy, so there is a reallocation of workers across sectors.

As previously mentioned, the effect on the clean sector is minimal. On the one hand, there is an increase in the cost of energy that reduces the amount that firms

<sup>&</sup>lt;sup>31</sup>It is worth mentioning, that I am abstracting of the plausible distortions caused by the negative externalities produced by the use of carbon-based energy that the carbon tax can help to correct.

demand, reducing the production per worker. On the other hand, their demand for workers increases because the sector becomes relatively more important through the substitution effect in the CES production function between dirty and clean intermediate goods. In general terms, the clean production also decreases, but always less than the dirty sector because of the substitution effect within the final good production.

Additionally, as the clean sector is less affected by the policy, the reduction of total output of the dirty sector yields an increase in the price of the dirty good, which implies that the price of the clean good decreases.

Thus, the policy generates considerable impacts on the economy and the welfare of workers. The effect on total output is comparable to 18 percent of the size of the effect of the Great Recession in the United States.<sup>32</sup> Figure 1 presents the values of production for different values of the carbon tax, these values ranging from 10 to 50 dollars, with the value of the social cost of carbon of 27 dollars marked by  $\times$ :

#### 5.3.2 Energy Consumption

Imposing a carbon tax equivalent to the social cost of carbon reduces the total demand for energy in the whole economy by 26.99 percent which follows from a decrease of 27.59 percent from the dirty sector, and a reduction of 24.98 percent from the clean one. These results imply that there exists a surplus of demand for energy relative to the socially optimal by not pricing carbon correctly. Figure 2

 $<sup>^{32}\</sup>mathrm{The}$  U.S. manufacturing sector decreased 20.2 percent between the last quarter of 2007 and the second quarter of 2009.



Figure 1: Production for Different Values of the Carbon Tax

Notes: The figure displays the value of production of the clean sector, the dirty sector and the total economy for different values of a carbon tax. The tax is given in dollar per metric ton of  $CO_2$ . Where  $\times$  marks the respective values for the social cost of carbon at \$ 27.

presents the percentage change in energy consumption for different values of the carbon tax, these values ranging from 10 to 50 dollars, with the value of the social cost of carbon of 27 dollars marked by  $\times$ :

As shown in the previous figure, the reduction in energy consumption is heterogeneous across sectors. The quantity demanded by each sector depends on the demand per each type of worker and the number of workers of each type. To clarify this, I will first describe the mechanisms through which the carbon tax affects the per



Figure 2: Percentage Change of Energy Consumption by Sector for Different Values of the Carbon Tax

Note: The figure plots the percentage change of energy consumption of the clean sector, the dirty sector and the total economy for different values of a carbon tax. The tax is given in dollar per metric ton of  $CO_2$ . Where the  $\times$  marks the respective values for the social cost of carbon at \$ 27.

worker energy consumption, and second, I will describe the effects on employment in the following subsection.

There are two effects that impact the amount of energy consumed per worker, a direct effect and an indirect effect. The direct effect is a result of a mechanical connection between tax rate and energy demand as made evident in the optimal energy demand, equation 14, for all firm types. This effect is higher for the dirty sector as it is more energy intensive  $(\alpha_d > \alpha_c)$ . The indirect effect is a result of the equilibrium changes in sectoral prices. As I discuss in the previous subsection, there is an increase in the dirty sector's price, which counters the direct effect but is not large enough to offset it. On the other hand, there is price reduction in the clean sector, complementing the direct effect.

#### 5.3.3 Unemployment and Employment by Sector

The policy increases the total unemployment rate by 0.06 percentage points, going from 4.62 in the baseline economy to 4.68.

This can be explained by the fact that the carbon tax generates an increase on the production cost for all firms, making the expected value for firms to post vacancies in all pools less valuable, which affects the dirty sector more. From the job creation condition (equation 10), in equilibrium, the expected value decreases, implying that the right-hand side of the job creation condition also decreases after the tax. In general, firms will want to hire fewer workers since the expected cost is higher. Since the clean sector is less affected, workers start shifting to this sector stirring the job finding probability of both sectors. Given that the clean sector is less productive, to restore the equilibrium, the value of the new tightness needed is smaller, making it impossible to take all new workers as firms prefer not to post vacancies once the value of posting is 0.

Even though unemployment increases more in the clean sector, there is also an increase in the dirty one, as workers realize that the job finding rate is affected by the movement across sectors, making some workers decide to stay. Moreover, not all types of unemployment increases. Indeed, there is a decrease in high-skilled dirty unemployed workers. This is because the value of posting vacancies in the low-skilled pool is relatively less affected and generates a shift from high-skilled to low-skilled workers. Table 8 and Figure 3 presents these results:

 Table 8: Baseline Simulation Results: Unemployment

At the same time, following a similar logic to unemployment, there is a reduction of the number of employed workers in the dirty sector of 2.42 percent. This partly becomes unemployment, and partly creates an increase of 1.04 percent of employment in the clean sector. Figure 5 presents the values of employment rate for different values of the carbon tax, with the value for social cost of carbon marked by  $\times$ :

Furthermore, as the effect for firms employing low-skilled workers is smaller, it becomes easier to fill a job. This generates a shift of workers from high to low. Lowskilled employment increases for both sectors by 3.62 and 0.42 percent in the clean and dirty sectors, respectively.

These results hinge on the assumption that the final good is aggregated using an elasticity of substitution greater than 1. Recall that in the baseline calibration I use a  $\chi = 0.5$  that implies a  $\sigma = 2$ . Implying that the dirty and clean goods are gross substitutes. An increase in the relative cost of the dirty sector generates that the clean sector becomes more attractive as it uses less amount of energy as input. This



Figure 3: Unemployment Rate for Different Values of the Carbon Tax

substitution effect within the production of the final good is important to understand some of the results displayed above.

In the next section I conduct some sensitivity analysis exercises decreasing the degree of substitution, hence putting this underlying assumption to test.

Note: The figure plots the values of the unemployment rate for different values of the carbon tax. The tax is given in dollar per metric ton of  $CO_2$ . Where the  $\times$  marks the respective values for the social cost of carbon at \$ 27.



Figure 4: Employment for Different Values of the Carbon Tax

Note: The upper panels display values of the employment for each sector for different values of the carbon tax. The lower panels display the share of employment for each sector for different values of the carbon tax. Carbon tax is given in dollar per metric ton of  $CO_2$ . Where the  $\times$  marks the respective values for the social cost of carbon at \$ 27.

Figure 5: Percent Change of Employment by Human Capital for Different Values of the Carbon Tax



Note: The left panels display the percent change of the employment for the clean sector by skilled for different values of the carbon tax. The right panel display the same for the dirty sector. Carbon tax is in dollar per metric ton of  $CO_2$ . Where the  $\times$  marks the respective values for the social cost of carbon at \$ 27.

## 6 Sensitivity Analysis and Policy Experiments

# 6.1 Sensitivity Analysis with respect to the Elasticity of Substitution

In the benchmark calibration, I selected an elasticity of substitution of 2 ( $\chi = 0.5$ ). This selection implies that I am assuming that the clean and dirty sectors are gross substitutes as inputs in the production of the final good.

In this section, I investigate the relevance of this assumption, in particular, to understand how it can affect policy predictions. As in the benchmark, I will discuss the results from the policy scenario where I impose a 27 dollars per metric ton that represents the social cost of carbon.

# 6.1.1 Cobb-Douglas ( $\chi = 0$ )

I start by reducing the value of  $\chi$  to 0, the Cobb-Douglas case, reducing the degree of substitution between  $Y_c$  and  $Y_d$  as inputs of the aggregate production.

Before analyzing the computational results, I want to talk about the potential implications of this assumption. Having a Cobb-Douglas technology implies that the optimal expenditure share for inputs is constant. This, together with the implicit assumption of inelastic labor supply and inelastic search intensity, after the tax, changes the prices of the clean and dirty inputs, maintaining the total sectoral labor demand almost constant.

Therefore, after imposing a carbon tax of 27 dollars per metric ton, the total production of the economy decreases by 1.91 percent where production decreases

4.26 and 0.81 percent in the dirty and clean sectors, respectively. This reduction is smaller relative to the benchmark, due to the fact that the total employment stays constant as it can be observed on panels (c) and (d) from figure 6. This smaller reduction happens because of a similar decline in sectoral energy consumption.

But within the sector, similar mechanisms as the ones described in the benchmark case occur. The total unemployment rate has a small increase of 0.05 percentage points. Also, as in the benchmark, clean unemployment decreasing slightly more than in the dirty. Furthermore, there is a substitution between the type of workers, increasing the number of low-skilled ones.

Figure 6 presents evidence on the extent to which my results are sensitive to the choice of  $\chi$ .



Figure 6: Sensitivity Analysis: Results for the Cobb-Douglas Case ( $\chi = 0$ )

Notes: In all panels, the dotted lines represent the benchmark equivalent graphs. Panel (a) Paige a 59 the percent change of the output, panel (b) plots the unemployment rates, panel (c) and (d) show the amount of employment for each sector, and panels (e) and (f), present the energy demand by sector, all for different values of the carbon tax. The carbon tax is given in dollar per metric ton of  $CO_2$ .

# 6.1.2 Gross Complements ( $\chi = -5$ )

Now, I reduce the value of elasticity of substitution further, to 0.16, or equivalently, reducing the parameter  $\chi$  to -5. This entails that  $Y_c$  and  $Y_d$  are gross complements in the production of the final good.

Let me first start by explaining the mechanisms that would drive the results of this new parameter value. In particular, the complementarity implies that the optimal expenditure shares for inputs is increasing as you need both goods to produce the output, driving resources to the most affected input.

Imposing a carbon tax of 27 dollars per metric ton, decreases the total production by 1.70 percent, which follows from a decrease of the dirty sector of 2.11 percent, while the clean sector is also reduced by 1.53 percent. These results contrast to the benchmark case, due to the complementarity of both sectors. Indeed, the higher increase of the cost for the dirty is shared, which in turn has a smaller decrease in the dirty sector, and higher one in the clean one, relative to the benchmark.

Surprisingly, the policy reduces clean sector employment. This reduction occurs because it is optimal to shift resources to smooth the impact on the dirty sector, causing an overall increase in the expenditure given by a decrease on the clean employment rate by 1 percent, and an increase of 2.1 percent in the dirty one. Similar to the benchmark case, there is a slight increase in total low-skilled workers and a decrease in total high-skilled ones. Also, the policy increases the total unemployment rate by 0.05 percentage points.

As a theoretical exercise, lets imagine that I set the elasticity to 0 ( $\chi = \infty$ ), the Leontief case, implying an identical change in both sectors as you need exactly

fix amount of both inputs. This thought experiment can be better visualized by analyzing panel (a) in figure 6 and panel (a) in figure 7.

As we can see, the effects on production and employment are highly sensitive to the value of  $\chi$ . Nevertheless, the effect on unemployment is pretty similar for all the cases. Moreover, the selection of  $\chi > 0$  is in line with the sectoral literature that assumes that sectors are substitutes. For example, I use the same value as Pilossoph (2014). Nevertheless, in this particular case that considers manufacturing industries where the energy intensive industries provide inputs to the non-energy intensive ones, leaves room to question the chosen value. Thus, future research can help shed light on the true value.



Figure 7: Sensitivity Analysis: Results for the Gross Complements Case ( $\chi = -5$ )

Notes: In all panels, the dotted lines represent the benchmark equivalent graphs. Panel (a) Paige a graph a graph a graph a graph and a graph a graph and a graph a graph and a graph an

### 6.2 Policy Experiment: Carbon Tax Dividend

I initially assumed that the revenue is used as unproductive expenditure.

$$\Omega_{1} = \sum_{i} \sum_{s} \tau_{w} w_{s}^{i} n_{s}^{i} - b(u_{c}^{l} + u_{d}^{l} + u_{c}^{h} + u_{d}^{h})$$
  
$$\Omega_{2} = \sum_{s} \tau^{e} (e_{s}^{l} n_{s}^{l} + e_{s}^{h} n_{s}^{h})$$

This is equivalent to throwing to the sea  $\Omega_2$ .

Now, let's study two alternative cases. First, the government returns it in a Lump-Sum fashion to all workers equally as a carbon dividend. This means each worker receives a general transfer  $T_{GLS}$ :

$$T_{GLS} = \frac{\Omega_2}{u_c^l + u_d^l + u_c^h + u_d^h + n_c^l + n_d^l + n_c^h + n_d^h}$$

which is just  $\Omega_2$  since the population is normalized to 1.

In the second case, policymakers are concerned only about unemployed workers. In this scenario,  $\Omega_2$  is only returned to unemployed workers. This implies that each unemployed worker receives:

$$T_{ULS} = \frac{\Omega_2}{u_c^l + u_d^l + u_c^h + u_d^h}$$

In the first case, the optimal employment is equal to the optimal employment with unproductive government spending. As it is standard with lump sum transfers, it only increases the consumption of workers, but it does not affect the optimal

decisions even after the tax.

It is important to mention, that all workers are better-off relative to the benchmark, as they receive higher income no matter what their employment state is, translating into higher consumption. Therefore, overall welfare increases which counteracts the effects of the carbon tax.

As for the second scenario, the lump sum transfer to unemployed workers further increases unemployment and decreases employment relative to the benchmark. Transfers affect the outside option of workers, being unemployed, in the Nash Bargaining problem they face with firms. This increases wages and decreases the labor demand relative to the benchmark. Nonetheless, both, employed and unemployed workers are better-off than compared to the benchmark, given that the wages decrease less for those employed, while the unemployed receive a higher transfer.

Still, workers are worse-off as compared to the first case, due to the reduction of job finding probabilities. Furthermore, despite the fact that the welfare of workers is higher relative to throwing the revenue to the sea, the total economy suffers as total production decreases. This leaves an open opportunity to studying better policy alternatives.

Table 9: Alternative Carbon Dividend

Carbon Dividend	$u_c$	$u_d$	u
Everybody	0.06	0.05	0.06
Unemployed	0.12	0.10	0.12
	0.06	0.05	0.06

# 7 Conclusion

The shift towards a cleaner energy economy would improve human health and ecological sustainability to the planet. However, this transition may have important reallocation costs. I use as an example the implementation of a carbon tax in the U.S. to show that environmental regulations may impose an important burden on workers. Also, I propose parallel policies that can be used to ease these transitional costs.

In this paper, I construct a two-sector general equilibrium search model with human capital accumulation. I calibrate it to match the U.S. economy during 2014. Then I implemented a carbon tax equivalent to the social cost of carbon estimated at 27 dollars per metric ton.

I find that under my benchmark calibration the total production decreases 3.64 percent, increases total unemployment by 0.06 percentage points, reduces the employment in the dirty sector by 2.42 percent, increases the clean employment by 1.04 percent. Also, I find that there occurred substitution out from high-skilled workers towards low-skilled ones. At the same time, I find that firms in both sectors reduce the demand for energy as it becomes a more expensive input.

Also, I find that the model is sensitive to degree of substitution between the production of the clean sector and the production of the dirty sector as inputs of an aggregate consumption good.

Lastly, I perform a policy experiment to fully explore the interactions between the labor market and a carbon tax. First, I explore the effect of three alternative options on the usage of revenue obtained from the carbon tax. I find that it is less distortionary to rebate it lump-sum to all workers relative to rebate it to unemployed workers.

A natural extension going forward will be to relax the assumption that the energy used in the model is carbon-based. Moreover, it could be a composite of different types of energy. The simpler way to implement this, is to re-scale energy by introducing energy supply elasticities for carbon emissions of producers, to be able to identify how the energy-intensity of energy generation will change with a carbon tax. So the energy used in the model would be cleaner and will pay less carbon tax.

Another exciting extension would be to consider the well-known effects of pollution on human capital. Taking some estimates from the literature, for example, from Graff Zivin & Neidell (2012), on how pollution affects human capital together with the relation between carbon dioxide ( $CO_2$ ) and particulate matter ( $PM_{2.5}$ ), and add it to my model as a function of worker's productivity as in Williams (2000). In the benchmark calibration, this will decrease the productivity of workers, while the introduction of the carbon tax would increase it.

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## A LOW-SKILLED UNEMPLOYED WORKER'S VALUE FUNCTION DERIVATION

I begin with equation 15 that reflects the value of an unemployed worker in a sector s:

$$U_{s}^{l}(\Lambda) = b + \Omega + \beta p(\theta_{s}^{l}) \mathbb{E}_{\Lambda',\epsilon'} [W_{s}^{l}(\Lambda') + \epsilon'_{s,i}] + \beta (1 - p(\theta_{s}^{l})) \mathbb{E}_{\Lambda',\epsilon'} [\max \left\{ U_{s}^{l}(\Lambda') + \epsilon'_{s,i}, U_{s-}^{l}(\Lambda') + \epsilon'_{s-,i} \right\}]$$

Integrating out the future idiosyncratic taste shock, exploiting Type I Extreme Value Theory, using the fact that the expectation of a  $Gumbel(-\rho\gamma, \rho)$  variables is zero, gives:

$$\begin{aligned} U_s^l(\Lambda) = &b + \Omega + \beta p(\theta_s^l) \mathbb{E}_{\Lambda'}[W_s^l(\Lambda')] \\ &+ \beta (1 - p(\theta_s^l)) \rho \mathbb{E}_{\Lambda'}[\log(\exp(\frac{U_s^l}{\rho}) + \exp(\frac{U_s^l}{\rho}))] \end{aligned}$$

Now, I add and subtract  $\pm \beta (1 - p(\theta_s^l)) \mathbb{E}_{\Lambda'}[U_s^l]$  from the equation:

$$U_{s}^{l}(\Lambda) = b + \Omega + \beta p(\theta_{s}^{l}) \mathbb{E}_{\Lambda'}[W_{s}^{l}(\Lambda')] \pm \beta(1 - p(\theta_{s}^{l})) \mathbb{E}_{\Lambda'}[U_{s}^{l}] + \beta(1 - p(\theta_{s}^{l}))\rho \mathbb{E}_{\Lambda'}[\log(\exp(\frac{U_{s}^{l}}{\rho}) + \exp(\frac{U_{s}^{l}}{\rho}))]$$

I divide and multiple the minus part by  $\rho$ , and use a transformation that does

not change the value given the functions properties  $\log(\exp(\cdot))$ :

$$\begin{split} U_s^l(\Lambda) = & b + \Omega + \beta p(\theta_s^l) \mathbb{E}_{\Lambda'}[W_s^l(\Lambda')] + \beta (1 - p(\theta_s^l)) \mathbb{E}_{\Lambda'}[U_s^l] - \rho \beta (1 - p(\theta_s^l)) \mathbb{E}_{\Lambda'}[\log(\exp(\frac{U_s^l(\Lambda')}{\rho}))] \\ & + \beta (1 - p(\theta_s^l)) \rho \mathbb{E}_{\Lambda'}[\log(\exp(\frac{U_s^l(\Lambda')}{\rho}) + \exp(\frac{U_{s-}^l(\Lambda')}{\rho}))] \end{split}$$

Next, using the rule of logarithm that log(x) - log(y) = log(x/y)

$$U_{s}^{l}(\Lambda) = b + \Omega + \beta p(\theta_{s}^{l}) \mathbb{E}_{\Lambda'}[W_{s}^{l}(\Lambda')] + \beta(1 - p(\theta_{s}^{l})) \mathbb{E}_{\Lambda'}[U_{s}^{l}] + \beta(1 - p(\theta_{s}^{l}))\rho \mathbb{E}_{\Lambda'}[\log(\frac{\exp(\frac{U_{s}^{l}(\Lambda')}{\rho}) + \exp(\frac{U_{s}^{l}(\Lambda')}{\rho})}{\exp(\frac{U_{s}^{l}(\Lambda')}{\rho})})]$$

Furthermore, I use the properties of the exponential function:

$$U_{s}^{l}(\Lambda) = b + \Omega + \beta p(\theta_{s}^{l}) \mathbb{E}_{\Lambda'}[W_{s}^{l}(\Lambda')] + \beta(1 - p(\theta_{s}^{l})) \mathbb{E}_{\Lambda'}[U_{s}^{l}] + \beta(1 - p(\theta_{s}^{l}))\rho \mathbb{E}_{\Lambda'}[\log(\exp(\frac{U_{s}^{l}(\Lambda')}{\rho} - \frac{U_{s}^{l}(\Lambda')}{\rho}) + \exp(\frac{U_{s}^{l}(\Lambda')}{\rho}) - \frac{U_{s}^{l}(\Lambda')}{\rho})]$$

As, exp(0) = 1:

$$\begin{aligned} U_s^l(\Lambda) = &b + \Omega + \beta p(\theta_s^l) \mathbb{E}_{\Lambda'}[W_s^l(\Lambda')] + \beta (1 - p(\theta_s^l)) \mathbb{E}_{\Lambda'}[U_s^l] \\ &+ \beta (1 - p(\theta_s^l)) \rho \mathbb{E}_{\Lambda'}[\log(1 + \exp(\frac{U_{s^-}^l(\Lambda')}{\rho}) - \frac{U_s^l(\Lambda')}{\rho})] \end{aligned}$$

Lastly, I use the definition of  $\pi_{stays}$ :

$$U_s^l(\Lambda) = b + \Omega + \beta p(\theta_s^l) \mathbb{E}_{\Lambda'}[W_s^l(\Lambda')] + \beta (1 - p(\theta_s^l)) \mathbb{E}_{\Lambda'}[U_s^l(\Lambda')]$$
$$+ \beta (1 - p(\theta_s^l)) \rho \mathbb{E}_{\Lambda'}[\log(\pi_{stays}^{-1})]$$

#### **B** ADDITIONAL VALUE FUNCTIONS

Similarly, I integrate out the future idiosyncratic taste shock, exploiting Type I Extreme Value Theory, and using the fact that the expectation of a  $Gumbel(-\rho\gamma, \rho)$  variables is zero, and rewrite the value functions:

High-skilled Unemployed Worker's Value Function:

$$\begin{split} U^h_s(\Lambda) = & b + \Omega + \beta p(\theta^h_s) \mathbb{E}_{\Lambda'}[W^h_s(\Lambda')] \\ & + \beta (1 - p(\theta^h_s)) \phi^{hl}_s \rho \mathbb{E}_{\Lambda'}[\log(\exp(\frac{U^l_s}{\rho}) + \exp(\frac{U^l_s}{\rho}))] \\ & + \beta (1 - p(\theta^h_s)) (1 - \phi^{hl}_s) \mathbb{E}_{\Lambda'}[U^h_s(\Lambda')] \end{split}$$

Low-skilled Employed Worker's Value Function:

$$W_s^l(\Lambda) = (1 - \tau_w)w_s^l + \Omega + \beta \delta_s \rho \mathbb{E}_{\Lambda'} [\log(\exp(\frac{U_s^l}{\rho}) + \exp(\frac{U_s^l}{\rho}))] \\ + \beta (1 - \delta_s)(\phi_s^{lh} \mathbb{E}_{\Lambda'}[W_s^h(\Lambda')] + (1 - \phi_s^{lh}) \mathbb{E}_{\Lambda'}[W_s^l(\Lambda')])$$

High-skilled Employed Worker's Value Function:

$$W_s^h(\Lambda) = (1 - \tau_w) w_s^h + \Omega + \beta \delta_s \mathbb{E}_{\Lambda', [U_s^h(\Lambda')]} \\ + \beta (1 - \delta_s) \mathbb{E}_{\Lambda'} [W_s^h(\Lambda')]$$

Alternatively, I can rewrite them, similar to the low-skilled unemployed worker's value, in terms of the probability of moving between sectors:

High-skilled Unemployed Worker's Value Function:

$$\begin{aligned} U_s^h(\Lambda) = &b + \Omega + \beta p(\theta_s^h) \mathbb{E}_{\Lambda'}[W_s^h(\Lambda')] \\ &+ \beta (1 - p(\theta_s^h)) \phi_s^{hl} \mathbb{E}_{\Lambda'}[U_s^l(\Lambda') + \rho \log(\pi_{stay_s}^{-1})] \\ &+ \beta (1 - p(\theta_s^h)) (1 - \phi_s^{hl}) \mathbb{E}_{\Lambda'}[U_s^h(\Lambda')] \end{aligned}$$

Low-skilled Employed Worker's Value Function:

$$W_s^l(\Lambda) = (1 - \tau_w) w_s^l + \Omega + \beta \delta_s \mathbb{E}_{\Lambda'} [U_s^l(\Lambda') + \rho \log(\pi_{stays}^{-1})] \\ + \beta (1 - \delta_s) (\phi_s^{lh} \mathbb{E}_{\Lambda'} [W_s^h(\Lambda')] + (1 - \phi_s^{lh}) \mathbb{E}_{\Lambda'} [W_s^l(\Lambda')])$$

# C DERIVATION OF WAGES FOR LOW-SKILLED WAGES

$$\begin{split} W_s^l(\Lambda) - U_s^l(\Lambda) = &(1 - \tau_w) w_s^l + \Omega + \beta \delta_s \mathbb{E}_{\Lambda'} [U_s^l(\Lambda')] + \beta \rho \delta_s \mathbb{E}_{\Lambda'} [log(\pi_{stay}^{-1})] \\ &+ \beta (1 - \delta_s) (\phi_s^{lh} \mathbb{E}_{\Lambda'} [W_s^h(\Lambda')] + (1 - \phi_s^{lh}) \mathbb{E}_{\Lambda'} [W_s^l(\Lambda')]) \\ &- (b + \Omega + \beta p(\theta_s^l) \mathbb{E}_{\Lambda'} [W_s^l(\Lambda')] + \beta (1 - p(\theta_s^l)) \mathbb{E}_{\Lambda'} [U_s^l(\Lambda')] \\ &+ \beta \rho (1 - p(\theta_s^l)) \mathbb{E}_{\Lambda'} [log(\pi_{stay}^{-1})]) \\ = &(1 - \tau_w) w_s^l - b + \beta \rho (\delta_s - (1 - p(\theta_s^l))) \mathbb{E}_{\Lambda'} [log(\pi_{stay}^{-1})] \\ &+ \beta (1 - \delta) \mathbb{E}_{\Lambda'} [W_s^h(\Lambda') - W_s^l(\Lambda')] + \beta (1 - \delta - p(\theta_s^l)) \mathbb{E}_{\Lambda'} [W_s^l(\Lambda') - U_s^l(\Lambda')] \\ = &(1 - \tau_w) w_s^l - b + \beta \rho (\delta_s - (1 - p(\theta_s^l))) \mathbb{E}_{\Lambda'} [log(\pi_{stay}^{-1})] \\ &+ \beta (1 - \delta) \phi_s^{lh} \mathbb{E}_{\Lambda'} [\eta (S_s^h - S_s^l) + (U_s^h - U_s^l)] + \beta (1 - \delta - p(\theta_s^l)) \mathbb{E}_{\Lambda'} [\eta S_s^l] \end{split}$$

$$\begin{split} J_{s}^{l}(\Lambda) =& p_{s}A_{s}(e_{s}^{*l})^{\alpha_{s}} - w_{s}^{l} - (p_{e} + \tau^{e})A_{s}e_{s}^{*l} \\ &+ \beta \mathbb{E}_{\Lambda'}[(1 - \delta_{s})(\phi_{s}^{lh}J_{s}^{h}(\Lambda') + (1 - \phi_{s}^{lh})J_{s}^{l}(\Lambda'))] \\ =& p_{s}A_{s}(e_{s}^{*l})^{\alpha_{s}} - (p_{e} + \tau^{e})A_{s}e_{s}^{*l} - w_{s}^{l} \\ &+ \beta \mathbb{E}_{\Lambda'}[(1 - \delta_{s})(\phi_{s}^{lh}(J_{s}^{h}(\Lambda') - J_{s}^{l}(\Lambda')) + (1 - \phi_{s}^{lh})J_{s}^{l}(\Lambda')] \\ =& p_{s}A_{s}(e_{s}^{*l})^{\alpha_{s}} - (p_{e} + \tau^{e})A_{s}e_{s}^{*l} - w_{s}^{l} \\ &+ \beta \mathbb{E}_{\Lambda'}[(1 - \delta_{s})(\phi_{s}^{lh}((1 - \eta)(S_{s}^{h} - S_{s}^{l}) + (1 - \phi_{s}^{lh})(1 - \eta)S_{s}^{l}] \end{split}$$

$$\begin{split} \eta(J_{s}^{l}(\Lambda)) = &(1 - \eta)(W_{s}^{l}(\Lambda) - U_{s}^{l}(\Lambda)) \\ \eta(p_{s}A_{s}(e_{s}^{*l})^{\alpha_{s}} - (p_{e} + \tau^{e})A_{s}e_{s}^{*l} - w_{s}^{l}) = &(1 - \eta)((1 - \tau_{w})w_{s}^{l} - b + \beta\rho(\delta_{s} - (1 - p(\theta_{s}^{l})))\mathbb{E}_{\Lambda'}[log(\pi_{stay}^{-1})] \\ &+ \beta(1 - \delta)\phi_{s}^{lh}\mathbb{E}_{\Lambda'}[U_{s}^{h} - U_{s}^{l}] - \beta p(\theta_{s}^{l})\mathbb{E}_{\Lambda'}[\eta S_{s}^{l}]) \end{split}$$

Define  $y_s^l = p_s A_s (e_s^{*l})^{\alpha_s} - (p_e + \tau^e) A_s e_s^{*l}$ 

$$\begin{split} w_{s}^{l}(\eta + (1 - \eta)(1 - \tau)) = &\eta y_{s}^{l} + (1 - \eta)(b + \beta\rho(1 - p(\theta_{s}^{l}) - \delta_{s})\mathbb{E}_{\Lambda'}[log(\pi_{stay}^{-1})] \\ &- \beta(1 - \delta)\phi_{s}^{lh}\mathbb{E}_{\Lambda'}[U_{s}^{h} - U_{s}^{l}] + \beta p(\theta_{s}^{l})\mathbb{E}_{\Lambda'}[\eta S_{s}^{l}]) \\ = &\eta y_{s}^{l} + (1 - \eta)(b + \beta\rho(1 - p(\theta_{s}^{l}) - \delta_{s})\mathbb{E}_{\Lambda'}[log(\pi_{stay}^{-1})] \\ &- \beta(1 - \delta)\phi_{s}^{lh}\mathbb{E}_{\Lambda'}[U_{s}^{h} - U_{s}^{l}] + \frac{\beta\eta p(\theta_{s}^{l})}{(1 - \eta)}\mathbb{E}_{\Lambda'}[J_{s}^{l}]) \\ = &\eta y_{s}^{l} + (1 - \eta)(b + \beta\rho(1 - p(\theta_{s}^{l}) - \delta_{s})\mathbb{E}_{\Lambda'}[log(\pi_{stay}^{-1})] \\ &- \beta(1 - \delta)\phi_{s}^{lh}\mathbb{E}_{\Lambda'}[U_{s}^{h} - U_{s}^{l}] + \frac{\eta p(\theta_{s}^{l})}{(1 - \eta)}\frac{\kappa_{s}^{l}}{q(\theta_{s}^{l})}) \\ = &\eta y_{s}^{l} + \eta \kappa_{s}^{l}\theta_{s}^{l} + (1 - \eta)(b + \beta\rho(1 - p(\theta_{s}^{l}) - \delta_{s})\mathbb{E}_{\Lambda'}[log(\pi_{stay}^{-1})] \\ &- \beta(1 - \delta)\phi_{s}^{lh}\mathbb{E}_{\Lambda'}[U_{s}^{h} - U_{s}^{l}] + \frac{\eta p(\theta_{s}^{l})}{(1 - \eta)}\frac{\kappa_{s}^{l}}{q(\theta_{s}^{l})}) \\ = &\eta y_{s}^{l} + \eta \kappa_{s}^{l}\theta_{s}^{l} + (1 - \eta)(b + \beta\rho(1 - p(\theta_{s}^{l}) - \delta_{s})\mathbb{E}_{\Lambda'}[log(\pi_{stay}^{-1})] \\ &- \beta(1 - \delta)\phi_{s}^{lh}\mathbb{E}_{\Lambda'}[U_{s}^{h} - U_{s}^{l}]) \end{split}$$

$$\begin{split} U_{s}^{h}(\Lambda) - U_{s}^{l}(\Lambda) &= b + \Omega + \beta p(\theta_{s}^{h}) \mathbb{E}_{\Lambda'}[W_{s}^{h}(\Lambda')] + \beta(1 - p(\theta_{s}^{h}))\phi_{hl}\mathbb{E}_{\Lambda'}[U_{s}^{l}(\Lambda')] \\ &+ \beta \rho(1 - p(\theta_{s}^{h}))\phi_{hl}\mathbb{E}_{\Lambda'}[\log(\pi_{stay}^{-1})] + \beta(1 - p(\theta_{s}^{h}))(1 - \phi_{hl})\mathbb{E}_{\Lambda'}[U_{s}^{h}(\Lambda')] \\ &- (b + \Omega + \beta p(\theta_{s}^{l})\mathbb{E}_{\Lambda'}[W_{s}^{l}(\Lambda')] + \beta(1 - p(\theta_{s}^{l}))\mathbb{E}_{\Lambda'}[U_{s}^{l}(\Lambda')] \\ &+ \beta \rho(1 - p(\theta_{s}^{l}))\mathbb{E}_{\Lambda'}[\log(\pi_{stay}^{-1})]) \\ &= \beta p(\theta_{s}^{h})\mathbb{E}_{\Lambda'}[W_{s}^{h}(\Lambda') - U_{s}^{h}(\Lambda')] - \beta p(\theta_{s}^{l})\mathbb{E}_{\Lambda'}[W_{s}^{l}(\Lambda') - U_{s}^{l}(\Lambda')] \\ &+ \beta \rho((1 - p(\theta_{s}^{h}))\phi_{hl} - (1 - p(\theta_{s}^{l})))\mathbb{E}_{\Lambda'}[\log(\pi_{stay}^{-1})] \\ &+ \beta(1 - \phi_{hl}(1 - p(\theta_{s}^{h})))\mathbb{E}_{\Lambda'}[U_{s}^{h}(\Lambda') - U_{s}^{l}(\Lambda')] \\ &= \frac{\beta p(\theta_{s}^{h})\mathbb{E}_{\Lambda'}[S_{s}^{h}] - \beta p(\theta_{s}^{l})\mathbb{E}_{\Lambda'}[S_{s}^{l}] + \beta \rho((1 - p(\theta_{s}^{h}))\phi_{hl} - (1 - p(\theta_{s}^{l})))\mathbb{E}_{\Lambda'}[\log(\pi_{stay}^{-1})] \\ &= \frac{p(\theta_{s}^{h})\frac{\kappa_{s}^{h}}{q(\theta_{s}^{h})} - p(\theta_{s}^{l})\frac{\kappa_{s}^{l}}{q(\theta_{s}^{h})} + \beta \rho((1 - p(\theta_{s}^{h}))\phi_{hl} - (1 - p(\theta_{s}^{l})))\mathbb{E}_{\Lambda'}[\log(\pi_{stay}^{-1})] \\ &= \frac{\theta_{s}^{h}\kappa_{s}^{h} - \theta_{s}^{l}\kappa_{s}^{l} + \beta \rho((1 - p(\theta_{s}^{h}))\phi_{hl} - (1 - p(\theta_{s}^{h})))\mathbb{E}_{\Lambda'}[\log(\pi_{stay}^{-1})]}{1 - \beta(1 - \phi_{hl}(1 - p(\theta_{s}^{h})))} \\ &= \frac{\theta_{s}^{h}\kappa_{s}^{h} - \theta_{s}^{l}\kappa_{s}^{l} + \beta \rho((1 - p(\theta_{s}^{h}))\phi_{hl} - (1 - p(\theta_{s}^{h})))\mathbb{E}_{\Lambda'}[\log(\pi_{stay}^{-1})]}{1 - \beta(1 - \phi_{hl}(1 - p(\theta_{s}^{h})))} \end{split}$$

$$\begin{split} w_{s}^{l}(\eta + (1 - \eta)(1 - \tau)) = &\eta y_{s}^{l} + \eta \kappa_{s}^{l} \theta_{s}^{l} + (1 - \eta)b - (1 - \eta)\beta(1 - \delta)\phi_{s}^{lh} \frac{\theta_{s}^{h} \kappa_{s}^{h} - \theta_{s}^{l} \kappa_{s}^{l}}{1 - \beta(1 - \phi_{hl}(1 - p(\theta_{s}^{h})))} \\ &+ (1 - \eta)\beta\rho(1 - p(\theta_{s}^{l}) - \delta_{s})\mathbb{E}_{\Lambda'}[log(\pi_{stay}^{-1})] \\ &- (1 - \eta)\beta(1 - \delta)\phi_{s}^{lh} \frac{\beta\rho((1 - p(\theta_{s}^{h}))\phi_{hl} - (1 - p(\theta_{s}^{l})))}{1 - \beta(1 - \phi_{hl}(1 - p(\theta_{s}^{h})))} \mathbb{E}_{\Lambda'}[log(\pi_{stay}^{-1})]) \end{split}$$

## D DERIVATION OF WAGES FOR HIGH-SKILLED WORKERS

$$\begin{split} W_s^h(\Lambda) &- U_s^h(\Lambda) = (1 - \tau_w) w_s^h + \Omega + \beta \delta_s \mathbb{E}_{\Lambda'} [U_s^h(\Lambda')] + \beta (1 - \delta_s) [W_s^h(\Lambda')]) \\ &- \left( b + \Omega + \beta p(\theta_s^h) \mathbb{E}_{\Lambda'} [W_s^h(\Lambda')] + \beta (1 - p(\theta_s^h)) \phi_s^{hl} \mathbb{E}_{\Lambda'} [U_s^l(\Lambda')] \right. \\ &+ \beta \rho \phi_s^{hl} (1 - p(\theta_s^h)) \mathbb{E}_{\Lambda'} [log(\pi_{stay}^{-1})] \right) + \beta (1 - p(\theta_s^h)) (1 - \phi_s^{hl}) \mathbb{E}_{\Lambda'} [U_s^h(\Lambda')] \\ &= (1 - \tau_w) w_s^h - b - \beta \phi_s^{hl} \rho (1 - p(\theta_s^h)) \mathbb{E}_{\Lambda'} [log(\pi_{stay}^{-1})] \\ &- \beta p(\theta_s^h) \mathbb{E}_{\Lambda'} [W_s^h(\Lambda') - U_s^h(\Lambda')] + \beta \phi_s^{hl} (1 - p(\theta_s^h)) \mathbb{E}_{\Lambda'} [U_s^h - U_s^l] \\ &= (1 - \tau_w) w_s^h - b - \beta \phi_s^{hl} \rho (1 - p(\theta_s^l)) \mathbb{E}_{\Lambda'} [log(\pi_{stay}^{-1})] + \beta \eta (1 - \delta_s) \mathbb{E}_{\Lambda'} [S_s^h(\Lambda')] \\ &- \beta \eta p(\theta_s^h) \mathbb{E}_{\Lambda'} [S_s^h(\Lambda')] + \beta \phi_s^{hl} (1 - p(\theta_s^l)) \mathbb{E}_{\Lambda'} [U_s^h - U_s^l] \end{split}$$

$$J_s^h(\Lambda) = y_s^h - w_s^h + \beta (1 - \delta_s) \mathbb{E}_{\Lambda'} [J_s^h(\Lambda')]$$
$$= y_s^h - w_s^h + \beta (1 - \delta_s) (1 - \eta) \mathbb{E}_{\Lambda'} [S_s^h(\Lambda')]$$

$$\eta(J_s^h(\Lambda)) = (1 - \eta)(W_s^h(\Lambda) - U_s^h(\Lambda))$$
  
$$\eta(y_s^h - w_s^h) = (1 - \eta)((1 - \tau_w)w_s^h - b - \beta\phi_s^{hl}\rho(1 - p(\theta_s^h))\mathbb{E}_{\Lambda'}[log(\pi_{stay}^{-1})]$$
  
$$-\beta\eta p(\theta_s^h)\mathbb{E}_{\Lambda'}[S_s^h(\Lambda')] + \beta\phi_s^{hl}(1 - p(\theta_s^h))\mathbb{E}_{\Lambda'}[U_s^h - U_s^l])$$

$$\begin{split} w_{s}^{h}(\eta + (1 - \eta)(1 - \tau)) &= \eta y_{s}^{h} + (1 - \eta)(b + \beta \phi_{s}^{hl} \rho(1 - p(\theta_{s}^{h})) \mathbb{E}_{\Lambda'}[log(\pi_{stay}^{-1})] \\ &+ \beta \eta p(\theta_{s}^{h}) \mathbb{E}_{\Lambda'}[S_{s}^{h}(\Lambda')] - \beta \phi_{s}^{hl}(1 - p(\theta_{s}^{h})) \mathbb{E}_{\Lambda'}[U_{s}^{h} - U_{s}^{l}]) \\ &= \eta y_{s}^{h} + (1 - \eta)(b + \beta \phi_{s}^{hl} \rho(1 - p(\theta_{s}^{h})) \mathbb{E}_{\Lambda'}[log(\pi_{stay}^{-1})] \\ &\eta p(\theta_{s}^{h}) \frac{\kappa_{s}^{h}}{q(\theta_{s}^{h})} - \beta \phi_{s}^{hl}(1 - p(\theta_{s}^{h})) \mathbb{E}_{\Lambda'}[U_{s}^{h} - U_{s}^{l}]) \\ &= \eta y_{s}^{h} + (1 - \eta)(b + \beta \phi_{s}^{hl} \rho(1 - p(\theta_{s}^{h})) \mathbb{E}_{\Lambda'}[log(\pi_{stay}^{-1})] \\ &\frac{\eta \theta_{s}^{h} \kappa_{s}^{h}}{1 - \eta} - \beta \phi_{s}^{hl}(1 - p(\theta_{s}^{h})) \mathbb{E}_{\Lambda'}[U_{s}^{h} - U_{s}^{l}]) \\ &= \eta y_{s}^{h} + \eta \theta_{s}^{h} \kappa_{s}^{h} + (1 - \eta)b + (1 - \eta)\beta \phi_{s}^{hl} \rho(1 - p(\theta_{s}^{h})) \mathbb{E}_{\Lambda'}[log(\pi_{stay}^{-1})] \\ &- (1 - \eta)\beta \phi_{s}^{hl}(1 - p(\theta_{s}^{h})) \mathbb{E}_{\Lambda'}[U_{s}^{h} - U_{s}^{l}] \end{split}$$

#### E MODEL WITHOUT HUMAN CAPITAL

To understand the importance of Human Capital, I have to compare two the equivalent model without human capital. In this section, I present the most relevant equations that differ from the model with human capital.

#### F Firm's Optimization

Vacant Firm's Value Equation:

$$V^{i}(\Lambda) = -\kappa^{i} + \beta q(\theta^{i}) \mathbb{E}_{\Lambda'}[J^{i}(\Lambda')] + \beta (1 - q(\theta^{i})) \mathbb{E}_{\Lambda'}[V^{i}(\Lambda')]$$

Firm's Value Equation:

$$J_s(\Lambda) = \max_{e_s} \left\{ p_s A_s(e_s)^{\alpha_s} - w_s - (p_e + \tau^e) e_s + \beta \mathbb{E}_{\Lambda'} [\delta_s V_s(\Lambda') + (1 - \delta_s) (J_s(\Lambda'))] \right\}$$

Optimal Energy Demands:

$$e_s = \left(\frac{p_s \alpha_s \psi_s A_s}{p_e + \tau^e}\right)^{\frac{1}{1 - \alpha_s}}$$

### G Worker's Problem

Unemployed Worker's Value Equation:

$$U_{s}(\Lambda) = b + \Omega + \beta p(\theta_{s}) \mathbb{E}_{\Lambda'}[W_{s}(\Lambda')] + \beta (1 - p(\theta_{s})) \mathbb{E}_{\Lambda'}[U_{s}(\Lambda')]$$
  
+  $\beta \rho (1 - p(\theta_{s})) \mathbb{E}_{\Lambda'}[log(\pi_{stay}^{-1})]$  (29)

Employed Worker's Value Function:

$$W_s(\Lambda) = (1 - \tau_w)w_s + \Omega + \beta \delta_s \mathbb{E}_{\Lambda'} [U_s(\Lambda') + \rho \log(\pi_{stays}^{-1})] + \beta (1 - \delta_s) W_s(\Lambda')$$

## H Wage Equation

$$w_{s}^{l} = \frac{\eta y_{s}^{l} + \eta \kappa_{s}^{l} \theta_{s}^{l} + (1 - \eta)(b + \beta \rho (1 - p(\theta_{s}^{l}) - \delta_{s}) \log(\pi_{stay}^{-1})}{(\eta + (1 - \eta)(1 - \tau))}$$

### I Worker Flow's

Unemployed Worker's Flow:

$$u'_{s} = \pi_{stay_{s}} [(1 - p(\theta_{s}))u_{s} + \delta_{s}n_{s}]$$
$$+ \pi_{mov_{s}} [(1 - p(\theta_{s})u_{s} + \delta_{s}n_{s}]]$$

Employed Worker's Flow:

$$n'_s = (1 - \delta_s)n_s + p(\theta_s)u_s$$

### J Government

$$\sum_{s} \tau^{e}(e_{s}n_{s}) + \sum_{s} \tau_{w}w_{s}n_{s} = b(u_{c} + u_{d}) + \Omega$$
(30)

#### K Job Creation Condition

$$\frac{\kappa_s}{\beta q_s(\theta_s)} = \frac{p_s A_s(e_s)^{\alpha_s} - w_s - (p_e + \tau_e)e_s}{1 - \beta(1 - \delta_s)}$$

#### L ALTERNATIVE MOMENT CONDITIONS

I describe a plausible alternative moments to calibrate parameters related to the matching function. As there is not data available for vacancies at the dis-aggregation level of NAICS 3 digit subsector codes, I can use instead the labor shortages for the manufacturing sector from the Quarterly Survey of Plant Capacity (QSPC). QSPC is a survey that collects data on actual production and respondents' estimates of full capacity. "Insufficient supply of local labor force/skill" is one of the answers that the survey offer to answer why is the plan not operating at full capacity. Even though the respondents reporting "insufficient supply of local labor force/skill" as a measure of binding labor supply constraints in manufacturing. The weighed average labor shortage in the dirty sector is 6.8 and in the clean sector is 7.3 percent. <sup>33</sup>

Table 10:	Sample	Statistics	from	QSPC
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	Sector	Labor Shortage		
	Clean	7.2~%		
	Dirty	6.8~%		
Source: Quarterly Survey of Plant Capacity (QSPC).				

 $<sup>^{33}</sup>$ I use the proportion of workers in each industry relative to the total in the sector as weights