Project Proposal:

Labor Market Outcomes of the Clean Energy Transition*

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This paper proposes a dynamic discrete choice framework to analyze the reallocation of workers from the fossil fuel "dirty" sector to the renewable energy "clean" sector. In the baseline model I focus on workers' decision-making processes and take the energy sector transition as an exogenous force. Workers' transition from the dirty to the clean sector lags the energy sector transition but occurs much more rapidly once it begins. High-skill workers are first to transition due to higher earnings potential in the clean sector while low-skill workers wait until the likelihood of losing their jobs in the dirty sector is too high to ignore. I then propose next steps for including human capital accumulation and erosion as well as multidimensional skill. I estimate the baseline model using the U.S. Energy and Employment Report, a detailed survey of 30,000 energy sector employers. Finally, I characterize the relationship between worker transition and energy sector transition for a variety of policy scenarios, including one that meets the current US goal of 100% clean power by 2035.

*I initially conceptualized the idea for this project in ECON 630 and benefited from the guidance of Costas Meghir. In addition, the baseline model presented here was partially developed in ECON 417/561 with the assistance of Tony Smith.

1 Introduction

Despite the salience of the "environment vs. jobs debate" in political discussions, the labor market outcomes associated with the transition to clean energy are not well documented or understood. A robust literature uses reduced-form empirical methods to evaluate the employment effect of existing environmental regulations (Berman and Bui, 1998; Greenstone, 2002; Walker, 2011), but treats unregulated yet similar firms in different regions as a control group. Estimates of job losses in the treatment group are therefore biased upward assuming these regulations cause a shift to firms in the unregulated regions (Hafstead and Williams, 2020). A small but growing literature uses computable general equilibrium (CGE) models to overcome this issue but the vast majority assume full employment. A recent set of papers have introduced search frictions (Hafstead and Williams, 2018; Hafstead et al., 2022; Aubert and Chiroleu-Assouline, 2019) and search frictions with worker heterogeneity (Intriago, 2021). However, both the reduced-form and structural literatures examine the effect of a particular environmental policy such as a carbon tax or clean electricity standard. This project, on the other hand, seeks to evaluate the labor market impact of the energy transition as a whole. While a related strand of literature has also focused on modeling the overall transition to clean energy (Acemoglu et al., 2012, 2016), these papers focus on technology and innovation rather than labor market outcomes.

The transition to clean energy will be among the most important labor market shifts of the 21st century. What will be the ratio between jobs losses in the fossil fuel industry and gains in the renewable energy industry? To what extent will reallocation offset job losses? How will workers of different skill levels be affected? Will workers transition to clean energy jobs quickly enough to meet mitigation targets? This project attempts to address these questions by building on the recent search-CGE models of Hafstead and Williams (2018) and Intriago (2021) but diverging from them to specify a relationship between the search-and-matching process and the energy transition writ-large.

In this proposal, I estimate a simple discrete choice model to represent workers' decisions to transition to the clean sector. Job destruction probabilities in the dirty sector are equivalent to clean energy market share. The probability of loosing one's job in the dirty sector is exactly equal to the probability of being offered a job in the clean sector. Importantly, clean energy market share, or state of the energy transition at a given time, is modeled exogenously. The baseline model captures the key idea that worker transition will lag behind sector transition; however, it clearly fails to account for several important dynamics. I propose a framework to account for human capital accumulation as well as the distinct skill requirements of dirty and clean sector jobs.

I calibrate the baseline model using data from the US Energy and Employment Report, which provides far more granular data on energy industry employment than BLS or Census data. I focus exclusively on the energy production, transmission, and distribution industries because energy is the same good irrespective of dirty or clean production. Future work, however, should consider spillovers to related industries (e.g., durable good manufacturing).

The rest of this proposal is organized as follows. Section 2 presents the baseline model and proposed next steps. Section 4 discusses data and calibration. Section 5 presents preliminary results and policy simulations. Section 6 briefly concludes.

2 Baseline model

Time is discrete, infinite, and indexed by $t \geq 0$. There are two sectors $s \in \{0, 1\}$ of the energy industry where 0 represents the dirty sector and 1 represents the clean sector. A grid of heterogeneous and risk-neutral workers i seek employment in many homogeneous firms, though I do not explicitly model the firm side to keep the baseline model relatively simple. Workers' utility is a function of log wages. Workers discount future payoffs at a common rate β.

I focus exclusively on the reallocation of workers between the dirty and clean sectors. Worker's internalize the likelihood and payoffs of unemployment in their decision-making process but never become unemployed. Each worker has human capital η_i which is sampled from a distribution that varies between sectors.

The model is driven by a sector evolution variable θ which represents the share of firms in the clean sector. Workers receive job offers and lose their jobs as a function of the share of firms in each sector. Employed workers' wages w_i^s depend on their human capital and vary by sector. Within each sector, higher skilled workers receive monotonically higher wages than lower skilled workers. Unemployed workers receive a benefit calculated as a fraction B of the mean wage conditional on human capital.

2.1 Energy sector evolution

In the main specification the clean energy market share θ_t evolves as a logistic function in order to match the S-curve shape of the transition from dirty to clean energy. I model θ_t as an exogenous force in order to simplify the model. However, this creates a puzzle as to how and why the sector transition begins at all if no labor is involved. Further, the model predicts that workers transition when the clean sector has sufficiently large enough market share, leading to a period of sector transition with no labor transition. The model therefore best reflects the subset of workers in the industry who observe the energy transition and decide whether to switch instead of the universe of workers in the energy industry.

Formally, θ_t evolves following the standard logistic model

$$\theta_t = \frac{K}{1 + e^{(-kt+b)}}, \tag{1}$$

where K reflects the market share of clean energy at the end of the transition; k reflects the curvature of the evolution path; and b reflects the point at which the transition begins.

2.2 Workers

The key contribution of the modeling framework is to specify a relationship between energy sector transition and the associated labor transition rather than simply evaluating the effect of a particular environmental policy. The model must therefore specify a relationship between clean energy market share θ_t and job arrival and destruction probabilities. In this simple model, I express job destruction as a function of θ_t and $1-\theta_t$. The probability of loosing one's job in the dirty sector is θ_t while the probability of loosing one's job in the clean sector is $1-\theta_t$:

$$\Pi_t^0 = \theta_t \qquad \Pi_t^1 = (1-\theta_t). \tag{2}$$

As θ approaches K, it becomes increasingly likely to lose a job in the dirty sector and receive a job offer in the clean sector, and vice versa.

Wages are a function of human capital, where human capital η for a given worker i is sampled from a log-Normal distribution. Wages are expressed as

$$w_i^0 = C^0(\eta_i^0) \qquad w_i^1 = C^1(\eta_i^1) \tag{3}$$

where C^1/C^0 reflects the ratio between mean wages in the dirty and clean sectors. Human capital distribution for each sector is expressed as

$$\eta_i^0 \sim lnN(0,\sigma^0) \qquad \eta_i^1 \sim lnN(0,\sigma^1) \tag{4}$$

such that both distributions are normalized to 1 but have distinct variance. To my knowledge, this set up would be the first to include a full distribution of worker skill rather than discretizing workers as high- or low-skill as in Intriago (2021).

In each period a given worker maximizes lifetime-discounted utility based on their choice of sector in the next period s'. This dynamic discrete choice problem can be written as a

Bellman equation where the state of the worker is given by her current sector s:

$$
\begin{aligned}
v_{i,t}(s_t) = \max_{s_{t'} \in \{0,1\}} [(1 - s_t) & \left((1 - \Pi_t^0) u(w_i^0) + \Pi_t^0 (u(B_i))\right) \\
& + s_t \left((1 - \Pi_t^1) u(w_i^1) + \Pi_t^1 (u(B_i))\right) \\
& + \beta \left(v_{i,t'}(s_{t'})\right)].
\end{aligned} \tag{5}
$$

In the current period a given worker can either keep her job with probability $(1 - \Pi_t^s)$ and receive the associated wage or become unemployed with probability Π_t^s and earn unemployment benefits.

2.3 Steady state analysis

Since θ_t asymptotes at K, I derive analytical solutions for the job destruction and job creation probabilities as well as the value function on the infinite horizon. This enables me to work backwards to recursively solve the value function in every period. I define $\bar{\Pi}^0$ and $\bar{\Pi}^1$ as the job destruction probabilities in the dirty and clean sectors in the steady state:

$$
\bar{\Pi}_i^0 = K \qquad \bar{\Pi}_i^1 = (1 - K) \tag{6}
$$

Solving for the value function at the end of the clean energy transition yields:

$$
\bar{v}_i(s) = (1 - s)\left((1 - \bar{\Pi}^0) u(w_i^0) + \bar{\Pi}^0 (u(B_i))\right) + s\left((1 - \bar{\Pi}^1) u(w_i^1) + \bar{\Pi}^1 (u(B_i))\right) + \beta \bar{v}_i(s)
$$

$$
\Longrightarrow
$$

$$
\bar{v}_i(s) = \frac{(1 - s)\left((1 - \bar{\Pi}^0) u(w_i^0) + \bar{\Pi}^0 (u(B_i))\right) + s\left((1 - \bar{\Pi}^1) u(w_i^1) + \bar{\Pi}^1 (u(B_i))\right)}{1 - \beta}. \tag{7}
$$

I then calculate the period at which $|\theta_t - K| < \epsilon$ and induct backwards from that period, treating all state variables after this period as having their asymptotic values.

3 Model next steps

This section presents three extensions of the baseline model, each of which builds on the previous one.

3.1 Temporary skill penalty

In the baseline model, workers remain at the same rank of the wage distribution when switching sectors (e.g., the 100th best worker in the dirty sector earns the wage of the 100th best worker in clean sector when they switch). This captures the idea that many workers in dirty energy industries have experience pertinent to clean industries. For example, some oil and gas workers have skills necessary for offshore wind, carbon capture utilization and storage, and low-carbon gas production and transport. Coal miners have skills needed to mine critical minerals such as lithium, copper and cobalt, which are expected to see a seven-fold growth in demand by 2050 under the International Energy Agency's net zero scenario (International Energy Agency, 2021).

Though this modeling decision is more realistic than assuming all workers enter the clean sector as low-skilled, it fails to capture the temporary skill penalty workers may face when transitioning sectors. In order to include this feature I modify the wage equation to evolve as a function of time and human capital:

$$w_{it}^s = \begin{cases} C^s(\eta_i^s)\rho & \text{if} \quad (t - t_{\text{switch}}) < P \\ C^s(\eta_i^s) & \text{otherwise} \end{cases} \tag{8}$$

where ρ is a skill penalty parameter moving workers down in rank in the skill distribution during the temporary period P immediately following a worker's transition.

3.2 Human capital accumulation

The addition of a temporary skill penalty is the simplest way to account for human capital erosion. Fully accounting for human capital accumulation and erosion would require modifying the value function to include the probability ϕ^s a worker increases in skill rank.

$$\begin{aligned}
v_{i,t}(s_t) = \max_{s_{t'} \in \{0,1\}} [(1 - s_t) \left((1 - \Pi_t^0)\phi^0 u(w_{i'}^0) + (1 - \Pi_t^0)(1 - \phi^0)u(w_i^0) + \Pi_t^0(u(B_i))\right) \\
+ s_t \left((1 - \Pi_t^1)\phi^1 u(w_{i'}^1) + (1 - \Pi_t^1)(1 - \phi^1)u(w_i^1) + \Pi_t^1(u(B_i))\right) \\
+ \beta\left(v_{i',t'}(s_{t'})\right)]. \qquad (9)
\end{aligned}$$

In each period, a given worker can now either keep her job with probability $(1 - \Pi_t^s)$ and increase in skill rank with probability ϕ^s to earn higher wages, keep her job and stay at the same skill rank and wage level, or become unemployed with probability Π_t^s and earn unemployment benefits.

3.3 Multidimensional skill

The baseline model sees skill as one-dimensional: workers have more or less of one "skill" which firms reward through higher wages. This representation is at odds with recent work demonstrating that cognitive, manual, and interpersonal skills are very different productive attributes (Lise and Postel-Vinay, 2020). Including multidimensional skill is particularly important in a model of sectoral transition with human capital accumulation: manual skills adjust quickly (they are easily accumulated on the job and relatively easily lost when unused) while cognitive skills are much slower to adjust. Interpersonal skills are essentially fixed over a worker's lifetime.

Further, though the skill requirements for some clean and dirty jobs overlap, critical differences in skill requirements emerge when considering multidimensional skill (Greenspon and Raimi, 2022). For example, as discussed above, the manual skill requirements for coal miners and critical mineral miners are quite similar. Yet cognitive and interpersonal skill requirements are more likely to vary. Vona et al. (2018) finds two core sets of skill requirements that differ between clean and dirty jobs: engineering skills for design and production of technology as well as managerial skills for setting up and monitoring environmental organization practices.

A simple accounting for multidimensional skill keeps the baseline structure in which skill is sampled from a log-Normal distribution, but models η as a skill bundle $\eta = (\eta_C, \eta_M, \eta_I)$ capturing workers' cognitive skills η_C, manual skills η_M, and interpersonal skills η_I (I drop the i subscripts for simplicity). Though there are of course more granular skill delineations, I follow Lise and Postel-Vinay (2020) for simplicity of exposition and empirical estimation. In both sectors, worker skill η^s is represented as:

$$\boldsymbol{\eta}^{\mathbf{s}} = \begin{pmatrix} \eta_C^s \\ \eta_M^s \\ \eta_I^s \end{pmatrix} \sim \begin{pmatrix} lnN(0, \sigma_C^s) \\ lnN(0, \sigma_M^s) \\ lnN(0, \sigma_I^s) \end{pmatrix} \tag{10}$$

I also follow Lise and Postel-Vinay (2020) and assume a linear adjustment for all skills as a function of job tenure such that the value function remains unchanged from equation 9 with the exception that $\boldsymbol{\phi}^{\mathbf{s}}$ is now composed of $\phi_C^s, \phi_M^s, \phi_I^s$.

4 Quantitative Strategy

4.1 Baseline data

I use data from the 2019 Wage Supplement to the U.S. Energy and Employment Report (USEER) to calibrate the baseline model.[1] The U.S. Energy and Employment Report is based on a 15-minute supplemental survey of approximately 30,000 employers that complements the employment data in the Quarterly Census on Employment and Wages (QCEW) from the

[1] I use 2019 data to avoid capturing the unique labor market dynamics of the COVID-19 period.

Bureau of Labor Statistics (BLS). BLS categorizes employment and wage statistics across 1,057 industry subsectors according to each firm's primary business focus under the North American Industrial Classification System (NAICS). The USEER was created to gather more granular data on the employers in five sectors: fuels; electric power generation; transmission, distribution, and storage; energy efficiency; and motor vehicles. Employment in each of these five sectors is spread across 186 NAICS subsectors. Some of these subsectors are 100 percent energy-related, while others are only partially composed of energy employment. Further, employees may spend a varying fraction of their time on energy-related tasks in each subsector. The USEER data accounts for these factors, which may be overlooked if using the QCEW.

Table 1 shows summary statistics on wages and employment across energy subsectors based on fuel type. For example, natural gas jobs span electric power generation, fuels, transmission, and distribution. The average median hourly wage is \$28.19 across clean sectors and \$28.54 across dirty sectors. Percent total energy employment does not add to 100 because I exclude subsectors that do not directly represent a clean or dirty fuel.

Table 1: Energy industry wages and employment, 2019

Sector	Industry	Median Hourly Wage (\$)	Percent National Median Wage	Total Employment	Percent Total Energy Employment
Clean	Nuclear	39.19	104.8	70,323	0.8
Dirty	Natural Gas	30.33	58.5	636,043	7.6
Dirty	Coal	28.69	49.9	185,689	2.2
Clean	Hydropower	26.97	40.9	67,772	0.8
Dirty	Oil	26.59	38.9	839,831	10.0
Clean	Wind	25.95	35.6	114,774	1.4
Clean	Solar	24.48	27.9	345,393	4.1
Clean	Storage (excl. fossil fuels)	24.36	27.3	80,550	1.0

Source: U.S. Energy and Employment Report, Bureau of Labor Statistics

4.2 Proposed data

In order to expand the baseline model to include human capital accumulation and multidimensional skill, I link data from the Occupational Informational Network (O*NET) and the Panel Study of Income Dynamics (PSID) to the USEER data through the NAICS codes system. Estimates of the occupation shares in each industry come from the BLS.

The PSID is well known and requires little explanation. I use it to capture heterogeneity among workers and to identify the parameters that differ across high- and low-skilled workers in each sector. I use the O*NET data to capture multidimensional skill. These data describe over 970 occupations in terms of skill and knowledge requirements, work practices, and work settings. Following Lise and Postel-Vinay (2020), I run Principal Component Analysis (PCA) on a large set of O*NET measures to create the cognitive, manual, and interpersonal skill requirement indices for jobs in each sector.

4.3 Calibration

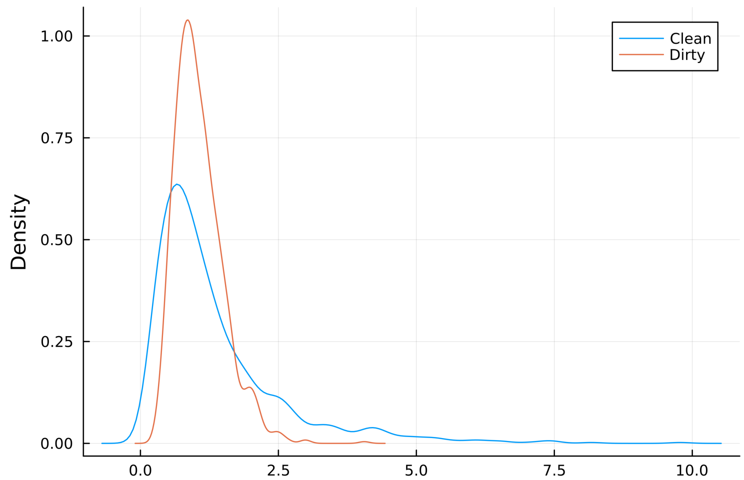
Table 2 summarizes the baseline calibration parameters. I use a monthly discount factor (β) of 0.996 to correspond to the average annualized interest rate of 4%. The ratio of the average median hourly wage in the dirty and clean sector (C^0/C^1) is 1.01 based on the USEER data. I follow Intriago (2021) and Hafstead and Williams (2020) and set the unemployment benefit replacement rate as 0.2. I calibrate human capital distribution to loosely match the USEER wage data.

Table 2: Parameter values

Definition	Parameter	Value
Discount factor	β	.996
Relative wage difference	C^1/C^0	1.01
Replacement rate	B	0.2
Standard deviation skill distribution clean	σ^0	0.8
Standard deviation skill distribution dirty	σ^1	0.4
Energy transition asymptote	K	1
Energy transition speed parameter	k	0.055
Energy transition timing parameter	b	-5

Figure 1 shows the human capital distribution for the dirty and clean sectors. Workers in the dirty sector have higher wages on average than workers in the clean sector. That said, workers in the clean sector are the highest earners, with workers in the nuclear industry earning 104.8% of the national median wage. Finally, I project θ_t since it is not possible to calibrate to any data. In the main specification, clean energy share begins at 0 in order to show the full stylized S-curve transition from dirty to clean.

Figure 1: Worker skill distribution



Notes: Figure shows calibrated skill distribution in the clean and dirty sectors.

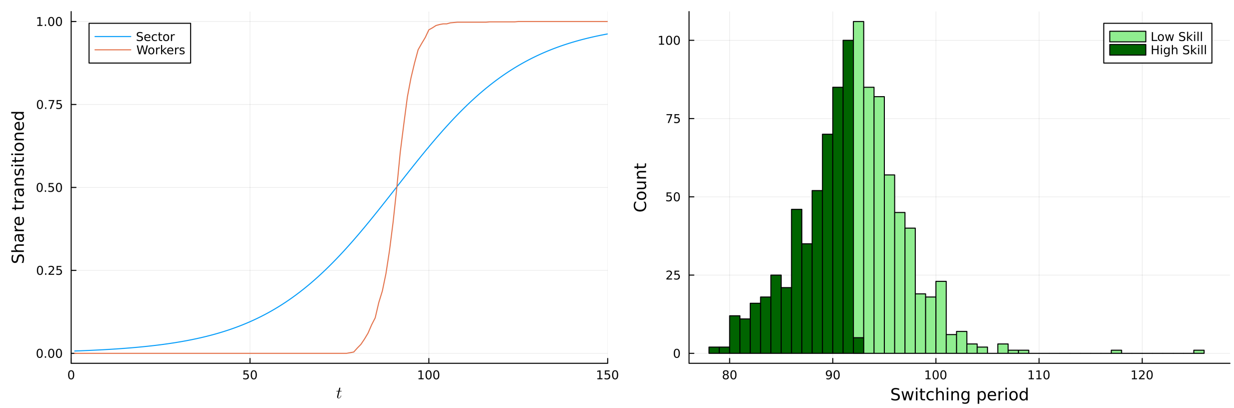
Extending the baseline model to account for a temporary skill penalty, human capital accumulation, and multidimensional skill would require the estimation of the additional parameters $\{\rho, P, \sigma^s_C, \sigma^s_M, \sigma^s_I, \phi^s_C, \phi^s_M, \phi^s_I\}$. While $\sigma^s_C, \sigma^s_M, \sigma^s_I$ can be inferred directly from the O*NET data, the remaining parameters would require estimation using the general method of moments.

5 Preliminary results

Figure 2 simulates the sector transitions of 1,000 workers who each begin in the dirty sector and eventually all transition to the clean sector. Overall, worker sectoral transition lags energy sector transition but occurs much more rapidly than energy sector transition once it begins. Workers transition based on two forces: (1) increasing job destruction probability in the dirty sector and job arrival probability in the clean sector and (2) for high skilled workers, higher earnings potential in the clean sector. No workers transitions back from the clean to dirty sectors because θ_t is monotonically increasing, though the model allows for switching back and forth.

The curvature of the worker transition pathway comes from the distribution of worker skill. The right panel of Figure 2 shows this result in more detail: high-skilled workers switch earlier than low-skill workers. I sort workers by human capital such that "worker 1" has the lowest skill and "worker 1000" has the highest skill. Since workers remain at the same rank of the wage distribution, high-skill workers in the dirty sector move to the long right tail of the clean sector wage distribution. This encourages high-skill workers to switch earlier and risk a greater chance of unemployment for greater wages. The lowest skilled workers are last to switch since their wages decrease when switching to the clean sector.

Figure 2: Worker transition lags sector transition

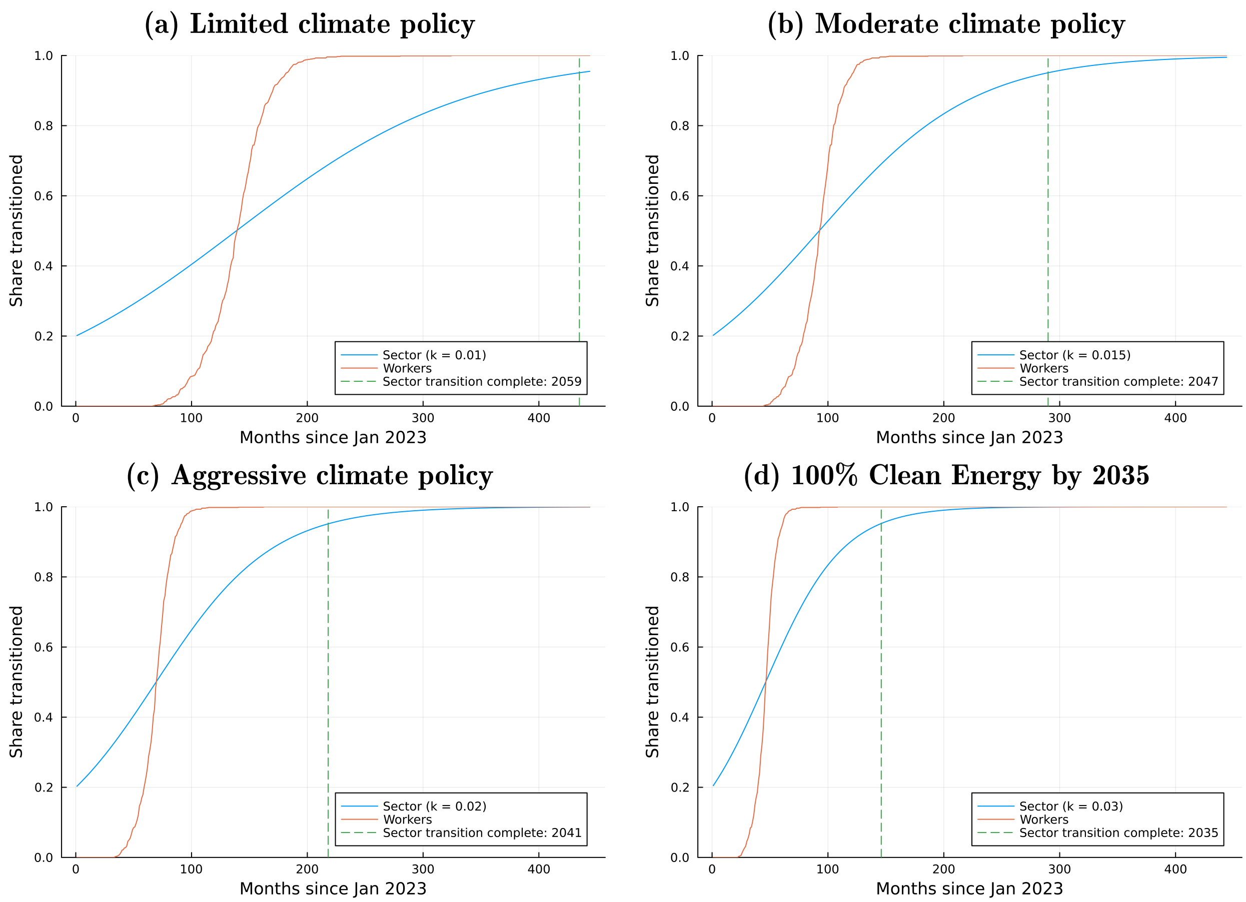


Notes: The left panel compares the worker transition to the sectoral energy transition. The right panel shows a histogram of the period in which workers transition. "Low-skilled" workers are workers 0-500 while "high-skilled" workers are workers 501-1000.

I now apply the model to evaluate the labor transition under current market conditions and potential policy scenarios. Figure 3 shows four scenarios, each of which increases in stringency: limited climate policy, moderate climate policy, aggressive climate policy, and 100% clean energy by 2035. While b is initially calibrated such that at time $t = 0$ the clean energy share (θ_0) is approximately 0, b is now calibrated such that θ_0 matches the current clean energy market share of 0.2. This eliminates the full S-shape of the sector transition curve. In addition, I label sector transition as "complete" when clean energy market share is more than 0.95, much before the final asymptotic value.

As in the full S-curve simulation, in each policy scenarios labor transition lags sector transition but is completed must faster than sector transition. Even in the most limited climate policy scenario, the vast majority of workers transition to the clean sector by 2030. This naturally begs the question: who continues working in the dirty sector in the final years before the transition is complete? The finding that the majority of these workers are low-skilled is consistent with that of Intriago (2021), who finds a reallocation from high-skill to low-skill work in both sectors following the imposition of a carbon tax.

Figure 3: Worker transition varies with energy sector transition



Notes: Figure shows potential pathways for the evolution of the energy sector mix. The upper left panel shows less aggressive climate policy than the main specification. The upper right panel corresponds to the same transition speed as the main specification but shifted to reflect the current clean energy share at 0.2. The lower left panel shows more aggressive climate policy than the main specification. The lower right shows most aggressive climate policy, aligned with what is needed to meet the Biden administration's goal of 100% clean energy by 2035.

6 Concluding remarks

This project aims to provide the first theoretical framework for evaluating workers' decision-making processes in the energy transition. That said, the focus on the worker's side limits the scope of analysis. I hope to eventually embed the model of the worker's problem in a general equilibrium framework. Doing so would enable me to capture several important missing forces in the model such as firm optimization, wage bargaining, and search frictions.

A general equilibrium framework would also enable industry size to grow or shrink over time to allow for net job creation as well as reallocation. Incorporating sector growth could for endogenous sector transition even if individual workers don't internalize their impact on sector transition. Indeed, perhaps the most uncertain element of the current modeling framework is the shape of the energy sector transition itself.

As it stands, however, the baseline model effectively captures the idea that the labor market transition lags the energy sector transition. Workers wait until the transition is well underway due to the possibility of wage cuts or job loss. High skill workers are attracted by high wages and are first to transition. Low-skill workers, on the other hand, do not switch until the likelihood of losing their jobs in dirty is sufficiently large. Both of these effects are already observable in the energy industry.

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