The Labor Market Consequences of a Rapid Climate Transition*

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Abstract

Should workers be concerned about the climate transition and the pace at which it occurs? As policymakers choose a timeline to achieve zero net carbon emissions, it is important to know how the pace of this transition will affect the labor market outcomes of workers employed in polluting sectors. We develop a life-cycle model with directed search, skill heterogeneity and retraining in which labor demand expands in a set of clean sectors and declines in polluting sectors. We show that the set of workers who win or lose from the transition is sensitive to its pace. Workers' lifetime earnings are strongly non-linear and even non-monotonic as a function of the pace at which the clean sector takes over. We structurally estimate the model using US data and use it to evaluate the distributional effects of climate transitions of various speeds. A baseline transition ending in 2060 induces sizable earnings losses, with large dispersion among workers. Accelerating the transition to end in 2050 is preferable for most workers, but thickens the left tail of losses.

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1 Introduction

As the world embarks on a climate transition, economic activity will shift from polluting to clean industries. This transition will entail a substantial and potentially costly reallocation for millions of workers currently employed in polluting industries. Job losses are expected to accelerate among these workers (Bassanini et al., 2024) and there is evidence that earnings losses are large for those who have already been displaced (Walker, 2013; Curtis et al., 2023). The prospect of earnings losses has fueled concerns about how ambitious climate goals should be. Indeed, survey evidence shows that these concerns are a significant obstacle to public support for these policies, particularly in the United States (Dechezleprêtre et al., 2025), and green transition employment movements predict voting behavior (Bombardini et al., 2025). While the benefits of curbing emissions are relatively well-understood and quantified (Bilal and Stock, 2025), we know much less about the labor market consequences of the climate transition for workers currently employed in polluting industries, or indeed of broader technological transitions where labor demand for one set of jobs declines but increases for another.

In this paper, we study the labor market consequences of the climate transition and how the *pace* of the transition affects the distribution of labor market outcomes among workers currently at risk of displacement from polluting industries. Understanding which workers win or lose from a faster transition is a crucial input for policymakers charged with setting a target date to achieve net zero carbon emissions, as they trade off these labor market considerations against competing goals such as climate benefits and fiscal costs associated to taxes and subsidies. Furthermore, public support for climate policies is influenced by their perceived labor market costs. It is therefore important to understand how costly it would be to compensate displaced workers in order to increase support for rapid climate transitions.

We tackle these questions using a model designed to capture the displacement and reemployment experience of workers currently employed in polluting industries. The model features finitely-lived workers with heterogeneous skills and a realistic labor market. A transition takes places between two sectors: relative to trend, the revenue product of labor grows exogenously in a clean sector while a polluting sector shrinks. Workers are endowed with different skills in the clean

sector. They may also retrain to accumulate skill in the clean sector over-and-above their endowment. Workers direct their search across sectors both on- and off-the-job as in Menzio and Shi (2011), giving rise to a job-ladder in each sector (Huckfeldt, 2022). Noise in the search process generates gross flows across sectors during the transition. Firms in the polluting industry lay off workers endogenously over the transition, while firms in the clean industry create vacancies that absorb some of these workers. Displaced workers may search for a vanishing number of jobs in their old polluting industry, switch to clean industries, or seek employment in an outside sector which is not subject to the transition. Using this rich model, we study how the pace at which labor demand exogenously shifts between the two sectors — due to unmodeled technological breakthroughs or government taxes and subsidies — affects workers' present discounted value of earnings (hereafter, "lifetime earnings").

Our first contribution is conceptual. Our model provides four novel qualitative insights. First, workers' lifetime earnings are highly *non-linear* in the speed of transition. For instance, a worker's earnings might be mostly unchanged if the transition is completed in 2055 rather than 2060, but the same worker's earnings might change considerably if the transition were completed in 2050. Second, workers' lifetime earnings can even be *non-monotonic* in the speed of transition. In particular, some workers experience a decline in lifetime earnings for small increases in the pace of transition; however, their lifetime earnings rise for major accelerations. Third, and relatedly, the set of workers who benefit or lose from a faster transition is endogenous and quite sensitive to how much we speed it up. A faster transition generally increases the mass of workers who benefit from it but generates a thicker tail of earnings losses. These results have important political economy implications when it comes to the support for ambitious climate goals. Finally, when firms find it costly to hire workers, the transition generates structural unemployment where a set of workers are persistently unable to find employment, the extent of which depends greatly on the pace of transition. Such structural unemployment changes the distribution of earnings changes arising from the transition both qualitatively and quantitatively.

We first illustrate the economic mechanisms underlying these insights in a transparent Walrasian limit of our model with competitive labor markets, where workers are paid their marginal product and there is full employment. Here, workers

frictionless move to the sector in which they are most productive. A faster transition has two opposing effects on individuals' lifetime earnings. On the one hand, it accentuates the decline in earnings while employed in the polluting sector; on the other, workers find it worthwhile to switch to the clean sector sooner, and realized faster increases in earnings after doing so. These forces combine to generate the stark non-linear and non-monotonic relationship between lifetime earnings and the pace of the transition. Workers of different birth cohorts and skills will be affected differentially by the pace of transition, since more skilled workers can more easily switch to the clean sector, while older workers have a shorter horizon over which to recoup the early losses from polluting sector declines. Therefore, the joint distribution of skills and age are a key determinant of the distribution of earnings losses from a faster transition.

These conceptual insights apply to a broader class of technological transitions in which a new sector takes over an obsolescing one, such as Schumpeterian industry dynamics where a new technology emerges over time (Aghion and Howitt, 1992) — e.g., the replacement of brick-and-mortar retail with warehousing — or situations where a burgeoning private sector takes over public activities in a formerly planned economy (Atkeson and Kehoe, 1996; Boeri, 2000). Studying how the pace of the transition affects workers' outcomes is particularly relevant in the context of the climate transition since it is expected to unfold quickly, affect a substantial part of the workforce, its pace is partly under the control of the government, and most of the transition yet has to take place.

Our second contribution is to apply the quantitative model to estimate the distribution of lifetime earnings losses arising from climate transitions of varying speeds, focusing on workers initially employed in the polluting sector. We suppose that the climate transition began with the signing of the Kyoto agreement in 2005. In our baseline scenario, we assume that the climate transition is complete in 2060 — the current consensus date when the US economy is expected to reach zero net carbon (Bain & Company, 2025). We use the initial stationary equilibrium of our full model to discipline various parameters to match a large number of features of U.S. labor markets pre-2005, including job flows, firms' average markdowns and average earnings changes upon switching to outside sectors, as well as available evidence on firms' propensity to lay off workers in response to productivity movements (Chan et al., 2023). There is great uncertainty about the long-run

impacts of the climate transition, which is inherent to our *prospective* analysis; we embrace this uncertainty and will consider a menu of scenarios for long-run labor demand consistent with the wide range of projections for employment in clean and polluting sectors by 2050 (Mayfield et al., 2023; IRENA, 2023b,a). The path of sectoral productivities is assumed to follow the same *S*-shape as the US Energy Information Administration (EIA) projects for the share of US clean energy sales from 2005–2050.

We structurally estimate the distribution of skill endowments and the re-training cost by developing a novel estimation strategy that leverages the block recursivity of competitive search equilibria. This property allows us to simulate bins of workers, indexed by their productivity in the new sector, independently from one another. We simulate each of these bins forward to produce time series of labor reallocation between the polluting and clean sectors by skill. By comparing these model-implied time series with observed job-switching behaviors over the early stages of the climate transition (2005-2024), one may back out the distribution of workers' productivity in the new sector. Repeating this exercise across multiple cohorts allows one to tease apart the contribution of retraining from the distribution of workers' skill endowments, assuming skill endowments are drawn from a time-invariant distribution.

We first quantify the distribution of lifetime earnings changes from a baseline transition ending in 2060. The model implies that the average worker attached to the polluting sector in 2005 stands to lose around 1.2% of lifetime earnings as a result of the transition, with significant dispersion based on workers' skill and age. This figure is somewhat smaller than the lifetime earnings losses for manufacturing workers arising from increased import competition from China (Traiberman, 2020), reflecting the infancy of the climate transition. The full model's losses are significantly larger than those implied by the Walrasian limit of our model, highlighting the crucial role of structural unemployment in this setting. Overall, we find that compensating workers for these losses would be moderately expensive, with an aggregate loss of around $78 billion in labor income.

Finally, we ask how changing the pace of the remaining transition affects workers' earnings. We find that a majority of workers would prefer to accelerate the transition to end in 2045, but doing so substantially thickens the tail of earnings losses with some workers losing up to an additional 2% of lifetime earnings from

this acceleration, relative to the baseline transition ending in 2060. Policymakers therefore face a trade-off between increasing the share of winners from the transition and harming those most exposed to its negative effects.

Our paper contributes to a growing body of work that studies the economic costs and benefits of a transition towards clean technologies (Bilal and Stock, 2025 for a review). A large literature estimates large economic costs of climate change (Barrage and Nordhaus, 2023; Bilal and Rossi-Hansberg, 2023; Bilal and Känzig, 2024; Nath et al., 2024), suggesting that a fast transition away from polluting technologies could generate substantial societal gains. However, there has been comparatively few studies on the labor market costs of this transition and how they depend on its pace. Curtis and Marinescu (2023) show that solar and wind job postings have more than tripled in the last decade, while Curtis et al. (2023) argue that the rate of transition from dirty to green jobs is rising rapidly and comes with potentially large costs to incumbent workers employed in polluting sectors. Vona et al. (2018) find that environmental regulation affects the demand for "green" skills while Hanson (2023) discusses various policies to ease the labor market transition away from fossil-fuel production. The 2024 OECD Employment Outlook (Bassanini et al., 2024) estimates the share of European economies engaged in polluting and "green" jobs, and shows large earnings losses for workers displaced from polluting sector. Känzig (2023) uses time series techniques to argue that the introduction of the European carbon market had sizable effects on unemployment,[1] while Bigio et al. (2025) studies the short-term welfare impacts of carbon pricing. Arkolakis and Walsh (2023, 2024) study the effect of increased availability of clean energy on aggregate growth. A complementary set of papers studies how policy can influence the speed of this transition (Acemoglu et al., 2012, Acemoglu et al., 2016, Acemoglu et al., 2023).

Our paper instead studies how the set of winners and losers from a climate transition depends on the pace at which it unfolds, evaluates the size of the earnings losses associated with this transition, and emphasizes non-linearities as the transition accelerates using a frontier model of the labor market. Estimating these earnings losses is a first step towards adopting social insurance programs that partially insure workers against the transition, and to build consensus for ambitious climate goals.

[1] Similarly, Känzig (2021) finds that shocks to energy prices have sizable effect on unemployment.

Many papers document large persistent earnings losses from job displacement and study how human capital specificity affects the speed of labor reallocation following an aggregate shock. Building on the seminal work of Jacobson et al. (1993), Braxton and Taska (2023) study the earnings losses on displacement in a setting with declining and emerging technologies, and show that workers displaced by technological change incur substantial losses when their skills render technology adoption difficult. Labor market frictions and involuntary employment are important determinants of these earnings losses (Jarosch, 2023; Fallick et al., 2025).

Autor et al. (2025) study a different setting in which a set of jobs secularly disappear — trade liberalization. They find that incumbent workers employed in manufacturing[2] saw persistent employment losses if their location was more exposed to Chinese import competition, while newly entering young workers found employment in local service sectors, echoing our emphasis on life cycles and skill heterogeneity. Dix-Carneiro (2014) estimates a dynamic equilibrium trade model with sector-specific human capital to study how labor market frictions impeded worker reallocation across sectors following a trade liberalization in Brazil. Caliendo et al., 2019 develop a "dynamic hat-algebra" approach to study the effects of trade liberalization on US employment and welfare in a model with competitive labor markets and without skill heterogeneity, life cycles or job-ladders, all of which are central to our analysis. Traiberman (2020) argues that trade shocks destroy occupation-specific human capital, which slowed labor reallocation and generated substantial welfare costs for workers in Denmark. Adão et al. (2024) show that the adoption of new technologies takes more time if existing workers do not possess the right skills to operate these technologies, with younger generations playing an important role in this adoption. Human capital specificity is central to our analysis too. In contrast to this literature, we study a counterfactual question: how large would earnings losses be if the transition accelerated? We show that the marginal cost to workers of speeding up transitions is highly non-linear and we identify the structural determinants of this non-linearity. We investigate this question in the context of the climate transition using a model that accounts for involuntary unemployment, which is important to capture workers' displacement experience.

Our paper also relates to a literature that studies how technological transitions

[2] There were 15.7 million workers employed in manufacturing in the US when China joined the WTO in December 2001, compared with 10-15 million workers in polluting sectors as of 2005.

affect employment and wages. The key takeaways in this literature are that faster technological change increases wage dispersion due to vintage human capital effects (Violante, 2002), and tends to reduce long-run employment due to job obsolescence (Postel-Vinay, 2002) or higher costs of technology updating (Mortensen and Pissarides, 1998). Bilal et al., 2021 study labor market dynamics in a model of creative destruction. Our analysis also considers transitions which make an old vintage of technology obsolete. In contrast, we highlight stark non-linearities in earnings as function of the pace of transition.

Finally, our work is connected to a literature which asks whether policy should intervene to slow down the adoption of new technologies or assist workers during these transitions. Guerreiro et al. (2021), Costinot and Werning (2023), Thuemmel (2023) and Lehr and Restrepo (2023) argue that taxing new technologies can be optimal to mitigate the distributional consequences of automation. Beraja and Zorzi (2024b) show that the pace of technological transitions is inefficiently fast when workers are unable to smooth consumption upon displacement. Braxton and Taska (2024) argue that governments should insure workers against technological change by expanding retraining subsidies. Relative to this literature, we emphasize strong non-linearities and non-monotonicities in earnings losses as transitions get faster, clarify the structural objects that underlie these effects, and quantify them in the context of the climate transition. In particular, we show that jointly modeling involuntary unemployment, on-the-job search, skill heterogeneity, and life cycles is key to quantitatively capture these non-linearities.

2 Model

In this section, we present a model that captures realistic features of the displacement and reemployment experience of workers initially employed in polluting industries. We will use this model to study how these workers fare under different transition scenarios. Section 2.1 describes the environment and Section 2.2 states the workers' problem recursively.

2.1 Environment

Time is continuous and indexed by $t \geq 0$. We consider a technological transition where demand for jobs rises in a clean sector and falls in a polluting one, leading to a reallocation of labor between the two. Workers can supply can labor to a "polluting" sector ($k = P$) or a "clean" sector ($k = C$). We refer to these jobs interchangeably as occupations, industries or sectors. In addition, workers can supply labor to an "outside" sector ($k = O$) which is not affected by the transition. Before period $t = 0$, the economy is in a steady state where clean jobs do not yet exist. The emergence and growth of the new technology becomes common knowledge in period $t = 0$. To maximize expositional clarity, we abstract from trend growth in the main text. This is without loss of generality: in Appendix A.1, we consider an economy that grows exogenously at rate g and show that our analysis should be interpreted as being in deviations from this balanced growth path.

2.1.1 Workers

Demographics and preferences. Workers live for J periods and are replaced by new workers upon retirement. Workers supply labor and consume at all ages $j \in [0, J]$.[3] Their preferences are represented by

$$\mathbb{E}_0 \left[\int_0^J \exp\left(-\rho t\right) u\left(c_t\right) dt \right] \tag{2.1}$$

where $u(c) \equiv c^{1-\sigma} / \left(1-\sigma\right)$ is the flow utility function, c_t is consumption in period t of life, and $0 < \rho < \infty$ is the discount rate. We let τ denote a worker's year of birth (or cohort), so that incumbents' age as of period 0 is $-\tau$. Workers regard the three sectors' output as perfect substitutes (e.g., they do not inherently value electric vehicles).[4]

[3] We abstract from consumption after retirement, which is without loss of generality given the asset structure that we assume (Section 2.1.3).

[4] Our focus is on the labor market consequences of the climate transition, rather than its welfare implications through consumption. In particular, we abstract from relative price changes which are important in other contexts such as structural transformation from agriculture to manufacturing. As we explain in Section 3, this assumption is innocuous for our exercise: we quantify the labor market consequences of an exogenous shifts in labor demands (or marginal revenue product of labor) across sectors without taking a stance on whether they are induced by changes

Skills. Workers' human capital in sectors $k \in \{C, P\}$ is given by

$$h\left(j, \boldsymbol{\psi}, k\right) \equiv \psi^{\star}\left(j\right) + \psi_{k}, \tag{2.2}$$

where $\psi^{\star}\left(j\right)$ is a life cycle component (e.g., workers become more productive as they age), $\boldsymbol{\psi}$ denotes a vector of sector-specific skill and k is a particular sector. A worker's specific skill in the clean sector is $\psi_C \equiv \psi_C^{\text{endow}} + \psi_C^{\text{train}}$, where ψ_C^{endow} is a heterogeneous endowment drawn from a distribution $G\left(\psi_C^{endow}\right)$ and ψ_C^{train} is the additional skill that they accumulate through training. We suppose that workers can train either at the beginning of their lives ($j = 0$) or when the emergence of the new sector is announced ($t = 0$). The cost of training to accumulate ψ_C^{train} units of the clean specific skill is $\Psi\left(\psi_C^{\text{train}}; \psi_C^{\text{endow}}\right)$.[5] Workers only retrain once in our model; it is without loss of generality to assume that retraining takes place in the first period $t = 0$ if the interest rate is exactly zero.[6] All workers have one unit of specific human capital in the polluting sector $\psi_P = 1$.[7] Given this normalization, we only keep track of a worker's skill in the clean sector $\psi \equiv \psi_C$ instead of the vector $\boldsymbol{\psi}$. Workers earn exogenous constant benefits if they work in the outside sector or are unemployed as described below.

2.1.2 Production

There is a continuum of firms in each sector $k \in \{C, P\}$. Each of these firms employs one worker and operates a linear technology

$$y_t\left(j, \psi, k\right) \equiv A_{k,t} \times h\left(j, \psi, k\right) \tag{2.3}$$

in market conditions or government policies.

[5] We abstract from specific skill accumulation on-the-job so ψ_k corresponds to present value production differences between sectors. Skill accumulation occurs symmetrically across sectors via $\psi^{\star}(j)$. In theory, workers' effective productivity could be indexed by time too, if new technologies become easier to operate over time (Hassan et al., 2025). We cannot identify this effect separately from an improvement in TFP among new occupations if it affects all skills uniformly.

[6] Otherwise, this assumption is an approximation that allows us to sidestep an additional stopping time problem (when to retrain) which would make our structural estimation infeasible.

[7] This normalization is without loss of generality for our analysis. The relevant object for a workers' outcome is their comparative advantage ψ_C/ψ_P. A different ψ_P would simply scale a workers' earnings up or down.

where $h(\cdot)$ is the worker's skill and $A_{k,t}$ is the detrended productivity of sector k in period t. The productivities $A_{k,t}$ act as labor demand shifters in each sector. In the following, we will consider scenarios where $A_{P,t}$ decreases and $A_{C,t}$ increases over time relative to trend: there is a transition from polluting to clean sectors.[8] Firms created in period t are owned by infinitely-lived entrepreneurs with discount rate ρ and linear flow utility.[9]

2.1.3 Markets and Incomes

Posting vacancies and hiring workers is costly. Firms therefore pay workers below their marginal product to recoup this hiring cost over time. These search frictions also generate involuntary unemployment spells over the transition, which are important to explain the extent of workers' earnings losses after displacement (Braxton and Taska, 2023; Fallick et al., 2025). Workers direct their search both within and across markets as in Menzio and Shi (2011). Workers search with intensity $\lambda^E > 0$ when on-the-job (employed) and with intensity $\lambda^U > 0$ when when off-the-job (unemployed). Workers can search for jobs in the clean, polluting or outside sectors.

Polluting and clean sectors. We suppose that workers and firms agree on contracts with fixed wages $w \geq 0$ for each unit of effective labor ψ that they supply.[10] Workers therefore earn $wh(j, \psi, k)$ if employed, and firms' flow profits are $(A_{k,t} - w) \times h(j, \psi, k)$. There are N submarkets in both the polluting and clean sector, indexed by worker's age j, skill ψ, sector k, and a wage w. On-the-job search allows workers to climb a job-ladder. In the following, we let $s \equiv (w, k)$ denote submarkets that a given worker can search in. A constant returns to scale matching function yields a job-finding probability for workers $f(\theta)$, where θ is market tightness de-

[8] Since firms' outputs are perfect substitutes, their price can be normalized to 1. We thus interpret $A_{k,t}$ as the marginal revenue product of labor in each sector. We discuss this point further in Section 3.

[9] While profits will be zero in steady state, *ex post* profits might not be zero during the transition to the new steady state. Assuming that profits are claimed by a separate group of investors is standard in search models. It also required to obtain block-recursive equilibria in directed search models (Menzio and Shi, 2011) which we leverage as part of our structural estimation.

[10] We abstract from renegotiation of wage per efficiency unit w, since wages rarely fall on-the-job (Grigsby et al., 2021). Workers' earnings rise on-the-job as they accumulate life-cycle human capital $\psi^\star(j)$.

fined as the ratio of vacancies to job-seekers and f is increasing and concave and satisfies usual Inada conditions. The corresponding job-filling probability for firms is $q(\theta) \equiv f(\theta)/\theta$ which decreases with θ. We let $V_t(j, \psi, s)$ denote the value to a firm employing a worker of age j and with skill ψ in market s. Firms post vacancies at a cost $\nu\psi^\star(j)$ with $\nu > 0$.[11,12] There is free entry in each market so is

$$q(\theta_t(j, \psi, s)) V_t(j, \psi, s) \leq \nu\psi^\star(j) \tag{2.4}$$

in every period t and market s, with equality if a positive measure of vacancies are posted. New cohorts ($\tau > 0$) are born unemployed.

Separations. Existing employment relationships in the polluting or clean sectors are dissolved for three reasons. First, workers retire at age J. Second, they may search on-the-job to climb a job-ladder or switch sectors. Finally, firms incur fixed costs to continue operations, which generate endogenous involuntary separations for workers.[13] Firms incur a cost at a constant rate $\chi_0 > 0$, at which point they draw a random cost $\varepsilon\psi^\star(j)$ where ε is log-normally distributed with location ϕ and scale γ_ϵ. These operating costs capture various forms of investment that are required to maintain the worker's productivity in their job. Like the hiring cost, these operating costs scale with a workers' life cycle productivity $\psi^\star(j)$, e.g., corporate training is more expensive for senior employees. We denote the probability that an operating cost exceeds the firm's value V, in which case the worker is involuntarily laid off, by

$$\mathcal{F}(V) \equiv \Pr\{\phi + \gamma_\epsilon\varepsilon^\star > \log(V)/\psi^\star(j)\} \tag{2.5}$$

with $\varepsilon^\star \sim \mathcal{N}(0,1)$. Since $A_{P,t}$ falls over time, polluting-sector firms become less

[11] As is common, we do not distinguish between the cost of posting a vacancy and hiring the worker if the match is successful.

[12] Searching for a junior employee is cheaper compared to a senior manager so this cost scales with a worker's life cycle productivity $\psi^\star(j)$. Without this assumption, firms would be substantially more likely to post vacancies for old workers. The reason is that the productivity $\psi^\star(j)$ that rationalizes earnings differences across age groups is almost twice as high for older workers. For the same reason, we suppose in the following that operating and amenity shocks scale with $\psi^\star(j)$.

[13] An alternative approach is to introduce idiosyncratic firm productivity shocks as in Hopenhayn (1992). Our approach economizes one state variable. Random fixed costs of operation or production are commonly used in the literatures on firm dynamics (Clementi and Palazzo (2016)), trade (Atkeson and Burstein, 2010), and macroeconomics more generally (Guerrieri et al., 2022).

likely to be willing to cover these costs, leading to separations over the transition.[14]

Other employment states. In addition to the polluting and clean sectors, workers can supply labor to the outside sector O when a search opportunity arises. We think of this sector as capturing jobs that workers can find relatively easily after being laid off and which offer relatively limited scope for professional progression. Accordingly, we assume that these jobs have a job-finding probability of 1 conditional on search and we abstract from job-ladders in the outside sector. Workers and receive a flow benefit $b^O \psi^\star(j) > 0$ in that sector and separate to unemployment at constant exogenous rate χ^O. Workers who are unemployed earn a flow benefit $b^U \psi^\star(j) > 0$. We assume that these benefits take the form of home production to abstract from taxation. In the following, we let $s = U, O$ denote the submarket associated with unemployment and the outside sector respectively.

Search hazard. To rationalize the fact that job switches often entail wage cuts (Sorkin, 2018), we suppose that workers' search is only partially directed. Specifically, a worker in market s searches in a given market s' with probability

$$p_t\left(s'; j, \psi, s\right) \equiv \frac{\exp\left(f\left(\theta_t\left(j, \psi, s'\right)\right)\left[W_t\left(j, \psi, s'\right) - W_t\left(j, \psi, s\right)\right]/\gamma_\zeta\right)}{\sum_{\hat{s}} \exp\left(f\left(\theta_t\left(j, \psi, \hat{s}\right)\right)\left[W_t\left(j, \psi, \hat{s}\right) - W_t\left(j, \psi, s\right)\right]/\gamma_\zeta\right)} \tag{2.6}$$

where the sum is over the submarkets they can consider, i.e., the worker is more likely to search in a given market s' if the expected improvement in its value is larger.[15] This search behavior can be microfounded by introducing idiosyncratic amenity shocks that are distributed i.i.d. according to a Type-1 Extreme Value distribution with and scale parameter γ_ζ (Artuç et al., 2010). Alternatively, this search hazard can be microfounded by assuming that workers have to acquire costly information about the jobs that they apply to (Matêjka and McKay, 2015).[16] The

[14] Many of these layoffs will be efficient. However, some may be inefficient in that the sense that they depend only on firm value, not total match surplus. Jäger et al. (2023) and Davis and Krolikowski (2025) provide evidence for such inefficient separations. In practice, firm's reluctance to decrease wages (Grigsby et al. (2021)) is an important obstacle to renegotiation. Accordingly, our model features fixed wage contracts. Blanco et al. (2024) present a model of inefficient separations arising from wage rigidity. We will directly target firms' propensity to fire workers in response to shocks in our quantification.

[15] In addition to rationalizing wage cuts on job switches and substantial gross flows (Pilossoph, 2014), the search hazard renders the model more numerically stable and easier to solve.

[16] As the recursive formulation (2.7) makes clear, we do not include any amenity value or informa-

parameter γ_ζ captures degree to which search is directed: the search is purely random when $\gamma_\zeta \to \infty$, and purely directed as $\gamma_\zeta \to 0$ as in canonical directed search.

Asset Markets. Financial markets are incomplete with respect to the aggregate shock, i.e., workers did not preemptively write contingent contracts against the risk that the climate transition might occur. Our main analysis focuses on the case with risk-neutral workers where $\sigma = 0$ as is standard in much of the labor search literature.[17] In this case, the degree of market completeness with respect to idiosyncratic risk is irrelevant as workers care solely about the expected present value of their income. The search decisions made by workers — and thus the total earnings impact of the transition — would be the same under our benchmark risk-neutral case if workers were risk averse $\sigma > 0$ but could borrow freely and had access to complete markets with respect to idiosyncratic shocks.[18]

2.2 Recursive Formulation and Equilibrium

Values. At any point in time, workers are indexed by three states: their age j; their specific skill in the clean sector ψ; and the market that they are currently in s. The value of an employed worker of age j with skill ψ in submarket s satisfies

$$\begin{aligned}\rho W_t(j,\psi,s) =& wh(j,\psi,k) + \lambda^E \sum_{s'} p_t(s';j,\psi,s)\, f\left(\theta_t(j,\psi,s')\right)\left[W_t(j,\psi,s') - W_t(j,\psi,s)\right] \\ &+ \chi_0 \mathcal{F}\left(V_t(j,\psi,s)\right)\left[W_t(j,\psi,U) - W_t(j,\psi,s)\right] \\ &+ \frac{d}{d\epsilon} W_{t+\epsilon}(j+\epsilon,\psi,s)\Big|_{\epsilon=0} \end{aligned} \tag{2.7}$$

for each age $j \in [0, J)$, where $W_t(j,\psi,U)$ is the value of being unemployed and $V_t(j,\psi,s)$ is the firm's value in period t, both of which we define below. The boundary condition is $W_t(J,\psi,s) = 0$ upon retirement at age $j = J$. This terminal conditions are similar for the other values that we present below so we omit them in the

tion processing cost in workers' values.

[17] See Krusell et al. (2010) for an exception.

[18] By this, we mean that workers can trade contingent securities against the risk of being unemployed for longer, not finding a high wage job etc. In this case, a workers' lifetime utility only depends on the present discounted value of its earnings over its remaining life span. In an extension, we will also consider the case with $\sigma > 0$ and hand-to-mouth households.

following. Workers discount at rate ρ. When employed, they earn $wh(j,\psi,k)$ and have the opportunity to search for another job at rate λ^E. The search in submarket s' with probability $p_t(s';j,\psi,s)$ (equation 2.6). The firm incurs an operating cost at rate χ_0, at which point the worker is involuntarily fired with probability $\mathcal{F}(V_t(j,\psi,s))$ and becomes unemployed. Finally, there is a drift in values both over time and over the life cycle.[19]

The value of an unemployed worker of age j and skill ψ satisfies

$$\rho W_t(j,\psi,U) = b^U\psi^\star(j) + \lambda^U \sum_s p_t\left(s';j,\psi,U\right) f\left(\theta_t(j,\psi,s)\right)\left[W_t(j,\psi,s) - W_t(j,\psi,U)\right] + \frac{d}{d\epsilon}W_{t+\epsilon}(j+\epsilon,\psi,U)\Big|_{\epsilon=0} \tag{2.8}$$

for $j < J$, since they receive benefits $b^U\psi^\star(j)$ and search for jobs with intensity λ^U. Similarly, the value of a worker employed in the outside sector satisfies

$$\rho W_t(j,\psi,O) = b^O\psi^\star(j) + \lambda^E \sum_s p_t\left(s';j,\psi,O\right) f\left(\theta_t(j,\psi,s)\right)\left[W_t(j,\psi,s) - W_t(j,\psi,O)\right] + \chi^O\left[W_t(j,\psi,U) - W_t(j,\psi,O)\right] + \frac{d}{d\epsilon}W_{t+\epsilon}(j+\epsilon,\psi,O)\Big|_{\epsilon=0} \tag{2.9}$$

for $j < J$, since they receive benefits $b^O\psi^\star(j)$, search for jobs with intensity λ^E and lose their job at rate χ^O.

Workers have the opportunity to invest in skills specific to the climate sector either when they are born at age $j = 0$ or when the climate transition emerges in period $t = 0$. When doing so, incumbent workers choose their final skill $\psi \geq \psi^{\text{endow}}$ to solve[20]

$$\max_{\psi \geq \psi^{\text{endow}}} W_t(j,\psi,s) - \Psi\left(\psi - \psi^{\text{endow}};\psi^{\text{endow}}\right) \tag{2.10}$$

[19] Since age advances one-for-one with time, the drift in both dimensions is characterized by the single index ϵ.

[20] Quantitatively, we find that a workers' employment status in $t = 0$ has minimal effect on their retraining decision since workers cycle in and out of employment at a relatively high frequency as in the data.

New workers born in period $\tau > 0$ solve a similar problem, except the relevant continuation value is $W_\tau(0, \psi, U)$ since they are unemployed when born at age $j = 0$.

The value of a filled job to a firm in sector k is given by

$$\begin{aligned}\rho V_t(j,\psi,s) = (A_{k,t} - w)\, h(j,\psi,k) - \chi_0 \left(1 - \mathcal{F}_t\left(V_t(j,\psi,s)\right)\right) \mathbb{E}\left[\varepsilon\psi^\star(j) | \varepsilon\psi^\star(j) \leq V_t(j,\psi,s)\right] \\ - \left[\chi_0 \mathcal{F}\left(V_t(j,\psi,s)\right) + \lambda^E \sum_{s'} f\left(\theta_t\left(j,\psi,s'\right)\right) p_t\left(s'; j,\psi,s\right)\right] V_t(j,\psi,s) \\ + \frac{d}{d\epsilon} V_{t+\epsilon}(j+\epsilon,\psi,s)\Big|_{\epsilon=0}\end{aligned} \tag{2.11}$$

for each age $j \in [0, J)$ with boundary condition $V_t(J, \psi, s) = 0$ when the worker retires at age $j = J$. Firms discount flows using the equilibrium interest rate $r \equiv \rho$ and receive flow profits so long as the match continues.[21] They incur operating costs at rate χ_0. With probability $1 - \mathcal{F}_t\left(V_t(j,\psi,s)\right)$, the match continues and the firm pays the operating cost, whose expectation is conditional on the cost being small enough to continue the match. The match may dissolve before workers reach retirement age either because the firm lays off the worker, which occurs at rate $\chi_0 \mathcal{F}_t\left(V_t(j,\psi,s)\right)$, or because workers voluntarily quit due to on-the-job search. The opportunity for on-the-job search arrives at rate λ^E and the probability of separating conditional on searching is given by $f\left(\theta_t(\cdot)\right)$ in the sector in which the employed worker searches, weighting each sector s' by the probability that the individual searches there $p_t\left(s'; j, \psi, s\right)$. The firm's value also features a drift over time and over workers' age.

Equilibrium. We define the equilibrium formally in Appendix. The block recursive nature of the equilibrium allows for an efficient computation of both the value functions and the distributions. Appendix B describes how we solve for this equilibrium. We initialize the economy in period 0 at a steady state assuming only the old sector exists.

[21] The equilibrium interest rate is $r = \rho$ since entrepreneurs have an inverse EIS of 0.

3 Institutional Context and Counterfactuals

Before developing our analysis further, it is useful to provide some institutional context to understand how we map the model to the data, describe the exact counterfactuals that we consider, and discuss other settings to which our model applies.

Institutional context. Although climate change was first recorded by the scientific community during the 1970s, international efforts to coordinate policy to address climate change began in 1992 with the establishment of the United Nations Framework Convention on Climate Change. The most important early agreement was the Kyoto Protocol, which established binding reduction targets for greenhouse gas (GHG) emissions for the 192 countries that ratified it, including the US. The Kyoto protocol was adopted in 1997 and entered into force in 2005. We therefore choose our period $t = 0$ to be the year 2005. Since the Kyoto protocol was adopted, many additional agreements have been adopted, including the Paris Climate Agreement of 2015 which pushed most developed countries to target the year 2050 as the date to achieve net-zero emissions.[22] The US, however, pulled out of the Paris Agreement and is not currently on track to meet this target by 2050. A recent survey of US Energy Executives suggest that 2060 is a more realistic timeline (Bain & Company, 2025). We therefore assume that the baseline transition in our model runs from 2005 to 2060. Of course, the exact date at which the US economy will reach this milestone is uncertain. This uncertainty is inherent to our *prospective* analysis; we embrace this uncertainty and will consider various sensitivity analyses.

Counterfactuals. We focus on workers who are initially employed in the polluting sector.[23] These 10-15 million workers are the ones at risk of displacement whose concerns are an obstacle to the support of ambitious climate goals.[24] This is a meaningful share of the economy: as a point of comparison, there were 15.7 million

[22] See Naser and Pearce (2022) for more on the history of international climate accords.

[23] In the data, we will focus on the set of workers "attached" to the polluting sector who are likely to work in the polluting sector based on observable characteristics. We define this set of workers precisely in Section 5.1, along with a clear definition of polluting and clean sectors.

[24] To be clear, not all such workers will reallocate during their lifetime. The ones with the least versatile skills might simply hold on to the polluting sector until retirement, potentially incurring large earning losses along the way.

workers employed in manufacturing in the US when China joined the WTO in December 2001. Assessing how these polluting-attached workers fare under different transition scenarios is a crucial step to understand how best to assist them and garner support for climate goals. We are interested in answering two questions. First, what is the distribution of lifetime earnings changes among these workers under the current transition scenario? Second, how much would these lifetime earnings change relative to this baseline if the pace of the transition were to change starting from 2025?

To answer these questions, we study how exogenous shifts in labor demand between polluting and clean sectors affect workers' labor market outcomes. In our model, labor demand is captured by $A_{k,t}$. We will therefore perturb the path of $A_{k,t}$ so that labor demand shifts from polluting to clean sectors at various paces.

Of course, sectoral labor demands can change for reasons other than changes in physical productivities. For example, investment in physical capital can raise the marginal product of labor the clean sector, the government can subsidize the purchase of goods produced in the clean sector or tax the output of the polluting sector, the relative price of these goods could move, etc.[25]

In our model, all these mechanisms are isomorphic to changes in $A_{k,t}$. They simply change the marginal revenue products of labor ($\text{MRPL}_{k,t}$) in the two sectors which are *sufficient statistics* to characterize firms' demand for labor in each sector and workers' outcomes. These alternative mechanisms map into different paths of $\text{MRPL}_{k,t}$ across sectors.[26] Because we study workers' *labor market outcomes*, we do not have to take a stance on the exact mechanisms behind the changes in $\text{MRPL}_{k,t}$, which are orthogonal to our analysis. Instead, we perform a positive analysis where we perturb the paths of $\text{MRPL}_{k,t}$ directly, with the understanding that such a change could be achieved through various mechanisms or policy instruments.[27] We will consider various scenarios where $\text{MRPL}_{k,t}$ declines relative

[25] We assume constant returns to scale in production so that one can consider one-worker firms without loss of generality. One might also think that a model with decreasing returns to scale in labor might stabilize wages over the transition as workers leave the sector. This force would also affect firms' labor demands.

[26] For example, consider a change in physical productivities across sectors. The relative price of these goods would also change if they are imperfect substitutes. This would either strengthen or dampen the change in MRPL. In the end, the only thing that matters for firm's labor demand and workers' output is the paths of MRPLs across sectors.

[27] Of course, a separate (and complementary) question would be to assess how expensive it would be to engineer given paths of $\text{MRPL}_{k,t}$ using various policy instruments. This exercise is orthog-

to trend in the polluting sector and rises in the clean sector. Such simultaneous change in $\text{MRPL}_{k,t}$ across sectors would naturally arise if, for instance, the government subsidized electric vehicles (EVs), propping up their demand at the expense of internal combustion engine (ICE) cars.

We assume that the paths of $A_{k,t}$ take the following form under a baseline transition

$$A_{k,t} = A_{k,0} + \bar{\Phi}(t) \times (A_{k,\infty} - A_{k,0}) \tag{3.1}$$

where $A_{k,0}$ and $A_{k,\infty}$ are the start and end values of labor productivity, which we take as fixed and exogenous. We assume $A_{C,\infty} > A_{C,0}$ and $A_{P,\infty} < A_{P,0}$: the clean sector grows while the polluting sector declines.[28] The timing of this sectoral shift is parameterized by the map $\bar{\Phi}(t)$, which is an increasing function mapping the real line to the $[0,1]$ interval, representing the share of the transition that is completed as of period t.

We then specify counterfactual paths of labor demands from 2025 onwards as

$$A_{k,t} = A_{k,0} + \bar{\Phi}(2025 + \eta(t - 2025)) \times (A_{k,\infty} - A_{k,0}), \quad \text{for } t \geq 2025 \tag{3.2}$$

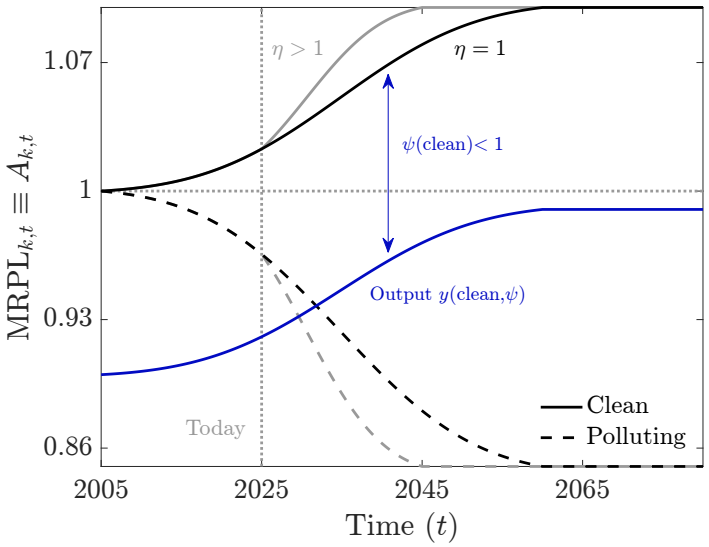
The parameter η governs the speed of transition. When $\eta = 1$, the path of $A_{k,t}$ aligns exactly with the benchmark transition. A higher η indicates that more of the transition occurs earlier. While we do not explicitly model the government sector, one may think of different government policies mapping into different values of η.

Figure 1 illustrates the path of sectoral productivities (3.2). The black curves correspond to our baseline transition with $\eta = 1$ where the transition is complete in 2060. The solid and dashed curves indicate the clean and polluting sectors, respectively. The blue curve indicates output $y(\text{clean}, \psi)$ in the clean sector, which depends on the workers' productivity ψ in that sector. Periods before 2005 correspond to our initial stationary equilibrium. We will use this initial steady state to discipline various parameters, such as those governing search, separations and the vacancy posting by matching a rich set of micro moments. The period ranging from 2005 to 2025 corresponds to the early phase of the transition for which we already observe labor flows between sectors. We will use this information to struc-

onal to the labor market outcomes that we focus on but is fertile ground for future research.

[28] Note that the fact that the old sector is declining relative to trend does not imply the old sector is declining in absolute terms, rather that it begins growing at a slower rate than previously.

Figure 1: Marginal revenues product of labor $A_{k,t}$



Notes: This figure illustrates the path of marginal revenue products of labor in the two sectors ($A_{k,t}$) under various transition scenarios. The black curves correspond to our baseline transition with $\eta = 1$, and the gray curves correspond to a faster one $\eta > 1$. The solid and dashed curves indicate the clean and polluting industries, respectively. The blue curve indicates output y (clean, ψ) in the clean sector, for some productivity $\psi < 1$ in that sector.

turally estimate the distribution of skill endowments ψ^{endow} and the re-training cost $\Psi\left(\psi^{\text{train}}; \psi^{\text{endow}}\right)$. There is great uncertainty around the long-run value of $A_{k,\infty}$; we will therefore present results for a menu of possible values for these parameters that are consistent with the range of estimates of the long-run impacts of the transition (Mayfield et al., 2023; Finkelstein Shapiro and Metcalf, 2023; IRENA, 2023b).

We will conduct counterfactual analyses over the remainder of the transition post-2025. We consider various transitions speeds $\eta \neq 1$ that affect the productivities $A_{k,t}$ from 2025 onward — the exercise that is most relevant to policymakers. The gray curves in Figure 1 illustrate one such transition with $\eta > 1$. For each of these counterfactual transitions, we will compute changes in lifetime earnings as

$$d\mathcal{W}\left(j, \psi, s; \eta = \hat{\eta}\right) \equiv \frac{W_{2025}\left(j, \psi, s\right)\big|_{\eta=\hat{\eta}}}{W_{2025}\left(j, \psi, s\right)\big|_{\eta=1}} - 1, \tag{3.3}$$

where $W_{2025}\left(j, \psi, s\right)\big|_{\eta=\hat{\eta}}$ corresponds to a worker's value function (2.7)-(2.9) when the transition speed is $\hat{\eta}$. In other words, we compute expected earnings changes

from the transition from 2025 onward, relative to the baseline transition that ends in 2060. In Section 6.1, we will conduct an alternative and more retrospective exercise where we compare workers' values as of 2005 under the baseline transition with $\eta = 1$ relative to no transition at all ($\eta = 0$). This exercise will allow us to compare the losses already incurred by workers due to the climate transition to those documented in the literature in the context of other technological transitions. Note that assuming curvature in utility and hand-to-mouth agents would increase implied labor market costs of the transition; we will do this as a sensitivity analysis.

Technology adoption within industries. The paths of $A_{k,t}$ reflect firms' incentives to employ workers using the clean and polluting technologies, respectively. Empirically, these two technologies might co-exist in the same industry. In fact, the same firm could decide to transition from the polluting to the clean technology. For instance, a manufacturer of ICE vehicles can begin producing EVs and the two technologies can co-exist within the firm. In practice, technology adoption leads to substantial worker displacement even when it occurs within the same firm. For example, the transition from ICE towards EVs requires substantial retraining among auto workers and has already resulted in large layoffs at auto manufacturers for workers producing inputs specific to ICE cars.[29] More generally, climate-friendly regulations lead to layoffs (Greenstone, 2002; Walker, 2011) and green jobs tend to require more cognitive skills and experience (Consoli et al., 2016; Marin and Vona, 2019). This dynamic appears to play out beyond the context of the climate transition: Braxton and Taska (2023) find that technology adoption leads to displacement and substantial earnings losses for incumbent workers who do not possess the right skills; Kogan et al. (2020) document a higher separation risk in industries that innovate more, as workers' skills become obsolete more rapidly.

Overall, the evidence supports that the labor reallocation from polluting to clean technology is frictional, as we have assumed in our setup. One can think

[29] Conventional cars use of many components that are not present in EVs, such as catalytic converters, fuel tanks and pumps and internal combustion engines, all of which rely of very specialized skills that are not directly portable to EVs. Similarly, EVs rely on their own specialized parts, most notably the car's battery, whose manufacture involves different skills. See, for example, the substantial layoffs at Ford, while Volkswagen workers are being retrained to build EVs. Meanwhile, the European Association of Automotive Suppliers projects half a million jobs will be lost from an EV transition, while the the Economic Policy Institute similarly projects large layoffs in the US (all articles accessed July 2, 2025).

of the $A_{k,t}$ as the penetration of each technology in the economy and the incentives to hire workers to operate these technologies, and ψ as the ability of workers to operate these technologies. Our model captures the idea that workers with a high ψ are more likely to operate the clean technology by switching employers. The same would be true if the firm could choose to reallocate workers to the clean technology on-the-job.[30]

Other transitions. While we apply our model in the context of the climate transition, it is worth noting that it is also applicable to a variety of settings in which demand falls one set of jobs and rises for another. Our setup can nest scenarios where one technology becomes obsolete (Aghion and Howitt, 1992; Violante, 2002) and is taken over by another, more productive one. Similarly, our model can be applied to trade shocks (Dix-Carneiro, 2014; Dix-Carneiro et al., 2023; Traiberman, 2020) that induce a cross-sectional reallocation of labor. We view the conceptual insights developed in Section 4 as portable to these other contexts. Studying how the pace of the transition affects workers outcomes is especially important in the context of the climate transition for several reasons. First, this transition is expected to take place over 35 years or so, which is much quicker compared to structural transformation from manufacturing to service sectors for instance. Second, a faster transition carries direct environmental benefits which increase the incentives to accelerate it — our paper focuses on the labor market implications of doing so. Third, the transition will be sizable and affect 10-15 million workers in polluting industries.

4 Economic Mechanisms

Before conducting a full quantitative analysis, we first examine the core economic mechanisms of our model. To make our conceptual points as transparently as possible, we momentarily strip our model from some of its quantitative features which matter for the exact numbers but do not alter the qualitative behavior of

[30] In these two scenarios, it is costly for the firm to familiarize the worker with the clean technology and production process (whether the worker is reallocated on-the-job or is hired from outside the firm). These costs are a large component of a workers' hiring ν in practice (Muehlemann and Strupler Leiser, 2018). Whether the switch takes place within or across firms is irrelevant in the case where reallocation within the firm requires an internal job posting with the same matching technology f.

our model. Specifically, we study in this section a Walrasian limit of our model where there are no vacancy-posting costs $\nu \to 0$ and the variance of amenity shocks vanishes. In this limit, workers are paid their marginal product and there is full employment.[31] We also abstract from retraining or life cycle human capital accumulation to streamline the exposition.[32] Accordingly, we let $\psi \equiv h(j, \psi, C)$ denote a worker's productivity in the clean sector to save on notation in this section. Throughout we will assume that workers are active from 25 to 65 years of age ($J = 40$) as in our calibration.

The left panel of Figure 2 plots the path of earnings over time for a particular worker in this Walrasian limit. The worker initially supplies labor to the polluting sector. At every instant, they compare their current earnings in that sector $A_{P,t}$ to their potential earnings in the clean sector $A_{C,t}\psi$, and thus supply labor in the clean sector if and only if $\psi \geq A_{P,t}/A_{C,t}$. The right-hand side of this inequality shrinks over time since the clean sector grows faster than the polluting sector. Therefore, a worker remains in the polluting sector until a stopping time $t^\star(\psi) \geq 0$, which depends on their comparative advantage in the new sector, and switches to the clean sector thereafter.[33] A worker switches sector if their stopping time occurs during their life span: $t^\star(\psi) < J + \tau$.

Workers' earnings decline following the path of $A_{P,t}$ while they remain in the polluting sector. Their earnings begin to recover after they switch sectors. Those with a higher productivity (in gray dashed) switch earlier and benefit more in the long-run. The right panel of Figure 1 illustrates how a worker's lifetime earnings change due to the transition. The shaded area indicates lifetime earnings changes in the baseline transition that ends in 2060. Most workers initially employed in polluting industries will lose from the early phase of the transition since the productivity gap between sectors opens up slowly and workers' skill are imperfectly transferable when $\psi < 1$. Thus the gray area is likely negative for most workers.

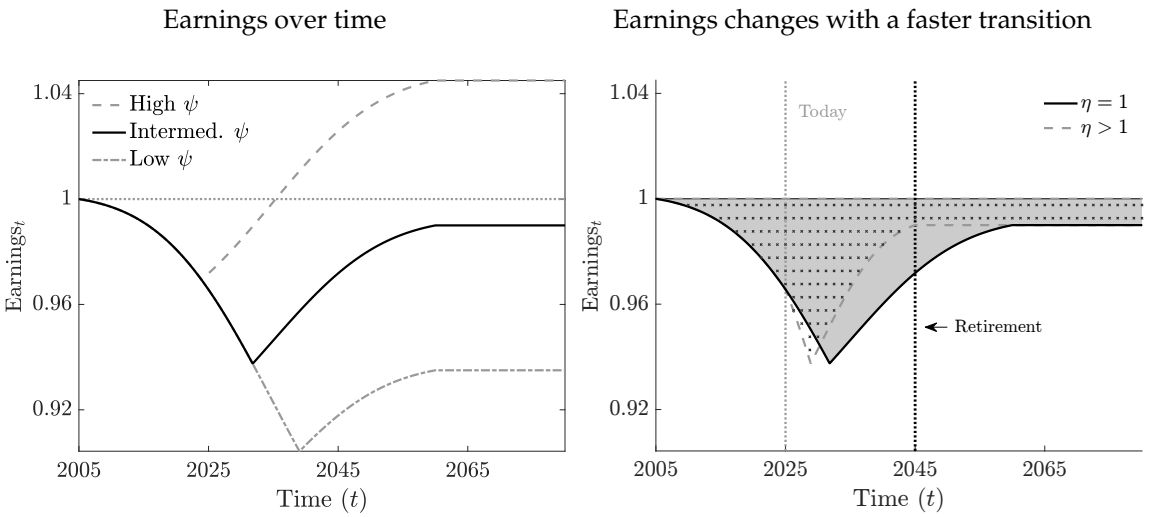
A faster transition (the checked region) has two opposing effects on a worker's lifetime earnings. On the one hand, it steepens the decline in income while the

[31] In this limit, the search intensities λ^E and λ^U are irrelevant if $f(\theta)$ is unbounded. All workers supply labor in the Walrasian limit when $b^U, b^O < A_{P,\infty}$, which will be the case in our quantification.

[32] In effect, this exercise assumes an infinite cost of retraining so that $\psi = \psi^{\text{endow}}$.

[33] Formally, $t^*(\psi)$ is the solution to the equation $\psi = A_{P,t^*(\psi)}/A_{C,t^*(\psi)}$, or $t^\star(\psi) \equiv 0$ or $t^\star(\psi) \equiv \infty$ if no solution exists and the worker either switches immediately or never at all.

Figure 2: Lifetime Earnings Losses From Transitions of Various Speeds



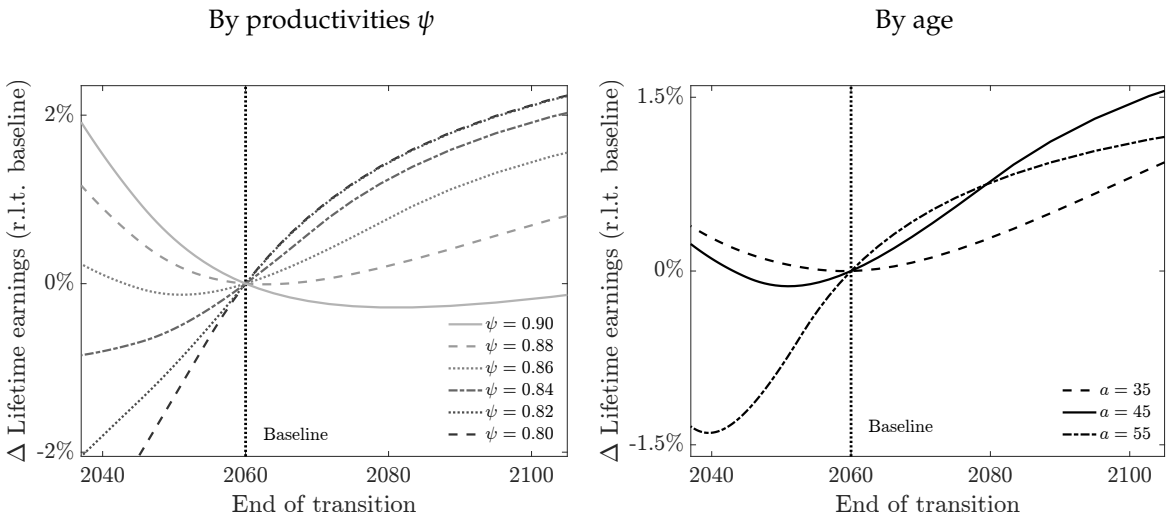
Notes: The left panel plots a worker's earnings over time in the Walrasian limit of our model, for various productivities ψ in the clean sector. The right panel indicates lifetime earnings changes in the baseline transition with $\eta = 1$ and how they change as the transition accelerates with $\eta > 1$.

worker remains in the polluting sector. On the other hand, earnings grow faster after the worker switches to the new sector and a larger share of the transition is completed before retirement. What's more, the worker switches to the new sector sooner and thus spends more time benefiting from the wage gains in that sector. The same forces are at play in our full model: a faster transition displaces workers earlier from polluting industries, but it also creates more job opportunities in the clean industries to absorb them.

The tension between these two forces means that workers' lifetime earnings can be highly non-linear or even non-monotonic in the speed of transition η. This is illustrated by the left panel of Figure 3, which plots changes in lifetime earnings as a function of the year when the transition (3.2) is complete: that is, under different transition speeds η. For each of these transitions, we compute the change in lifetime earnings (from 2025 onwards) relative the baseline transition ending in 2060. We repeat this experiment for workers with various productivities ψ in the clean sector, and who have 20 years of work remaining (i.e., the median age).

Two interesting facts stand out. First, changes in lifetime earnings can be very *non-linear* in the speed of transition. Some workers gain from a faster transition while others lose. However, these marginal changes are not constant — in fact, they vary sharply as the transition accelerates. For instance, a worker with $\psi =$

Figure 3: Average lifetime earnings changes



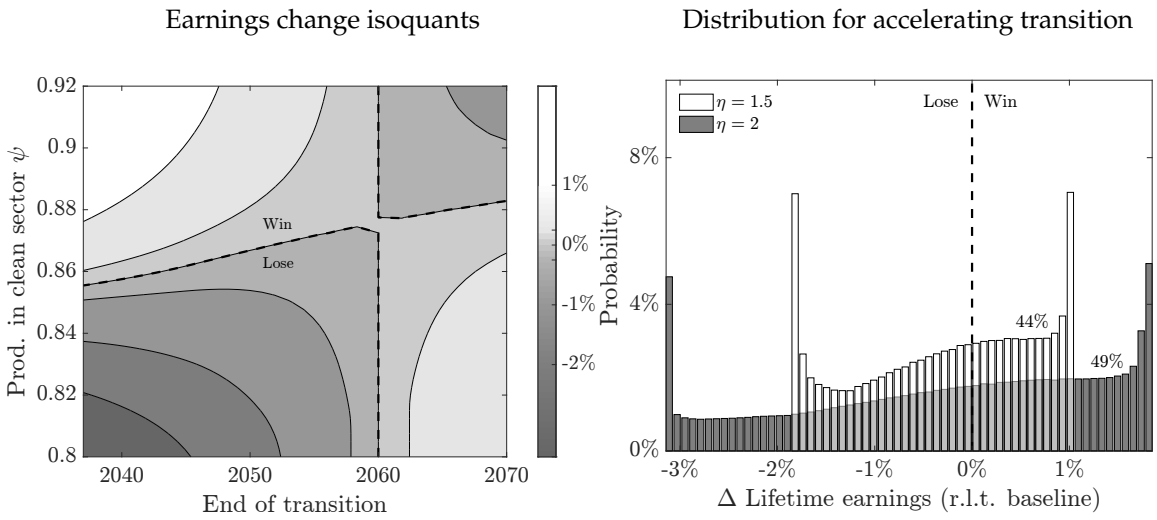
Notes: The left panel plots workers' average lifetime earnings changes in the Walrasian limit of our model as a function of the pace of transition η, for various values of the productivity ψ in the clean sector. All earnings changes are relative to the baseline transition ending in 2060, and faster transitions are parametrized as in equation (3.2). The horizontal axis corresponds to the end date of the transition considered. All workers have 20 years remaining in their careers (median age). The right panel repeats the same exercise for various ages as of 2025, when fixing the productivity $\psi = 0.86$ in the clean sector. We suppose all workers are born at 25 years old and retire at 65.

0.88 is mostly indifferent at first when the transition accelerates starting from 2060. Yet, the same worker starts benefiting more and more as the pace of the transition accelerates further. Overall, policymakers should be cautious about extrapolating from small changes around the 2060 timeline.

Second, earnings changes can be *non-monotonic* or U-shaped: some workers who initially lose from a faster transition end up benefiting from an even faster one. For instance, the worker with $\psi = 0.88$ would benefit from either a slower or a faster transition. For this worker, a *medium-speed* transition that ends 2060 represents the worst of all worlds: it is sufficiently fast that they experience all polluting sector losses before retirement, but sufficiently slow that they retire before their earnings recover from clean sector growth.[34] These non-monotonicities occur for workers who have intermediate productivities ψ in the clean sector. Specifically, non-monotonicities arise for any worker who might switch sectors during some period $0 < t < \infty$ under *some* transition speed. These are exactly the workers

[34] Graphically, this occurs when the area in the gray triangle in Figure 2 is maximized — this is the case when the worker's switching time $t^*(\psi)$ is close to their retirement age.

Figure 4: Average lifetime earnings changes



Notes: The left panel plots isoquants of lifetime earnings changes in the space of productivities in the clean sector ψ and the speed of the transition η. All earnings changes are relative to a baseline transition ending in 2060, and faster transitions are parametrized as in equation (3.2). The horizontal axis corresponds to the end date of the transition considered. All workers have 20 years remaining in their careers (median age). The right panel illustrates how the distribution of earnings changes as the transition accelerates with $\eta = 1.5$ or $\eta = 2$ when assuming that ψ is distributed normally with mean 0.85 and standard deviation 0.05. Again, all earnings changes are relative to the baseline transition with $\eta = 1$.

who form the bulk of the cross-sector reallocation.[35] We formalize these results in Appendix A.3.[36]

The right panel of Figure 3 repeats the same exercise for various ages, when fixing the productivity $\psi = 0.86$ in the clean sector. The magnitude and shape of these non-linearities are quite sensitive to a workers' age. The reason is that older workers have a shorter remaining horizon: they experience earnings changes for a shorter period of time. In the example depicted here, older workers spend less time in the clean sector receiving earnings gains. As a result, they are more likely to experience a decrease in overall lifetime earnings as the transition accelerates. Therefore, both workers' skill ψ and cohort τ are crucial inputs to their earnings losses from transitions of different speeds.

[35] Workers who either switch sectors immediately or never switch have a monotonic earnings profile over time. Therefore, they always gain or lose from a faster transition.

[36] We prove that there are two cutoffs $\underline{\psi} < \bar{\psi}$ such that all workers with $\psi < \underline{\psi}$ are strictly worse off as the transition accelerates, those with $\psi > \bar{\psi}$ are strictly better off, while all the workers with $\psi \in \left[\underline{\psi}, \bar{\psi}\right]$ workers have earnings losses which are U-shaped in the speed of transition.

The non-monotonicity that we document has an important corollary: the set of workers who win and lose from the transition is endogenous and can be quite sensitive to the speed of transition. Put differently, the *identity* of the "winners" and "losers" (with positive and negative earnings changes, respectively) varies as the transition accelerates. The left panel of Figure 3 plots isoquants of lifetime earnings changes in the space of productivities in the clean sector ψ and the end date of the transition. Earnings changes are measured relative to a baseline transition ending in 2060; thus all workers have zero earnings change from a transition ending in 2060 by construction. The region to the left of 2060 represents a faster transition. In this region, workers with a high productivity in the clean sector ψ benefit more and more from a faster transition while those with very low productivity lose more and more. Some workers with intermediate productivity ψ experience earnings losses for marginally faster transitions but then recover. Importantly, some workers – such as a worker with $\psi = 0.86$ – *switch* from "losers" to "winners;" that is, the set of people who benefit from a faster transition depends on the speed of transition under consideration.[37]

Indeed, a faster transition presents a trade-off: it may increase the mass of workers who benefit from the transition, but also generate a thicker tail among those who lose from it. The right panel of Figure 3 illustrates this trade-off in particular example where ψ is distributed normally with mean 0.86 and standard deviation 0.05: while a faster transition leads to a larger share of winners, the workers most affected by the transition are hurt much more.[38] This trade-off has important political economy considerations if voters are strongly motivated by their anticipated labor market outcomes (Dechezleprêtre et al., 2025) and may present a conundrum for policymakers.

The introduction of an outside option does not change the qualitative insights developed here; rather if the worker can receive a constant b^O in the outside sector at any point, their earnings profile will feature a flat region at b^O whenever $A_{P,t} \leq b^O \leq A_{C,t}\psi$. Accelerating the transition will still steepen the initial earnings decline, which will still be traded off against potentially larger gains after switching to the clean sector. Thus the non-linearity and non-monotonicities emphasized

[37] The region to the right of 2060 represents a slower transition than baseline. Slowing down the transition also changes the share of winners and losers, as well as the degree to which they lose, reflecting that those who would prefer a faster transition are also locally harmed by a slower one.
[38] We will estimate this distribution structurally in the context of our full model (Section 5.4).

above survive. Of course, the existence of an earnings floor at b^O will affect the quantitative behavior of the model; it will therefore be crucial to discipline this parameter appropriately as discussed below.

So far, we have studied earnings changes if the transition speeds up starting in 2025 – this is the relevant exercise for present-day policymaking. We have expressed these earnings changes relative to the baseline transition that ends in 2060. By doing so, we have effectively differenced out the "level" of earnings losses that workers have already experienced by 2025 under the baseline transition relative to a counterfactual without a transition. Put differently, we have abstracted from the shaded triangle to the left of 2025 in the right panel of Figure 2. While our focus is on 2025 onward, it is worth pointing out that workers initially employed in polluting industries might already be substantially worse off in 2025.[39] We revisit this question in Section 6.1.

To sum up, the Walrasian limit offers four main conceptual insights. First, the labor market consequences of the climate transition are highly non-linear in its pace: the marginal cost or benefit to workers varies quite sharply as the transition accelerates. Second, lifetime earnings losses can even be non-monotonic: some workers suffer the most from medium-speed transitions that displace them early from the polluting sector without improving their prospects sufficiently in the clean sector. These non-monotonicities arise for marginal workers who optimally switch sectors for some $0 < t < \infty$. Third, these non-linearities are very sensitive to workers' age, which determines the horizon over which a worker's earnings can recover after they switch sector, and new-sector skill, which determines the timing and cost of sector switches. Fourth, the set of "winners" and "losers" can be quite sensitive to the speed of transition. A faster transition generally increases the mass of workers who benefit from the transition, but it also generates a thicker tail among those who lose from it, presenting a trade-off for policymakers. These conceptual insights are applicable more broadly to settings in which one demand for one set of jobs gradually declines while another expands.

The Walrasian limit studied in this section captures the *qualitative* essence of our full model. However, it abstracts from an essential feature: hiring workers is costly, which creates room for structural unemployment over the transition. As

[39] Indeed, since $0.9 \times 1.1 < 1$, all worker types depicted in Figure 3 would prefer no transition to have occurred than suffer the earning losses from 2005 onwards.

we will soon see, such labor market imperfections will turn out to be important quantitatively. We therefore now bring our full model to the data and estimate the distribution of productivities ψ in the clean sector in order to quantify the losses from climate transitions of different speeds.

5 Bringing the Model to the Data

In this section, we describe how we discipline our full quantitative model empirically. As previewed in Section 3, we use three periods to calibrate our model. The period before the Kyoto protocol came into effect in 2005 corresponds to the initial stationary equilibrium of our model. We use it to discipline several parameters related to search, job destruction and job posting by matching a rich set of micro moments. The final stationary equilibrium of our model in our baseline transition corresponds to the post-2060 period. We pin down the path of $A_{k,t}$ using external forecasts of clean energy production and study a menu of long-run labor demands $A_{k,\infty}$. Finally, we use the early phase of the transition from 2005–2025 to structurally estimate the distribution of skill endowments ψ^{endow} and the training cost $\Psi\left(\psi^{\text{train}}\right)$. We discuss each of these steps below. Appendix C provides further details.

Before proceeding with our estimation, it is worth reiterating that our analysis is *prospective*. There is obviously great empirical uncertainty regarding long-run changes that have yet to occur. The results that we present are therefore suggestive of overall trends, but exact estimates should be taken with a grain of salt. We will test the sensitivity of our results under alternative scenarios for long-run labor demand in the clean and dirty sectors, alternative empirical classifications for clean and dirty industries, and various assumptions about market incompleteness and preferences.

5.1 Defining Polluting and Clean Sectors

The first step of our empirical approach is to define polluting and clean sectors in the data. The existing literature has suggested various approaches and classifica-

tions.[40] To define "polluting" industries, we follow tthe 2024 OECD employment report (Bassanini et al., 2024). We first obtain information on emissions intensity — measured as kilograms of CO2-equivalent gas emissions per dollar of output — by 6-digit NAICS industry codes from the Supply Chain Greenhouse Gas Emission Factors published by the Environmental Protection Agency (EPA).[41] This measure accounts for emissions produced throughout the supply chain of production of each commodity. An industry is deemed to be "high-emissions" if it is in the top decile of emissions intensities, weighted by employment. Examples of industries classified as dirty in this way include "Petroleum refineries," "Beef cattle ranching and farming" and "Industrial gas manufacturing." We then handcode a few sectors for which emissions data are unavailable as being polluting; for instance, the emissions data do not provide information on "Fossil fuel electric power generation," while "Gasoline stations" are not themselves polluting since the act of selling gasoline does not produce many emissions, but demand for gas stations is likely to fall as electric cars become more common. We review all such choices in Appendix C.

To define "clean" industries, we combine two approaches. First, we follow the output-based approach of Bontadini and Vona (2023), who find that 95% of the production of "green goods" is concentrated in just 13 out of 119 4-digit European NACE industries and that green and polluting production does not occur in the same sector.[42] We adopt their list of green sectors by merging these 4-digit NACE industries to 6-digit NAICS codes. Examples of the 54 sectors that are green by this definition include "Automatic environmental control manufacturing," "Electric power and specialty transformer manufacturing," and "Turbine and turbine generator set units manufacturing." While this approach provides a useful starting point, it only permits goods-producing sectors to be clean. Therefore, we supplement this output-based approach with the task-based approach employed by the US Energy Employment Report (Granholm, 2024). This approach uses data

[40] See Merino-Saum et al. (2020) for a meta-analysis of 140 definitions of "green" sectors, and Granholm (2024) and Bassanini et al. (2024) for additional conceptual discussion. Appendix C provides additional details on our approach.

[41] Specifically, we use version 1.3 which is available here (accessed March 7, 2025).

[42] The list of green goods employed by Bontadini and Vona (2023) is based on the Combined List of Environmental Goods (CLEG) of the OECD and considers goods which are useful for the green transition. For instance, solar panels and wind turbines are classified as "green goods" even if their production is relatively emission-intensive.

from the Green Goods and Services (GGS) survey produced by US Bureau of Labor Statistics (BLS) to study the share of workers employed in each industry that are engaged in green tasks. These green tasks can be conservation efforts, clean energy generation, or energy efficiency efforts, among others. We consider sectors to be green if a majority of its workers are engaged in green tasks. This adds an additional 59 sectors, such as "Solar electric power generation" and power generation from other renewable sources, "Materials recovery facilities" (i.e. recycling) and "Primary battery manufacturing." If an industry ends up being classified as both as green and polluting, we classify it as neither. All other sectors form the basis of the "outside" category.

Applying these definitions to employment numbers from the Quarterly Census of Employment and Wages (QCEW), 11.4 million workers were employed in the polluting sector as of the fourth quarter of 2004. This amounts to around 15% of all employment. By the second quarter of 2024, these sectors accounted for only 13.2% of employment. The clean sector, meanwhile, accounted for about 2.6% of employment in 2024, or 2.1 million workers. Polluting sector jobs are relatively high paying, with an average annual income of $39,233 in 2004, and so constituted almost $455 billion of wage payments in 2004 alone.

5.2 Steady State Calibration

We discretize our continuous time model into short periods corresponding to half a month which allow us to capture high-frequency movements in and out of employment, with a unit length of time corresponding to a year. Matching conventional measures of job flows at the monthly level is important for our quantitative analysis, even if we study a technological transition that takes place over many years. For instance, matching quarterly flows instead would underestimate firms' propensity to lay off workers since many workers who experience U-E transitions would in fact appear to experience E-E transitions at the quarterly level.

We start by calibrating externally some standard parameters (Table 1). We then discipline 12 parameters internally by matching 12 empirical moments at the initial stationary equilibrium (Table 2). All job flows are computed over one month and account for the possibility that workers might experience multiple job transitions within the same month, so that our flows are directly comparable to standard

Table 1: External calibration

Parameter	**Description**	**Value**	**Source**
Preferences			
J	Lifespan	40	Career length
ρ	Discount rate	0.05	Davis and von Wachter (2011)
Technology			
α	Elast. of matching function	1.599	Schaal (2017)
χ_0	Operating cost (arrival rate)	4	Quarterly review of workers

empirical estimates.[43] All targets are matched to numerical precision. Appendix B provides details about our numerical implementation.

External calibration. Workers live for 40 years ($J = 40$) and we set the discount rate $\rho = 0.05$ as in Davis and von Wachter (2011).[44] Our baseline exercise considers risk-neutral workers so that workers' values correspond to present discounted values of incomes and do not depend on assumptions about market completeness with respect to idiosyncratic risk (Section 2.1.3). Following Den Haan et al. (2000), we parameterize the matching function so that the job-finding and job-filling rates are given by $f(\theta) = (1 + \theta^{-\alpha})^{-1/\alpha}$ and $q(\theta) = (1 + \theta^{\alpha})^{-1/\alpha}$, respectively, and we set $\alpha = 1.6$ as in Schaal (2017). Finally, we pick $\chi_0 = 4$ so that operating cost shocks arise quarterly on average, reflecting quarterly performance reviews.

Search behavior. We calibrate the search intensity for unemployed workers λ^U to target a monthly UE rate of 25% (Shimer, 2005). Similarly, we pick the search intensity for employed workers λ^E to match the monthly EE rate of 2.5% (Fujita et al., 2024). We set the scale of job amenity shocks γ_ζ to replicate the fact that 37% of job-switchers experience a wage cut (Grigsby et al., 2021). We obtain a standard deviation of 0.022, which is relatively small relative to average flow wages.

Vacancy creations and job separations. We set the vacancy posting cost ν to match

[43] For instance, a worker for which we observe an E-E transition in the CPS over one month can, in fact, have experienced an E-U-E transition in the model.

[44] Empirically, we assume workers enter the workforce at age 25 and work until age 65.

Table 2: Internal calibration

Parameter	Description	Value	Moment	Source	Target	Model
Search						
λ^U	Search intensity (U)	7.024	UE rate (M)	Shimer (2005)	25%	25%
λ^E	Search intensity (E)	2.766	EE rate (M)	Fujita et al. (2024)	2.5%	2.5%
γ_ζ	Amenity (scale)	0.022	Share of wage cuts	Grigsby et al. (2021)	32.5%	32.5%
b^U	U benefit	0.304	Average UI replac.	US UI Rules	40%	40%
b^O	O benefit	0.493	Wage change (EUO)	CPS ORG	–35%	–35%
Vacancies						
ν	Vacancy post. cost	0.070	Average markdown	Berger et al. (2022)	25%	25%
Separations						
ϕ	Oper. costs (loc.)	-13.36	Unempl. rate	US Average	5%	5%
γ_ϵ	Oper. costs (scale)	6.006	Elasticity of separ.	Chan et al. (2023)	-2.0	-2.0
χ^O	Separation rate (O)	0.0380	Separation rate (M)	US Average	8%	8%
Life cycle						
a_0	Life cycle (lin.)	4.526	Match data on avg	CPS ORG	–	–
a_1	Life cycle (quadr.)	-2.514	Timing of hump	CPS ORG	–	–

an average markdown of 25%, which is in the middle of the range surveyed by Berger et al. (2022). This is a natural moment to target: if vacancy posting costs are high, firm values must also be high for the free entry condition (2.4) to hold, which pushes for a higher markdown. The markdown on wages determines the profitability of each job, and hence firms' incentives to create vacancies in the clean sector to absorb workers displaced by the transition. Targeting the average markdown is thus important to get the response of structural unemployment right along the transition. We obtain a vacancy posting cost of 7% of annual output, which is slightly below the estimate of Shimer, 2005 reflecting the fact that firms must additionally pay operating costs in our model, which reduces their steady state values *ceteris paribus*.

Turning to separations, the average log operating cost ϕ governs the rate at which matches are endogenously destroyed. We pick ϕ to match an average steady

state unemployment rate of 5%.[45] The scale of the log operating costs γ_ϵ controls the elasticity with which firms destroy matches when experiencing a productivity decline. In particular, the elasticity of separation to productivity shocks goes to zero as $\gamma_\epsilon \to \infty$ and to infinity as $\gamma_\epsilon \to 0$.[46] We target an elasticity of separations of –2 following a 15% permanent idiosyncratic productivity change, based on the evidence from Chan et al. (2023).[47] Targeting the separation elasticity is important in our context: a higher separation elasticity results in more job displacement and higher structural unemployment over the transition for incumbent workers. We set the exogenous separation rate in the outside sector to be equal to the mean separation rate of old-sector workers in steady state (0.038).

Replacement rates. The unemployment benefit b^U is chosen so that workers who get laid off have an average replacement rate of 40% as a share of their previous wage. We obtain $b^U = 0.304$ which reflects the fact that workers' wages are less than 1 in equilibrium and the selection among those who lose their job.[48] We discipline the flow payoff of the outside sector b^O using data from the Current Population Survey (CPS). The CPS is a monthly rotating panel designed to be representative of the US population. Households remain in the sample for four consecutive months, before rotating out for 8 months and back in for an additional four month spell. In the final month of each of these four-month "rotations," the CPS asks about individuals' wages in the "Outgoing Rotations Group" (ORG) supplement.[49] As discussed in Section 3, we focus on workers initially attached to the polluting sectors. We define these workers as those who spend the entire first rotation of the survey

[45] This is equivalent to matching the EU rate directly, since our calibration also targets the UE and EE rates.

[46] Of course, ϕ must also adjust in the limit $\gamma_\epsilon \to +\infty$. See Beraja and Zorzi (2024a) for an application to durable spending.

[47] Note this estimate comes from Denmark. This elasticity is also in line with the estimates of Carlsson et al. (2021). The 15% shock lies between the standard deviations of productivity shocks reported in these two papers. Separations include EU and EE transitions, both in the model and in the data. In the model, we consider a partial equilibrium exercise that only affects one firm and its worker. All aggregate quantities remain unchanged and so are workers' outside options.

[48] In particular, separation rates vary endogenously over the life cycle. On the one hand, older workers have accumulated more human capital $\psi^\star(j)$ which makes the matches more profitable and reduces the separation rate. On the other hand, older workers have a shorter active life which makes them more likely to be laid off.

[49] We deflate all nominal earnings to real terms using the CPI-U.

(four consecutive months) employed in the polluting sector.[50] We then measure the weekly earnings change of workers initially attached to polluting industries who first undergo an E-U transition followed by an U-E transition to any outside sector in their second rotation. The average replacement rate following such transition is 65%, which we target to pin down $b^O = 0.493$.

Life cycle. Finally, we assume that life-cycle productivity is $\psi^{\text{age}}(j) \equiv 1 + a_0 j + a_1 j^2$ to allow for the usual hump-shape in earnings. We choose the slope $a_0 > 0$ to ensure that there are no deviations on average between the life cycle profile of earnings among employed workers in the model and the life cycle profile of real wages from the Current Population Survey Outgoing Rotation Group (CPS ORG) over the period 1980–2019. Finally, we choose the quadratic coefficient $a_1 < 0$ to match the age at which average earnings peak.

5.3 The Path of Sectoral Productivities

The path of sectoral productivities is given by (3.1). We suppose that the transition function $\bar{\Phi}(t)$ follows the usual *S*-shape that characterizes technology adoption (Griliches, 1958) and which is often used in the context of clean energy and electric vehicle adoption (Schilling and Esmundo, 2009; Shepherd et al., 2012). Accordingly, we parameterize the shape of the transition $\bar{\Phi}(t)$ to take the form of a truncated normal CDF

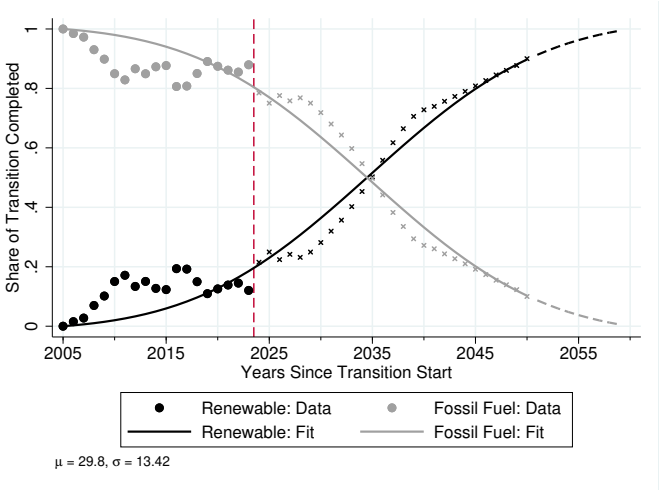
$$\bar{\Phi}(t; \mu, \sigma, T) = \min \left\{ \frac{\Phi\left(\frac{t-\mu}{\sigma}\right) - \Phi\left(\frac{0-\mu}{\sigma}\right)}{\Phi\left(\frac{T-\mu}{\sigma}\right) - \Phi\left(\frac{0-\mu}{\sigma}\right)}, 1 \right\} \qquad \text{for } t \geq 0, \tag{5.1}$$

where $\Phi(\cdot)$ is the CDF of a standard normal distribution, T is the horizon of the transition when $\eta = 1$, and μ and σ parametrize the normal distribution. If $\sigma \to 0$, the transition looks like a step-function at μ. On the contrary, if $\sigma \to \infty$, the transition becomes linear and $A_{k,t} = A_{k0} + \min\{t/T, 1\}(A_{k,\infty} - A_{k,0})$.

We fit μ and σ to match the shape of the transition from fossil fuels to renewable energy generation. Specifically, we use data and forecasts from the U.S. Energy Information Administration (EIA) on the share of power generated by fossil fuels

[50] Appendix C reports summary statistics about the workers attached to polluting- industries and the observables that predict this status.

Figure 5: Estimated S-curve of energy generation transmission



Notes: This figure plots the estimated S-curve of the transition, which is assumed to follow truncated normal CDF as in equation (5.1). The dashed lines indicate years in which we use projections instead of realized data.

and renewable sources between 2005 and 2050. We compute the share of total energy production produced by renewables and fossil fuels in each year. Then we subtract the minimal share of production from each fuel type so that the share of the transition completed in 2005 is 0. Finally, we normalize shares by the maximal share observed in the range so that the share of transition completed is equal to 90% in 2050 — the end of the US EIA projection. We then fit a truncated normal CDF to these normalized shares. As Figure 5 shows, the estimated curve fits the raw data well. Figure 1 plots the corresponding paths for the sectoral productivities $A_{k,t}$. The assumption underlying our approach is that the shape of the path of labor demand in the clean and polluting sectors will be well-approximated by the projected path of relative production of clean and polluting energy. We will perform various sensitivity analyses with respect to the parameters μ and σ.

There is great uncertainty about the long-run productivities of clean and polluting sectors $A_{k,\infty}$. We therefore study a menu of possible scenarios for $A_{k,\infty}$. The literature offers a wide range of estimates when it comes to the long-run employment effects of the energy transition. Most studies find only small impacts on the total level of employment in the economy (Finkelstein Shapiro and Metcalf, 2023; Weitzel et al., 2023; Eurofound, 2023; Borgonovi et al., 2023; Vandeplas et al., 2022). However, there is substantial debate about changes in the composition of jobs be-

tween clean and polluting in the long-run.[51] Our baseline analysis assumes 10% changes in productivity: $A_{C,\infty} = 1.1$ and $A_{P,\infty} = 0.9$.

5.4 Estimating the Skill Distribution and Training Cost

At this point, there are still two key objects to estimate: the distribution of skill endowments ψ^{endow}, and the training cost $\Psi\left(\psi^{\text{train}}; \psi^{\text{endow}}\right)$. Our goal is to estimate a set of skills that best matches some features of the data, conditional on the assumed scenario for labor demands $A_{k,t}$.

Identification. We identify the distribution of skill endowments non-parametrically by matching the observed labor reallocation between the clean and polluting sectors over the period 2005–2025. The idea is simple and can be understood by inspecting the left panel of Figure 2. In the Walrasian limit of Section 4, workers with higher ψ reallocate earlier. In particular, all workers with $\psi \geq A_{P,t}/A_{C,t}$ reallocate before period t so the share of workers who have already switched by period t is $1 - G\left(A_{P,t}/A_{C,t}\right)$. Labor reallocation over time therefore allows us to trace the distribution $G\left(\psi^{endow}\right)$ non-parametrically given the paths for $A_{k,t}$.[52] Of course, the process of labor reallocation is richer in our full quantitative model: workers differ in their employment statuses, some retrain while others do not, they are subject to

[51] In brief, the International Renewable Energy Agency (IRENA) estimates that 27.9% of energy sector employment will be in renewable energy, compared with 14.3% in conventional energy sectors, and 57.9% in "other transition-related sectors" such as grid upgrades, which implies that between 27.9% and 85.8% of jobs will be "clean" depending on what one assumes about the other transition-related sectors (IRENA, 2023b). A McKinsey report implies that 34.3% of jobs will be in clean industries (McKinsey & Company, 2022). Meanwhile, Mayfield et al. (2023) provide forecasts of US employment in sectors exposed to the climate transition under various scenarios to achieve net zero carbon emissions. Since their sectors are not defined at a sufficiently granular level to match our classifications of clean and polluting industries, we instead leverage the fact that "clean" sectors in our model are simply the set of jobs with rising labor demand and "polluting" sectors are those with declining labor demand, relative to trend. We therefore define "clean" sectors to be the set of sectors with above average growth in employment in Mayfield et al.'s reference case. This exercise implies that 65% of employment exposed to the climate-transition will be in clean sectors at the end of the transition. There is thus a fairly wide range.

[52] We consider a menu of terminal values $A_{k,\infty}$ in our analysis. Different terminal values generate different paths for relative productivities $A_{P,t}/A_{C,t}$, which in turn changes the estimated distribution $G\left(\psi^{\text{endow}}\right)$ that matches reallocation patterns in the data. However, we only match reallocation patterns from 2005-2024 for estimation of $G\left(\psi^{\text{endow}}\right)$. The long-run behavior of reallocation will still depend on the exact choice of $A_{k,\infty}$ given our time-invariant estimated distribution of skill endowments. Our baseline choice of $A_{k,\infty}$ is in-line with predictions elsewhere in the literature regarding both the scale and composition of employment in 2050.

amenity shocks, etc. However, we will show below that the same insight applies in our model, allowing us to estimate the distribution G.

It is worth noting that the aggregate path of sectoral labor reallocation does not separately identify the innate and acquired components of skill $\psi \equiv \psi^{\text{endow}} + \psi^{\text{train}}$. To disentangle the distribution of endowments from the training cost, we must therefore compare two cohorts born in different periods τ. The younger cohort has a longer life span and hence more time to recoup the training cost. As a result, it retrains more and hence reallocates more to the clean sector. This prediction is consistent with the data, as we discuss below.

We estimate the distribution of endowments $G\left(\psi^{\text{endow}}\right)$ non-parametrically, but specify a functional form for the training cost to reduce the dimensionality of our problem. Since the level of labor productivity in the clean sector $A_{C,\infty}$ cannot be separately disentangled from clean-sector skills, we normalize the highest clean sector skill to 1. Training costs are then assumed to take the form

$$\Psi\left(\psi^{\text{train}};\psi^{\text{endow}}\right) \equiv \frac{\varrho}{2} x\left(\psi^{\text{train}};\psi^{\text{endow}}\right)^2 \quad \text{with} \quad x\left(\psi^{\text{train}};\psi^{\text{endow}}\right) \equiv \frac{\psi^{\text{train}}}{1-\psi^{\text{endow}}},$$

where $\varrho > 0$ is the parameter to estimate and $x(\cdot)$ is the share of the skill gap $1-\psi^{\text{endow}}$ that the worker closes through training.

Our identification problem boils down to choosing the distribution G and the training cost ϱ to solve

$$\min_{G,\varrho} \sum_{\tau} \int_{2005}^{2024} \left(z_{\tau,t}^{\text{data}} - \int_0^1 z_{\tau,t}^{\text{model}}\left(\psi^{\text{endow}};\varrho\right) G\left(\mathrm{d}\psi^{\text{endow}}\right)\right)^2 dt, \tag{5.2}$$

where $z_{\tau,t}^{\text{data}}$ indicates the empirical share of workers in cohort τ that have reallocated between period 0 and t and $z_{\tau,t}^{\text{model}}\left(\psi^{\text{endow}};\varrho\right)$ indicates the share of workers in the same cohort and endowed with skill ψ^{endow} that have reallocated over the same period in the model.[53] The latter is a function of the training cost ϱ.

Threats to Identification. In our model, workers reallocate on the basis of their id-

[53] As discussed in section 2, we abstract from differences in absolute advantage. Doing so is without loss of generality for our analysis. However, this assumption prevents us from comparing wages in the model and in the data, since wages in the data are subject to composition effects. Studying wages would thus necessitate estimating a joint distribution of \psi_{P} and \psi_{C}, which would drastically complicate the estimation.

iosyncratic productivity ψ and the sectoral productivities $A_{k,t}$. Given a path of $A_{k,t}$ (Section 5.3), we use workers' labor reallocation to trace out the distribution G of idiosyncratic productivities ψ. One possible concern is that workers could also reallocate for amenity reasons, i.e., they enjoy supplying labor to the clean sector. We argue that this distinction is unimportant in our context. To understand why, consider the Walrasian limit of Section 4. Let us allow the relative amenity value of working in the clean sector to have both an idiosyncratic component ξ (some workers are more concerned with the environment than others) and an aggregate component Λ_t (working in the climate sector becomes more fashionable over time). Specifically, suppose that the flow payoffs from working in the clean sector are $A_{C,t}\Lambda_t\psi\xi$. Workers will supply labor to the clean sector if and only if the product of their idiosyncratic productivity ψ and their relative amenity ξ in the clean sector are sufficiently large relative to the relative sectoral productivities and the aggregate amenity, i.e., $\psi\xi \geq A_{P,t}/\left(\Lambda_t A_{C,t}\right)$. This condition is isomorphic to the one in Section 4, when setting

$$\psi' \equiv \psi\xi \quad \text{and} \quad A'_{C,t} \equiv \Lambda_t A_{C,t}$$

Accordingly, the path of sectoral productivities $A_{k,t}$ that we feed in (Section 5.3) should reflect the relative amenity value of supplying labor in the clean sector — this is partly the reason why we conduct various sensitivity analyses.[54] Given this path, our estimation backs out the distribution of $\psi\xi$ which determines workers' incentives to reallocate and values.

The picture is more complicated in the full model, where firm values influence vacancy posting and separations, but the same economics hold: if workers systematically prefer to work in the clean sector, they accept lower wage payments leading to higher firm values, exactly as if they were more skilled in that sector. Thus the distinction between amenities and productivity is not crucial for understanding the labor market effects of the climate transition in our context. Besides amenities, our estimates of ψ can also capture other forms of reallocation costs,

[54] One could attempt to infer this amenity value using data on the workers' wage gap across sectors. This exercise is complicated by the fact that the average wage in the polluting sector is subject to a strong survival bias among workers who decide to remain in the polluting sectors. In particular, the relative amenity value of supplying labor to the clean sector is not separately identified from the distribution of absolute advantage ψ_P in the polluting sector when the latter correlates with the comparative advantage $\psi \equiv \psi_C/\psi_P$ that we focus on (see footnote 7).

e.g., due to geographic mobility between employers. Regardless of its exact interpretation, the distribution of ψ that we estimate reflects the barriers to reallocation that workers incur when switching from polluting to clean jobs.

Finally, skill accumulation over time is partially accounted for by $\psi^\star(j)$. However, this term does not differ across sectors. Therefore, the estimated ψ captures the expected differential human capital accumulation in clean relative to polluting sectors over workers' remaining life. The training cost ϱ therefore captures both training costs and other reasons why present value human capital may differ across cohorts, such as differential human capital accumulation across sectors.

Estimation. We leverage the block recursivity of our directed search model (Menzio and Shi, 2011) to solve the problem (5.2) efficiently. This property allows us to solve workers' reallocation shares $z_{\tau,t}^{\text{model}}\left(\psi^{\text{endow}};\varrho\right)$ *independently* from the distribution G: there are no congestion externalities or general equilibrium price effects. The problem (5.2) boils down to solving for the distribution G given these optimal policies.

Our problem is further simplified by the assumption that incumbents workers only retrain in period $t = 0$. This assumption allows us to index workers' reallocation shares $\tilde{z}_{\tau,t}^{\text{model}}(\psi)$ by their productivity ψ *after training* which no longer depends on the training cost. Accordingly, the original problem becomes

$$\min_{G,\varrho} \sum_{\tau} \int_{2005}^{2024} \left(z_{\tau,t}^{\text{data}} - \int_0^1 \left(\int_0^1 \mathcal{P}_\tau \left(d\psi |\, \psi^{\text{endow}}, \varrho \right) \tilde{z}_{\tau,t}^{\text{model}}(\psi)\, d\psi \right) G\left(\mathrm{d}\psi^{\text{endow}} \right) \right)^2 dt,$$

where $\mathcal{P}_\tau\left(\cdot |\, \psi^{\text{endow}}, \varrho\right)$ indicates the post-training skill chosen by a worker endowed with ψ^{endow} given a cost ϱ.[55] This formulation offers an important computational advantage that makes the problem possible to solve: it allows us to compute the policies $\tilde{z}_{\tau,t}^{\text{model}}(\psi)$ only *once* and then *independently* solve for the distribution G and the training cost ϱ without having to recompute these policies.

Empirical implementation. The empirical series that we use for $z_{\tau,t}^{\text{data}}$ is the share of workers initially attached to polluting industries (Section 5.2) that reallocated

[55] Formally, this choice takes the form of a Dirac measure at a particular skill ψ. In our numerical implementation, we introduce preference shifters with a very small variance to smooth the skill accumulation problem (2.10).

to the clean sector, relative to those still employed in either clean or polluting. We will use the CPS to construct this series. There are two empirical challenges. First, the industry codings in the CPS from the Census are less granular than those uses for the definition of clean and polluting sectors (Section 5.1). To capture the reallocation that takes place within these coarser industry codings, we apply a correction of employment in clean and polluting sectors by attributing a fraction of manufacturing employment to clean and to polluting. The fraction allocated to clean is the share of cars sold that are electric as opposed to fossil fuel powered, as provided by the US EIA. The assumption is that workers' overall tendency to move to clean jobs within manufacturing is well-approximated by the movement towards clean output in the motor vehicle manufacturing sector.

The second challenge with the CPS is that it does not allow us to track specific workers over long periods of time. We therefore calculate the probability that an individual is attached to polluting industries in the pre-2005 period based on their education $\times$ sex $\times$ race $\times$ marital status $\times$ most granular available geography (county, CBSA, state, or national, depending on the cell). We then weight individuals in later waves of the CPS by the probability that they would have been attached to the polluting sector (Section 5.2) in the pre-2005 period according to their observables.

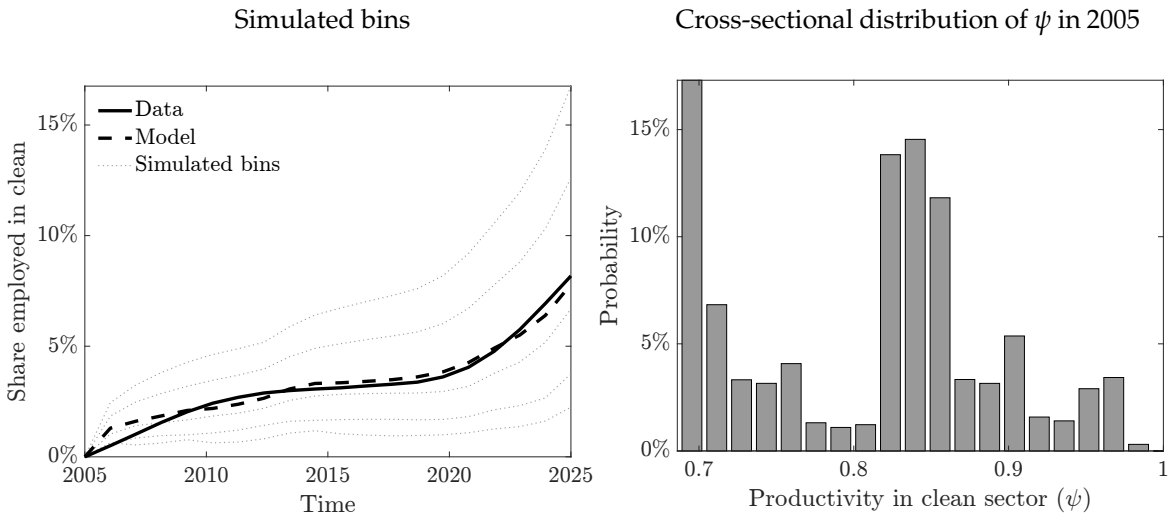
We repeat this exercise for two cohorts born in $\tau = 1960$ and $\tau = 1975$ that were either 30 or 45 years old in 2005.[56] Figure 10 in Appendix C plots the series $z_{\tau,t}^{\text{data}}$ for these two cohorts. According to our estimates, roughly 16% of workers initially attached to polluting industries have already reallocated to clean industries. This transition was slow at first but has accelerated more recently. As expected, younger workers are more likely to reallocate. The left panel of Figure 6 plots the same series after pooling these two cohorts for legibility (solid curve).

To implement our non-parametric estimation, we start by discretizing the grid for the productivity ψ into discrete bins. We simulate each of these bins forward, for each of our two cohorts τ. The left panel of Figure 6 plots $\tilde{z}_{\tau,t}^{\text{model}}(\psi)$ for productivity levels ψ chosen optimally by workers with various skill endowments ψ^{endow} after pooling the two cohorts together (dotted curves).[57] Workers with higher skill endowments reallocate more. Even those with relatively small endowment reallo-

[56] As a reminder, we assume that workers enter the labor force at 25.

[57] Formally, we plot $1/2 \sum_{\tau} \int_0^1 \mathcal{P}_{\tau}\left(d\psi | \psi^{\text{endow}}, \varrho\right) \tilde{z}_{\tau,t}^{\text{model}}(\psi) d\psi$.

Figure 6: Estimation of the skill distribution



Notes: The left panel plots the share of workers employed in the clean sector, relative to those employed either in the clean or polluting sectors. Workers are weighted by the probability that they are attached to the polluting sector, based on their observables and pre-2005 relationship between those observables and the likelihood of being attached to the polluting sector. We pool the two cohorts used for the estimation (born in 1960 and 1975) for legibility. The solid curve is the data from the CPS. The dotted curves correspond to simulated bins associated to various values of ψ^{endow}. For each of those, we solve for the training choice (2.10) to recover their choice of post-training productivity ψ given the estimated training cost ϱ. The dashed curve corresponds to the model-generated reallocation when using the estimated distribution of ψ^{endow}. The right panel plots the cross-sectional distribution of post-training productivity ψ in the population in 2005.

cate with some positive probability due to amenity shocks.[58] Our estimation then consists of running a non-parametric OLS regression of the observed time series $z^{\text{data}}_{\tau,t}$ on these simulated bins, imposing the constraint that the weight associated with these bins sum to 1. The dashed line indicates the fit of our model using the estimated distribution of skill endowments G and training cost ϱ. Our model matches the reallocation patterns very well.

The right panel of Figure 6 plots the cross-sectional distribution of post-training skills ψ induced by our estimates of G and ϱ. The distribution generally shows two types of workers. First, there is a mass of workers who have relatively high skill in the clean sector (above 0.85). These are the workers who reallocate quite quickly

[58] Absent amenity shocks, workers with an endowment ψ^{endow} below a certain cutoff do not reallocate by 2024; as a result, the distribution would not be identified below this cutoff. The presence of amenity shocks circumvents this issue by assuming that all workers have a positive probability to reallocate. Of course, the density could be less precisely estimated for small values of ψ^{endow}.

in the data; still, they give up at least 15% of their skill in order to benefit from the higher productivity in the clean sector. There is also a mass of workers with substantially lower skill in the clean sector (around $= 0.7$) who is much less likely to reallocate given the productivity gap across sectors (Figure 1). The estimation requires a mix between these two types to rationalize the slow start in labor reallocation and its recent uptick. We estimate a training cost of $\varrho = 0.0169$.

6 The Distribution of Lifetime Earnings Changes

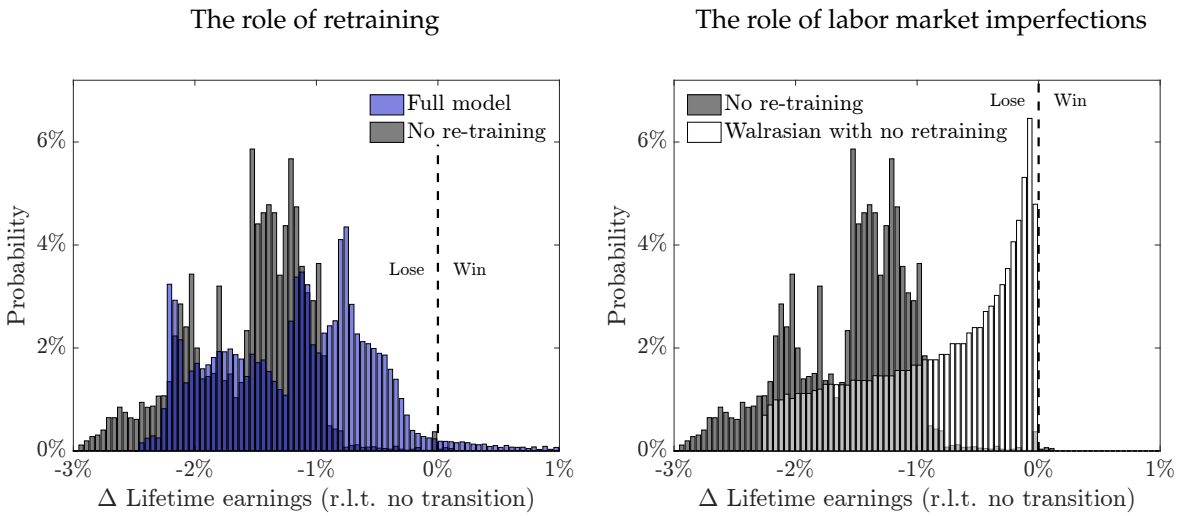
In this section, we use our estimated model to quantify the distributional effects of the climate transition and how they depend on its pace. Specifically, we use our model to answer two questions. First, what is the distribution of lifetime earnings losses that incumbents workers experienced as of 2005? Second, how would the distribution of earnings be affected if we changed the speed of the transition starting from 2025?

6.1 The Early Phase of the Transition

We start by computing the distribution of lifetime earnings changes, as of 2005, arising from a baseline climate transition ending in 2060 relative to a world without a transition (i.e. $A_{k,t} = 1$ forever in both sectors). This exercise provides us with a *level* that we will study *deviations* from in Section 6.2 as the transition accelerates. Effectively, we first quantify the gray area in Figure 2, before studying how this area changes from 2025 onwards as the pace of the transition picks up.

Figure 7 plots and decomposes the cross-sectional distribution of lifetime earnings changes for incumbent workers who were alive in 2005. The left panel reports the earnings changes produced by our full model (in blue). Most workers initially attached to polluting industries lose *in level* from the early phase of the transition, i.e., the gray area in Figure 2 is negative for them. This is unsurprising: our estimates suggest that workers initially attached to polluting industries have a productivity $\psi < 1$ in the clean sector. Only a few workers accumulate sufficient skills in the clean sector to benefit from the early phase of the transition. As we will see below, a substantial share of workers will *win* relative to this level as the transition accelerates from 2025 onwards.

Figure 7: Changes in expected lifetime earnings under the baseline transition



Notes: This figure plots the cross-sectional distribution of changes in lifetime earnings associated to the baseline transition that ends in 2060, relative to no transition at all. These earnings changes are those before we conduct counterfactuals where we change the speed of transition. We report *ex ante* expected earnings changes as of 2005. The left panel compares the distribution of earnings changes predicted by full model (in blue) and by a version with no retraining (in gray). The right panel contrasts these earnings changes to those predicted by the Walrasian model of Section 4 (in white). To ensure that the models are comparable, we use the same calibration, the same transition, and the same distribution of skill endowments ψ^{endow} in all models.

Workers who lose from the transition experience on average a 1.2% decrease in lifetime income as a result of the transition, but some workers experience losses up to twice as large. Importantly, these figures correspond to *ex ante* changes in expected lifetime earnings, i.e., the change in workers' values (Section 2.2). Some workers will experience much larger earnings changes *ex post* if they are displaced.[59]

As a point of comparison, the earnings losses that we estimate over the early phase of the transition are somewhat smaller than those documented in the influential literature on import competition from China. In particular, Traiberman (2020) finds that lifetime earnings fell by 5% for Danish workers exposed to rising import competition while Dix-Carneiro (2014) documents similar costs following trade liberalization in Brazil.[60] The fact that we find smaller earnings losses in

[59] Of course, welfare losses could be larger if workers are risk averse. We will add an extension with risk aversion.

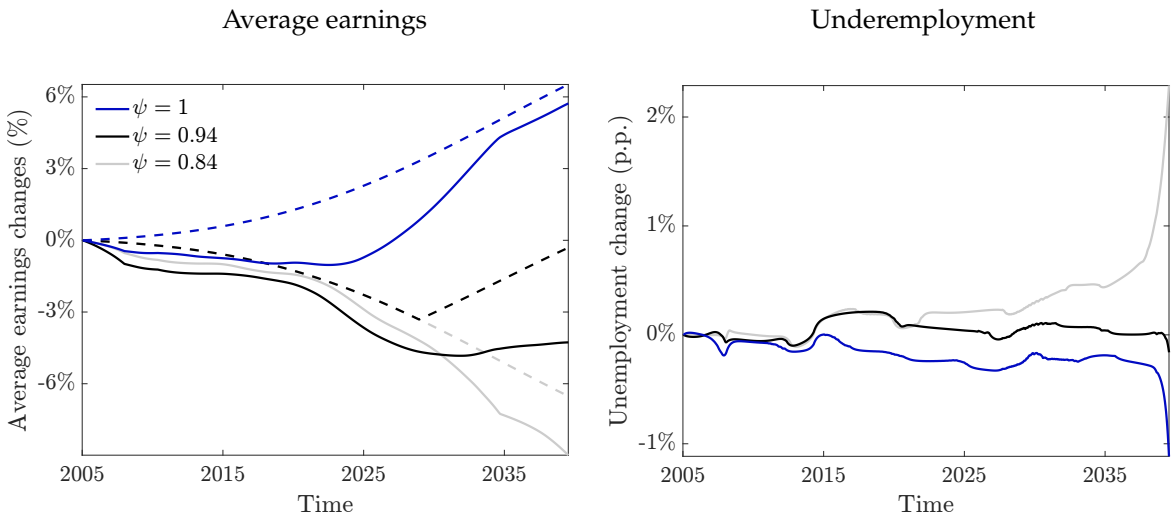
[60] Dix-Carneiro (2014) finds that intersectoral mobility costs are between 1.4 and 2.7 times annual average wages. This translates to roughly $3.5\% - 6.75\%$ when spread over a 40-year career.

our context is not particularly surprising since we report earnings changes for incumbents workers who were alive in 2005 when the climate transition was in its infancy — by 2025, less than 20% of the transition has played out. The nature of the transition is different too: import competition contributed to a decline in manufacturing that was not met by a boom in industries where the skills of displaced workers were in high demand; in contrast, workers' skills are more likely to be transferable between polluting and clean industries. Still, some workers will incur relatively large losses due to the climate transition. Therefore, it is perhaps unsurprising that it is met with political resistance since labor market disruptions can have a major impact on workers' political beliefs and behavior (Stantcheva, 2022; Autor et al., 2020).

Compensating workers who lose from the transition would be relatively expensive. We proceed as follows to express these losses in monetary terms. We start by computing each worker's lifetime earnings, i.e., the present discounted value of their earnings over their remaining life span. We combine this information with their loss in lifetime earnings due to the transition (Figure 7). This step accounts for the fact that some workers have a longer remaining lifespan than others, making it more costly to compensate them. We average the resulting number across workers to obtain an estimate of the present discounted value of earnings losses per capita. We express this amount in dollars by dividing that figure by the average annual earnings in the model and multiplying it by \$39,000 — the average earnings in 2004 that we measure in the CPS for workers attached to polluting industries. We obtain an average monetary loss of roughly \$6,830 per capita. Finally, we multiply this figure by 11.4 million, which is the number of workers attached to these industries in 2004 (Section 5.1). Compensating these workers would cost more than \$78 billion in present discounted terms, or \$3.65 billion per year in our model. For comparison, the U.S. Congress budgets roughly half a billion per year for the Trade Adjustment Assistance for Workers (TAA), a program that assists workers who lost their job to foreign competition. While expensive, compensating workers who suffer from the climate transition would still result in at a lower price tag than the \$300 billion in stimulus checks sent in early 2020.

We decompose these earnings changes to understand the role that retraining and labor market imperfections play in our results. In the left panel of Figure 7, we consider a version of our model in which workers cannot retrain over their

Figure 8: Earnings paths under the baseline transition



Notes: The left panel plots average earnings over time for workers who are 30 years old as of 2025, relative to a scenario with no transition. We consider a high-skill worker with $\psi = 1$ (in blue), a medium-skill worker with $\psi = 0.94$ (in black) and a lower-skill worker with $\psi = 0.84$ (in gray). The solid curves corresponds to the full model. The dotted curves correspond to the Walrasian model of Section 4. Average earnings includes unemployed workers, who receive flow benefits and workers in the low-paying outside sector O. The right panel plots the evolution of underemployment, i.e., the sum of the unemployment rate and the employment rate in O, relative to a scenario with no transition.

endowed level of skill ψ^{endow} (in gray). Unsurprisingly, removing the option to retrain increases the losses that workers incur. The average loss among workers who suffer from the transition increases by roughly 1/3, with some workers losing up to 3% of lifetime income.

In turn, the right panel of Figure 7 considers the Walrasian limit that we studied in Section 4 where labor markets are frictionless. The average loss among workers who suffer from the transition is essentially halved. In this limit, the distribution of losses is skewed to the left, i.e., most workers only experience small earnings losses. Overall, the distribution of expected earnings losses is qualitatively and quantitatively different than the one that we obtained in our full model. In other words, the quantitative features of our model — namely, search frictions, job-ladders, outside options, amenities, and endogenous separations — are important to assess the labor market implications of the climate transition.

Figure 8 helps explain the role that these quantitative features play in our model. The left panel plots the path of average earnings in our model relative to a scenario

with no transition. We consider various workers with different post-training skills ψ in the clean sector and who are 30 years old as of 2005. We report average earnings in our model (solid curves) and earnings in the Walrasian model where everyone is employed (dashed curves). Average earnings in our model include unemployed workers who receive flow benefits and workers in the low-paying outside sector O. We consider a high-skill worker with $\psi = 1$ (in blue) for whom the path of earnings is strictly increasing in the Walrasian limit; a middle-skill worker with $\psi = 0.94$ (in black) who switches during their lifetime in the Walrasian limit; and a lower-skill worker $\psi = 0.84$ (in gray) who remains in the polluting sector during their lifetime. The right panel plots the response of unemployment (in p.p.) for the same workers relative to the scenario with no transition.

Several features stand out. First, earnings changes in our model broadly track their Walrasian counterparts but still differ substantially from those. These differences are accounted for by three features that are not captured by the Walrasian model: the response of underemployment (i.e., a transition to unemployment or the low-paying O sector), the response of markdowns, and workers' search behaviors.

The role of underemployment is best exemplified by looking at low-skill workers. These workers experience an increase in underemployment toward 2035 when the transition picks up (Figure 1).[61] The reason is simple: the firing rate rises and the hiring rate declines in the polluting sector; at the same time, these workers are not sufficiently productive in the clean sector that firms find it profitable to post costly vacancies for them. Low-ψ workers thus face an unpleasant choice: they may either remain in their declining sector and search for a shrinking set of jobs with higher layoff risk, or they can seek a near-unattainable job in the growing sector. These workers therefore remain persistently underemployed and experience large earnings losses as a result.

The role of endogenous markdowns is best illustrated by looking at medium-skill workers. These workers do not experience any significant uptick in underemployment. Yet, their earnings changes are substantially below those predicted by the Walrasian model. As the transition unfolds, the marginal revenue product of

[61] The workers that we track also approach retirement by 2035. Their life cycle productivity $\psi^\star(j)$ plateaus and eventually declines slightly, therefore shutting off a force that was so far making these vacancies profitable.

labor goes down in the polluting sector. Posting vacancies becomes less and less profitable in that sector. In response, firms are only willing to offer lower wages to recoup the vacancy-posting or hiring costs. The markdowns on wages widens endogenously as a result.

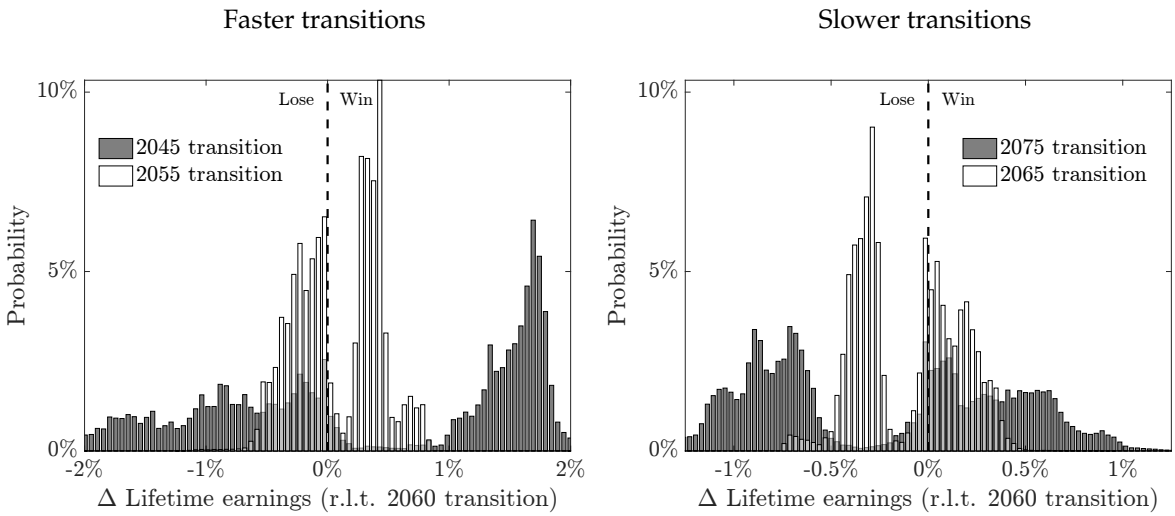
Finally, the role of workers' search behavior can be best understood by looking at high-skill workers. Their earnings remain flat at first in our model (and even decrease slightly), whereas they increase quickly in the Walrasian model. The reason is that workers' search behavior (2.6) is only partially directed in our model and hence imperfectly elastic to wage changes. In particular, workers are mostly indifferent at first between searching for a job in the clean sector where firms post higher wages, or in the polluting sector where firms post lower wages. As time passes, the wage gap between these two sectors widens and workers become more likely to direct their search towards the clean sector. As a result, earnings progressively catch up with their Walrasian counterparts.

6.2 Counterfactual Transitions Speeds

We now turn to our counterfactual analysis. We simulate various transitions, from 2025 onward, that end in 2055 and 2045, etc. as opposed to 2060 in our baseline transition. These counterfactual transitions satisfy equation (3.2), holding fixed the path of productivities until 2025. For each of these transitions, we compute the distribution of changes in workers' expected lifetime earnings relative to the baseline transition ending in 2060.

The left panel of Figure 9 considers two faster transitions — one ending in 2045 (in gray) and one ending in 2055 (in white). Two main features stand out. First, earnings changes are non-linear in the speed of the transition, i.e., the distribution associated to the 2045 transition is not simply a linearly "stretched" version of the other one. In particular, the left tail gets thicker as the transition accelerates. Second, a slight majority of workers would prefer to speed up the transition relative to 2060. Yet, a faster transition also induces substantial losses among some workers. A transition ending in 2045 leads some of them to lose an additional 2% of lifetime earnings relative to the baseline transition ending in 2060 — essentially doubling the earnings losses for low-ψ workers relative to a scenario with no transition at all. These findings echo those previewed in Section 4: while speeding up the tran-

Figure 9: Changes in expected lifetime earnings under counterfactual transitions



Notes: This figure plots the distribution of expected lifetime earnings changes from accelerating or slowing down the transition. The left panel consider two faster transitions ending in 2045 (gray bars) and 2055 (white bars), while the right panel considers two slower transitions ending in 2065 (white bars) and 2075 (gray bars). All earnings changes are expressed relative to a transition ending in 2060. Counterfactual transitions are computed following equation (3.2).

sition can increase the share of winners, it will also generate large losses for those who do not have the skills to reallocate to the clean sector. Again, it is worth noting that Figure 9 reports changes in expected earnings. Some workers can experience much large changes *ex post* if they get displaced. Overall, compensating workers who lose from a faster transition would also cost in the tens of billions of dollars. The fiscal cost of this intervention could be reduced if the government is able to tax workers who benefit from a faster transition.

Slowing down the transition also generates winners and losers, as shown in the right panel of Figure 9. Workers with low skills in the clean sector benefit from a slower transition, since it postpones the decline in the polluting sector that they are employed in. Meanwhile, workers who used to switch early to the clean sector under the 2060 transition now lose from a slower transition since fewer jobs opportunities are created in that sector.

The losses that we estimate stem principally from the forces described in Section 4: a faster transition leads to steeper declines while workers are in the polluting sector and faster gains after they switch to the clean sector. Relative to the Walrasian model, however, gains and losses are realized through job flows: losses

are incurred by separations to unemployment and falling off the job ladder in the polluting sector, while gains are realized through poaching and climbing the job ladder in the clean sector. Firms' values change with the speed of transition, affecting separations and job posting throughout the job ladder. Endogenous changes in employment and markdowns are quantitatively important for the earnings losses from the transition, as we discussed in Section 6.1.

As mentioned throughout this paper, we conduct a prospective analysis which comes with a substantial empirical uncertainty. We will therefore explore the sensitivity of our results by considering a range of targets for long-run employment shares, using alternative specifications for the shape of the transition's S-curve, and adjusting the thresholds at which a sector is considered polluting or clean. Finally, we will study the welfare losses for workers when they are hand-to-mouth and have curvature in their utility.

7 Conclusion

This paper studies the labor market consequences of changing the pace of the climate transition. We develop a life-cycle model in which workers with heterogeneous skills direct their job search across a polluting sector that declines over time and a clean sector that grows. The speed of transition generally has nonlinear or even non-monotonic effects on workers' lifetime earnings. In particular, policymakers face a trade-off between increasing the share of workers who benefit from the transition and thickening that tail of workers who lose from it. Two key features govern how the speed of transition affects lifetime earnings: the joint distribution of skill and age, and the response of structural unemployment. We discipline the response of unemployment by matching firms' propensity to separate from workers in response to productivity shocks. In turn, we estimate the joint distribution of skill and age using a novel estimation technique leveraging the block recursivity of directed search models. We find that workers attached to polluting sectors lose about 1.2% of lifetime earnings on average from a baseline climate transition ending in 2060. Accelerating the transition to complete by 2050 will lead many workers to be better off, but will exacerbate the losses suffered by those with the least transferable skills. Compensating workers who lose from a faster transition would cost in the tens of billions of dollars. Sensitivity analysis

for these numbers is ongoing.

The conceptual points raised in this paper inform the policy debate surrounding the climate transition. While the social benefits of curbing carbon emissions faster are well understood and quantified, we know much less about the costs imposed on workers as the transition gets faster. Quantifying the costs to workers initially attached to polluting sectors is a crucial and necessary first step to decide how ambitious climate goals should be and how to compensate these workers to raise support for such policies. Future work should study optimal policy when the transition speed is endogenously determined by market forces and fiscal policy, or when labor displacements spill over to the rest of the local economy.

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A Model Appendix

This section provides additional derivations and proofs about the model that we introduce in Section 2 and its Walrasian limit that we study in Section 4.

A.1 An Economy with Constant Growth Rates

This section studies a version of our model with long-run growth. We conceptualize long-run growth as operating through human capital; specifically, we assume that general human capital $\psi_t^\star(j)$ grows exogenously at rate g, so workers become more productive in all pursuits at the same constant rate g.

The set up is the same as the one presented in Section 2 with a few key exceptions. First, the cost of vacancy posting ν_t, the distribution of stochastic operating costs, and the variance of amenity shocks all grow at the same rate as productivity: $\nu_t = \nu e^{gt}, \phi_t = \phi e^{gt}, \gamma_{\epsilon,t} = \gamma_\epsilon e^{gt}$ and $\gamma_{\zeta,t} = \gamma_\zeta e^{gt}$. This implies that the separation function is now $\mathcal{F}(V_t e^{-gt})$, so that its input is the value of the firm scaled by the exogenous growth rate. Similarly, the training costs scale with the exogenous growth rate $\Psi_t(\psi^{\text{train}}; \psi^{\text{endow}}) = \Psi(\psi^{\text{train}}; \psi^{\text{endow}})e^{gt}$. Finally, we assume that entrepreneurs are risk-neutral.

Free entry becomes

$$q\left(\theta_t(j,\psi,s)\right) V_t(j,\psi,s) \leq \nu e^{gt}$$

in every period t and market s, with equality if a positive measure of vacancies are posted. This condition implies that the probability that a worker searching in a particular sector is able to find a job is given by a time-varying function $\tilde{f}_t(V_t) \equiv f\left(q^{-1}\left(e^{gt}\nu/V_t\right)\right)$. We can write the value of value of an employed worker in submarket s as

$$\begin{aligned}\rho W_t(j,\psi,s) =& wh(j,\psi,k)e^{gt} + \lambda^E \sum_{s'} p_t\left(s'; j,\psi,U\right) f\left(\theta_t\left(j,\psi,s'\right)\right)\left[W_t\left(j,\psi,s'\right) - W_t\left(j,\psi,s\right)\right] \\ &+ \chi_0 \mathcal{F}\left(V_t(j,\psi,k)e^{-gt}\right)\left[W_t\left(j,\psi,U\right) - W_t\left(j,\psi,s\right)\right] \\ &+ \left.\frac{d}{d\epsilon} W_{t+\epsilon}\left(j+\epsilon,\psi,s\right)\right|_{\epsilon=0}. \end{aligned} \tag{A.1}$$

Similarly, the value of an unemployed worker is

$$\rho W_t(j,\psi,U) = b^U \psi^\star(j) e^{gt} + \lambda^U \sum_s p_t(s;j,\psi,U) f(\theta_t(j,\psi,s)) [W_t(j,\psi,s) - W_t(j,\psi,U)] + \frac{d}{d\epsilon} W^U_{t+\epsilon}(j+\epsilon,\psi,U)\Big|_{\epsilon=0}. \quad \text{(A.2)}$$

The value of a worker employed in the outside sector O is

$$\rho W_t(j,\psi,O) = b^O \psi^\star(j) e^{gt} + \lambda^E \sum_s p_t(s;j,\psi,O) f(\theta_t(j,\psi,s)) [W_t(j,\psi,s) - W_t(j,\psi,O)] + \chi^O [W_t(j,\psi,U) - W_t(j,\psi,O)] + \frac{d}{d\epsilon} W_{t+\epsilon}(j+\epsilon,\psi,O)\Big|_{\epsilon=0}. \quad \text{(A.3)}$$

The retraining problem becomes

$$\max_\psi W_t(j,\psi,s) - \Psi\left(\psi - \psi^{\text{endow}};\psi^{\text{endow}}\right) e^{gt}. \quad \text{(A.4)}$$

The assumption that amenity shocks are distributed according to a Type-1 Extreme Value Distribution ensures that the probability that a worker with (j,ψ,s) chooses to search in submarket s' in period t is

$$p_t(s';j,\psi,s) \equiv \frac{\exp\left(f(\theta_t(j,\psi,s'))[W_t(j,\psi,s') - W_t(j,\psi,s)] / \left(\gamma_\zeta e^{gt}\right)\right)}{\sum_{\hat{s}} \exp\left(f(\theta_t(j,\psi,\hat{s}))[W_t(j,\psi,\hat{s}) - W_t(j,\psi,s)] / \left(\gamma_\zeta e^{gt}\right)\right)} \quad \text{(A.5)}$$

Finally, a firm's value is

$$\begin{aligned}\rho V_t(j,\psi,s) = {} & (A_{k,t} - w) h(j,\psi,k) e^{gt} \\ & - \chi_0 \left(1 - \mathcal{F}\left(V_t(j,\psi,k)e^{-gt}\right)\right) \mathbb{E}\left[\varepsilon\psi^\star(j)e^{gt} | \varepsilon\psi^\star(j)e^{gt} \le V_t(j,\psi,s)\right] \\ & - \left[\chi_0 \mathcal{F}\left(V_t(j,\psi,k)e^{-gt}\right) + \lambda^E \sum_{s'} f\left(\theta_t\left(j,\psi,s'\right)\right) p_t\left(s';j,\psi,s\right)\right] V_t(j,\psi,s) \\ & + \frac{d}{d\epsilon} V_{t+\epsilon}(j+\epsilon,\psi,s)\Big|_{\epsilon=0} \end{aligned} \quad \text{(A.6)}$$

We now define the following normalized value functions:

$$\tilde{W}_t(j,\psi,s) \equiv W_t(j,\psi,s)e^{-gt} \quad , \quad \tilde{V}_t(j,\psi,s) \equiv V_t(j,\psi,s)e^{-gt}$$

Note that we can write the job-finding rate as a function only of $\tilde{V}_t$ which does not change over time: $\tilde{f}\left(\tilde{V}_t\right) \equiv f\left(q^{-1}\left(\nu/\tilde{V}\right)\right)$ by using the free-entry condition to solve for θ. Substituting these normalized value functions into equations (A.2)-(A.6), dividing by e^{gt} and re-arranging yields an expression for the normalized values of employed workers

$$\begin{aligned}(\rho-g)\,\tilde{W}_t\left(j,\psi,s\right) =& wh(j,\psi,k) + \lambda^E \sum_{s'} p_t\left(s';j,\psi,s\right) f\left(\theta_t\left(j,\psi,s'\right)\right)\left[\tilde{W}_t\left(j,\psi,s'\right) - \tilde{W}_t\left(j,\psi,s\right)\right] \\ &+ \chi_0 \mathcal{F}\left(\tilde{V}_t(j,\psi,s)\right)\left[\tilde{W}_t\left(j,\psi,U\right) - \tilde{W}_t\left(j,\psi,s\right)\right] \\ &+ \left.\frac{d}{d\epsilon}\tilde{W}_{t+\epsilon}\left(j+\epsilon,\psi,s\right)\right|_{\epsilon=0}, \end{aligned} \tag{A.7}$$

Similarly, the normalized value for unemployed workers is

$$\begin{aligned}(\rho-g)\,\tilde{W}_t(j,\psi,U) =& b^U\psi^\star(j) + \lambda^U \sum_{s} p_t\left(j,\psi,s\right) f\left(\theta_t\left(j,\psi,s\right)\right)\left[\tilde{W}_t\left(j,\psi,U\right) - \tilde{W}_t\left(j,\psi,U\right)\right] \\ &+ \left.\frac{d}{d\epsilon}\tilde{W}^U_{t+\epsilon}(j+\epsilon,\psi,U)\right|_{\epsilon=0} \end{aligned} \tag{A.8}$$

and the firm values of a filled job is

$$\begin{aligned}(\rho-g)\,\tilde{V}_t\left(j,\psi,s\right) =& \left(A_{k,t}-w\right)h(j,\psi,k) - \chi_0\left(1-\mathcal{F}\left(\tilde{V}_t(j,\psi,s)\right)\right)\mathbb{E}\left[\psi^\star\left(j\right)\varepsilon|\psi^\star\left(j\right)\varepsilon \leq \tilde{V}_t(j,\psi,s)\right] \\ &- \left[\chi_0\mathcal{F}\left(\tilde{V}_t(j,\psi,s)\right) + \lambda^E\sum_{s'} f\left(\theta_t\left(j,\psi,s'\right)\right) p_t\left(s';j,\psi,s\right)\right] V_t\left(j,\psi,s\right) \\ &+ \left.\frac{d}{d\epsilon}\tilde{V}_{t+\epsilon}(j+\epsilon,\psi,s)\right|_{\epsilon=0}. \end{aligned} \tag{A.9}$$

These value functions take the same form as equations (2.7) through (2.11) in the main text with $g = 0$, as do analogous "tilde" equations for the value of the outside sector. The only difference is that agents' effective discount rate is now $\rho - g$.

Therefore, the model with growth has the same value functions as the model without growth, calibrated to a different discount rate.

It remains to show that search probabilities and training decisions are the same in both the normalized economy and the full economy. First note that one can divide the problem (A.4) by e^{gt} to arrive at

$$\max_{\psi} \tilde{W}_0(j,\psi,s) - \Psi\left(\psi - \psi^{\text{endow}}; \psi^{\text{endow}}\right)$$

which is the same as equation (2.10) in the main text, only with the normalized values. Thus, training decisions will be the same in the economy with and without trend growth. Finally, substituting the definition of $\tilde{W}(\cdot)$ into equation (A.5) gives

$$p_t\left(s'; j,\psi,s\right) \equiv \frac{\exp\left(f\left(\theta_t\left(j,\psi,s'\right)\right)\left[\tilde{W}_t\left(j,\psi,s'\right) - \tilde{W}_t\left(j,\psi,s\right)\right] / \left(\gamma_\zeta e^{gt}\right)\right)}{\sum_{\hat{s}} \exp\left(f\left(\theta_t\left(j,\psi,\hat{s}\right)\right)\left[\tilde{W}_t\left(j,\psi,\hat{s}\right) - \tilde{W}_t\left(j,\psi,s\right)\right] / \left(\gamma_\zeta e^{gt}\right)\right)},$$

which is the same as what would be chosen in zero growth economy as well. Therefore, all choices and (normalized) value functions in the economy with growth are the same as in the economy with no growth, calibrated to a different discount rate. As a result, it is without loss of generality to study the zero-growth economy and interpret the sectoral transitions as being relative to a long run exogenous trend.

A.2 Equilibrium Definition

An equilibrium consists of the value functions for workers $W_t(j,\psi,s)$ and firms $V_t(j,\psi,s)$ defined in Section 2.2, search decisions $p_t(s';j,\psi,s)$ and training decisions $\psi_t^{\text{train}}(j,\psi^{\text{endow}},s)$, and distributions $\boldsymbol{\mu}_t(j,\psi,s)$ over ages, skills and employment states. As is standard of directed search models (Menzio and Shi, 2011), the equilibrium features a block recursive structure.

Definition 1. Given a speed of transition η and an initial distribution of worker ages, skills and employment states $\boldsymbol{\mu_0}(j,\psi,s)$, a *block-recursive equilibrium (BRE)* consists of value functions for workers $W_t(j,\psi,s)$ and firms $V_t(j,\psi,s)$, as well as policy functions $p_t(s';j,\psi,s)$ and $\psi_t^{\text{train}}\left(j,\psi^{\text{endow}},s\right)$, and distributions $\boldsymbol{\mu}_t(j,\psi,s)$. These functions satisfy the following conditions:

1. The value of employed workers in submarket s, $W_t(j, \psi, s)$, satisfies the Bellman equation (2.7) with boundary condition $W_t(J, \psi, s) = 0 \ \forall t, \psi, s$,

2. The value of unemployed workers, $W_t(j, \psi, U)$, satisfies the Bellman equation (2.8) with boundary condition $W_t(J, \psi, U) = 0 \ \forall t, \psi$,

3. The value of workers in the outside sector, $W_t(j, \psi, O)$, satisfies the Bellman equation (2.9) with boundary condition $W_t(J, \psi, O) = 0 \ \forall t, \psi$,

4. The value of a filled job in sector k, $V_t(j, \psi, s)$, satisfies Bellman equation (2.11) with boundary condition $V_t(J, \psi, s) = 0 \ \forall t, \psi, s$,

5. Workers' search behavior $p_t(s'; j, \psi, s)$ satisfies expression (2.6),

6. Workers' training decisions $\psi_t^{\text{train}}\left(j, \psi^{\text{endow}}, s\right)$ solve problem (2.10) where $\psi^{\text{train}} \equiv \psi - \psi^{\text{endow}}$,

7. Vacancy posting satisfies the free entry condition (2.4) in every period t and submarket s, with equality if a positive measure of vacancies are posted, and

8. The evolution of the distribution of workers across employment states $\boldsymbol{\mu_t}(j, \psi, s)$ is consistent with the flows implied by the value functions.

A.3 Results in the Walrasian Model

This section formalizes the discussion of Section A.1 where we consider a Walrasian limit of our model. We show that the results that we discussed in that section generalize to weaker conditions on the transition and arbitrary CRRA preferences with weak risk aversion (i.e., not just the risk neutral case). Throughout this section, we depart from the S-curved transition assumed in the main text to instead impose Assumption 1 which is more general. In the rest of this proof, we interpret the initial period $t = 0$ as the year 2025 to capture the counterfactuals that we conduct in Section A.1.

Assumption 1. *Let $A_{k,t}(\eta)$ denote the marginal revenue product of labor in sector k in period t when the speed of transition is η. Assume:*

1. $A_{k,t}(\eta)$ and $\hat{A}_t(\eta) \equiv \frac{A_{C,t}(\eta)}{A_{P,t}(\eta)}$ are twice differentiable in t and η at $t = 0$ and almost everywhere,

2. *For all* t *and* η, $\partial_t A_{P,t}(\eta) \leq 0 \leq \partial_t A_{C,t}(\eta)$, $\partial_\eta \partial_t A_{C,t}(\eta) \geq 0$, $\partial_\eta \partial_t A_{P,t}(\eta) \leq 0$, *and*

3. $\lim_{\eta \to \infty} \hat{A}_t(\eta) = \dfrac{A_{C,\infty}}{A_{P,\infty}}$ *for all* t *and* $\partial_t A_{P,t}(0) = \partial_t A_{C,t}(0) = 0$

4. *There exists some* $n > 0$ *such that the* n^{th} *partial derivative of* $A_{P,t}(\eta)$ *with respect to* η *is bounded at* $t = 0$ *in the limit as* $\eta \to \infty$: $\left| \lim_{\eta \to \infty} \dfrac{\partial^n A_{P,0}(\eta)}{\partial \eta^n} \right| < \infty$.

The first assumption means that the transition is smooth almost everywhere. The second assumption defines the kinds of transitions we can consider, i.e., the polluting sector declines (relative to trend) while the clean sector grows. A larger η speeds up the transition in the sense that it translates into a faster productivity growth in the clean sector and a faster decline in the polluting sector. The third assumption states that, in the limit as η goes to infinity, the ratio of clean-to-polluting productivity instantly jumps to its long run level. On the contrary, there is no transition at all if $\eta = 0$. The fourth is a technical condition to ensure that as the transition grows infinitely fast, some rate of change of the old sector's technology path is bounded. Overall, this set of assumptions is strictly weaker than those presented in Section A.1 — i.e., our claims about non-monotonicity do not dependent on the particular transition that we assumed in that section.

We start by showing that the set of workers (ψ, τ) can be partitioned into three groups, based on their optimal stopping time $t^\star(\psi; \eta) = 0$. With an abuse of notation, we let $\psi \equiv \psi_C / \psi_P$denote a worker's relative skills in clean versus polluting sectors as we did in Section A.1.

Lemma 1. *The set of workers* (ψ, τ) *can be partitioned into:*

1. ***Always switchers*** *with* $\psi \geq \hat{A}_0^{-1}$ *who move immediately to the clean sector as* $t^\star(\psi; \eta) = 0$ *for any* η,

2. ***Never switchers*** *with* $\psi \leq \hat{A}_\infty^{-1}$ *who never move to the clean sector as* $t^\star(\psi; \eta) = \infty$ *for any* η,

3. ***Occasional switchers*** *with* $\psi \in \left(\hat{A}_\infty^{-1}, \hat{A}_0^{-1}\right)$ *who potentially move to the clean sector as* $0 < t^\star(\psi; \eta) < \infty$. *For these workers,* $t^\star(\psi; \eta)$ *strictly decreases with the relative productivity in the clean sector* ψ *and the transition speed* η *and satisfies* $t^\star(\psi; \eta) \to 0$ *as* $\eta \to \infty$. *Furthermore, these workers actually switch sectors during*

their lifetime if they are sufficiently young and the transition is sufficiently fast that $t^\star(\psi;\eta) \leq J + \tau$.

The proof is straightforward: always-switchers prefer to be in the clean sector from period 0 onwards even if the clean sector never takes off relative to its initial level; never-switchers prefer to be in the polluting sector even after the transition is complete and $\hat{A}_t$ has reached its maximum value; and occasional switchers lie in between and switch during their lifetime if the transition is fast enough.

We let $t_0(\tau) \equiv \min\{0, \tau\}$ denote the first period a worker works after the beginning of transition. Accordingly, we define a worker's lifetime welfare as

$$\begin{aligned}\mathcal{W}(\tau, \boldsymbol{\psi}; \eta) = &\int_{t_0(\tau)}^{t^\star(\hat{\psi};\eta)} e^{-\rho(t-t_0(\tau))} u\left(A_{P,t}(\eta)\right) dt \\ &+ \psi \int_{t^\star(\hat{\psi};\eta)}^{J+\tau} e^{-\rho(t-t_0(\tau))} u\left(A_{C,t}(\eta)\,\psi\right) dt \end{aligned} \tag{A.10}$$

when normalizing the productivity $\psi_P \equiv 1$ in the polluting sector (see footnote 7).

Proposition 1. *Changes in lifetime earnings* $d\mathcal{W}(\tau, \psi; \eta)/d\eta$ *are*

1. ***Increasing*** *in* η *for the always-switchers with* $\psi \geq \hat{A}_0^{-1}$,
2. ***Decreasing*** *in* η *for the never-switchers with* $\psi \leq \hat{A}_\infty^{-1}$,
3. ***U-shaped*** *in* η *for the occasional switchers with* $\psi \in \left(\hat{A}_\infty^{-1}, \hat{A}_0^{-1}\right)$. *Formally, for each relative productivity* ψ *and birth date* τ, *there exist critical speeds* $0 < \eta_l(\psi, \tau) < \eta_h(\psi, \tau) < \infty$ *such that* $\mathcal{W}(\tau, \psi; \eta)$ *is decreasing in* η *for* $\eta < \eta_l(\psi, \tau)$ *and increasing in* η *for* $\eta > \eta_h(\psi, \tau)$.

Proof. First, consider the always-switchers. These individuals switch as soon as the clean sector appears, regardless of the transition speed, i.e., $t^\star(\hat{\psi};\eta) = 0$ for all η. Their earnings increase monotonically over time, so they are trivially made better off by a faster transition. On the contrary, never-switchers stay put in the polluting sector, i.e., $t^\star(\hat{\psi};\eta) = \infty$ for all η. Their earnings decrease monotonically over time, so they are trivially made better off by a faster transition.

We therefore focus on the occasional-switchers in the remaining of this proof. For these workers, there exists some transition speed η that will incentivize them to

switch sector. We claim that there exist some transition speeds $0 < \eta_l < \eta_h < +\infty$ such that $\partial_\eta \mathcal{W}(\tau, \psi; \eta) < 0$ for all $\eta \leq \eta_l$ and $\partial_\eta \mathcal{W}(\tau, \psi; \eta) > 0$ for all $\eta \geq \eta_h$. In other words, worker's welfare is decreasing at first in the speed of transition but eventually increasing in it.

To establish this result, we consider an arbitrary worker (ψ, τ) who is an occasional switcher as defined in Lemma 1. We start by characterizing the lower cutoff $\eta_l(\psi, \tau)$. By definition, $0 < t^\star(\hat{\psi}; \eta) < \infty$ for this worker. Note that $t^\star(\hat{\psi}; \eta)$ is continuous and decreasing in η since $\hat{A}_t(\eta)$ is continuous and increasing in η. Furthermore, this worker never switches absent a transition, i.e., $t^\star(\hat{\psi}; \eta) \to +\infty$ as $\eta \to 0$, and switches immediately if the transition is instantaneous, i.e., $t^\star(\hat{\psi}; \eta) \to 0$ as $\eta \to +\infty$. By the Intermediate Value Theorem, there exists some transition speed η_l such that the worker switches precisely in the period when they retire $t^\star(\hat{\psi}; \eta_l) = J + \tau$. Then, for all transition speeds slower than that $\eta < \eta_l$, the worker remains in the polluting sector for its whole career and is made worse off by a faster transition.

We next characterize the upper cutoff $\eta_h(\psi, \tau)$. The change in welfare associated to a faster transition is

$$\begin{aligned}
\frac{d\mathcal{W}(\tau, \psi; \eta)}{d\eta} &= \int_0^{t^\star(\psi;\eta)} e^{-\rho t} u'\left(A_{P,t}(\eta)\psi_P\right) \frac{\partial A_{P,t}(\eta)}{\partial \eta} dt \\
&\qquad + \psi \int_{t^\star(\psi;\eta)}^{J+\tau} e^{-\rho t} u'\left(A_{C,t}(\eta)\psi_C\right) \frac{\partial A_{C,t}(\eta)}{\partial \eta} dt \\
&\geq u'\left(b^U\right) \int_0^{t^\star(\psi;\eta)} e^{-\rho t} \frac{\partial A_{P,t}(\eta)}{\partial \eta} dt \\
&\qquad + u'\left(A_{C,\infty}\psi_C\right) \psi \int_{t^\star(\psi;\eta)}^{J+\tau} e^{-\rho t} u'\left(A_{C,t}(\eta)\psi_C\right) \frac{\partial A_{C,t}(\eta)}{\partial \eta} dt \qquad \text{(A.11)}
\end{aligned}$$

The equality uses a version of the envelope theorem and the fact that $t^\star(\hat{\psi}; \eta)$ is chosen optimally.[62] In turn, the inequality uses the fact that workers' marginal utility $u'(c)$ is weakly increasing, that the marginal revenue product of labor decreases in the polluting sector and increases in the clean sector so $\partial A_{P,t}(\eta)/\partial \eta < 0 < \partial A_{C,t}(\eta)/\partial \eta$ and $A_{C,t}(\eta) \leq A_{C,\infty}$ for all t, and that workers always have the option to become unemployed and receive benefits b^U.

[62] In particular, the two integrands are equal to one another in period $t = t^\star(\psi; \eta)$.

The right-hand side of (A.11) features a negative term and a positive one. We will show that that there exists some $\eta_h(\psi,\tau) < \infty$ such that the second term dominates for all transition speeds $\eta > \eta_h(\psi,\tau)$ .To do so, note again that the worker switches instantaneously $t^\star\left(\hat{\psi};\eta\right) \to 0$ in the limit $\eta \to \infty$ where the transition is instantaneous. In this limit, the first term on the right-hand side of (A.11) vanishes, leaving only the positive second term, so long as $\dfrac{\partial A_{P,t}(\eta)}{\partial \eta}$ grows to infinity slower than $t^*(\psi;\eta)$ goes to zero, which is guaranteed by condition 4 of Assumption 1 and applying L'Hopital's rule. By continuity, there exists indeed some $\eta_h(\psi,\tau) < \infty$ so that the second term dominates.

B Computational Appendix

B.1 Workers' and Firm's Values

In this appendix, we formulate workers' and firms' values recursively.

States. Workers are indexed by their age j; their productivity ψ in the clean sector; their employment status $e = E, O, U$; and, if employed, their occupation k; and their wage w. The last three states can be combined into a single state s which corresponds to a market (k,w) when the worker is employed, or to O or U when the worker is employed in the outside sector or unemployed.

Workers. The value of an employed worker satisfies

$$\begin{aligned}\rho W_t(j,\psi,s) = {} & w(s)\,h(j,\psi,k) \\ & + \lambda^E \sum_{s'} p_t\left(s';j,\psi,s\right) f\left(\theta_t\left(j,\psi,s'\right)\right)\left\{W_t\left(j,\psi,s'\right) - W_t(j,\psi,s)\right\} \\ & + \chi_0 \mathcal{F}\left(V_t(j,\psi,s)\right) \times \left[W_t(j,\psi,U) - W_t^E(j,\psi,s)\right] \\ & + \frac{d}{d\epsilon} W^E_{t+\epsilon}(j+\epsilon,\omega,z,s)\Big|_{\epsilon=0}\end{aligned} \tag{B.1}$$

for all ages before retirement $j \in [0,J)$, productivity ψ in the clean sector and markets $s \equiv (k,w)$. Employed workers can search for jobs in sector $k \in \{P,C,O\}$.[63]

[63] The transition to the outside sector is immediate $f(\theta_t(j,\psi,O)) = 1$. So is the transition from

Expression (B.1) uses the fact that the amenity shocks follow a Type-1 Extreme Value distribution so the value of job search can be expressed in closed firm (Artuç et al., 2010). The probability that worker searches in market s' when they receive a search opportunity and are employed in sector s is

$$p_t\left(s';j,\psi,s\right) \equiv \frac{\exp\left(f\left(\theta_t\left(j,\psi,s'\right)\right)\left[W_t\left(j,\psi,s'\right)-W_t\left(j,\psi,s\right)\right]/\gamma_\zeta\right)}{\sum_{\hat{s}}\exp\left(f\left(\theta_t\left(j,\psi,\hat{s}\right)\right)\left[W_t\left(j,\psi,\hat{s}\right)-W_t\left(j,\psi,s\right)\right]/\gamma_\zeta\right)} \tag{B.2}$$

The value of an unemployed worker satisfies

$$\begin{aligned}\rho W_t\left(j,\omega,U\right) = {} & b^U\psi^\star\left(j\right) \\ & + \lambda^U\sum_s p_t\left(s;j,\psi,U\right)f\left(\theta_t\left(j,\psi,s\right)\right)\left\{W_t\left(j,\psi,s\right)-W_t\left(j,\psi,U\right)\right\} \\ & + \frac{d}{d\epsilon}W^U_{t+\epsilon}\left(j+\epsilon,\omega,D\right)\Big|_{\epsilon=0},\end{aligned} \tag{B.3}$$

for all ages before retirement $j \in [0,J)$ and productivity ψ in the clean sector. Unemployed workers can search for jobs in sector $k \in \{P,C,O\}$ or transition to non-employment N. We omit the values for workers employed in the outside sector (2.9) since they are similar to the ones stated above. The main difference is that workers out of the labor no longer search for jobs, i.e., they retire early. The boundary conditions associated to the workers' values are

$$W_t\left(J,\psi,s\right) = W_t\left(J,\psi,U\right) = W_t\left(J,\psi,O\right) = 0 \tag{B.4}$$

for all workers when they retire at age $j = J$.

Firms. The value of a firm $V_t\left(j,\psi,s\right)$ determines the firing probabilities $\mathcal{F}\left(V_t\left(j,\psi,s\right)\right)$ and the equilibrium tightnesses $\theta_t\left(j,\psi,s\right)$. The value of a firm, excluding vacancy-posting and current operating costs, satisfies

$$\begin{aligned}rV_t\left(j,\psi,s\right) = {} & \left(A_{k(s),t}-w\left(s\right)\right)h\left(j,\psi,k\right)+\chi_0\left\{\mathcal{O}_t\left(j,\psi,s\right)-V_t\left(j,\psi,s\right)\right\} \\ & - \lambda^E Q_t\left(j,\psi,s\right)V_t\left(j,\psi,s\right) \\ & + \frac{d}{d\epsilon}V_{t+\epsilon}\left(j+\epsilon,\psi,s\right)\Big|_{\epsilon=0},\end{aligned} \tag{B.5}$$

unemployment to non-employment $f\left(\theta_t\left(j,\psi,N\right)\right)=1$ in expression (B.3).

for all ages before retirement $j \in [0, J)$, produtivity ψ in the clean sector, and markets $s \equiv (k, w)$, where $r \equiv \rho$ is the interest rate. The firm incurs a fixed cost of production with flow probability χ_0 and continues operating when this cost is lower than the firm's continuation value of keeping the worker. The expected value of the resulting discrete choice is

$$\mathcal{O}_t(j, \psi, s) \equiv \Phi\left(\frac{\log\left(V_t(j, \psi, s) / \psi^\star(j)\right) - \phi}{\gamma_\epsilon}\right) V_t(j, \omega, z, s) \tag{B.6}$$

$$- \psi^G(j) \exp\left(\phi + \frac{1}{2}\gamma_\epsilon^2\right) \Phi\left(\frac{\log\left(V_t(j, \psi, s) / \psi^\star(j)\right) - \phi - \gamma_\epsilon^2}{\gamma_\epsilon}\right) \tag{B.7}$$

where Φ is the cumulative distribution function of a standard normal distribution and ϕ and γ_ϵ are the location and scale parameters of the distribution of operating costs. The firm continues operation and pays the operating cost whenever this cost is less than the value of the firm, i.e., $\exp(\phi + \gamma\epsilon) \leq V_t^{\text{keep}}(j, \omega, z, s)$ where $\epsilon \sim \Phi$. The first line in (B.6) corresponds to the expected continuation value and the second line corresponds to the expected operating cost paid by the firm when it continues operation.[64] Accordingly, the firm dissolves the match and fires the worker with probability

$$\mathcal{F}(V_t(j, \psi, s)) = 1 - \Phi\left(\frac{\log\left(V_t(j, \psi, s) / \psi^\star(j)\right) - \phi}{\gamma_\epsilon}\right) \tag{B.8}$$

The match may also dissolve if the worker searches on-the-job at rate λ^E and separates from the firm when this search is successful with probability $Q(j, \psi, s)$. The boundary condition associated with (B.5) is

$$V_t(J, \psi, s) = 0 \tag{B.9}$$

for all workers (ψ, s) when they retire at age $j = J$.

Free entry. The equilibrium tightnesses $\theta(j, \omega, z, s)$ are pinned down by the firms'

[64] Formally, the second line is equal to $\int_{-\infty}^{\bar{\epsilon}} \exp(\gamma\epsilon + \phi) \exp\left(-\frac{\epsilon^2}{2}\right) / \sqrt{2\pi} d\epsilon$ with $\bar{\epsilon} \equiv \left(\log\left(V_t(j, \omega, s)\right) - \phi\right) / \gamma$.

free entry condition

$$q\left(\theta_t\left(j,\psi,s\right)\right)V_t\left(j,\psi,s\right)=\nu\psi^{\star}\left(j\right) \tag{B.10}$$

B.2 Solving for the Workers' and Firms' Values

Discretized system. We start by discretizing the differential equations of Appendix B.1.[65] Our finite difference scheme is implicit with respect to the markets s, except when it involves non-linear terms that depend on the workers' values. For instance, $p_t\left(s';j,\psi,s\right)$ is defined by (B.2) and depends non-linearly on W_t. We use an explicit scheme for these terms, i.e., we compute we evaluate these terms in $t+\Delta$. As usual, the scheme is explicit in age j and time t.

After discretization, the value of being employed becomes

$$\begin{aligned}\rho W_t\left(j,\psi,s\right)=&\,w\left(s\right)h\left(j,\psi,k\left(s\right)\right)\\&+\lambda^E\sum_{s'}p_{t+\Delta}\left(s';j,\psi,s\right)f\left(\theta_{t+\Delta}\left(j+\Delta,\psi,s'\right)\right)\\&\qquad\times\left[W_{t+\Delta}\left(j+\Delta,\psi,s'\right)-W_{t+\Delta}\left(j+\Delta,\psi,s\right)\right]\\&+\chi_0\mathcal{F}\left(V_{t+\Delta}\left(j+\Delta,\psi,s\right)\right)\\&\qquad\times\left[W_t\left(j,\psi,U\right)-W_t\left(j,\psi,s\right)\right] &\text{(B.11)}\\&+\frac{W_{t+\Delta}\left(j+\Delta,\psi,s\right)-W_t\left(j,\psi,s\right)}{\Delta} &\text{(B.12)}\end{aligned}$$

for all markets $s\equiv(k,w)$ excluding unemployment, where $\Delta>0$ denotes the time step. The terms that enter the expression above non-linearly are evaluated using the values in the *following* period (as usual) so the remaining system is linear in the values in period t.

In turn, the value of being unemployed is

[65] Workers' productivity in the clean sector ψ is permanent after their training choice. Therefore, workers' and firms' values can be solved separately for different values of ψ.

$$\begin{aligned}\rho W_t(j,\omega,U) = b^U\psi^\star(j) \\ &+ \lambda^E \sum_s p_{t+\Delta}(s;j,\psi,U) f(\theta_{t+\Delta}(j+\Delta,\psi,s)) \\ &\qquad \times [W_{t+\Delta}(j+\Delta,\psi,s) - W_{t+\Delta}(j+\Delta,\psi,U)] \\ &+ \frac{W^U_{t+\Delta}(j+\Delta,\omega) - W^U_t(j,\omega)}{\Delta}\end{aligned} \tag{B.13}$$

and the value of being employed in the outside sector O is defined similarly.

Finally, the value of a firm becomes

$$\begin{aligned}\rho V_t(j,\psi,s) = &\left(A_{k(s),t} - w(s)\right) h(j,\psi,k) + \chi_0 \{\mathcal{O}_{t+\Delta}(j,\omega,z,s) - V_t(j,\psi,s)\} \\ &- \lambda^E Q_{t+\Delta}(j+\Delta,\psi,s) V_{t+\Delta}(j+\Delta,\psi,s) \\ &+ \frac{V_{t+\Delta}(j+\Delta,\psi,s) - V_t(j,\psi,s)}{\Delta}\end{aligned} \tag{B.14}$$

for all markets $s \equiv (k,w)$, with $\mathcal{O}_{t+\Delta}(j+\Delta,\omega,z,s)$ still defined by (B.6). The boundary conditions associated to (B.12)–(B.14) are still given by (B.4) and (B.9).

Workers' and firms' values are characterized by the system (B.12)–(B.14) together with the definition of $\mathcal{O}_t$ (B.6), the definition of $\mathcal{F}(V_t)$ (B.8), and the free entry condition (B.10) that pins down θ_t. Note that this system is independent of the distribution of workers' states — this is the block-recursive property of directed search model (Menzio and Shi, 2011).

Numerical solution. We explain below how we solve for workers' and firms' values.

Algorithm 1. Solve for workers' and firms' values separately for each value of ψ.

Step 0. Let the terminal values for workers $W_T(J,\psi,s)$, $W_T(J,\psi,U)$ and firms $V_T(j,\psi,s)$ satisfy the boundary conditions (B.4) and (B.9) at retirement at age J. Fix job finding probabilities $Q_t(j,\psi,s)$, firms' expected values after operating costs $\mathcal{O}_T(j,\psi,s)$ and tightnesses $\theta_T(j,\psi,s)$. Initiate the recursion by setting the time index to $t = T - \Delta$ and the age index to $j = J - \Delta$.

Step 1. Solve for workers' values $W_t(j,\psi,s)$ and $W_t(j,\psi,U)$:

Solve for the values

$$\mathbf{W}_t\left(j,\psi\right)=\left(\rho+\frac{1}{\Delta}\right)^{-1}\left\{\mathbf{B}_t\left(j,\psi\right)-\mathbf{M}_{t+\Delta}\left(j+\Delta,\psi\right)\mathbf{W}_{t+\Delta}\left(j,\psi\right)\right\}, \quad \text{(B.15)}$$

where the vector $\mathbf{W}_t\left(j,\psi\right)$ contains workers' values, the transition matrix $\mathbf{M}_{t+\Delta}\left(j+\Delta,\psi\right)$ captures workers' transitions across states other than those involving search, and the vector $\mathbf{B}_t\left(j,\psi\right)$ contains workers' flow earnings and the non-linear changes in continuation value due to search. Formally, the workers values are

$$\mathbf{W}_t\left(j,\psi\right)_{[s,1]}\equiv W_t\left(j,\psi,s\right) \quad \text{(B.16)}$$

and the transition matrix and the flows take the form

$$\mathbf{M}_t\left(j,\omega\right)\equiv\begin{bmatrix}\mathbf{M}_{1,1,t}\left(j,\omega\right) & \mathbf{M}_{1,2,t}\left(j,\omega\right) & \mathbf{M}_{1,3,t}\left(j,\omega\right)\\ \mathbf{M}_{2,1,t}\left(j,\omega\right) & M_{2,2,t}\left(j,\omega\right) & M_{2,3,t}\left(j,\omega\right)\\ \mathbf{M}_{3,1,t}\left(j,\omega\right) & M_{3,2,t}\left(j,\omega\right) & M_{3,3,t}\left(j,\omega\right)\end{bmatrix} \quad \text{(B.17)}$$

and

$$\mathbf{B}_t\left(j,\omega\right)\equiv\begin{bmatrix}\mathbf{B}_{1,t}\left(j,\omega\right)\\ B_{2,t}\left(j,\omega\right)\\ B_{3,t}\left(j,\omega\right)\end{bmatrix} \quad \text{(B.18)}$$

We start by describing the terms involving workers employed in the polluting or clean sectors, i.e., $s\neq O,U$. We define the square matrix

$$\mathbf{M}_{1,1,t}\left(j,\omega\right)_{[s,s']}\equiv\begin{cases}\chi_0\mathcal{F}\left(V_{t+\Delta}\left(j+\Delta,\psi,s\right)\right) & \text{if } s'=s\\ 0 & \text{otherwise}\end{cases}, \quad \text{(B.19)}$$

the column vector

$$\mathbf{M}_{1,2,t}\left(j,\omega\right)_{[s,1]}=0, \quad \text{(B.20)}$$

and the column vector

$$\mathbf{M}_{1,3,t}\left(j,\omega\right)_{[s,1]}\equiv-\chi_0\mathcal{F}\left(V_{t+\Delta}\left(j+\Delta,\psi,s\right)\right). \quad \text{(B.21)}$$

Their flow is

$$\begin{aligned}\mathbf{B}_{1,t}\left(j,\omega\right)_{[s,1]} \equiv\ & w\left(s\right)h\left(j,\psi,k\left(s\right)\right)\\ &+\lambda^{E}\sum_{s'}p_{t+\Delta}\left(s';j+\Delta,\psi,s\right)f\left(\theta_{t+\Delta}\left(j+\Delta,\psi,s'\right)\right)\\ &\qquad\times\left[W_{t+\Delta}\left(j+\Delta,\psi,s'\right)-W_{t+\Delta}\left(j+\Delta,\psi,s\right)\right]\\ &+\frac{W_{t+\Delta}\left(j+\Delta,\psi,s\right)}{\Delta}\end{aligned} \tag{B.22}$$

We now turn to workers employed in the outside sector, i.e., $s = O$. We define the row vector

$$\mathbf{M}_{1,1,t}\left(j,\omega\right)_{[1,s']} \equiv 0, \tag{B.23}$$

for all workers employed in markets s' in the polluting or clean sectors, the scalar

$$M_{2,2,t}\left(j,\omega\right) = \chi_0\bar{\mathcal{F}}, \tag{B.24}$$

with $\bar{\mathcal{F}}$ denoting the exogenous separation hazard in $s = O$, and the scalar

$$M_{2,3,t}\left(j,\omega\right)_{[s,1]} \equiv -\chi_0\bar{\mathcal{F}}. \tag{B.25}$$

Their flow is

$$\begin{aligned}B_{2,t}\left(j,\omega\right) \equiv\ & b^{O}\psi^{\star}\left(j\right)\\ &+\lambda^{U}\sum_{s}p_{t+\Delta}\left(s;j+\Delta,\psi,O\right)f\left(\theta_{t+\Delta}\left(j+\Delta,\psi,s\right)\right)\\ &\qquad\times\left[W_{t+\Delta}\left(j+\Delta,\psi,s\right)-W_{t+\Delta}\left(j+\Delta,\psi,O\right)\right]\\ &+\frac{W_{t+\Delta}\left(j+\Delta,\omega,O\right)}{\Delta}\end{aligned} \tag{B.26}$$

Finally, we consider unemployment workers, i.e., $s = U$. We define the row vector and scalars

$$\mathbf{M}_{3,1,t}\left(j,\omega\right)_{[1,s]} = M_{3,2,t}\left(j,\omega\right) = M_{3,3,t}\left(j,\omega\right) = 0, \tag{B.27}$$

for all workers employed in markets s in the polluting or clean sectors. The

flow for unemployed workers is

$$\begin{aligned} B_{3,t}(j,\omega) \equiv\ & b^{U}\psi^{\star}(j) \\ & + \lambda^{U}\sum_{s} p_{t+\Delta}(s; j+\Delta,\psi,U)\, f\left(\theta_{t+\Delta}(j+\Delta,\psi,s)\right) \\ & \qquad \times \left[W_{t+\Delta}(j+\Delta,\psi,s) - W_{t+\Delta}(j+\Delta,\psi,U)\right] \\ & + \frac{W_{t+\Delta}(j+\Delta,\omega,U)}{\Delta} \end{aligned} \tag{B.28}$$

Step 2. Solve for the firms' values $V_t(j,\psi,s)$:

Solve for the values

$$\mathbf{V}_t(j,\psi) = \left(\rho + \frac{1}{\Delta}\right)^{-1} \left\{\mathbf{C}_t(j,\psi) - \mathbf{P}_{t+\Delta}(j+\Delta,\psi)\,\mathbf{V}_{t+\Delta}(j+\Delta,\psi)\right\} \tag{B.29}$$

where the vector $\mathbf{V}_t(j,\psi)$ contains firms' values, the transition matrix $\mathbf{P}_{t+\Delta}(j+\Delta,\psi)$ captures workers' flows out of the firms, and the vector $\mathbf{C}_t(j,\psi)$ contains firm' profit flow earnings. Formally, we define the vector

$$\mathbf{V}_t(j,\psi)_{[s,1]} \equiv V_t(j,\psi,s), \tag{B.30}$$

the diagonal matrix

$$\mathbf{P}_t(j,\omega)_{[s,s']} \equiv \begin{cases} \lambda^{E}\sum_{s'} p_t(s'; j,\psi,s)\, f\left(\theta_t(j,\psi,s')\right) & \text{if } s' = s \\ 0 & \text{otherwise} \end{cases}, \tag{B.31}$$

and the column vector

$$\begin{aligned} \mathbf{C}_t(j,\omega)_{[s,1]} = & \left(A_{k(s),t} - w(s)\right) h(j,\psi,k) + \chi_0 \mathcal{O}_{t+\Delta}(j+\Delta,\psi,s) \\ & + \frac{V_{t+\Delta}(j+\Delta,\psi,s)}{\Delta} \end{aligned} \tag{B.32}$$

where the values $\mathcal{O}_t$ are defined by (B.6).

Step 3. Compute the new values $\mathcal{O}_t(j,\omega,z,s)$ using (B.6) and the tightnesses $\theta_t(j,\omega,z,s)$ using (B.10).

Step 4. Set the age $j' = j - \Delta$, repeat Steps 1–3, and continue until $j = 0$.

Step 5. When solving for transitions, set $t' = t - \Delta$, repeat Steps 1–4 in that period, and continue until $t = 0$. This last step is redundant when solving for the steady state.

B.3 Distribution of Workers' States

We denote the density of wokers' states by $\mu_t(\mathbf{x})$. This density is a continuous function of age j and the productivity in the clean sector ψ, and a discrete function of the sector k. While the wage w is a continuous variable, only a subset of markets are active in equilibrium. Therefore, the distribution admits mass points along this continuous dimension. Accordingly, we define an integral of the form $\int f(s, \mathbf{x}_{-1}) \mu_t(ds, \mathbf{x}_{-1})$ as a discrete sum over markets $s \equiv (k, w)$ with positive mass, where $\mathbf{x}_{-1}$ denotes the other states.

As usual, the law of motion of the distribution and the recursive formulation of workers' values are closely related. In fact, the matrices $\mathbf{M}_t(j, \omega)$ introduced in Appendix B.2 encode all the information required to iterate on the distribution (Achdou et al., 2022). This is intuitive: the matrices $\mathbf{M}_t(j, \omega)$ capture the outflows from the current state and the inflows into subsequent ones. The only flows that are not captured by $\mathbf{M}_t(j, \omega)$ are those associated to the workers' job search, which are directly captured by the terms (B.22), (B.26) and (B.28). We therefore define a new matrix $\widetilde{\mathbf{M}}_t(j, \omega)$ similarly to $\mathbf{M}_t(j, \omega)$ in Appendix B.2, with the exception that it accounts for the flows associated to job search.

For instance, for workers employed in the polluting or clean sectors or clean sectors, i.e. $s \neq O, U$, we define the square matrix

$$\widetilde{\mathbf{M}}_{1,1,t}(j, \omega) \equiv \widetilde{\mathbf{M}}^A_{1,1,t}(j, \omega) + \widetilde{\mathbf{M}}^B_{1,1,t}(j, \omega), \tag{B.33}$$

the diagonal matrix

$$\widetilde{\mathbf{M}}^A_{1,1,t}(j, \omega)_{[s,s']} \equiv \begin{cases} \lambda^E \sum_{s'} p_{t+\Delta}(s'; j+\Delta, \psi, s) f(\theta_{t+\Delta}(j+\Delta, \psi, s')) & \\ \quad + \chi_0 \mathcal{F}(V_{t+\Delta}(j+\Delta, \psi, s)) & \text{if } s' = s \\ 0 & \text{otherwise} \end{cases}, \tag{B.34}$$

the square matrix

$$\widetilde{\mathbf{M}}^{B}_{1,1,t}\left(j,\omega\right)_{[s,s']} \equiv -\lambda^{E} p_{t+\Delta}\left(s';j+\Delta,\psi,s\right) f\left(\theta_{t+\Delta}\left(j+\Delta,\psi,s'\right)\right), \tag{B.35}$$

and the column vector

$$\widetilde{\mathbf{M}}_{1,2,t}\left(j,\omega\right)_{[s,O]} = -\lambda^{E} p_{t+\Delta}\left(O;j+\Delta,\psi,s\right) f\left(\theta_{t+\Delta}\left(j+\Delta,\psi,O\right)\right)$$

We proceed similarly for the workers employed in the outside sector, i.e., $s = O$, and unemployed workers, i.e., $s = U$. We omit these expressions for brevity.

In the limit $\Delta \to 0$, the law of motion of the workers' distribution is

$$\frac{\boldsymbol{\mu}_{t+\Delta}\left(j,\omega\right) - \boldsymbol{\mu}_{t}\left(j-\Delta,\omega\right)}{\Delta} = -\widetilde{\mathbf{M}}_{t}\left(j,\omega\right)' \boldsymbol{\mu}_{t}\left(j,\omega\right), \tag{B.36}$$

for all ages $j \in [0, J-\Delta)$, where

$$\begin{gathered} \boldsymbol{\mu}_{t}\left(j,\omega\right)_{[(z,s),1]} \equiv \mu_{t}\left(j,\psi,s\right) \quad \boldsymbol{\mu}_{t}\left(j,\omega\right)_{[\text{end-1,1}]} \equiv \mu_{t}\left(j,\omega,O\right) \\ \boldsymbol{\mu}_{t}\left(j,\omega\right)_{[\text{end,1}]} \equiv \mu_{t}\left(j,\omega,U\right) \end{gathered} \tag{B.37}$$

Equivalently,

$$\boldsymbol{\mu}_{t+\Delta}\left(j,\omega\right) = \left\{\mathbb{I} - \widetilde{\mathbf{M}}_{t}\left(j,\omega\right)'\Delta\right\} \boldsymbol{\mu}_{t}\left(j-\Delta,\omega\right) \tag{B.38}$$

Finally, the boundary conditions associated with the law of motion (B.38) are

$$\mu_{t}\left(0,\psi,s\right) = 0 \quad \text{and} \quad \mu_{t}\left(0,\psi^{\text{total}}\left(0,d\psi^{\text{endow}},U\right),U\right) = \mu^{R}_{t} \times G\left(d\psi^{\text{endow}}\right) \tag{B.39}$$

for all (ψ,s) at age $j = 0$ and all skill endowments ψ^{endow}. New cohorts are endowed with $\psi^{\text{endow}} \sim G$ and these workers choose the productivity $\psi^{\text{total}}\left(0,\psi^{\text{endow}},U\right)$ that solves the optimal skill accumulation problem (2.10). These workers are unemployed initially so $s = U$. Finally, the flow of newborns is

$$\mu^{R}_{t} = \int\int \mu_{t-\Delta}\left(J,d\psi,ds\right) \tag{B.40}$$

Stationary distribution and transition. The economy starts from a stationary distribution where the clean sector is absent, i.e., $A^{\text{clean}} \equiv 0$. Workers choose $\psi = \psi^{\text{endow}}$ at the initial stationary equilibrium since they have no reason to invest in skills

specific to a sector that they are not yet aware of. We normalize the stationary distribution so it has a unit mass. The climate transition is announced in period $t = 0$.

B.4 Calibration

We discretize our continuous time model into short periods corresponding to half a month for the reasons discussed in Section 5.2. We explain below how we compute the moments that we use in our calibration.

Employment flows. We compute the EE, EU and UE probabilities over one month ($T \equiv 1/12$) to be consistent with the empirical targets that we match. We account for the possibility that workers might experience multiple job transitions within the same month. For illustration, we describe how we compute EU flows. Given our two-week time step ($\Delta \equiv 1/24$), two events would be measured as an EU flow: either the worker experiences an EU transition in the first period and remains unemployed; or they do *not* experience an EU transition in the first period but do so in the second one. To compute the probability of the first event, we use the law of motion (B.38) with an alternative matrix $\widetilde{\mathbf{M}}_t^0(j,\omega)$ which is defined as in Appendix B.3 with the important difference that its *inflows* (i.e., the negative terms) are all zero except for those into unemployment starting from any employment state (in the polluting, clean or outside sectors). Iterating on (B.38) gives us a new distribution $\boldsymbol{\mu}_{t+\Delta}$ after a two-week period. Starting with this new distribution, we then iterate a second time on the law of motion using another matrix $\widetilde{\mathbf{M}}_t^0(j,\omega)$ which is again defined as in Appendix B.3 with the difference that its inflows are zero except for those into unemployment starting from unemployment.

We proceed similarly for the second event where the worker experiences the EU flow in the second period. The EU probability is the sum of the probabilities associated to these two events since they are mutually exclusive. We proceed similarly for all combinations of initial states (j,ψ,s) where the worker is employed initially. We restrict our attention to workers who are sufficiently young that they do not retire over the following year, i.e., $j \in \{j'|j' \leq J - T\}$. We weight these individual EU probabilities by the stationary distribution $\boldsymbol{\mu}$ conditional on being employed.

In addition to these job flows, we also compute the average separation probability at the annual level ($T \equiv 1$). This moment captures *any* separation that occurs during the year — either when a firm lays off a worker, or when a worker moves to another employer. This moment serves as an input in our calibration to match the empirical estimates of Chan et al. (2023) of the separation elasticity following an idiosyncratic firm productivity shock. We proceed as follows to compute this moment. We define $\widetilde{\mathbf{M}}^0(j,\omega)$ as in Appendix B.3 with the difference that we set all the *inflows* to zero except for the events where the workers is fired from the firm or moves to another employer. This correction allows us to keep track exclusively of "surviving" workers who do not experience a separation. We then iterate on the law of motion over a year

$$\tilde{\boldsymbol{\mu}}_T(j+T,\psi) = \prod_{t=0}^{T-\Delta} \left\{ \mathbb{I} - \widetilde{\mathbf{M}}^0(j,\psi)' \Delta \right\} \tilde{\boldsymbol{\mu}}_t(j,\psi) \tag{B.41}$$

for all ages j, productivities ψ in the clean sector, and periods $t = 0, \Delta, \ldots, T-\Delta$. The distribution $\tilde{\boldsymbol{\mu}}_0(j,\omega)$ is the stationary distribution conditional on employment. The probability of experiencing a separation over a time interval T is then given by

$$\text{Separation} \equiv 1 - \int\int\int\int \tilde{\mu}_T(j+T,\psi,s)\,\mathrm{d}s\mathrm{d}\psi\mathrm{d}j \tag{B.42}$$

Elasticity of separation rate w.r.t. output change. We compute the elasticity of the separation rate following a permanent and unanticipated decrease $\alpha \in (0,1)$ in a firm's output. We compute this elasticity over the year following the shock to be consistent with the empirical target that we match (Chan et al., 2023). This is a partial equilibrium exercise that only affects one firm and its worker. All aggregate quantities remain unchanged and so are workers' outside options. We then compute the average response across such firms and workers subject to this change.

We start by computing alternative values for the workers $\widehat{W}_t(j,\psi,s)$ and firms $\widehat{V}_t(j,\psi,s)$ that are subject to this shock. These new values satisfy recursions similar to the ones of Appendix B.2 with a few differences. First, output is now $(1-\alpha) A_{k,t} h(j,\psi,k)$. Second, the continuation values $W_t(j,\psi,s)$ in *other states* are treated as exogenous in (B.12) and evaluated at steady state since the outside options are unchanged. The worker's job finding probabilities $f(\theta_t(j,\psi,s))$ are also

exogenous. In constrast, the search behavior of employed workers and $p_t(s'; j, \psi, s)$ and firms' firing decisions $\mathcal{F}(V_t(j, \psi, s))$ are endogenous. We compute workers' and firms' values accordingly, as in Appendix B.2, keeping the exogenous objects constant. In our comparative statics, we consider a permanent productivity change of $\alpha = 0.15$. We then use the new transition matrices to compute annual separations as described above. Finally, we compare this new separation probability to the one that prevails in steady state and we express this change as an elasticity in terms of $1 - \alpha$.

C Empirical Appendix

C.1 Sector Definitions

As discussed in the main text, there have been many attempts to define clean and polluting industries. Our baseline sector definitions use data from the US Environmental Protection Agency (EPA), Bureau of Labor Statistics (BLS) and the OECD's list of green goods and services. To define polluting industries, we use data on emissions intensity – measured as the kilograms of CO2-equivalent gas emissions per dollar of output – by 6-digit NAICS industry codes from the Supply Chain Greenhouse Gas Emission Factors published by the Environmental Protection Agency (EPA), which accounts for emissions produced throughout the supply chain of production of each commodity. An industry is deemed to be "high-emissions" if it is in the top decile of emissions intensities, weighted by employment. Employment information comes from the Quarterly Census of Employment and Wages (QCEW), which is a quarterly census of the total total employment and average wages of all establishments in the United States.

These emissions data do not provide information on emissions in the energy sector and are missing for some other key sectors. Some sectors are not polluting themselves, but produce polluting output. We therefore handcode some additional sectors as polluting. These sectors are: "Fossil fuel electric power generation," "Crude Oil & Natural Gas Extraction," various coal mining sectors (NAICS 212114, 212115, 213111, 213112), "Manufacturing of oil and gas field machinery," "Pipelines for oil and gas," "Petroleum product manufacturing," "Petroleum merchant wholesalers," "Construction of oil and gas pipelines," "Pipelines for oil and

gas," and "Coal and other mineral merchant wholesalers."

To define "clean" sectors, we combine two approaches as described in the main text. First, we follow the output based approach of Bontadini and Vona (2023), who find that 95% of the production of "green goods"[66] is concentrated in just 13 out of 119 4-digit European NACE industries and that green and polluting production does not occur in the same sector. We classify these 13 European sectors – Bicycle manufacturing, manufacture of railway locomotives, manufacture of steam generators, shaping and processing of flat glass (which is used for solar panels), manufacture of electricity distribution and control apparatus, manufacture of instruments and appliances for measuring/testing, manufacture of cooling/ventilation equipment, manufacture of engine and turbines excluding aircraft and gasoline engines, manufacture of electronic components, manufacture of electric lighting equipment, manufacture of non-electric domestic appliances and installation of industrial machinery and equipment – as clean. Examples of the 54 sectors that are green by this definition include "Automatic environmental control manufacturing," "Electric power and specialty transformer manufacturing," and "Turbine and turbine generator set units manufacturing."

We supplement this output-based approach with the task-based approach employed by the US Energy Employment Report (Granholm (2024)). We use data from the 2012 Green Goods and Services (GGS) survey produced by US Bureau of Labor Statistics (BLS) to study the share of workers employed in each industry that are engaged in green tasks and define a sector as clean if at least 50% of their employees work on green tasks. The BLS GGS surveys workers in 325 6-digit NAICS industries and encodes green activities as either 1) producing energy from renewable sources (60 sectors), 2) energy efficiency (132 sectors), 3) pollution reduction and removal, greenhouse gas reduction, and recycling and reuse (122 sectors), 4) natural resource conservation (74 sectors), or 5) environmental compliance, education and training, and public awareness (45 sectors; sectors can belong to more than one category). Finally, we handcode battery manufacturing as green, since this is a crucial input to electrification of transport, and is not included in these other definitions.

[66] The list of green goods employed by Bontadini and Vona (2023) is based on the Combined List of Environmental Goods (CLEG) of the OECD and considers goods which are useful for the green transition. For instance, solar panels and wind turbines are classified as "green goods" even if their production is emission-intensive, since the goods themselves are green by nature.

Table 3: Largest Polluting and Clean Industries

Industry	2019 Employment (000s)
Polluting	
Gasoline stations with convenience stores	840.4
Couriers and express delivery services	707.0
General freight trucking, long-distance	524.2
Scheduled passenger air transportation	447.5
Plastics product manufacturing (other)	306.8
TOTAL	11,945
Clean	
Semiconductors and related device mfg.	184.6
Other motor vehicle parts mfg.	156.1
Search, detection, and navigation instruments	133.9
Recyclable material merchant wholesalers	103.1
Remediation services	91.7
TOTAL	2,280

Table 3 reports the 5 largest polluting and clean sectors according to 2019 employment. The largest polluting sectors are gas stations, sectors related to delivery, air travel and plastic product manufacturing. The largest clean sectors are semiconductor manufacturing (a key input to solar panels), other motor vehicle parts manufacturing (which includes car batteries), and recyclable material merchant wholesalers. Around 12 million jobs remain in the polluting sectors as of 2019, suggesting substantial scope for job displacement still to come.

To calibrate the shape of the S-curve for productivity $\bar{\Phi}(t)$, we turn to data from the US Energy Information Authority (US EIA), who provide information and projections on energy production by type from 2005 to 2050. We calculate the share of energy produced by fossil fuels and renewable sources in every year. We then normalize the share of the transition that is complete as of 2005 to be 0, and then assume that the projected shares in 2050 constitute 90% of the transition being completed. This yields the data points in Panel A of Figure 5. We then fit a normal CDF, truncated between 2005 (year 0) and 2060 (year 55). We estimate that the mean of the underlying normal distribution is 29.8 (i.e. half of the transition will be completed by the year 2035) and the standard deviation is 13.42.

C.2 Current Population Survey – Cleaning and Targets

The source of many of the moments used in our calibration is the Current Population Survey (CPS), which is a large, nationally-representative survey of U.S. households that has been running since the 1970s. The CPS has a rotating panel structure whereby households enter the sample for a four-month rotation, before leaving for 8 months and returning for a subsequent four months. All individuals within a household are surveyed, and one can link individuals through time so long as they remain at the same address throughout the sample period. In addition, respondents are asked additional questions about their usual weekly earnings and hourly wage in the final month of each rotation (month 4 and 8 in the sample). We use the IPUMS sample produced by Flood et al. (2024). We restrict attention to those aged 25 to 65 years in surveys years 2000 through 2025, and use the survey to measure employment in clean and polluting sectors, as well as wage changes as one switches from polluting to other sectors.

To construct these moments, we must merge our sector definitions with the industries in the CPS. The CPS uses Census industry codings, which are generally at a coarser level of granularity than 6-digit NAICS codes. We use Census industry to NAICS crosswalks provided by the Census, available at https://www.census.gov/topics/employment/industry-occupation/guidance/code-lists.html. We then assign CPS industry codes a polluting versus clean status iteratively. We first merge our CPS data, which now include NAICS codings, with our classifications at the 6-digit level. Of the 10,949 unique industry x year codings present in the CPS, 901 merge at the 6 digit level. We then progressively merge at coarser levels. At each coarser level, we assign clean vs polluting vs other status according to the classification of the majority employment at the 6-digit NAICS within the coarser level. For instance, suppose there is a 5-digit NAICS code which contains two 6-digit NAICS codes, one of which is clean and the other of which is polluting. If the 6-digit NAICS code associated with the clean sector is larger (smaller) than the 6-digit NAICS associated with polluting, then the 5-digit NAICS code will be coded as clean (polluting). Employment data from this procedure come from the QCEW. Proceeding in this way merges 2,016 industry-years at the 5-digit level, 6,691 industry-years at the four-digit level, 1,329 at the 3-digit level, and 307 at the 2-digit level. The remaining unmerged industries are all in the public sector and dropped from the analysis.

At this stage, there remain a couple of industries that remain uncoded, because it does not have a majority of employment in either clean, polluting or other (e.g. 1/3 of the broader sector is in each of the three categories). These we handcode as follows. We define the industry "Cycles and misc. transportation equipment" as clean, supposing that a climate transition may involve more clean commuting.[67] We define the "Sanitary Services" industry as clean, since it includes some recycling and sanitation services and does not have polluting subindustries.

Given the industry groupings, we must then define polluting-attached workers. In the 2000 through 2004 period – the pre-transition period – we call an individual "polluting-attached" if they are employed in the polluting sector for four consecutive months during the first rotation. By this metric, 4.4% of workers qualify as polluting-attached before 2005. To calculate the moment used in our calibration of b^O – the average wage change of an individual going from polluting to unemployed to outside – we first measure the real wage of polluting-attached workers in the final month of their first rotation. We then condition on individuals appearing as unemployed at some point in their second rotation, before being employed in an other sector in the final month of the second rotation, when we measure their real wage again.[68] All wages are deflated by the CPI-U. By focusing on individuals who have at least one spell of unemployment before joining the outside sector, we remove individuals who might switch to the outside sector due to an unmodeled career opportunity in that sector.

Of course, focusing solely on individuals who remain employed in the polluting sector for the first rotation would introduce substantial composition bias as the transition gets underway. We therefore instead weight individuals by the likelihood that they are polluting-attached based on their observables. To do so, we proceed as follows. We first recode the provided education, race and marital status variables so that the education groupings are High School or Less, Some College, Bachelor's Degree, and Master's Degree or Higher, the race groupings are White, Black, or Other, and the marital status variable is an indicator for be-

[67] Indeed, the largest subindustry of this industry group is bicycle manufacturing, but this is offset by a variety of military industries such as tank manufacturing, which are likely not subject to the climate transition.

[68] We target a wage cut of 24%, consistent with the behavior of hourly wages. Weekly earnings fall an average of 35.5%. Targeting a smaller wage cut makes the outside sector more attractive in the calibration and thus provides a conservative of the cost of the transition.

ing married. We additionally use geographic information, which the CPS partially provides down to the county level. The Census Bureau has changed confidentiality rules regarding individuals living in small geographic areas over time. As a result, some counties and metro areas appear in some waves of the CPS but not others. In order to have a consistent probability of being polluting-attached, we require consistent geographic codings over time. To harmonize geographic codings, we therefore focus on county and metropolitan statistical area (MSA) codes that are present no fewer than all but one in every year from 2000 through 2025.[69] This yields 194 counties and 209 metro areas. State information is included for all years. We then compute the probability of an individual i being polluting-attached given a vector of observables (education $\times$ race $\times$ marital status $\times$ sex $\times$ geography) X as $Pr_i = \mathbb{E}\left[1\left\{i \text{ is polluting-attached}\right\}|X\right]$ in the pre-transition period. We apply this same probability to all individuals with the same vector of observables X during the early transition years (2005-2025). In effect, we study the effect of the transition on people who, based on observable characteristics, are likely to have been working in the polluting sector were the transition not to have occurred. Since some combinations of observables do not exist in all years, we begin by calculating Pr_i using the most granular geographic level to the coarsest (county $\rightarrow$ MSA $\rightarrow$ state $\rightarrow$ national). While the unconditional probability that a worker is polluting-attached is 3.9%, the 99th percentile probability of being polluting-attached is 27.7% based on observables, with some individuals having a 100% probability of being polluting-attached given their observables. These individuals are located in traditional mining communities (parts of Texas and West Virginia), are lower education and male. The median observation in our sample has a 1.8% chance of being old-attached, while 25% of individuals are assigned a zero likelihood of being old attached and are thus dropped from our analysis.

Table 4 reports the characteristics of probabilistically polluting-attached workers who hold jobs in polluting sectors and clean sectors as of 2006 and 2024. The workers holding polluting jobs are substantially less educated than those holding clean jobs in both periods, suggesting that high human capital workers join the clean sector. In addition, those working in clean sectors are younger than those in

[69] Many counties appear only in 2004 when a recode in the CPS occurred. We continue to include these counties since we can use information aggregate from the full pre-transition sample to construct polluting-attached probabilities.

Table 4: Characteristics of Workers Holding Clean and Polluting Sector Jobs

	Polluting		Clean	
	2006	2024	2006	2024
% $\leq$ High School	64.4	58.1	49.4	42.2
% Some College	24.3	26.3	31.2	29.2
% Bachelor's	9.4	14.1	16.6	22.7
% $>$ Bachelor's	1.9	1.5	2.8	5.9
% Age: 45+	49.3	51.0	47.7	49.9
% White	86.2	94.5	85.8	82.8

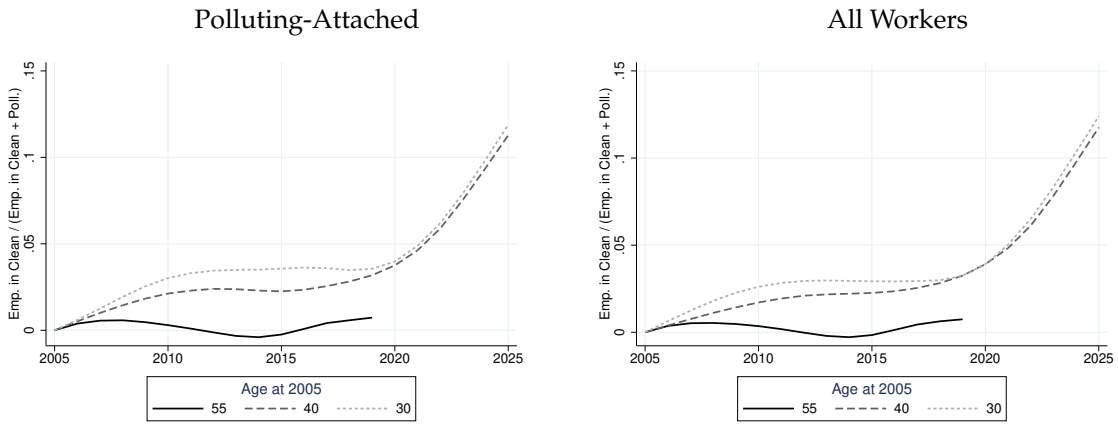
polluting sectors.

We then calculate the share of individuals are employed in the clean or the polluting sector at every point in time, weighting by the product of their survey weight and probability of being old attached. To correct for misspecification from overly coarse industry classifications and within-industry shifts in technology, we ascribe a fraction of manufacturing employment to clean and polluting sectors based on the share of cars sold that run on alternative fuel (hybrid, plug-in hybrid, electric, or biofuel).[70] This correction has the added benefit of partially accounting for within-industry transition: the industry classifications associated with motor vehicle manufacturing do not distinguish between internal combustion engine and EV vehicles, despite the fact that the skills needed to produce those two types of cars may be quite different and those two subindustries will be subject to very different paths of labor demand. Finally, we extract the trend component of employment shares using a Hodrick-Prescott filter. We then target the share of employment in either clean or polluting sectors that is in clean sectors as part of our estimation in section 5.4.

While our main target uses the probabilistic polluting-attached workers, this reweighting does not drive our results. Figure 10 reports employment in clean sectors as a share of employment in either clean or polluting for three cohorts:

[70] To calculate these shares, we use data from the US Bureau of Transportation on total car sales by year, available from https://www.bts.gov/content/annual-us-motor-vehicle-production-and-factory-wholesale-sales-thousands-units, and on alternative energy vehicle sales, available from https://www.bts.gov/content/gasoline-hybrid-and-electric-vehicle-sales (both accessed June 3, 2025). Total car sales data go through 2021 while alternative-fuel sales go to 2024. We therefore extrapolate total car sales assuming a constant log-linear trend.

Figure 10: Employment by Age in Clean and Polluting Sectors



those born who are 30, 45, or 55 years old in 2005. Panel A plots the patterns for polluting-attached workers, which is an input to our estimation, while Panel B weights only by survey weights and not the probability that an individual is polluting-attached. The figure is little changed across the two panels. This suggests that individuals who are not likely to be attached to the polluting sector either a) make similar choices between polluting and clean sectors as the polluting-attached workers, or b) do not engage in either the clean or polluting sector and are thus unaffected by the transition. In either case, our focus on the polluting-attached individuals does not appear to bias our estimates of the skill distribution.