The Labor Market Consequences of a Rapid Climate Transition*

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Abstract

As policymakers choose a timeline for the climate transition, 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 skill accumulation in which labor demand expands in a set of clean sectors and declines in polluting sectors. Workers' lifetime earnings are strongly non-linear and even non-monotonic as a function of the pace at which the clean sector takes over, and the set of workers who win or lose from the transition is sensitive to its pace. 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 a large dispersion among workers. Accelerating the transition to end in 2050 is preferable for most workers, but thickens the tail of earnings losses.

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1 Introduction

As the world embarks on a climate transition, economic activity will shift from polluting to clean industries, necessitating large labor reallocation. There are currently 10-15 million workers employed in high-emission industries in the US whose jobs are potentially at risk, while millions of new jobs expected to be created in clean industries. There is growing evidence that job losses are accelerating among workers employed in polluting industries (Bassanini et al., 2024) and that earnings losses are high among those who have already been displaced (Walker, 2013; Curtis et al., 2023). The prospect of a painful transition fuels concerns about how ambitious climate goals should be, with evidence from surveys and voting behavior suggesting labor market concerns are a significant obstacle to public support for climate action (Dechezleprêtre et al., 2025; 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 employed in polluting industries.

In this paper, we study the distribution of labor market consequences of the climate transition among workers currently employed in polluting industries (i.e., those most at risk of displacement), and how they depend on the *timeline* over which the transition unfolds. As policymakers consider target dates of net zero carbon emissions, they must trade off these labor market consequences against competing goals such as climate benefits and the fiscal costs of implementing a particular transition. Understanding how costly it would be to compensate displaced workers in order to increase public support is therefore an essential first step to decide how ambitious the transition timeline should be.

We build a model designed to capture the displacement and reemployment experience of workers initially attached to polluting industries. The model features finitely-lived workers with heterogeneous skills who may seek employment in a clean sector, a polluting sector, or an outside sector which encompasses the rest of the economy. Labor markets are subject to search frictions, and workers direct their search both on- and off-the-job as in Menzio and Shi (2011), leading to a job-ladder in each sector (Huckfeldt, 2022). Changes in preferences and technological innovation induce a transition of economic activity away from the polluting sector and towards the clean sector.

The government can speed up the transition by using subsidies on the output produced by the clean and polluting sectors (e.g. a subsidy on electric vehicles sales), or sector-specific R&D subsidies, using lump sum taxes on workers to balance its budget. We establish that the government can implement *any* arbitrary path of marginal revenue products of labor (MRPLs) across sectors, given these tools. In turn, these paths of MRPLs are sufficient statistics to characterize workers' labor market outcomes, i.e., their probability of being employed in a given sector, their position in the job ladder, etc. These two results suggest that the government can consider two questions in isolation: first, how does the path of MRPLs affect the distribution of workers' lifetime earnings? Second, what is the fiscal cost of implementing a particular path for the MRPL in each sector? The focus of our paper is on the first question.[1] Specifically, we study how exogenous perturbations in the paths of MRPL in clean and polluting sectors, corresponding to more or less ambitious timelines and reflecting different government subsidies, affect the distribution of workers' present discounted value of their future earnings (hereafter, their "lifetime earnings").

Three conceptual insights emerge from our analysis. First, workers' lifetime earnings are highly *non-linear* in the pace of the transition. In other words, speeding up the transition by 5 or 10 years can have dramatically different implications for workers. In fact, earnings changes can even be *non-monotonic*: some workers suffer at first when the transition accelerates, then recover, and eventually benefit from an even faster transition. The reason is that a faster transition has two opposing effects on workers' earnings: it displaces them from polluting sectors faster, accentuating earnings losses early in the transition; at the same time, it creates more good, high-paying jobs in clean sectors before they retire. Workers generally suffer the most for *medium-speed* transitions where the transition is fast enough that the worker experiences all of the earnings decline in the polluting sector, but slow enough that they retire before sufficiently benefiting from growth in the clean sector.

Second, and relatedly, the set of workers who benefit or lose from the transition

[1] The second question is of course essential to conduct optimal policy analysis. However, answering it requires knowledge of a number of additional parameters that are difficult to estimate, including the elasticity of innovation with respect to R&D subsidies, the strength of knowledge spillovers across sectors, changes in preferences as more electric chargers are installed, etc. This exercise is outside the scope of this paper, which focuses on labor markets.

is sensitive to the pace at which it unfolds. When speeding up the transition, the government faces a trade-off between increasing the mass of workers who benefit at the extensive margin and thickening the tail of earnings losses at the intensive margin. Older workers are more likely to lose from the transition (keeping skills constant), as they have a shorter horizon over which to recoup the short-run losses after being displaced from the polluting sector. These results have important political economy implications for climate policy.

Finally, frictional labor markets amplify the non-linearities in earnings losses as the transition accelerates. Unemployment spells and movements down the job ladder are essential to explain substantial and persistent earnings losses from job displacement in the data (Jacobson et al., 1993; Krolikowski, 2017; Huckfeldt, 2022; Fallick et al., 2025)..

These conceptual insights apply to a broader set of technological transitions where one technology becomes obsolete and is taken over by a newer and more productive one, such as Schumpeterian industry dynamics (Aghion and Howitt, 1992) 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 affect a substantial share of the workforce, its pace is partly under the control of the government, and most of the transition has yet to take place.

After establishing these conceptual insights, we bring the model to the data. We start by augmenting the model with three key features for quantitative analysis: workers have multi-dimensional skills which they accumulate on-the-job (Guvenen et al., 2020; Lise and Postel-Vinay, 2020); separations are endogenous, capturing the fact that firings and firm exits respond to economic conditions (Fujita and Ramey, 2009; Clementi and Palazzo, 2016a; Chan et al., 2023); and workers' job search is partially directed, reflecting the fact that job-to-job switches often entail wage cuts (Sorkin, 2018) and that there are large gross flows between industries (Pilossoph, 2014).

We interpret the initial stationary equilibrium of our model as the period immediately before the signing of the Kyoto agreement of 2005. We use this initial steady state to discipline many parameters to match a rich set of features of U.S. labor markets. Our baseline scenario assumes that the status quo transition com-

pletes in 2060, which is the current consensus date when the US economy is expected to reach net zero carbon (Bain & Company, 2025). The prospective nature of our analysis means that there is a substantial empirical uncertainty about long-run outcomes, particularly relative employment in clean and polluting sectors several decades away. We therefore consider a menu of scenarios for the long-run marginal products of labor across sectors, spanning the range of existing predictions (Mayfield et al., 2023; Finkelstein Shapiro and Metcalf, 2023; IRENA, 2023).

We use the early part of the transition (2005–2025) to structurally estimate the two most important objects in our analysis: the distribution of relative skill endowments across sectors, and the rate at which workers accumulate specific skills. We develop a novel strategy that leverages the block recursivity of competitive search equilibria, which allows us to solve for workers' policy functions independently from the distribution of skill endowments. The timing with which workers reallocate between polluting and clean sectors in the data allows us to trace the distribution of skill endowments non-parametrically. In turn, the rate at which workers accumulate specific skills is disciplined by the extent to which old workers, who had more time to accumulate specific skills in the polluting sector, are less likely to switch sectors in the data.

The estimated model implies that the average worker attached to the polluting sector in 2005 loses around 1.2% of lifetime earnings as a result of this baseline 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 imperfect labor markets in this setting.

Finally, we ask how changing the pace of the remaining transition will affect 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 an additional 2% of lifetime earnings from this acceleration in expectation, 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 (see Bilal and Stock, 2025 for a review). The large economic costs of climate change commonly estimated suggest substantial societal gains from a fast transition away from polluting technologies (Barrage and Nordhaus, 2023; Arkolakis and Walsh, 2023; Bilal and Rossi-Hansberg, 2023; Bilal and Känzig, 2024; Nath et al., 2024). However, there have been comparatively few studies on the labor market costs of this transition and how they depend on its pace. A variety of papers describe the employment and wage patterns in clean and polluting jobs over the early phase of the transition, and how various policies have affected these patterns (Curtis et al., 2023; Känzig, 2023; Vona et al., 2018; Curtis and Marinescu, 2023; Bassanini et al., 2024; Hanson, 2023). Consoli et al. (2016) argue "green" jobs use a different set of skills to non-green jobs. 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.

Finally, our work connects to a literature studying other transitions, and asking whether policy should intervene to address rapid adoption of new technologies. Autor et al. (2025) document that incumbent workers employed in manufacturing experienced persistent employment losses when exposed to Chinese import competition, while newly entering young workers found employment in service sectors. Their findings motivate our emphasis on skill specificity and life cycles. 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. Traiberman (2020) argues that trade shocks destroyed occupation-specific human capital, which slowed labor reallocation and generated substantial welfare costs for workers in Denmark. Caliendo et al. (2019) develop dynamic-hat algebra approaches to study the effect of trade liberalizations on workers in a rich setting with labor mobility frictions, geography and input-output linkages, but without skill specificity and accumulation and without involuntary unemployment and job ladder. Braxton and Taska (2023a) study the earnings losses from 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. 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. In contrast to this literature, we study a counterfactual question: how large would earnings losses be if the transition is accelerated or slowed?

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, earnings scarring, on-the-job search, skill heterogeneity, and life cycles is key to quantitatively capture these non-linearities.

2 Preferences, Technology, and Government

In this section, we lay out the foundation of our analysis by specifying workers' preferences, firms' technologies, and the government's policy instruments. The setup has the minimal ingredients required to convey the main conceptual insights. Our quantitative model enriches this setup by allowing for skill accumulation and a richer labor market (Section 5).

2.1 Environment

Time is continuous and indexed by $t \geq 0$. There are three sectors k: a "clean" sector ($k = C$); a "polluting" sector ($k = P$); and an "outside" sector ($k = O$). Workers may also be unemployed ($k = U$). The climate transition is a scenario where the polluting sector declines relative to its initial trend, while the clean sector rises relative to trend. The outside sector is not affected by the climate transition.

2.1.1 Workers

Demographics and preferences. Workers live for J periods and are replaced by new ones upon retirement. Workers supply labor and consume in ages $j \in [0, J]$. 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 c_t is consumption of numeraire, $u(c) \equiv c^{1-\sigma}/\left(1-\sigma\right)$ is the flow utility function, and $0 < \rho < \infty$ is the discount rate. We let τ denote a worker's birth date, or cohort, so that incumbents' age as of period 0 is $-\tau$.

Skills. Workers supply labor in the polluting, clean and outside sectors and have heterogeneous labor productivities. We let ψ denote the total units of human capital that the worker supplies if employed in sector P, and $\hat{\psi}$ denote a worker's relative skill in sector C. Workers may transfer a share $b^O \in (0,1)$ of their skills in the polluting sector to the outside sector and earns an unemployment benefit b^U per unit of skill ψ. Therefore, a worker's productivities may be summarized by

$$h\left(\psi, \hat{\psi}, k\right) = \begin{cases} \psi & \text{if } k = P \\ \psi \times \hat{\psi} & \text{if } k = C \\ \psi \times b^k & \text{if } k = O, U \end{cases} \tag{2.2}$$

We assume that all workers are endowed with $\psi = 1$ and draw an endowment of $\hat{\psi}$ from a distribution $G\left(\hat{\psi}\right)$. In the simple model studied here, we assume that these productivities are fixed over a worker's life, and we relax this assumption in the quantitative model of Section 5.

2.1.2 Firms

We start by describing the production and innovation processes in the polluting and clean sectors, before turning to the outside sector. In the following, we assume that all firms are owned by a continuum of infinitely-lived and risk-neutral entrepreneurs who discount flows at the same rate ρ as workers.

Final good. A representative producer combines the output of the polluting and clean sectors to produce the final good according to

$$Y_t = Z_t F_t \left(X_t^P, X_t^C \right), \tag{2.3}$$

where Z_t is aggregate TFP, and X_t^k are intermediate outputs produced in the these two sectors. The aggregator F_t has constant returns-to-scale and is weakly concave in each argument.[2] We will consider the case where the two intermediates are substitutes in production, though not necessarily perfect substitutes, e.g., EVs and ICEs.

Intermediates. The two intermediate goods X_t^k are produced by combining a continuum of mass 1 of varieties x_t^k using a CES aggregator with elasticity of substitution larger than one. The firms producing these varieties compete monopolistically. These firms produce using labor services $x_t^k = a_t^k n_t^k$, where a_t^k are labor productivities and n_t^k is the amount of labor services used.

Labor services. A continuum of atomistic firms in each sector each hires one worker to produce labor services. They sell their labor services intermediate goods firms at price P_t^k which they take as given. The labor services produced by firm i depends on the idiosyncratic productivity of the worker that they hire: $l^k(i) = h\left(\psi, \hat{\psi}, k\right)$.

Productivities. Carbon emissions can inflict damages to the economy, by reducing aggregate productivity Z_t. In turn, entrepreneurs who own the intermediate goods firms can invest resources to improve their productivity a_t^k, thus increasing profits and we allow for technological spillovers across sectors (Eaton and Kortum, 1999). Our specification ensures that the economy admits a balanced growth path where output grow at rate $g > 0$. As we explain in Section 3.1, our results do not depend on the exact specification for the evolution of Z_t and a_t^k . We therefore relegate the exposition of these features to Appendix A.2 to economize space.

[2] We assume F_t has bounded derivatives so goods prices are finite when the transition begins and the clean sector is in its infancy. Otherwise, the marginal revenue product of labor would be so high initially that all workers would rush to the clean sector in $t = 0$, which is clearly counterfactual.

Outside sector and unemployment. The rest of the economy is unaffected by the climate transition. Workers receive an income of $b^O \exp(gt)$ of final goods in the outside sector, and of $b^U \exp(gt)$ when they are unemployed, where g is the growth rate of output along a balanced-growth path.

2.1.3 Labor Markets

Directed search. We suppose that workers direct their search, as in Menzio and Shi (2011), within and across sectors. They search for jobs with intensity $\lambda^U > 0$ off-the-job and $\lambda^E > 0$ on-the-job, giving rise to a job-ladder in the polluting and clean sectors. Labor markets in the polluting and clean sectors are indexed by: a worker's age j; their relative skill $\hat{\psi}$ in the clean sector; the sector k that they search in; and the wage rate w that workers and firms agree on throughout the duration of the match. We abstract from renegotiation in w since wages rarely fall on-the-job in practice (Grigsby et al., 2021) and discussions about pay cut rarely take place even if they could save jobs (Davis and Krolikowski, 2025).[3] The wage rate w is paid for each unit of effective labor $h\left(\psi, \hat{\psi}, k\right)$ that they supply. Furthermore, we suppose that effective wages are indexed by the growth rate g that prevails along the balanced-growth paths. Employed workers therefore earn $wh\left(\psi, \hat{\psi}, k\right) \exp(gt)$ and firms claim the rest of revenues. Matches are destroyed exogenously at rate $\chi_0 > 0$.

Firm entry. A constant returns to scale matching function yields a job-finding probability for workers $f(\theta)$ within each market, where θ is market tightness defined as the ratio of vacancies to job-seekers and f is increasing and concave. The corresponding job-filling probability for firms is $q(\theta) \equiv f(\theta)/\theta$ which decreases with θ. We let $V_t\left(j, \hat{\psi}, s\right)$ denote the value to a firm employing a worker of age j and with skill in market s. Firms post vacancies at a cost $\nu \exp(g^\star t) > 0$, where ν represents both a vacancy and expected hiring cost. This cost grows at rate $g^\star$ to ensure that the economy admits a balanced-growth path. There is free entry in each market so

[3] Wage rigidities are an important feature to explain employment dynamics during sectoral reallocations (Rodriguez-Clare et al., 2025). Matches are destroyed exogenously for now, so separations are efficient.

is

$$q\left(\theta_t\left(j,\hat{\psi},s\right)\right)V_t\left(j,\hat{\psi},s\right) \leq \nu \exp\left(g^\star t\right) \tag{2.4}$$

in every period t and market s, with equality if a positive measure of vacancies are posted.

Outside sector and unemployment. We think of the outside sector as capturing jobs that workers can find relatively easily and which offer relatively limited scope for professional progression. For this reason, we assume that jobs in the outside sector have an exogenous job-finding probability of f^O conditional on search and we abstract from the job-ladder in this outside sector. Similarly, workers can freely transition to unemployment when given a search opportunity.[4] New cohorts ($\tau > 0$) are born unemployed.

2.1.4 Government

The government has two instruments at disposal to influence the climate transition after it begins in $t = 0$. First, the government can subsidize the purchase of two intermediate goods, e.g., a subsidy on EV sales. We suppose that the government uses subsidies τ_t^k on the sale price. Second, it can use subsidies ς_t^k on innovation (or investment) in each sector, e.g., a subsidy on R&D to develop efficient battery cells. We suppose that the government balances its budget in every period using lump sum transfers to workers.

2.1.5 Financial 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, i.e., $\sigma = 0$, as is standard in much of the labor search literature (Menzio and Shi, 2011; Bilal et al., 2022; Braxton and Taska, 2023b). The search decisions made by workers, and thus the total earnings impact of the transition, would be the same if workers were risk-averse $\sigma > 0$ but faced complete markets for idiosyncratic risk: that is, they could trade contingent securities against all idiosyn-

[4] Formally, we set $f\left(\theta_t\left(j,\hat{\psi},U\right)\right) \equiv 1$ for the unemployment state.

cratic risks of job-finding or separations. In both cases, workers value the present discounted value of earnings, which will be our main object of interest.[5]

2.1.6 Workers' and Firms' Values and Equilibrium

We state workers' and firms' values recursively in Appendix A.1. To avoid redundancy, we do so in the context of our full quantitative model which nests the present model. All firms and workers act competitively, except the firms who produce the varieties of each intermediate which compete monopolistically. We define a equilibrium formally in Appendix A.3. The labor market block of the model satisfies a block recursive equilibrium as is standard in this class of directed search models (Menzio and Shi, 2011).

3 Status Quo and Counterfactual Transitions

Pollution externalities create a motive for policy intervention. The government can use various instruments to speed up the climate transition. Before understanding how speeding up the transition affects workers' labor market outcomes, we first describe the set of allocations that the government can implement with its policy tools. We then discuss the status quo transition that would prevail without further intervention, before describing the counterfactuals that we conduct.

3.1 Implementable Allocations

Our goal is to study how workers' lifetime earnings change as one changes the pace at which the transition unfolds. On the surface, doing so seems a daunting task, as it appears to require knowledge of a number of difficult-to-estimate parameters, such as the degree of knowledge spillovers across sectors $\beta_k^{k'}$, the shape of the innovation production function $\iota(\cdot)$, how preferences across the two goods change over time $F_t\left(X_t^P, X_t^C\right)$ and the form of the climate damage function $Z_t(\cdot)$. To make progress, we leverage two convenient features of our model. Define firms' in sector k's marginal revenue products of labor in sector k as

$$\text{MRPL}_t^k \equiv \left(1+\tau_t^k\right) a_t^k P_t^k. \tag{3.1}$$

[5] In an extension, we consider the case with $\sigma > 0$ and hand-to-mouth households.

The first useful feature of our model is that the MRPL_t^k summarizes all relevant information needed to characterize workers' labor market outcomes: the innovation technologies, the strength of spillovers between clean and polluting sectors, the elasticity of substitution between intermediates, how it changes over time, the extent of climate damages, etc. do *not* affect workers' outcomes beyond their effect on the marginal revenue products of labor (3.1). This holds because the MRPL determines the surplus that firms and workers share in the labor services sector. One can thus consider the paths of MRPL_t^k as *sufficient statistics* to characterize workers' labor market outcomes. To formalize this claim, we define the de-trended marginal products

$$A_t^k \equiv \text{MRPL}_t^k / \exp(gt), \tag{3.2}$$

where g still denotes the rate at which output grows along the balanced-growth path. We then establish the following result.

Lemma 1. *Workers' labor market outcomes, i.e.,the probability that they are employed in a given sector, their position in the job ladder, etc., depend on endogenous prices and government subsidies exclusively through the sequences of normalized marginal revenue products of labor A_t^k.*

Proof. See Appendix A.7. □

The second useful feature of our model is that the government can implement any arbitrary path of MRPLs using its subsidies on intermediates τ_t^k and subsidies on innovations ς_t^k, even if prices, innovation and spillovers respond endogenously.

Proposition 1. *The government can use its policy instruments to implement any arbitrary path of marginal revenue products of labor A_t^k in each sector.*

A proof of this proposition is contained in Appendix A.8. Intuitively, this result holds because there is a mapping between the marginal revenue products of labor A_t^k and all other aspects of the economy, such as the innovation decision or demand for each good k. Suppose, for instance, that the government introduces a subsidy on electrical vehicles. This subsidy increases the demand for these vehicles and reduces demand for gasoline vehicles; it also raises the incentives to innovate on EVs and lowers the incentives to improve ICEs. Firms create more vacancies in the clean sector, and fewer in the polluting sector. Workers are more likely to reallocate to the clean sector which affects sectoral outputs and further feeds back into

prices and innovations in general equilibrium. However, all of these mechanisms ultimately translate into a mapping between tax policy and MRPLs. By adjusting tax policy, the government can then implement any path of MRPLs it wants.[6]

These two results imply that policymakers can proceed *sequentially* when forming climate policy. In particular, they may separately answer two distinct questions. First: What are the distributional labor market consequences of different paths for the marginal revenue products of labor A_t^k across sectors? Then, conditional on these labor market consequences, one might ask "what are the fiscal costs and benefits of implementing a particular path of A_t^k?"

This paper is concerned with answering the first question. We view this as the first step for policymakers: how expensive would it be to compensate workers who suffer from the climate transition for given paths of A_t^k? As Proposition 1 makes clear, this question is *orthogonal* to the rest of the economy and, in particular, from parameters that are difficult to estimate including the spillovers between clean and polluting sectors, changes in the elasticity of substitution between intermediates over time, the extent of climate damages, how the government rebates the net proceedings to different workers and generations, etc.[7] Instead, the paths of A_t^k is all one must know to characterize workers' outcomes. This approach also preserves the block-recursive property (Menzio and Shi, 2011) that makes it manageable to tackle this first question quantitatively.

The second question is *much more* difficult to answer. Doing so requires not only a good model of workers' labor supplies (the focus of this paper), but also knowledge of all the elasticities listed in the previous paragraph and the efficacy of government R&D policy tools. These empirical challenges deserve their own paper. These complex interdependences also break block-recursivity, making this second question computationally more difficult.

Our goal is thus a *positive* analysis: we investigate how different paths of MRPLs associated to faster or slower transitions affect the distribution consequences of the climate transition. To that end, we henceforth focus on the labor market block of

[6] It is worth noting that the government can implement given paths of MRPLs even without knowing all these objects. Indeed, paths of MRPLs map one-to-one to aggregate labor supplies across sectors n_t^k. The government knows this map if it has access to the same model of the labor market as we do. The government can therefore adjusts its instruments by tâtonnement, raising and lowering their subsidies until current and forecasted employment lines up with the government's target.

[7] Linear utility implies that the distribution of tax revenues does not worker search decisions.

the model taking as given paths of A_t^k. However, the innovation and final goods production blocks provide guidance on reasonable shapes for the transition to follow, as we now discuss.

3.2 Status Quo Transition

The status quo transition is the one that prevails under the current policy regime before further government intervention.[8] The paths of marginal revenue products of labor are assumed to take the form

$$A_t^k = A_0^k + \bar{\Phi}^k(t) \times \left(A_\infty^k - A_0^k\right) \tag{3.3}$$

under the status quo transition, where A_0^k and A_∞^k are the start and end values of labor productivity. We assume $A_\infty^C > A_0^C$ and $A_\infty^P < A_0^P$, i.e., the clean sector grows while the polluting sector declines.[9] The timing of this sectoral shift is parameterized by the functions $\bar{\Phi}^k(t)$, which are increasing functions from the real line to the $[0,1]$ interval, representing the share of the transition that is completed as of period t.

To characterize the status quo transition, it is useful to first provide some 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.[10] The US, however, pulled out of

[8] The government might have *already* intervened under the current policy regime, e.g., there are subsidies to innovation and to EV adoption, etc.

[9] 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 over the transition than it did previously.

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

the Paris Agreement and is not currently on track to meet this target by 2050. The median response in a recent survey of US energy CEOs 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, and our counterfactual analyses consider speeding up these transitions.

We normalize the initial value of $A_0^P = 1$ as the scale of the economy without loss of generality. The period before 2005 corresponds to our initial balanced-growth path which grows at rate $\bar{g} > 0$, so A_t^P is constant. We assume there is no demand for the good produced in the clean sector along this initial balanced-growth path, so its price is zero and there are no incentives to hire or innovate.[11]

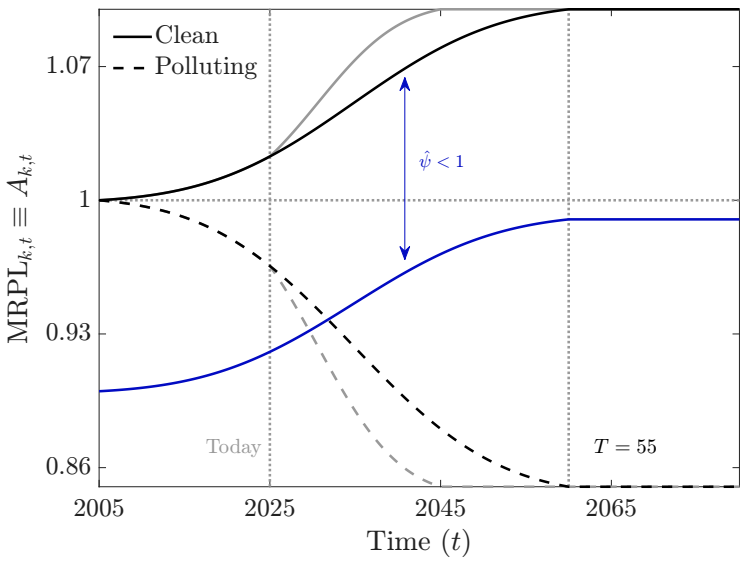
The transition is initiated by a change in F_t in favor of the good produced in the clean sector, reflecting either a change in government mandates or regulation or a change in preferences (e.g., increased awareness on climate issues). As a result, the price of the good produced in the clean sector becomes positive. Therefore, the marginal revenue product of labor A_t^C given by (3.1)–(3.2) becomes positive in 2005.[12] As we will discuss in Section 6, the level of A_0^C in the clean sector when the transition begins in 2005 is not separately identified from the mean of the distribution of skill endowments G, since workers could be productive in the clean sector on average either because A_0^C is high or because they have high skills there. For this reason, we can also normalize $A_0^C = 1$.

The initial shock sets off a transition during which workers reallocate to the clean sector and firms innovate in both sectors. Productivities rise in the clean sector and decline in the polluting sector over the transition. Over the status quo transition, the productivities A_t^k follow S-shaped curves that are characteristic of innovation and technology adoption (Griliches, 1958; Shepherd et al., 2012). As we explain in Appendix A.6, the S-curve in the clean sector reflects higher returns to innovation in that sector early on, followed by smooth convergence to a new balanced growth path in the long run. The opposite happens in the polluting sector, where the growth rate declines as the price of the intermediate good falls and firms innovate innovation, before settling on the final balanced-growth path. We assume

[11] Focusing on an initial steady state where the clean sector is absent will allow us to calibrate internally ten parameters at this initial steady state, independently from the distribution G and the accumulation rate $\hat{\delta}$ of the relative skill $\hat{\psi}$ in the clean sector (Section 6.2).

[12] The presence of technological spillovers along the initial balanced-growth path implies that the initial physical productivity a_t^k is positive in the clean sector, despite the lack of direct innovation.

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, $\hat{\psi}$) in the clean sector, for some productivity $\hat{\psi} < 1$ in that sector.

that the transition in A_t^k is mostly complete by 2060, at which point MRPLs settle down to their long-run balanced growth path.

Figure 1 illustrates two such paths of sectoral productivities (in black). The solid curve corresponds to the clean sector, and the dashed one to the polluting sector. The blue curve indicates a workers' detrended output $A_t^k h\left(\hat{\psi}, k\right)$ in the clean sector, which depends on the workers' relative productivity $\hat{\psi}$. Of course, there is great empirical uncertainty surrounding this transition and, in particular, the long-run impacts of the transition (Mayfield et al., 2023; Finkelstein Shapiro and Metcalf, 2023; IRENA, 2023). We will therefore present results for a menu of paths of A_t^k under the status quo, including different long-run levels.

3.3 Counterfactuals

We have argued that the government can implement any arbitrary path of A_t^k given the instruments it has access to (Proposition 1). We now consider counterfactuals where government policy accelerates or slows the transition starting in 2025 —

the exercise that is most relevant to policymakers today. Specifically, we consider counterfactuals in which, starting from 2025, A_t^k evolves according to

$$A_t^k = A_0^k + \bar{\Phi}_t^k \left(2025 + \eta \left(t - 2025\right)\right) \times \left(A_\infty^k - A_0^k\right), \quad \text{for } t \geq 2025 \tag{3.4}$$

after 2025, where the parameter η governs the speed of transition. The paths of A_t^k align exactly with the benchmark transition when $\eta = 1$. A higher η indicates that more of the transition occurs earlier, e.g., the government subsidizes EV purchases early during the transition. In our benchmark counterfactuals, we focus on temporary interventions which hold fixed the long-run balanced growth path and levels of A_∞^k.[13] As an extension, we will also consider counterfactuals where both η and the long-run levels A_∞^k change. The gray curves in Figure 1 illustrate one such counterfactual transition associated to some $\eta > 1$.

For each counterfactual transition, we will compute changes in workers' lifetime earnings as

$$d\mathcal{W}\left(j, \hat{\psi}, s; \eta = \hat{\eta}\right) \equiv \frac{W_{2025}\left(j, \hat{\psi}, s\right)\big|_{\eta=\hat{\eta}}}{W_{2025}\left(j, \hat{\psi}, s\right)\big|_{\eta=1}} - 1, \tag{3.5}$$

where $W_{2025}\left(j, \hat{\psi}, s\right)\big|_{\eta=\hat{\eta}}$ corresponds to a worker's value function (Appendix A.1) evaluated in 2025 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 7.1, we conduct a more retrospective exercise where we compare workers' values as of 2005 under the baseline transition with $\eta = 1$ relative to no transition at all.

We focus on incumbent workers, i.e., those already alive in 2025, who are initially employed in the polluting sector.[14] These 10-15 million workers are the ones at risk of displacement whose concerns are an obstacle to the support of ambitious climate goals. Our estimates allow one to assess how expensive it might be to compensate these workers for their lost labor income in order to garner support

[13] For instance, suppose that the government eventually reverts to the same long-run subsidies (or taxes) that prevail at the laissez-faire. In this case, our innovation process ensures that the level of the long-run balanced-growth path is unchanged.

[14] 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 6.1, along with a clear definition of polluting and clean sectors.

for ambitious climate goals. It is worth noting that the climate transition could, to a lesser extent, also affect workers who were not initially employed in polluting industries, e.g., white collar workers moving to administrative positions in clean industries as they take off. While it would be interesting to study how the transition affects these workers as well, doing so would require us keeping track of a joint distribution of skills in clean, polluting and other sectors, which is computationally infeasible. We pursue a more modest but highly policy-relevant goal by focusing on the workers who are most at risk from the transition.

4 Economic Mechanisms

Before conducting a quantitative analysis, we examine the core economic mechanisms of our model and establish our key conceptual insights. Since the role of labor market frictions is a quantitative point, we delay its discussion until we have quantified the full model.

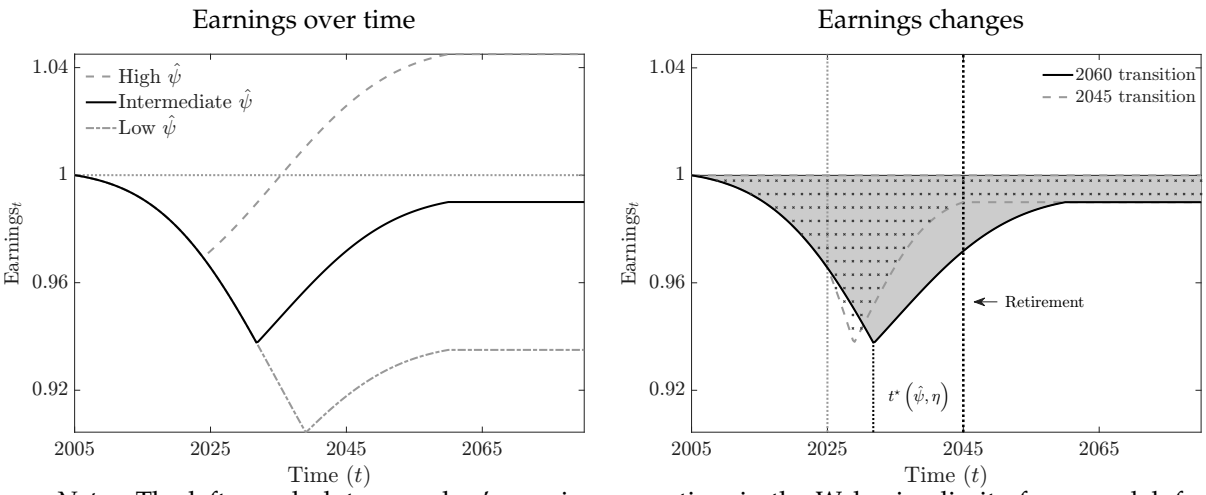
4.1 Non-Linear Effects of Transition Pace

To maximize transparency, we first consider a Walrasian limit of our model where workers are paid their marginal product and there is full employment, with no outside sector.[15] Throughout, workers are assumed to be active from 25 to 65 years of age ($J = 40$).

The left panel of Figure 2 plots the path of earnings over time for a particular worker in this Walrasian limit under a baseline transition ($\eta = 1$). The worker initially supplies labor to the polluting sector. At every instant, they compare their earnings in that sector A_t^P to their potential earnings in the clean sector $A_t^C\hat{\psi}$, and supply labor in the clean sector if and only if $\hat{\psi} \geq A_t^P / A_t^C$. 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 $t^\star\left(\hat{\psi}\right) \geq 0$, which depends on their relative skill $\hat{\psi}$, and switches to the clean

[15] This limit holds when the vacancy posting cost $\nu \to 0$. 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.

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 $\hat{\psi}$ 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 $\eta > 1$.

sector thereafter.[16] A worker switches sector if their stopping time occurs during their life span: $t^\star\left(\hat{\psi}\right) < J + \tau$.

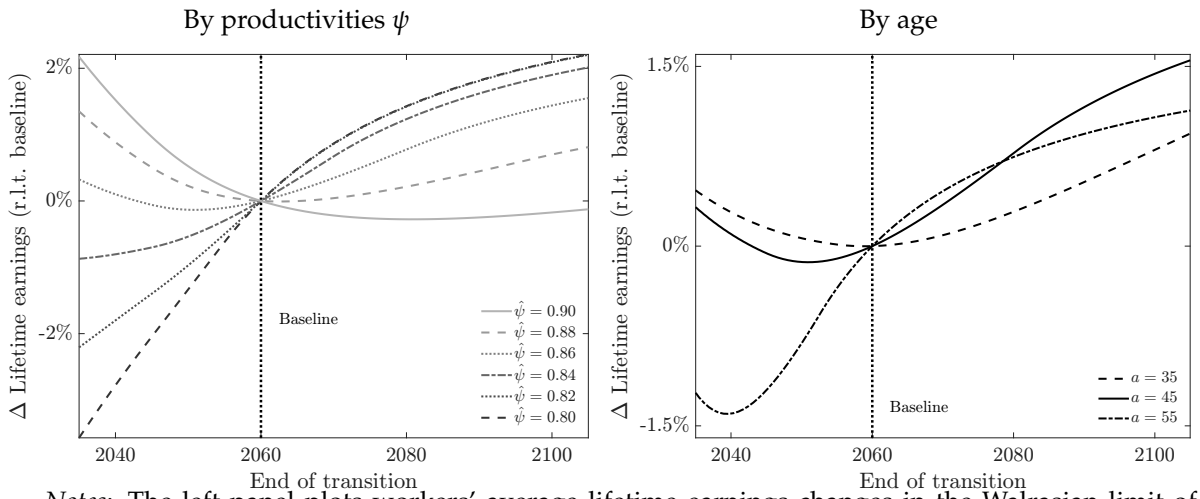
Workers' earnings decline following the path of A_t^P while they remain in the polluting sector. Their earnings rise with A_t^C after they switch sectors. Those with a higher relative skill (in gray dashed) switch earlier and benefit more in the long-run.

The effect of a baseline transition on worker's lifetime earnings is given by the area between the realized earnings path and 1 discounted by rate ρ until the worker retires. This is depicted by the gray shaded area in the right panel of Figure 1. Polluting-sector workers with imperfectly transferable skills ($\hat{\psi} < 1$) lose from the early phase of the transition since the productivity gap between sectors opens up slowly. Thus the gray area is likely negative for many workers. Our first quantitative goal will be to estimate the distribution of earnings losses from the baseline transition – the gray areas – in the full model.

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 worker remains in the polluting sector. On the other hand, the worker switches

[16] Formally, $t^*(\hat{\psi})$ is the solution to the equation $\hat{\psi} = A^P_{t^*(\hat{\psi})} / A^C_{t^*(\hat{\psi})}$, or $t^\star\left(\hat{\psi}\right) \equiv 0$ or $t^\star\left(\hat{\psi}\right) \equiv \infty$ if no solution exists and the worker either switches immediately or never at all.

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 $\hat{\psi}$ in the clean sector. All earnings changes are relative to the baseline transition ending in 2060, and faster transitions are parameterized as in equation (3.4). 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 $\hat{\psi} = 0.86$ in the clean sector. We suppose all workers are born at 25 years old and retire at 65.

to the clean sector sooner, earnings grow faster after the worker switches and a larger share of the transition is completed before retirement. This is depicted by the checked area in the right panel of Figure 2. Our second quantitative goal in the full model will be to estimate the distribution of differences between the gray and checked areas for various transition speed η.[17]

The interplay of these two forces generates highly non-linear or even non-monotonic relationships between the speed of transition η and workers' lifetime earnings. This is illustrated by Figure 3, which plots changes in lifetime earnings as a function of the year when the transition (3.4) 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 – thus all lifetime earnings changes are zero for a transition ending in 2060 by construction. Moving to the right on the plot represents slowing down the transition. The left panel repeats this experiment for workers with various relative

[17] Note that the gray area will generally be negative for most workers – workers employed in the polluting sector would generally prefer there to be no transition. This should be held in mind when assessing counterfactual earnings changes from faster transitions beginning in 2025.

productivities $\hat{\psi}$ and who have 20 years of work remaining.

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 vary sharply as the transition accelerates. For instance, a worker with $\hat{\psi} = 0.88$ is mostly indifferent when the transition slightly accelerates starting from 2060. Yet, the same worker benefits 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.

Earnings changes can even be *non-monotonic* in the pace of transition: some workers who initially lose from a faster transition end up benefiting from an even faster one. For instance, the worker with $\hat{\psi} = 0.88$ 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, but sufficiently slow that they retire before their earnings recover from clean sector growth.[18] A simple way to understand the U-shape is by considering a worker who retires at exactly the moment they would have switched to clean sector under the baseline transition ($t^*\left(\hat{\psi}\right) = J + \tau$).[19] This worker spends their whole career in the polluting sector and thus clearly prefers a slower transition. But they may also prefer a faster transition, as they now switch to the clean sector during their career and benefit from the productivity increases there. This gives rise to the U-shape.

Non-monotonicities occur for any worker with intermediate relative productivities $\hat{\psi}$ who would switch sectors during some period $0 < t < \infty$ under *some* transition speed. These are exactly the workers who form the bulk of the cross-sector reallocation. We formalize these results in Appendix A.9.[20]

Initial age also matters. The right panel of Figure 3 repeats the same exercise for various ages as of 2005, fixing the relative productivity $\hat{\psi} = 0.86$. The magnitude

[18] 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.

[19] The U-shape can survive with standard discounting rather than retirement; however, the model with retirement is both realistic and most transparently illustrates the economics.

[20] 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. 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.

and shape of these non-linearities are sensitive to a workers' age because older workers have a shorter remaining horizon and 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 $\hat{\psi}$ and cohort τ are crucial inputs to their earnings losses from transitions of different speeds.

The introduction of an outside option does not change the qualitative insights developed here. If the worker can receive a constant b^O in the outside sector at any point, their earnings profile features a flat region at b^O whenever $A_t^P \leq b^O \leq A_t^C \hat{\psi}$. Accelerating the transition still steepens the initial earnings decline, which is still traded off against potentially larger gains after switching to the clean sector. Thus the non-linearity and non-monotonicities emphasized above survive. Of course, the earnings floor at b^O will affect the quantitative behavior of the model.

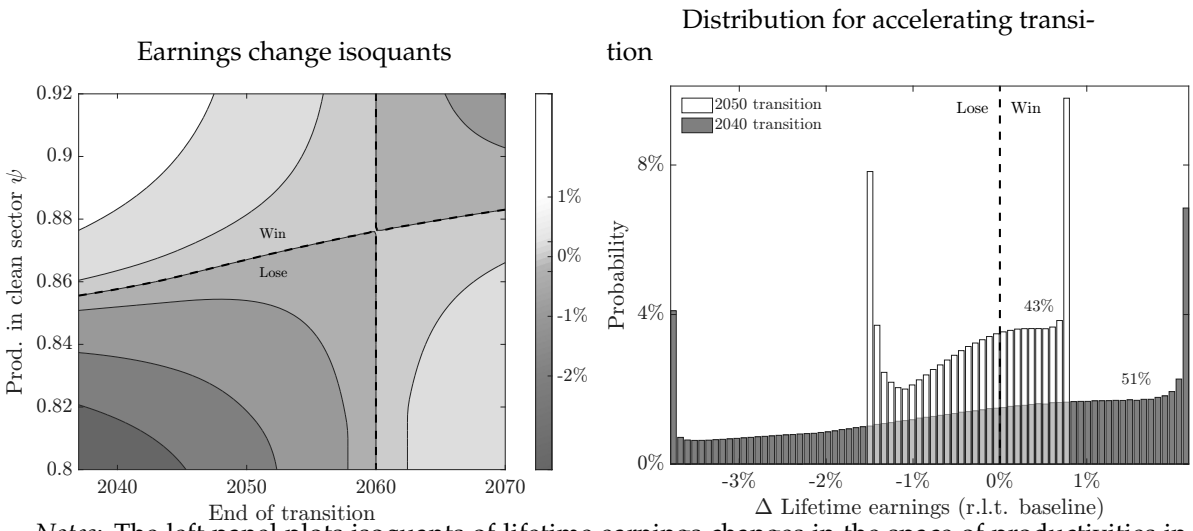
4.2 The Set of Winners and Losers

This non-monotonicity has an important corollary: the set of workers who win and lose – i.e. have positive or negative lifetime earnings changes – from the transition is sensitive to its speed. The left panel of Figure 3 plots isoquants of lifetime earnings changes relative to the baseline transition in the space of relative productivities $\hat{\psi}$ and the end date of the transition. The region to the left of 2060 represents a faster transition. Workers with high $\hat{\psi}$ benefit from faster transitions while those with very low relative productivity lose more and more. Importantly, some workers – such as a worker with $\hat{\psi} = 0.86$ – *switch* from "losers" to "winners;" that is, the set of people who benefit from the transition depends on its speed.[21]

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. One can see this by the fact that the dividing line between winners and losers is upward sloping, so the range of $\hat{\psi}$ that wins grows as the transition grows faster, but the darkest colors are to the far left of the plot. This trade-off has important political economy considerations if voters are strongly

[21] 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.

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 parameterized as in equation (3.4). 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 $\eta = 1$.

motivated by their anticipated labor market outcomes (Dechezleprêtre et al., 2025) and may present a conundrum for policymakers.

4.3 Summary and Discussion

Our model offers three novel conceptual insights. First, the labor market consequences of the climate transition are highly non-linear in its pace to the point that they can be U-shaped: 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 before retirement. These non-monotonicities arise for any marginal worker who switches sectors for some $0 < t < \infty$, and their degree is determined by workers' relative skills and age. Second, the set of "winners" and "losers" is sensitive to the speed of transition. A faster transition generally increases the mass of workers who benefit from the transition, but generates a thicker tail among those who lose, presenting a trade-off for policymakers. Third, we will additionally show that labor market frictions quantitatively

amplify these forces through structural underemployment and the job-ladder.

While we apply our model in the context of the climate transition, it is also applicable to other settings in which demand falls one set of jobs and rises for another. Our setup nests scenarios where one technology becomes obsolete (Aghion and Howitt, 1992; Violante, 2002) and is taken over by another more productive one, or trade shocks that induce a reallocation of labor (Dix-Carneiro, 2014; Dix-Carneiro et al., 2023; Traiberman, 2020). The conceptual insights developed here appear 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.

Before proceeding to quantitative analysis, it is worth discussing the interpretation of our A_t^k. The paths of A_t^k 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.[22] 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

[22] 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).

dynamic appears to play out beyond the context of the climate transition: Braxton and Taska (2023a) 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 of the A_t^k as the penetration of each technology in the economy and the incentives to hire workers to operate these technologies, and $\hat{\psi}$ as the relative ability of workers to operate these technologies. Our model captures the idea that workers with a high $\hat{\psi}$ 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.[23]

5 A Quantitative Model of the Labor Market

With an eye towards quantitative analysis, we enrich the model from Section 2 to reckon with three important aspects of the data. First, we allow workers to invest in their skill and accumulate them on-the-job (Jacobson et al., 2005; Lise and Postel-Vinay, 2020). Second, workers' search is imperfectly directed in practice: job switches often entail wage cuts (Sorkin, 2018) and there are gross flows across occupations and sectors (Moscarini and Thomsson, 2007; Pilossoph, 2014). Finally, job separations and firm exit respond to economic conditions (Fujita and Ramey, 2009; Clementi and Palazzo, 2016a), so we allow for endogenous separations.

5.1 Skill Accumulation

Skill accumulation. Workers have multi-dimensional skills that accumulate endogenously. There is a general skill ψ^G, which applies to all pursuits, and specific skills ψ^P and ψ^C which apply to one sector only. Workers' overall productivities in pol-

[23] It is costly for the firm to familiarize the worker with the clean technology and production process regardless of 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 if reallocation within the firm requires an internal job posting with the same matching technology f.

luting and clean sectors are $\psi^G\psi^P$ and $\psi^G\psi^C$, respectively. Workers are endowed with a unit of general skill $\psi^G \equiv 1$ at birth and one unit of specific skill $\psi^P \equiv 1$ in the polluting sector. They are endowed with a heterogeneous specific skill at birth $\psi^C \sim G$ in the clean sector. After this initial endowment, workers accumulate the general skill ψ^G at rate δ_j^+ when employed in the polluting or clean sectors, δ_j^O in the outside sector, and $\delta^U < 0$ when unemployed. Specific skills ψ^P and ψ^C grow at rate $\hat{\delta}$ when employed in the corresponding sector. In the following, we will establish that we can keep track of a reference skill $\psi \equiv \psi^G\psi^P$ and a relative skill $\hat{\psi} \equiv \psi^C/\psi^P$ instead of ψ^P, ψ^G and ψ^C separately. Workers' productivity $h\left(\psi, \hat{\psi}, k\right)$ is then defined as in equation (2.2).[24]

5.2 Noisy Search and Endogenous Separations

Labor markets are modeled as in Section 2.1.3, with the following additions.

Job search. Search is not perfectly directed in practice. Accordingly, we suppose that a worker of type $\mathbf{x} \equiv \left(j, \psi, \hat{\psi}\right)$ in market s searches in a given market s' with probability

$$p_t\left(s'; \mathbf{x}, s\right) \equiv \frac{\exp\left(f\left(\theta_t\left(\mathbf{x}, s'\right)\right)\left[W_t\left(\mathbf{x}, s'\right) - W_t\left(\mathbf{x}, s\right)\right]/\zeta\right)}{\sum_{\hat{s}} \exp\left(f\left(\theta_t\left(\mathbf{x}, \hat{s}\right)\right)\left[W_t\left(\mathbf{x}, \hat{s}\right) - W_t\left(\mathbf{x}, s\right)\right]/\zeta\right)}, \tag{5.1}$$

where the sum is over the sectors $k = P, C$ and wages $w \in \{w_1, \ldots, w_N\}$, as well as the outside sector O and unemployment U.[25] Worker are more likely to search in a given market s' if the expected improvement in its value is larger. 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 ζ (Artuç et al., 2010). Alternatively, this hazard can be generated by assuming that workers have to acquire costly information about the jobs that they apply to (Matêjka and McKay, 2015).[26] The parameter ζ captures the degree

[24] In particular, flow payoffs in unemployment and the outside sector continue to scale with ψ.

[25] We discretize the grid for wages, for numerical convenience. The continuous case obtains when $N \to +\infty$. We allow for a relatively fine grid for wages in our numerical implementation. We suppose that workers only search in markets with positive vacancies so as not to "spend" their search effort on markets that they have no chance of finding a job in.

[26] The first formulation would increase workers' values by allowing them to enjoy job-specific

to which search is directed: search is purely directed as $\zeta \to 0$ as in canonical directed search, and purely random when $\zeta \to \infty$.[27]

Endogenous separations. Firms incur operating costs at a constant Poisson arrival rate $\chi_0 > 0$, at which point they draw a random cost $\varepsilon\psi \exp(\bar{g}t)$ where ε is log-normally distributed with location ϕ and scale γ.[28] Operating costs scale with a workers' reference skill ψ to capture the fact that, for instance, corporate training is more expensive for senior employees. They also increase at the overall growth rate $\bar{g}$ to ensure that the economy admits a balanced-growth path. These operating costs capture various forms of investment and expenses that are required for the worker to keep producing, including down payments to acquire machines, interest rate payments, rent, insurance, etc. Firms separate endogenously from their worker when the operating cost exceeds the firm's value V, which occurs with probability

$$\mathcal{F}_t(V, \psi) \equiv 1 - \Phi\left(\frac{\log\left(V / \left(\psi \exp\left(\bar{g}t\right)\right)\right) - \phi}{\gamma}\right) \tag{5.2}$$

for $\Phi(\cdot)$ the CDF of the standard normal distribution. Since A_t^P falls over time, polluting-sector firms become less likely to be willing to cover these costs, leading to separations over the transition.[29] Workers are separated exogenously from the outside sector at constant and exogenous rate $\chi_0 \bar{\mathcal{F}}$, where $\bar{\mathcal{F}}$ is the average firing hazard (5.2) that prevails in the polluting sector along the initial balanced-growth path. Similarly, workers find jobs at constant and exogenous rate f^O in the outside sector, where f^O is the average job finding probability that prevails in the polluting sector initially. We assume in the following that the vacancy posting cost now scale

amenities. On the contrary, the second would decrease them by assuming that workers have to acquire costly information. We follow Traiberman (2020) and do not include the amenity value or information processing cost in workers' values since we focus on earnings changes.

[27] Firms know the characteristics of the worker they are matching with, which preserves the block-recursive nature of the equilibrium (as in Menzio and Shi, 2011).

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

[29] Many of these layoffs will be efficient. However, some may be inefficient since wages are rigid downward on-the-job as in the data (Grigsby et al., 2021). Jäger et al. (2023) and Davis and Krolikowski (2025) provide evidence for such inefficient separations. Blanco et al. (2024) present a model of inefficient separations arising from wage rigidity. In our quantification, we directly target firms' propensity to fire workers.

with a worker's reference skill $v\psi \exp(\bar{g}t)$.

5.3 Recursive Formulation and Equilibrium

We state workers' and firms' values recursively in Appendix A.1.[30] We define the equilibrium formally in Appendix A.3. Finally, we establish in Appendix A.4 that the values are linear in $\psi \exp(g^* t)$ which allows us to track *only* the relative skill $\hat{\psi} \equiv \psi^C / \psi^P$ as an explicit state variable when characterizing values, which makes the model and its estimation computationally manageable.[31] We next outline our approach to disciplining the model empirically.

6 Bringing the Model to the Data

Our calibration proceeds in two steps. We first discipline several parameters by matching a rich set of micro moments from the period before 2005, which corresponds to the initial stationary equilibrium of our model. We then use early phase of the transition from 2005–2025 to structurally estimate the distribution of skill endowments $G(\psi^C)$ and the relative skill accumulation parameter $\hat{\delta}$. Appendix C provides further details.

It is worth reiterating that our analysis is *prospective*. There is thus uncertainty regarding long-run changes that have yet to occur. 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. No individual estimate should thus be taken as definitive.

6.1 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-

[30] The simpler model introduced in Section 2 obtains as a special case when there is no skill accumulation, i.e., $\delta_j^+ = \hat{\delta}_j = 0$, search is perfectly directed, i.e., $\zeta \to 0$, and separations are exogenous, i.e., $\gamma \to +\infty$.

[31] Economizing the state variable ψ is possible because the operating and vacancy posting costs both scale with ψ.

tions.[32] To define "polluting" industries, we follow the 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).[33] This measure accounts for emissions produced throughout the supply chain of production of each commodity. An industry is deemed to be polluting 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 first 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.[34] 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 clean 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 from the Green Goods and Services (GGS) survey produced by US Bureau of Labor Statistics (BLS) to study

[32] 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.

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

[34] 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.

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 is both as green and polluting, we classify it as neither. All other sectors form the basis of the "outside" category. We define polluting-attached workers in the Current Population Survey (CPS) as those employed in the polluting sector for the entirety of their first 4-month CPS wave.[35]

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.

6.2 Steady State Calibration

External Calibration. A unit length of time corresponds to a year. Workers live for 40 years ($J = 40$) and we set the discount rate $\rho = 0.03$. 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, with $\alpha = 1.45$ as in Schaal (2017). We pick $\chi_0 = 2$ so that operating cost shocks arise semiannually on average, reflecting performance reviews.

Turning to skill accumulation, we suppose that the rate $\hat{\delta}$ at which workers accumulate the specific skill is age-invariant. We directly measure the rate $\delta_j^+ + \hat{\delta}$ in

[35] Appendix C describes the CPS data and reports summary statistics about the workers attached to polluting industries.

Table 1: External calibration

Parameter	**Description**	**Value**	**Source**
Preferences			
J	Lifespan	40	Career length
ρ	Discount rate	0.03	3% Interest Rate
Technology			
α	Elast. of matching function	1.45	Schaal (2017)
χ_0	Operating cost (arrival rate)	2	Semi-annual review of workers

the CPS using on-the-job wage growth among workers attached to polluting sectors before the transition starts. We structurally estimate the contribution of $\hat{\delta}$ in this sum in Section 6.4. Workers' in the outside sector see wage increases at the same rate the economy grows, so we set $\delta_j^O = 0$. Finally, we let $\delta_j^U = -0.096$, corresponding to a 0.8% loss in human capital per month of unemployment following evidence from Schmieder et al. (2016).

Internal Calibration. The search intensity for unemployed workers λ^U targets a monthly UE rate of 25% (Shimer, 2005), while the search intensity for employed workers λ^E targets a monthly EE rate of 2.5% (Fujita et al., 2024). The degree of noise in search ζ replicates the fact that 32.5% of job-switchers experience a wage cut (Grigsby et al., 2021).[36] We obtain a standard deviation of 0.075, which is small relative to average flow wages.

We set the vacancy posting cost ν to match an average markdown of 20%, (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 plays a key role in the model: it determines the profitability of each job, and hence firms' incentives to create vacancies and fire workers along the transition. We obtain a vacancy posting cost of 16.5% of annual output, which is around the estimate of Shimer, 2005.

The average log operating cost ϕ governs the rate at which matches are endoge-

[36] Tjaden and Wellschmied (2014) and Sorkin (2018) report very similar numbers.

Table 2: Internal calibration

Parameter	Description	Value	Moment	Source	Target	Model
Search						
λ^U	Search intensity (U)	4.748	UE rate (M)	Shimer (2005)	25%	25%
λ^E	Search intensity (E)	0.457	EE rate (M)	Fujita et al. (2024)	2.5%	2.5%
ζ	Search Directedness	0.075	Share of wage cuts	Grigsby et al. (2021)	32.5%	32.5%
b^U	U benefit	0.350	Average UI replac.	US UI Rules	40%	40%
b^O	O benefit	0.538	Wage change (EUO)	CPS ORG	–24%	–24%
Job finding						
ν	Vacancy post. cost	0.165	Average markdown	Berger et al. (2022)	25%	25%
f^O	Job Finding Rate in O	0.686	Average markdown	Berger et al. (2022)	25%	25%
Separations						
ϕ	Oper. costs (loc.)	-4.534	Unempl. rate	US Average	5%	5%
γ	Oper. costs (scale)	2.320	Elasticity of separ.	Chan et al. (2023)	-2.0	-2.0
χ^O	Separation rate (O)	0.077	Separation rate (M)	US Average	8%	8%

nously destroyed. We pick ϕ to match an average steady state unemployment rate of 5%. The scale of the log operating costs γ controls the elasticity of job destruction to drops in productivity.[37] We target an elasticity of separations of -2.29 following a negative 10% permanent idiosyncratic productivity change, based on the evidence from Chan et al. (2023).[38] 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.

The unemployment benefit b^U is chosen so that workers who get laid off have an average replacement rate of 50% as a share of their previous wage, reflecting a mix of home production and unemployment insurance. We obtain $b^U = 0.350$

[37] See Beraja and Zorzi (2024a) for an application to durable spending.

[38] Note this estimate comes from Denmark. This elasticity is also in line with the findings of Carlsson et al. (2021). The literature consistently finds a standard deviation of 10% to 15% for idiosyncratic and permanent TFP shocks (Carlsson et al., 2021; Maibom and Vejlin, 2021; Friedrich et al., 2025). 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 and workers' outside options remain unchanged.

which reflects both selection in who loses their job and the fact that workers' wages are less than 1 in equilibrium. We choose the flow payoff of the outside sector b^O by targeting the mean wage change of workers initially attached to polluting industries who undergo an E-U transition followed by an U-E transition to any outside sector in consecutive years of the CPS Outgoing Rotation Group (ORG) supplement. The average hourly wage change following such transition is -24%, which we leads us to estimate $b^O = 0.538$.

6.3 The Path of Sectoral Productivities

The path of sectoral productivities is given by equation (3.3). 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

$$\bar{\Phi}\left(t;\mu,\sigma,T\right) = \min\left\{\frac{\Phi\left(\frac{t-\mu}{\sigma}\right) - \Phi\left(\frac{0-\mu}{\sigma}\right)}{\Phi\left(\frac{T-\mu}{\sigma}\right) - \Phi\left(\frac{0-\mu}{\sigma}\right)}, 1\right\} \qquad \text{for } t \geq 0, \tag{6.1}$$

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 parameterize 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 $A_t^k = A_0^k + \min\left\{t/T, 1\right\}\left(A_\infty^k - A_0^k\right)$.

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 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 Appendix Figure 9 shows, the estimated curve fits the raw data well. 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. We therefore study a menu of scenarios for A_∞^k. 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 between clean and polluting in the long-run. Our baseline analysis assumes 10% changes in productivity: $A_\infty^C = 1.1$ and $A_\infty^P = 0.9$, which aligns with predictions elsewhere in the literature regarding both the scale and composition of employment in 2050.[39] Figure 1 plots the paths for the sectoral productivities A_t^k implied by this S-shape and long-run labor demands A_∞^k.

6.4 Estimating the Skill Distribution

At this point, there are still two key objects to estimate: the distribution of skill endowments $G\left(\psi^C\right)$,[40] and the rate of specific skill accumulation $\hat{\delta}$. 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 $A_{k,t}$.

[39] 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, 2023). 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.

[40] Since all workers are endowed with one unit of general and polluting sector skill, one can equivalently conceptualize $G\left(\cdot\right)$ as the distribution of relative skill $\hat{\psi}$ at birth, which we term $\hat{\psi}^{\text{endow}}$.

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 best understood by inspecting the left panel of Figure 2. In the Walrasian limit of Section 4, workers with higher $\hat{\psi}$ reallocate earlier. In particular, all workers with $\hat{\psi} \geq A_t^P / A_t^C$ reallocate before period t so the share of workers who have already switched by period t is $1 - G\left(A_t^P / A_t^C\right)$. Labor reallocation over time therefore allows us to trace the distribution $G\left(\hat{\psi}\right)$ non-parametrically given the paths for A_t^k.[41] Of course, the process of labor reallocation is richer in our full quantitative model: workers differ in their employment statuses and skill accumulation histories, and reallocation is frictional. However, we will show below the same insight applies in our model, allowing us to estimate the endowment distribution G.

To disentangle the distribution of endowments from skill accumulation, we compare two cohorts born in different periods τ. The older cohort has spent more time in the polluting sector by the beginning of the transition, and thus has more skills specific to P and lower $\hat{\psi}$'s. As a result, they reallocate to the clean sector slower. This prediction is consistent with the data, as we discuss below.

Threats to Identification. In our model, workers reallocate on the basis of their relative productivity $\hat{\psi}$ and the sectoral productivities A_t^k. One possible concern is that workers could also reallocate for amenity reasons: 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, augmented to allow for amenities. Specifically, suppose that the flow payoffs from working in the clean sector are $A_t^C \Lambda_t \hat{\psi} \xi$, where ξ is an idiosyncratic component of the relative amenity (some workers are more concerned with the environment than others) and Λ_t is an aggregate component of the relative amenity (working in the climate sector becomes more fashionable over time). Workers supply labor to the clean sector if and only if the product of their idiosyncratic productivity ψ and their relative

[41] We consider a menu of terminal values A_∞^k in our analysis. Different terminal values generate different paths for relative productivities A_t^P / A_t^C, which in turn changes the estimated distribution $G\left(\hat{\psi}\right)$ in order to match the data. However, we only match reallocation patterns from 2005-2024 for estimation of $G\left(\cdot\right)$. The long-run behavior of reallocation will still depend on the exact choice of A_∞^k given our time-invariant estimated distribution of skill endowments.

amenity ξ in the clean sector are sufficiently large relative to the relative sectoral productivities and the aggregate amenity, i.e., $\hat{\psi}\xi \geq A_{P,t}/\left(\Lambda_t A_{C,t}\right)$. This condition is isomorphic to the one in Section 4, when setting

$$\hat{\psi}' \equiv \hat{\psi}\xi \quad \text{and} \quad A_t^{C\prime} \equiv \Lambda_t A_t^C$$

Accordingly, the path of sectoral productivities A_t^k that we feed in (Section 6.3) should reflect the relative amenity value of supplying labor in the clean sector — this is partly the reason why we conduct various sensitivity analyses. Given this path, our estimation backs out the distribution of $\hat{\psi}\xi$ which determines workers' incentives to reallocate and values.

The dynamic is more complicated in the full model, where agents are forward-looking and labor markets are frictional, but the same economics hold: if workers systematically prefer to work in the clean sector, they accept lower wage payments. This leads 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, so long as one is willing to interpret our estimates as being a broader measure of worker well-being which includes their valuation of amenities. Besides amenities, our estimates of ψ also capture other forms of reallocation costs, e.g., due to geographic mobility between employers. Regardless of its exact interpretation, the distribution of $\hat{\psi}$ that we estimate reflects the reasons why workers are slow to switch from polluting to clean jobs.

Estimation. The estimation problem is to choose a distribution G and rate of specific skill accumulation $\hat{\delta}$ to solve

$$\min_{G,\hat{\delta}} \sum_{\tau} \int_{2005}^{2024} \left(z_{\tau,t}^{\text{data}} - \int_0^1 z_{\tau,t}^{\text{model}} \left(\hat{\psi}^{\text{endow}}; \hat{\delta} \right) G \left(\mathrm{d}\hat{\psi}^{\text{endow}} \right) \right)^2 dt, \tag{6.2}$$

where $z_{\tau,t}^{\text{data}}$ indicates the empirical share of workers in cohort τ that have reallocated between period 0 and t and $z_{\tau,t}^{\text{model}}\left(\hat{\psi}^{\text{endow}}; \hat{\delta}\right)$ is the share of workers in the same cohort and endowed with skill $\hat{\psi}^{\text{endow}}$ that have reallocated over the same period in the model.[42] The latter is a function of specific skill accumulation $\hat{\delta}$.

[42] We do not use wage data in our estimation due to challenges relating to composition effects.

We leverage the block recursivity of our directed search model (Menzio and Shi, 2011) to solve the problem (6.2) efficiently. This property allows us to solve workers' reallocation shares $z_{\tau,t}^{\text{model}}\left(\hat{\psi}^{\text{endow}};\hat{\delta}\right)$ *independently* from the distribution G: there are no congestion externalities or general equilibrium price effects.[43] The problem (6.2) boils down to solving for the distribution G given these optimal policies and a guess of $\hat{\delta}$, then updating our guess of $\hat{\delta}$ until convergence.

Empirical implementation. We measure $z_{\tau,t}^{\text{data}}$ as the share of workers initially attached to polluting industries that reallocated to the clean sector, relative to those still employed in either clean or polluting in the CPS.[44] Industry codings in the CPS from the Census are less granular than those used for the definition of clean and polluting sectors (Section 6.1). 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. This has the added benefit of partially capturing clean technology adoption within manufacturing.

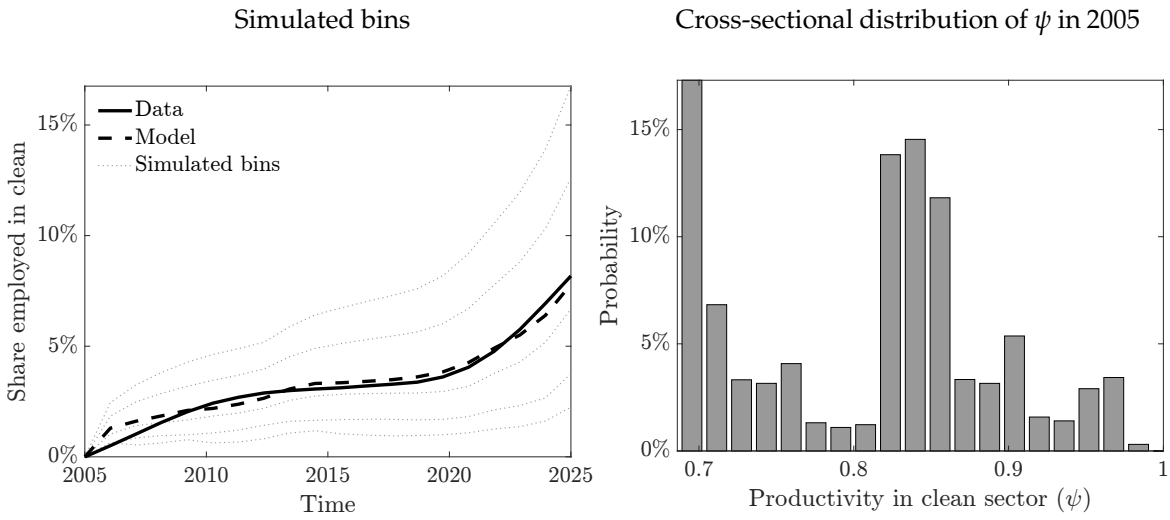
We conduct this exercise for two cohorts born in $\tau = 1960$ and $\tau = 1975$ that were either 30 or 45 years old in 2005. Figure 10 in Appendix C plots the series $z_{\tau,t}^{\text{data}}$ for these two cohorts. According to our estimates, roughly 16% of workers initially attached to polluting industries 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 5 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 relative productivity $\hat{\psi}$. We simulate each discretized bins forward for each

[43] Recall that general equilibrium effects on, say, innovation rates or the relative price of clean sector goods are accounted for by the path of A_t^k and can be freely counteracted by appropriate government policy (Proposition (1)).

[44] The CPS does not allow us to track workers over long periods. We therefore weight individuals in later waves of the CPS by the probability that they would have been attached to the polluting sector in the pre-2005 period according to their observables. Appendix C provides more details.

Figure 5: 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 $\hat{\psi}^{\text{endow}}$ under the estimated $\hat{\delta}$. The dashed curve corresponds to the model-generated reallocation when using the estimated distribution of $\hat{\psi}^{\text{endow}}$. The right panel plots the cross-sectional distribution of relative productivity $\hat{\psi}$ in the population in 2025.

of cohort τ. The left panel of Figure 5 plots $\tilde{z}^{\text{model}}_{\tau,t}\left(\hat{\psi}^{\text{endow}};\hat{\delta}\right)$ for workers with various skill endowments $\hat{\psi}^{\text{endow}}$ after pooling the two cohorts together (dotted curves). Workers with higher skill endowments reallocate more. Even those with relatively small endowment reallocate with some positive probability due to noisy search.[45] 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 $\hat{\delta}$. Our model matches the reallocation patterns very well.

The right panel of Figure 5 plots the cross-sectional distribution of relative skills $\hat{\psi}$ in 2025 induced by our estimates of G and $\hat{\delta}$. The distribution generally shows two types of workers. First, there is a mass of workers who have relatively high

[45] Absent noisy search, workers with skill $\hat{\psi}$ 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.

skill in the clean sector (above 0.85). These are the workers who reallocate quite quickly 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 skill accumulation rate cost of $\hat{\delta} = 0.03$ so that skills grow at 3% per year.

7 The Distribution of Lifetime Earnings Changes

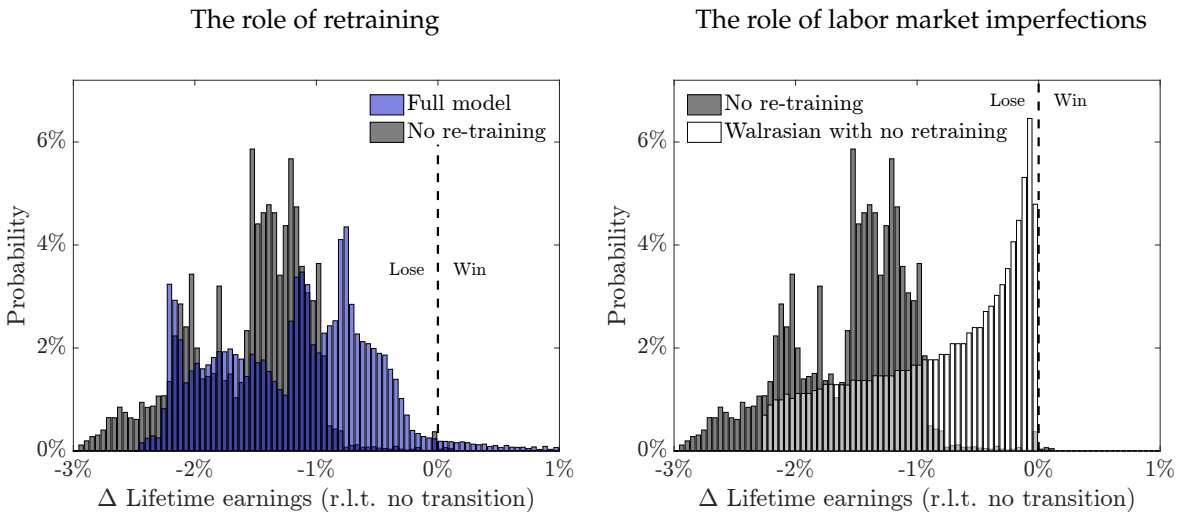
In this section, we use our estimated model to quantify the distributional effects of the climate transition and how they depend on its pace. Specifically, we use our model to answer two questions. First, what is the distribution of lifetime earnings losses that incumbents workers experienced as of 2005?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

7.1 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 7.2 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 6 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 $\hat{\psi} < 1$ 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

Figure 6: 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 skill accumulation (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 $\hat{\psi}^{\text{endow}}$ in all models.

below, a substantial share of workers will *win* relative to this level as the transition accelerates from 2025 onwards.

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 5.3). Some workers will experience much larger earnings changes *ex post* if they are displaced.

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.[46] The fact that we find smaller earnings losses in

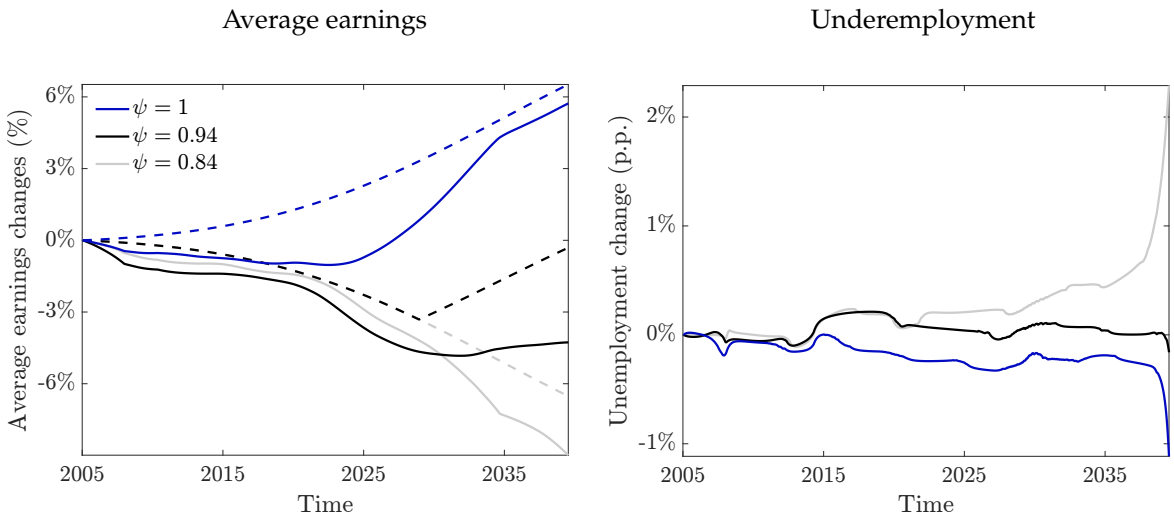
[46] Dix-Carneiro (2014) finds that intersectoral mobility costs are between 1.4 and 2.7 times annual average wages. This translates to roughly 3.5% − 6.75% when spread over a 40-year career.

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 6). 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 6.1). 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.

The role of labor frictions We decompose these earnings changes to understand the role that skill accumulation and labor market imperfections play in our results. In the left panel of Figure 6, we consider a version of our model in which workers cannot accumulate skill over their endowed level of skill $\hat{\psi}^{\text{endow}}$ (in gray). Re-

Figure 7: 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 $\hat{\psi} = 1$ (in blue), a medium-skill worker with $\hat{\psi} = 0.94$ (in black) and a lower-skill worker with $\hat{\psi} = 0.84$ (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.

moving skill accumulation 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 6 considers the Walrasian limit studied in Section 4 where labor markets are frictionless. The average loss among workers who suffer from the transition is roughly 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 7 helps explain the role that these 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 relative skills $\hat{\psi}$ 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 $\hat{\psi} = 1$ (in blue) for whom the path of earnings is strictly increasing in the Walrasian limit; a middle-skill worker with $\hat{\psi} = 0.94$ (in black) who switches during their lifetime in the Walrasian limit; and a lower-skill worker $\hat{\psi} = 0.84$ (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.

Earnings changes in our model broadly track their Walrasian counterparts but still differ substantially. 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). 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 for firms to post costly vacancies for them. Low-$\hat{\psi}$ 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 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

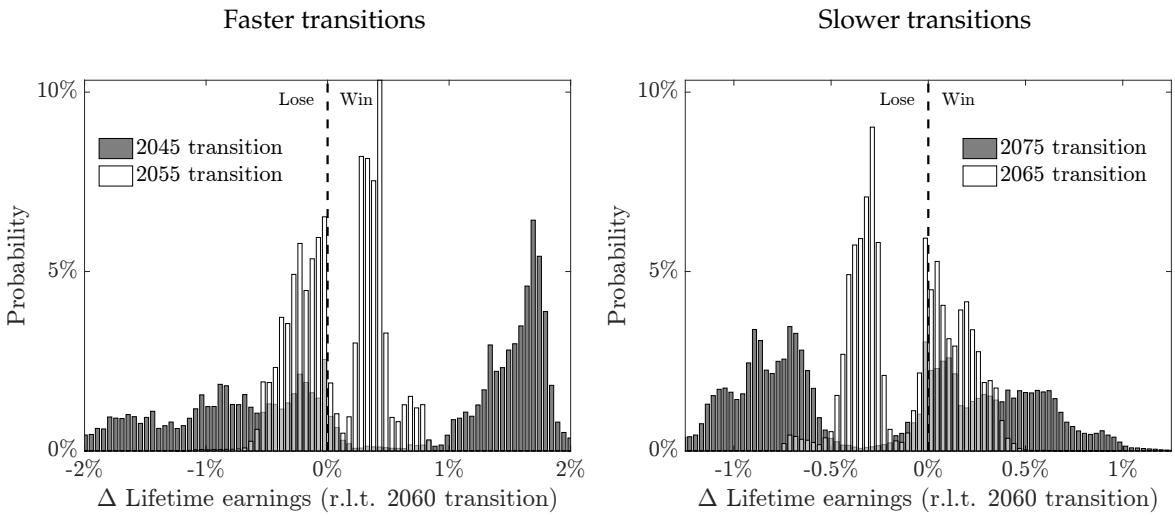
at high-skill workers. Their earnings remain flat at first in our model (and even decrease slightly), whereas they increase quickly in the Walrasian model. The reason is that workers' search behavior (5.1) is only partially directed in our model and hence imperfectly elastic to wage changes. In particular, 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.

7.2 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 (3.4), 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 8 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-$\hat{\psi}$ workers relative to a scenario with no transition at all. These findings echo those previewed in Section 4: while speeding up the transition 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 8 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 tens of billions of dollars.

Figure 8: 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 (3.4).

Slowing down the transition also generates winners and losers, as shown in the right panel of Figure 8. 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.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.

8 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 hetero-

geneous 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 non-linear 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.

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

This appendix provides additional derivations and proofs about our full model introduced in Section 5. Section A.1 states workers' and firms' values recursively. Section A.2 characterizes firms' optimal choices for production and innovation. Section A.3 defines the equilibrium formally. Finally, Section A.4 shows that values satisfy some homogeneity property that allows us to characterize them in terms of de-trended marginal revenue products of labor A_t^k, but also allows us not to keep track of a worker's overall skill ψ in our state space.

A.1 Workers' and Firms' Values

Skill accumulation. Before stating workers' and firms' values, it is useful to perform a change of variable and define the "overall" skill $\psi \equiv \psi^G \psi^P$ and the "relative" skill $\hat{\psi} \equiv \psi^C / \psi^P$. Using the laws of motions that we described in Section 5.1, the overall skill ψ grows at rate

$$\delta_t^\star(k) \equiv \begin{cases} \delta_j^+ + \hat{\delta}_j & \text{if } k = P \\ \delta_j^+ & \text{if } k = C \\ \delta_j^k & \text{if } k = O, U \end{cases} \tag{A.1}$$

depending on the worker's employment status. In turn, the relative skill grows at rate

$$\hat{\delta}_t^\star(k) \equiv \begin{cases} -\hat{\delta}_j & \text{if } k = P \\ \hat{\delta}_j & \text{if } k = C \\ 0 & \text{if } k = O, U \end{cases} \tag{A.2}$$

In the following, we let

$$h\left(\psi, \hat{\psi}, k\right) = \begin{cases} \psi & \text{if } k = P \\ \psi \times \hat{\psi} & \text{if } k = C \\ \psi \times b^k & \text{if } k = O, U \end{cases} \tag{A.3}$$

denote a workers' total productivity across sectoral. After this change of variable, workers are indexed by five states at any points in time: their age j; their overall

skill ψ; their relative skill in the clean sector $\hat{\psi}$; their employment status $e = E, O, U$; and, if employed, their sector 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.

Worker values. The value of an employed worker of age j with skills ψ and $\hat{\psi}$ that is currently in submarket s satisfies

$$\begin{aligned}\rho W_t\left(j,\psi,\hat{\psi},s\right) &= w\left(s\right)h\left(\psi,\hat{\psi},k\left(s\right)\right)\exp\left(g^{\star}t\right) \\ &+ \lambda^{E}\sum_{s'}p_t\left(s';j,\psi,\hat{\psi},s\right)f\left(\theta_t\left(j,\psi,\hat{\psi},s'\right)\right)\left[W_t\left(j,\psi,\hat{\psi},s'\right)-W_t\left(j,\psi,\hat{\psi},s\right)\right] \\ &+ \chi_0\mathcal{F}_t^{k(s)}\left(V_t\left(j,\psi,\hat{\psi},s\right)\right)\left[W_t\left(j,\psi,\hat{\psi},U\right)-W_t\left(j,\psi,\hat{\psi},s\right)\right] \\ &+ \frac{d}{d\epsilon}W_{t+\epsilon}\left(j+\epsilon,\psi\exp\left(\delta^{\star}\left(k\left(s\right)\right)\epsilon\right),\hat{\psi}\exp\left(\hat{\delta}_j^{\star}\left(k\right)\epsilon\right),s\right)\Big|_{\epsilon=0}\end{aligned} \tag{A.4}$$

for each age $j \in [0, J)$, where $W_t\left(j,\psi,\hat{\psi},U\right)$ is the value of being unemployed and $V_t\left(j,\psi,\hat{\psi},s\right)$ is the firm's value in period t, both of which are defined below. Workers discount flows at rate ρ. When employed, they earn $w\left(s\right)h\left(\psi,\hat{\psi},k\left(s\right)\right)\exp\left(g^{\star}t\right)$, with their productivity given by expression (A.3). As discussed in Section 2.1.3, wages grow at rate $g^{\star}$ to ensure that they admit a stationary distribution along a balanced-growth path. Workers have the opportunity to search for another job at rate λ^{E}. The search in submarket s' with probability $p_t\left(s';j,\psi,\hat{\psi},s\right)$ given by expression (5.1). The firm incurs an operating cost at rate χ_0, at which point the worker is laid off and and becomes unemployed with probability $\mathcal{F}^{k(s)}\left(\cdot\right)$ given by expression (5.2). Finally, there is a drift in values over time, over the life cycle, and over the overall and relative skills ψ and $\hat{\psi}$ at rates (A.1)–(A.2).[47] The boundary condition is $W_t\left(J,\psi,\hat{\psi},s\right) = 0$ upon retirement at age $j = J$. The terminal conditions are similar for the the values below so we omit them for concision. It is worth noting that workers might receive transfers for the government. These lump sum transfers do not distort workers' labor supply decisions when workers are risk-neutral (or have access to perfect borrowing), as we assume in this paper. Therefore, we exclude these transfers from workers' values, allowing us to inter-

[47] These drifts are characterized by the single index ϵ.

pret these values as the present discounted value of future earnings — the object of interest in this paper.

In turn, the value of a worker employed in the outside sector satisfies

$$\begin{aligned}\rho W_t\left(j,\psi,\hat{\psi},O\right) &= h\left(\psi,\hat{\psi},O\right)\exp\left(g^{\star}t\right) \\ &+ \lambda^{E}\sum_{s} p_t\left(s;j,\psi,\hat{\psi},O\right) f\left(\theta_t\left(j,\psi,\hat{\psi},s\right)\right)\left[W_t\left(j,\psi,\hat{\psi},s\right)-W_t\left(j,\psi,\hat{\psi},O\right)\right] \\ &+ \chi_0\bar{\mathcal{F}}\left[W_t\left(j,\psi,\hat{\psi},U\right)-W_t\left(j,\psi,\hat{\psi},O\right)\right] \\ &+ \frac{d}{d\epsilon}W_{t+\epsilon}\left(j+\epsilon,\psi\exp\left(\delta_j^{\star}\left(O\right)\epsilon\right),\hat{\psi},O\right)\Big|_{\epsilon=0}\end{aligned} \tag{A.5}$$

for $j < J$, since they receive benefits $h\left(\psi,\hat{\psi},O\right)\exp\left(g^{\star}t\right)$, search for jobs with intensity λ^{E} and lose their job at rate $\chi_0\bar{\mathcal{F}}$. Similarly, the value of an unemployed worker satisfies

$$\begin{aligned}\rho W_t\left(j,\psi,\hat{\psi},U\right) &= h\left(\psi,\hat{\psi},U\right)\exp\left(g^{\star}t\right) \\ &+ \lambda^{U}\sum_{s} p_t\left(s;j,\psi,\hat{\psi},U\right) f\left(\theta_t\left(j,\psi,\hat{\psi},s\right)\right)\left[W_t\left(j,\psi,\hat{\psi},s\right)-W_t\left(j,\psi,\hat{\psi},U\right)\right] \\ &+ \frac{d}{d\epsilon}W_{t+\epsilon}\left(j+\epsilon,\psi\exp\left(\delta^{\star}\left(U\right)\epsilon\right),\hat{\psi},s\right)\Big|_{\epsilon=0}\end{aligned} \tag{A.6}$$

for each age $j \in [0,J)$, since they receive benefits $h\left(\psi,\hat{\psi},U\right)\exp\left(g^{\star}t\right)$ and search for jobs with intensity λ^{U}.

Firm values. The value of a filled job in submarket s is given by

$$\begin{aligned}\rho V_t\left(j,\psi,\hat{\psi},s\right) = &\left(\mathcal{P}_t^{k(s)}-w\left(s\right)\right)h\left(\psi,\hat{\psi},k\left(s\right)\right)\exp\left(g^{\star}t\right) \\ &- \chi_0\left[\mathcal{F}_t^{k(s)}\left(V_t\left(j,\psi,\hat{\psi},s\right)\right)V_t\left(j,\psi,\hat{\psi},s\right)+\mathcal{O}_t\left(j,\psi,\hat{\psi},s\right)\right] \\ &- \lambda^{E}\sum_{s'} f\left(\theta_t\left(j,\psi,\hat{\psi},s'\right)\right)p_t\left(s';j,\psi,\hat{\psi},s\right)V_t\left(j,\psi,\hat{\psi},s\right) \\ &+ \frac{d}{d\epsilon}V_{t+\epsilon}\left(j+\epsilon,\psi\exp\left(\delta_j^{\star}\left(k\left(s\right)\right)\epsilon\right),\hat{\psi}\exp\left(\hat{\delta}_j^{\star}\left(k\right)\epsilon\right),s\right)\Big|_{\epsilon=0}\end{aligned} \tag{A.7}$$

for each age $j \in [0, J)$, where $\mathcal{P}_t^k$ denotes the de-trended prices of labor services provided in the polluting or clean sectors that satisfy the equilibrium conditions (A.14) below and the

$$\begin{aligned}\mathcal{O}_t\left(j,\psi,\hat{\psi},s\right) \equiv \left[1-\mathcal{F}_t^{k(s)}\left(V_t\left(j,\psi,\hat{\psi},s\right)\right)\right] \times \\ \mathbb{E}\left[\varepsilon h\left(\psi,\hat{\psi},k\left(s\right)\right)\exp\left(g^{\star}t\right) \right. \\ \left. \left|\varepsilon h\left(\psi,\hat{\psi},k\left(s\right)\right)\exp\left(g^{\star}t\right) \leq V_t\left(j,\psi,\hat{\psi},s\right)\right.\right]\end{aligned} \tag{A.8}$$

corresponds to the expected value of the operating costs conditional on the firm not shutting down. The boundary condition is $V_t\left(J,\psi,\hat{\psi},s\right)=0$ when the worker retires at age $j=J$. Firms discount flows using the equilibrium interest rate $r \equiv \rho$.[48] They incur operating costs at rate χ_0. With probability $1-\mathcal{F}_t^{k(s)}\left(\cdot\right)$, the operating cost is smaller than the continuation value of the match; the firm pays the operating cost and the match is preserved. The match may dissolve if the firm lays off the worker, which occurs at rate $\chi_0\mathcal{F}_t^{k(s)}\left(\cdot\right)$, 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 each market s', weighted 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, over workers' age, and over their skills.

A.2 Production and Innovation

Production. The representative final good producer uses the technology

$$Y_t = Z_t F_t\left(X_t^P, X_t^C\right), \tag{A.9}$$

taking the climate damages

$$Z_t = Z_t^{\star}\left(\left\{X_s^P, X_s^C\right\}\right) \tag{A.10}$$

as given. We allow the function $Z_t^{\star}$ to depend on the entire history of sectoral productions (possibly with some decay). We suppose that this function is homogenous of degree $-z$, where $z \in (0,1)$ controls the extent to which climate damages

[48] The equilibrium interest rate is $r=\rho$ since entrepreneurs have linear utility.

reduce long-term growth. As usual, the technology (2.3) can alternatively be interpreted as workers' preferences over these two goods.

Innovation process. Entrepreneurs who own the intermediate goods firms can invest resources to improve their productivity a_t^k, thus increasing profits. Their productivity evolves according to $da_t^k = \left(z_t^k - \delta_a^k a_t^k\right) dt$, where z_t^k is gross investment and δ_a^k is the rate at which a firm's technology becomes obsolete relative to newer ideas (Caballero and Jaffe, 1993; Akcigit et al., 2022). Following Eaton and Kortum (1999), we allow for technological spillovers

$$z_t^k = \sum_{k'} \beta_{k'}^k \times \left[\int_{-\infty}^{t} \exp\left(-\beta_{k'}^k (t-s)\right) \times \iota\left(I_s^{k'}\right) ds\right] \times g\left(a_t^{k'}\right) dt, \tag{A.11}$$

where ι reflects decreasing returns to innovation. We use I_t^k to denote the investment rate on each technology, so the level of investment is $I_t^k a_t^k$; this investment is expressed in terms of a bundle of intermediates with constant-returns-to-scale. In turn, the coefficients $\beta_{k'}^k > 0$ capture the innovation spillovers across sectors, and g determines the long-run growth rate of the economy.[49] We suppose that the spillover coefficients are positive, symmetric and satisfy $\sum_{k'} \beta_{k'}^k = 1$. In our benchmark scenario, we set $g(a) = a$ in the law of motion (A.11) so there exists a balanced-growth path where output in the clean and polluting sectors grow at the same rate $\bar{g} > 0$ (Appendix A.5). In this initial balanced-growth path, productivity is much lower in the clean sector as there are no incentives to innovate. We model the climate transition as a form of technological change that affects the *level* of economic activity and its allocation across sectors, but not the long-term growth rate of the economy. We place appropriate restrictions on the innovation technology ι and $\beta_{k'}^k$ to ensure that the economy converges to a new balanced-growth path that grows at rate $\bar{g}$.[50]

[49] In equilibrium, entrepreneurs choose the same innovation in all firms in a given sector. The specification (A.11) can easily be extended to allow for innovation spillovers *within* sectors. Alternative and multiplicative formulations are sometimes used in the literature, e.g., Acemoglu (2002). In our context, these formulations have the disadvantage that they allow laggard sectors to bring down the rest of the economy; this feature is particularly problematic since we consider an initial balanced-growth path where the climate sector is not active yet.

[50] While we interpret the stock as a_t^k as intangible capital, it is worth noting that it could be alternatively interpreted as tangible capital if $g(a) = 1$ and there are no technological spillovers. The initial and final growth rates are $\bar{g} = 0$ in this case.

Equilibrium prices and innovations. The final good producer chooses its demand for intermediates so that

$$P_t^k = Z_t \frac{d}{dX_t^k} F_t \left(X_t^P, X_t^C \right), \tag{A.12}$$

where P_t^k is the purchase price of intermediates. In turn, the supply of intermediates is

$$X_t^k = a_t^k n_t^k, \tag{A.13}$$

since there is a continuum symmetric firms of of mass 1 which produce these intermediaries. The labor demands from these monopolistic firms imply that

$$\left(1 + \tau_t^k\right) a_t^k P_t^k = \frac{\epsilon^k}{\epsilon^k - 1} \mathcal{P}_t^k \exp\left(g^\star t\right) \tag{A.14}$$

in equilibrium, where P_t^k is the purchase price of the intermediate good in a given sector, τ_t^k is the output subsidy received by the producer, a_t^k is the productivity that prevails in that sector, $\mathcal{P}_t^k$ is the price of labor services in that sector, and $\epsilon^k > 1$ is the elasticity of substitution between varieties produces in a given sector. The prices $\mathcal{P}_t^k$ are de-trended using the growth rate $g^\star \equiv (1 - z)\, \bar{g}$, where $\bar{g}$ is still the rate at which output grows in the polluting and clean sectors and z parameterizes the climate damages (A.10). This normalization ensures that the prices $\mathcal{P}_t^k$ are stationary along a balanced-growth path (Appendix A.5).

Turning to the innovation problem, entrepreneurs solve

$$\begin{aligned} \max_{\left\{I_t^k, a_t^k\right\}} & \int_0^{+\infty} \exp\left(-rt\right) \left[\left(1 + \tau_t^k\right) P_t^k a_t^k n_t^k - \left(1 - \varsigma_t^k\right) \mathcal{C}\left(P_t^P, P_t^C\right) I_t^k a_t^k \right] \\ \text{s.t. } & da_t^k = \left(z_t^k - \delta_a^k a_t^k\right) dt, \\ & z_t^k = \sum_{k'} \beta_{k'}^k \times \left[\int_{-\infty}^t \exp\left(-\beta_{k'}^k \left(t - s\right)\right) \times \iota\left(I_s^{k'}\right) ds \right] \times a_t^{k'} dt \end{aligned} \tag{A.15}$$

in the polluting and clean sectors, given some initial condition for a_0^k and taking innovations $I_t^{k'}$ and technologies $a_t^{k'}$ as given in the other sector $k' \neq k$. The unit cost function $\mathcal{C}\left(P_t^P, P_t^C\right)$ is homogeneous of degree 1 and reflects the constant-returns-to-scale bundle that firms use to invest in innovation (Section 2.1.2). By the Principle of Optimality, entrepreneurs can choose their investment rate I_t^k and stock

a_t^k, keeping fixed their optimal labor demands n_t^k. In equilibrium, these labor demands coincide with aggregate sectoral labor supplies.

Investing resources I_t^k allows to improve productivity a_t^k and hence revenues, but is comes at a cost. At optimum, the marginal benefit of investing equals the marginal cost

$$\iota'\left(I_t^k\right)\int_0^{+\infty}\mu\left(t+s\right)\beta_k^k\exp\left(-\beta_k^k s\right)a_{t+s}^k ds=\left(1-\varsigma_t^k\right)\mathcal{C}\left(P_t^P,P_t^C\right)a_t^k, \tag{A.16}$$

where $\mu\left(t\right)$ is the multiplier on the law of motion for a_t^k, and the marginal benefits reflect changes in revenues

$$\left(1+\tau_t^h\right)P_t^k n_t^k-\left(1-\varsigma_t^k\right)I_t^k\mathcal{C}\left(P_t^P,P_t^C\right)=r\mu\left(t\right)-\dot{\mu}\left(t\right) \tag{A.17}$$

This system characterizes the optimal solution to the problem (A.15), along with the law of motion

$$da_t^k=\left(z_t^k-\delta_a^k a_t^k\right)dt \tag{A.18}$$

with

$$z_t^k=\sum_{k'}\beta_{k'}^k\times\left[\int_{-\infty}^t\exp\left(-\beta_{k'}^k\left(t-s\right)\right)\times\iota\left(I_s^{k'}\right)ds\right]\times a_t^{k'}dt \tag{A.19}$$

and the initial condition for a_0^k.

A.3 Equilibrium Definition

We define the equilibrium of the model in two steps. We first define equilibrium in the labor market which satisfies a block recursive structure, before defining equilibrium for the full economy.

Definition 1. *Labor Market Block Recursive Equilibrium (BRE)*: Given a path for A_t^k and an initial distribution of worker ages, skills and employment states $\boldsymbol{\mu_0}(j,\omega)$, a block-recursive equilibrium (BRE) consists of value functions for workers $W_t\left(j,\psi,\hat{\psi},s\right)$ and firms $V_t\left(j,\psi,\hat{\psi},s\right)$, as well as policy functions $p_t\left(s';j,\psi,\hat{\psi},s\right)$, market tightness $\theta_t\left(j,\psi,\hat{\psi},s\right)$ and distributions $\boldsymbol{\mu}_t\left(j,\psi,\hat{\psi},s\right)$, satisfying:

1. The value of employed workers in submarket s, $W_t(j,\psi,\hat{\psi},s)$, satisfies the Bellman equation (A.4) with boundary condition $W_t(J,\psi,\hat{\psi},s)=0\ \forall t,\psi,\hat{\psi},s$,

2. The value of unemployed workers, $W_t(j, \psi, \hat{\psi}, U)$, satisfies the Bellman equation (A.6) with boundary condition $W_t(J, \psi, \hat{\psi}, U) = 0 \; \forall t, \psi, \hat{\psi}$,

3. The value of workers in the outside sector, $W_t(j, \psi, \hat{\psi}, O)$, satisfies the Bellman equation (A.5) with boundary condition $W_t(J, \psi, \hat{\psi}, O) = 0 \; \forall t, \psi$,

4. The value of a filled job in sector k, $V_t(j, \psi, \hat{\psi}, s)$, satisfies Bellman equation (A.7) with boundary condition $V_t(J, \psi, \hat{\psi}, s) = 0 \; \forall t, \psi, s$,

5. Workers' search behavior $p_t(s'; j, \psi, \hat{\psi}, s)$ satisfies expression (5.1),

6. Market tightness 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

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

An equilibrium consists of workers' and firms' values $W_t(j, \psi, s)$ and $V_t(j, \psi, s)$ defined in Appendix A.1, search decisions $p_t(s'; j, \psi, s)$, 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 labor market equilibrium features a block recursive structure.

Definition 2. Given a path of government policy $\left(T_t, \{\varsigma_t^k, \tau_t^k\}_k\right)_t$ and the aggregate production function $F_t(\cdot)$, a recursive competitive equilibrium is a labor market block-recursive equilibrium, as well as paths for innovation investment decisions I_t^k, productivities a_t^k, prices p_t^k, labor demands n_t^k and outputs (X_t^k, Y_t) satisfying:

1. Normalized marginal revenue products of labor are $A_{k,t} = (1 + \tau_t^k) p_t^k a_t^k$

2. Innovation decisions are optimal, satisfying (A.16)-(A.19).

3. Demand for X_t^k satisfies the final goods' producer's optimality conditions (A.12)

4. Demand for labor services in k satisfies k's producer's optimality (A.13)

5. The markets for labor services, final goods, and sector k's output clear

As shown in Appendix A.4, we can characterize this equilibrium without keeping track of the state ψ.

A.4 Normalized and De-Trended Values

This appendix establishes that workers' and firms' are linearly homogenous in $\psi \exp(g^\star t)$, where $g^\star \equiv (1-z)\,\bar{g}$ with $\bar{g}$ still denoting the rate at which output grows in the polluting and clean sectors and z parameterizing the climate damages (A.10). This homogeneity property offers two benefits. First, it allows us to characterize de-trended values that are constant over a balanced-growth path, which is required for our numerical implementation. Second, it allows us not keep track of the overall skill ψ in our state space, making our analysis computationally feasible. Formally, we will show that workers' and firms' values satisfy

$$W_t\left(j,\psi,\hat{\psi},s\right) = \psi \exp\left(g^\star t\right) W_t^\star\left(j,\hat{\psi},s\right) \tag{A.20}$$

$$V_t\left(j,\psi,\hat{\psi},s\right) = \psi \exp\left(g^\star t\right) V_t^\star\left(j,\hat{\psi},s\right), \tag{A.21}$$

for some $W_t^\star$ and $V_t^\star$ that do not depend on workers' overall skill ψ and depend on time only through the price of labor services $\mathcal{P}_t^k$, which are constant along a balanced-growth path (A.5). While establishing this property, we will also show that

$$\mathcal{O}_t\left(j,\psi,\hat{\psi},s\right) = \psi \exp\left(g^\star t\right) \mathcal{O}_t^\star\left(j,\hat{\psi},s\right) \tag{A.22}$$

and

$$\begin{gathered}\theta_t\left(j,\psi,\hat{\psi},s\right) = \theta_t^\star\left(j,\hat{\psi},s\right) \quad , \quad p_t\left(s';j,\psi,\hat{\psi},s\right) = p_t^\star\left(s';j,\hat{\psi},s\right) \\ \mathcal{F}_t^{k(s)}\left(V_t\left(j,\psi,\hat{\psi},s\right)\right) = \mathcal{F}^{k(s),\star}\left(V_t^\star\left(j,\hat{\psi},s\right)\right)\end{gathered} \tag{A.23}$$

for some $\mathcal{O}_t^\star$, $\theta_t^\star$, $p_t^\star$, $\mathcal{F}^{k(s),\star}$ and that do not depend on workers' overall skill ψ and whose dependence on time is only due to changes in prices over the transition. In the following, we use the fact that $h\left(\psi,\hat{\psi},k\right) \equiv \psi h^\star\left(\hat{\psi},k\right)$ with $h^\star\left(\hat{\psi},k\right) \equiv h\left(1,\hat{\psi},k\right)$ using the definition (A.3).

Note that workers' and firms' are interdependent. We will therefore guess and verify that the properties (A.20)–(A.23) hold jointly. First, consider the value of a worker employed in market s. Using the definition (A.4), the law of motion of ψ, the two properties above and expanding the time derivative with respect to ϵ, we

obtain

$$\begin{aligned}\rho\frac{W_t\left(j,\psi,\hat{\psi},s\right)}{\psi\exp\left(g^{\star}t\right)} &= w\left(s\right)h^{\star}\left(\hat{\psi},k\left(s\right)\right)\\ &+\lambda^{E}\sum_{s'}p_t^{\star}\left(s';j,\hat{\psi},s\right)f\left(\theta_t^{\star}\left(j,\hat{\psi},s'\right)\right)\left[W_t^{\star}\left(j,\hat{\psi},s'\right)-W_t^{\star}\left(j,\hat{\psi},s\right)\right]\\ &+\chi_0\mathcal{F}^{k(s),\star}\left(V_t^{\star}\left(j,\hat{\psi},s\right)\right)\left[W_t^{\star}\left(j,\hat{\psi},U\right)-W_t^{\star}\left(j,\hat{\psi},s\right)\right]\\ &+\left(g^{\star}+\delta^{\star}\left(k\left(s\right)\right)\right)W_t^{\star}\left(j,\hat{\psi},s\right)+\hat{\psi}\hat{\delta}_j^{\star}\left(k\left(s\right)\right)\frac{\partial}{\partial\hat{\psi}}W_t^{\star}\left(j,\hat{\psi},s\right)\\ &+\frac{\partial}{\partial j}W_t^{\star}\left(j,\hat{\psi},s\right)+\frac{\partial}{\partial t}W_t^{\star}\left(j,\hat{\psi},s\right),\end{aligned}\tag{A.24}$$

which confirms that $W_t\left(j,\psi,\hat{\psi},s\right)$ indeed scales with $\psi\exp\left(g^{\star}t\right)$, and hence satisfies expression (A.20). Therefore, the normalized and de-trended value evolves as

$$\begin{aligned}\rho^{\star}W_t^{\star}\left(j,\hat{\psi},s\right) &= w\left(s\right)h^{\star}\left(\hat{\psi},k\left(s\right)\right)\\ &+\lambda^{E}\sum_{s'}p_t^{\star}\left(s';j,\hat{\psi},s\right)f\left(\theta_t^{\star}\left(j,\hat{\psi},s'\right)\right)\left[W_t^{\star}\left(j,\hat{\psi},s'\right)-W_t^{\star}\left(j,\hat{\psi},s\right)\right]\\ &+\chi_0\mathcal{F}^{k(s),\star}\left(V_t^{\star}\left(j,\hat{\psi},s\right)\right)\left[W_t^{\star}\left(j,\hat{\psi},U\right)-W_t^{\star}\left(j,\hat{\psi},s\right)\right]\\ &+\delta^{\star}\left(k\left(s\right)\right)W_t^{\star}\left(j,\hat{\psi},s\right)+\hat{\psi}\hat{\delta}_j^{\star}\left(k\left(s\right)\right)\frac{\partial}{\partial\hat{\psi}}W_t^{\star}\left(j,\hat{\psi},s\right)\\ &+\frac{\partial}{\partial j}W_t^{\star}\left(j,\hat{\psi},s\right)+\frac{\partial}{\partial t}W_t^{\star}\left(j,\hat{\psi},s\right)\end{aligned}\tag{A.25}$$

where $\rho^{\star}\equiv\rho-g^{\star}$. Proceeding similarly for the values (A.5)–(A.6) also confirms that $W_t\left(j,\psi,\hat{\psi},O\right)$ and $W_t\left(j,\psi,\hat{\psi},U\right)$ scale with $\psi\exp\left(g^{\star}t\right)$ and yields the law of motions for the normalized values, which we spell out explicitly in Appendix B.1.

Turning to firm's values (A.7), following the steps above confirms our guess.

The normalized and de-trended value evolves as

$$\begin{aligned} r^{\star}V_t^{\star}\left(j,\hat{\psi},s\right) = & \left(\mathcal{P}_t^{k(s)} - w\left(s\right)\right) h^{\star}\left(\hat{\psi},k\left(s\right)\right) \\ & - \chi_0\left[\mathcal{F}^{k(s),\star}\left(V_t^{\star}\left(j,\hat{\psi},s\right)\right) V_t^{\star}\left(j,\hat{\psi},s\right) + \mathcal{O}_t^{\star}\left(j,\hat{\psi},s\right)\right] \\ & - \lambda^E \sum_{s'} f\left(\theta_t^{\star}\left(j,\hat{\psi},s'\right)\right) p_t^{\star}\left(s';j,\hat{\psi},s\right) V_t^{\star}\left(j,\hat{\psi},s\right) \\ & + \delta^{\star}\left(k\left(s\right)\right) V_t^{\star}\left(j,\hat{\psi},s\right) + \hat{\psi}\hat{\delta}_j^{\star}\left(k\right) \frac{\partial}{\partial\hat{\psi}} V_t^{\star}\left(j,\hat{\psi},s\right) \\ & + \frac{\partial}{\partial j} V_t^{\star}\left(j,\hat{\psi},s\right) + \frac{\partial}{\partial t} V_t^{\star}\left(j,\hat{\psi},s\right), \end{aligned} \tag{A.26}$$

where $r^{\star} \equiv r - g^{\star}$ with $r = \rho$ in equilibrium. We will establish in Appendix A.5 that the price of labor services $\mathcal{P}_t^k$ given by (A.14) is constant along a balanced-growth path.

Having verified the properties (A.20), we now show that the properties (A.23)–(A.23) also hold. Starting with the expected operating costs,

$$\begin{aligned} \mathcal{O}_t^{\star}\left(j,\hat{\psi},s\right) = & \left[1 - \mathcal{F}^{k(s),\star}\left(V_t^{\star}\left(j,\hat{\psi},s\right)\right)\right] \times \\ & \mathbb{E}\left[\varepsilon h^{\star}\left(\hat{\psi},k\left(s\right)\right)\right. \\ & \left.\left|\varepsilon h^{\star}\left(\hat{\psi},k\left(s\right)\right) \leq V_t^{\star}\left(j,\hat{\psi},s\right)\right.\right], \end{aligned} \tag{A.27}$$

which confirms that $\mathcal{O}_t\left(j,\psi,\hat{\psi},O\right)$ scales with $\psi\exp\left(g^{\star}t\right)$. Using the free entry condition (2.4) and the fact that the vacancy posting costs scale with ψ in Section 5,

$$q\left(\theta_t^{\star}\left(j,\hat{\psi},s\right)\right) V_t^{\star}\left(j,\hat{\psi},s\right) \leq \nu h^{\star}\left(\hat{\psi},k\left(s\right)\right) \tag{A.28}$$

with the usual complementary slackness condition, which confirms that $\theta_t^{\star}\left(j,\hat{\psi},s\right)$ depends neither on the overall skill ψ nor the growth rate g. In turn, the separation hazard (5.2) is

$$\begin{aligned} \mathcal{F}\left(V_t\left(j,\psi,\hat{\psi},s\right)\right) & \equiv \Pr\left\{\phi + \gamma\varepsilon^{\star} > \log\left(V_t\left(j,\psi,\hat{\psi},s\right) / \left(h\left(\psi,\hat{\psi},k\left(s\right)\right)\exp\left(\bar{g}t\right)\right)\right)\right\} \\ & = \Pr\left\{\phi + \gamma\varepsilon^{\star} > \log\left(V_t^{\star}\left(j,\hat{\psi},s\right) / h^{\star}\left(\hat{\psi},k\left(s\right)\right)\right)\right\} \\ & \equiv \mathcal{F}^{k(s),\star}\left(V_t^{\star}\left(j,\hat{\psi},s\right)\right) \end{aligned} \tag{A.29}$$

with $h^{\star}\left(\hat{\psi},k\right) \equiv h\left(1,\hat{\psi},k\right)$, which also confirms that $\mathcal{F}^{k(s),\star}$ does not depend on

these objects. Proceeding similarly, the search decisions

$$p_t\left(s';\tilde{\mathbf{x}},s\right)\equiv\frac{\exp\left(f\left(\theta_t\left(\tilde{\mathbf{x}},s'\right)\right)\left[W_t\left(\tilde{\mathbf{x}},s'\right)-W_t\left(\tilde{\mathbf{x}},s\right)\right]/\zeta\right)}{\sum_{\hat{s}}\exp\left(f\left(\theta_t\left(\tilde{\mathbf{x}},\hat{s}\right)\right)\left[W_t\left(\tilde{\mathbf{x}},\hat{s}\right)-W_t\left(\tilde{\mathbf{x}},s\right)\right]/\zeta\right)} \tag{A.30}$$

do not depend on these objects either, with $\tilde{\mathbf{x}}\equiv\left(j,\hat{\psi}\right)$.

The homogeneity property (A.20) implies that we can economize one state variable when computing workers' and firms' values or iterating on the distribution of workers' states (Appendix B). In particular, none of the moments that we target in Section 6.2 depend on the level of the overall skill ψ. In Section 7, we compute *ex post* welfare changes after idiosyncratic uncertainty is resolved. In this case, the level of ψ and its evolution are relevant; we use stochastic simulations to track the workers' states over time.

A.5 Balanced-Growth Path

In this appendix, we establish the growth rates at which various quantities and prices must grow along a balanced-growth path. We are interested in characterizing workers' outcomes as the economy transitions from one balanced-growth path to another after the clean sector effectively emerges (Section 3).

Lemma 2. *Consider a balanced-growth path where government subsidies τ_t^k and ς_t^k are constant over time. Then, the amount of intermediates X_t^P and X_t^C produced in the polluting and clean sectors grow at the same rate $\bar{g}>0$. However, aggregate output Y_t grows at a lower rate $g^\star\equiv(1-z)\,\bar{g}$ due to climate damages parameterized by $z\in(0,1)$. The normalized prices of labor services $\mathcal{P}_t^k$ defined in Appendix A.2 are constant.*

Proof. We guess and verify that, along a balanced-growth path, the productivities a_t^k and the outputs of intermediaries X_t^k grow at rate $\bar{g}$, the aggregate output Y_t grow at rate $g^\star\equiv(1-z)\,\bar{g}$, the price of intermediaries grow at rate $-z\bar{g}$, and the normalized prices of labor services $\mathcal{P}_t^k$ and sectoral labor supplies n_t^k are constant.

Starting with the firms' vacancy posting and workers' labor supplies, note that workers' equilibrium labor supplies are entirely determined by the coupled system of partial differential equations that define workers' and firms' values (A.25)–(A.26), together with the free entry condition (A.28), the separation hazard (A.29), and the search probabilities (A.30). This is a closed system: it does not depend

on the rest of the economy, except for the prices of labor services $\mathcal{P}_t^k$. If prices are constant along a balanced-growth path, then sectoral labor supplies n_t^k are as well.

Turning to the production of intermediates, if technologies a_t^k grow at rate $\bar{g}$ and sectoral labor supplies n_t^k are constant, then the technology (A.13) implies that the outputs of intermediaries X_t^k indeed grow at rate $\bar{g}$. Furthermore, if productivities a_t^k grow at rate $\bar{g}$ and the price of intermediaries P_t^k grows at rate $-z\bar{g}$, then the labor demands (A.14) imply that the normalized prices of labor services $\mathcal{P}_t^k$ are indeed constant.

Considering final good production, if the output of intermediaries X_t^k grow at rate $\bar{g}$, then the technology (A.9) implies that aggregate output Y_t indeed grows at rate $(1-z)\,\bar{g}$ since Z_t is homogeneous of degree $-z$. Similarly, the demand for intermediaries (A.12) implies that the price of intermediaries P_t^k indeed grows at rate $-z\bar{g}$, since the first derivatives of F_t are homogeneous of degree 0 by Euler's theorem, and Z_t is homogeneous of degree $-z$.

Finally, we turn to the innovation choices. Suppose that the prices of the final goods P_t^P and P_t^C grow at rate $-z\bar{g}$, that sectoral labor supplies n_t^k are constant, and that $I_t^{k'}$ is constant and $a_t^{k'}$ grows at rate $\bar{g}$ in the other sector $k' \neq k$. Then, we can guess and verify that I_t^k is constant and a_t^k is constant using the optimality conditions (A.16)–(A.19).

In summary, we have established what rate quantities and prices must grow at along any balanced-growth path. We do not establish formally the existence and stability of a balanced-growth path since this is not the goal of our paper. However, it is worth noting that spillovers in the innovation process (A.11) ensures that the asymptotic growth rate of productivities a_t^k must be the same across sectors. To see that, suppose by contradiction that the polluting sector grows faster asymptotically than the clean sector, i.e., $\bar{g}^P > \bar{g}^C$. Then, $a_t^C / \exp\left(\bar{g}^P t\right) \to 0$ as $t \to +\infty$, so that

$$\frac{z_t^C}{\exp\left(\bar{g}^P t\right)} \to \beta_P^C \times \left[\int_{-\infty}^{t} \exp\left(-\beta_P^C\,(t-s)\right) \times \iota\left(I_s^P\right) ds\right] \times a_t^P dt$$

using the innovation process (A.11). Therefore, productivity in the clean sector must grow at the same rate as in the polluting sector, which yields the desired contraction. The argument is symmetric if the clean sector were to grow faster. □

A.6 S-Shaped Transitions

Our model naturally generates S-shaped transitions for the marginal revenue products of labor A_t^k. This type of S-curves are characteristic of innovation and technology adoption (Griliches, 1958; Shepherd et al., 2012).

Accordingly, we will show below that the paths for A_t^C is S-shaped and the path of A_t^P is inverse S-shaped when the intermediates are sufficiently substitutable, and technological spillovers, climate damages and government subsidies are not too large.[51] To do so, we proceed in several steps. First, we consider a limit economy where intermediates are perfectly substitutable, and there are no technological spillovers, climate damages or government subsidies. Using this economy, we show that the levels of A_t^C and A_t^P are higher and lower, respectively, along the final balanced-growth path compared to the initial one. We argue that the transition between these stationary levels is indeed S-shaped or inverse S-shaped. The final step appeals to the continuity of the equilibrium with respect to its parameters to show that the S-curves are preserved away from the limiting economy, i.e., when allowing for imperfect substitutes, some spillovers, climate damages, etc.

Limiting economy. We momentarily consider the limit where the intermediates are perfect substitutes in the technology (2.3), there are no technological spillovers $\beta_{k'}^k \to 0$ for $k' \neq k$, there are no climate damages so $Z_t \to 1$ and $z \to 0$ in expression (A.10), and there are no policy interventions $\tau_t^k = \varsigma_t^k = 0$ for each $k = P, C$ and all t.[52] In the following, we will use the fact that $g^\star \equiv (1-z)\,\bar{g} = \bar{g}$ in this limit.

Step 1 (long-run levels). We have shown in Appendix A.5 that A_t^k is constant along a balanced-growth path. Starting with the initial balanced-growth path, there is no demand for the intermediate produced by the clean, so the demand for intermediates (A.12) implies that $P_t^C = P^C = 0$. The innovation choice (A.16)–(A.19) implies that there is no investment in the clean sector, so $a_t^C / \exp(\bar{g}t) \to 0$. Therefore, $A_t^C \equiv a_t^C P^C / \exp(\bar{g}t) \to 0$. Furthermore, $P_t^P = P^P > 0$ in the polluting sector so firms innovate and $A_t^P > 0$ along the initial balanced-growth path.

[51] These conditions ensure that the MRPL in the two sectors do not co-move too strongly.

[52] Spillovers remain positive as we take this limit, so the economy still admits balanced-growth paths where the two sectors grow at the same rate (Appendix A.5). Of course, the level and transition between these balanced-growth depend on the strength of these spillovers.

The transition starts with a change in F_t in favor of the good produced in the clean sector. The demand for intermediates (A.12) implies that $P_t^C = P^C > 0$, where the equality holds in the limit where the intermediates are perfect substitutes and there are no climate damages (by assumption). There are thus incentives to invest in both sectors. The innovation choice (A.16)–(A.19) implies that $a_t^c / \exp(\bar{g}t) > 0$ along the final balanced-growth path. Therefore, $A_t^C \equiv a_t^C P^C / \exp(\bar{g}t) > 0$.

As shown at the beginning of this section, the A_t^k terms determines workers' incentives to supply labor across sectors. At least *some* workers will supply labor to the clean sector since $A_t^C > 0$ and G has full support. Therefore, $n_t^C > 0$ along the final balanced-growth path, and n_t^P is lower in the polluting sector than it used to be along the initial balanced-growth path. Furthermore, the demand for intermediates (A.12) implies that $P_t^P = P^P$ is unchanged in the limit where the intermediates are perfect substitutes. The innovation choice (A.16)–(A.19) implies that $a_t^P / \exp(\bar{g}t) > 0$ must be lower than along the initial balanced-growth path since the number of employed workers n_t^P is lower. Therefore, $A_t^P \equiv a_t^P P^P / \exp(\bar{g}t) > 0$ decreases between the initial and final balanced-growth paths.

In summary, the levels of A_t^C and A_t^P are higher and lower, respectively, along the final balanced-growth path compared to the initial one.

Step 2 (transitions). The only way for $A_t^C \equiv a_t^C P_t^C / \exp(\bar{g}t)$ to reach its higher level is for a_t^C to rise at a rate *higher* than $\bar{g}$ initially and then a *lower* rate. After detrending at rate $\bar{g}$, the path of A_t^C is therefore S-shaped in the clean sector. The opposite happens in the polluting sector and the path of A_t^P is inverse S-shaped.

Step 3 (continuity). By continuity of the equilibrium with respect to its parameters, the paths of A_t^k are still S-shaped or inverse S-shaped away from the limit that we took above, i.e., even if we allow for imperfect substitutability, some spillovers, some climate damages, etc.

A.7 Proof of Lemma 1

We established in Appendix A.5 that workers' outcomes are entirely determined by a closed system that depends on the rest of the economy exclusively through the

normalized prices of labor services $\mathcal{P}_t^k$. Using the definition of marginal revenue products of labor (3.1)–(3.2) and the equilibrium condition (A.14), we have

$$\mathcal{P}_t^k = \left(1 + \tau_t^k\right) a_t^k P_t^k / \exp\left(g^\star t\right) \equiv A_t^k \tag{A.31}$$

Therefore, workers' outcomes can be expressed exclusively as a function of the marginal revenue products of labor A_t^k.

A.8 Proof of Proposition 1

First, we show in Lemma 3 that sectoral productivities and the price of intermediates can be expressed exclusively in terms of marginal revenue products of labor A_t^k and innovation subsidies ς_t^k, i.e., they do not depend separately on other endogenous prices or subsidies. Combining Lemmas 1 and 3, we then show that the government can choose appropriate subsidies to implement any paths of A_t^k.

Lemma 3. *Productivities a_t^k and intermediate prices P_t^k can be expressed exclusively in terms of marginal revenue products of labor A_t^k and innovation subsidies ς_t^k.*

Proof. The inventors' optimal innovation choice (A.16)–(A.19) that determines productivities a_t^k depends on four objects: the marginal revenues products of labor $A_t^k \equiv \left(1 + \tau_t^k\right) P_t^k a_t^k / \exp\left(\bar{g}t\right)$; sectoral labor demands n_t^k; the subsidies ς_t^k; and the unit cost $\mathcal{C}\left(P_t^P, P_t^C\right)$ of innovation. By Lemma 3, sectoral labor demands n_t^k are entirely determined by the sequence of A_t^k, however. Furthermore, the demand for intermediaries (A.12) imply that the prices of intermediates P_t^k can also be expressed in terms of the outputs of intermediates X_t^k, which themselves depend only on a_t^k and n_t^k using the technology (A.13). Putting all these elements together, productivities a_t^k can be expressed solely as a function of the marginal revenues products of labor $A_t^k \equiv \left(1 + \tau_t^k\right) P_t^k a_t^k / \exp\left(\bar{g}t\right)$ and the subsidies ς_t^k. The same is true for the intermediate prices P_t^k. □

Proposition 1 follows as a corollary. Instead of showing how changes in subsidies τ_t^k affects innovation, equilibrium prices, and how they feed back into marginal revenue products of labor A_t^k, we can leverage Lemma 3 to show that the government can first set its desired path of A_t^k and then back out subsidies residually.

Proof of Proposition 1. Suppose that the government seeks to implement arbitrary paths of marginal revenue products of labor $\mathbf{A} \equiv \left\{A_t^k\right\}$ and subsidies on innovation $\boldsymbol{\varsigma} \equiv \left\{\varsigma_t^k\right\}$. By Lemma 3, sectoral productivities a_t^k and P_t^k can be expressed directly as a function of these two sequences $\mathbf{A}$ and $\boldsymbol{\varsigma}$. By definition (3.1)–(3.2), the sequence of distortionary subsidies on purchases of intermediates

$$\tau_t^k = \frac{A_t^k \exp\left((1+z)\,\bar{g}t\right)}{a_t^k\left(\mathbf{A},\boldsymbol{\varsigma}\right) P_t^k\left(\mathbf{A},\boldsymbol{\varsigma}\right)} - 1 \tag{A.32}$$

implement the path in equilibrium $\mathbf{A}$, where we have made the dependence of the numerator on $\mathbf{A}$ and $\boldsymbol{\varsigma}$ explicit. Therefore, the government can indeed implement any path of marginal revenue products it desires. Finally, the government chooses lump sum taxes to balance its budget. As discussed in Appendix A.2, these taxes are non-distortionary and do not affect equilibrium quantities or prices. □

A.9 Results in the Walrasian Limit

This section formalizes the discussion of Section A.4 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.4.

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. $\lim_{\eta\to\infty} \hat{A}_t(\eta) = \frac{A_{C,\infty}}{A_{P,\infty}}$ 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* $\eta \to \infty$*:* $\left|\lim_{\eta\to\infty} \frac{\partial^n A_{P,0}(\eta)}{\partial \eta^n}\right| < \infty$.

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.4 — 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 $(\tau, \hat{\psi})$ can be partitioned into three groups, based on their optimal stopping time $t^\star(\hat{\psi}; \eta) = 0$.

Lemma 4. *The set of workers* $(\tau, \hat{\psi})$ *can be partitioned into:*

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

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

3. ***Occasional switchers*** *with* $\hat{\psi} \in \left(\hat{A}_\infty^{-1}, \hat{A}_0^{-1}\right)$ *who potentially move to the clean sector as* $0 < t^\star(\hat{\psi}; \eta) < \infty$*. For these workers,* $t^\star(\hat{\psi}; \eta)$ *strictly decreases with the relative productivity in the clean sector* ψ *and the transition speed* η *and satisfies* $t^\star(\hat{\psi}; \eta) \to 0$ *as* $\eta \to \infty$*. Furthermore, these workers switch sectors during their lifetime if they are sufficiently young and the transition is sufficiently fast that* $t^\star(\hat{\psi}; \eta) \leq J + \tau$*.*

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 earnings as

$$\begin{aligned}\mathcal{W}\left(\tau, \hat{\psi}; \eta\right) = &\int_{t_0(\tau)}^{t^\star\left(\hat{\psi};\eta\right)} e^{-\rho(t-t_0(\tau))} A_{P,t}\left(\eta\right) dt \\ &+ \int_{t^\star\left(\hat{\psi};\eta\right)}^{J+\tau} e^{-\rho(t-t_0(\tau))} A_{C,t}\left(\eta\right) \hat{\psi} dt \end{aligned} \tag{A.33}$$

when normalizing the productivity $\psi_P \equiv 1$ in the polluting sector (Section 4). We now show that workers' lifetime earnings are U-shaped in the pace of transition η for all occasional switchers.

Proposition 2. *Changes in lifetime earnings $d\mathcal{W}\left(\tau, \hat{\psi}; \eta\right)/d\eta$ are*

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

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.

Now consider the occasional-switchers, for whom $\hat{\psi} \in \left(\hat{A}_\infty^{-1}, \hat{A}_0^{-1}\right)$. For these workers, there exists some η for which $0 < t^\star\left(\hat{\psi}; \eta\right) < \infty$. For these workers, we claim that there exists some η_h for which $\partial_\eta \mathcal{W}\left(\tau, \hat{\psi}; \eta\right) > 0$ for all $\eta \geq \eta_h$ and $\eta_l < \eta_h$ such that $\partial_\eta \mathcal{W}\left(\tau, \hat{\psi}; \eta\right) < 0$ for all $\eta \leq \eta_l$: that is, the worker's welfare is increasing in η for some values of η and decreasing for others.

First note that $t^\star(\hat{\psi};\eta)$ is continuous and decreasing in η since $\hat{A}_t(\eta)$ is continuous and increasing in η. Consider workers who are not born as of period 0; that is $\tau > 0$. Under Assumption 1, since there exists some η for which $0 < t^\star(\hat{\psi};\eta) < \infty$ and $\tau > 0$, the Intermediate Value Theorem implies that there must be some η_h for which $t^\star(\hat{\psi};\eta_h) = \tau$ (the worker switches immediately) and some η_l for which $t^\star(\hat{\psi};\eta_l) = J + \tau$ (the worker would switch after retirement). Then, for all $\eta < \eta_l$, the worker remains in the old sector for their whole career and are made worse off by a faster transition, while for all $\eta > \eta_h$ they remain in the new sector their whole career and are made better off by a fast transition. Thus welfare is non-monotone in η for cohorts not yet born.

Now consider an incumbent worker $\tau < 0$ for whom there exists some η for which $0 < t^\star(\hat{\psi};\eta) < \infty$. First, note that one can derive η_l in the same way as above: for slow enough transitions such that the worker does not want to switch before retirement, the worker acts like a never-switcher. Now we prove the existence of an η_h. Consider an η with $0 \leq t^\star(\hat{\psi};\eta) \leq J + \tau$: that is, an η such that the worker would like to switch at some point before retirement. We have

$$\begin{aligned}\frac{d\mathcal{W}(\tau,\hat{\psi};\eta)}{d\eta} = &\int_0^{t^\star(\hat{\psi};\eta)} e^{-\rho t}\frac{\partial A_t^P(\eta)}{\partial \eta}dt \\ &+ \hat{\psi}\int_{t^\star(\hat{\psi};\eta)}^{J+\tau} e^{-\rho t}\frac{\partial A_t^C(\eta)}{\partial \eta}dt\end{aligned}$$

Factor out the smallest possible (or most negative) value of $\dfrac{\partial A_t^k(\eta)}{\partial \eta}$ and evaluate the remaining integral to arrive at:

$$\begin{aligned}\frac{d\mathcal{W}(\tau,\omega;\eta)}{d\eta} \geq &\frac{1}{\rho}\inf_{0\leq t\leq t^\star(\hat{\psi};\eta)}\left(\frac{\partial A_t^P(\eta)}{\partial \eta}\right)\left(1 - e^{-\rho t^\star(\hat{\psi};\eta)}\right) \\ &+ \frac{\hat{\psi}}{\rho}\inf_{t^\star(\hat{\psi};\eta)\leq t\leq J+\tau}\left(\frac{\partial A_t^C(\eta)}{\partial \eta}\right)\left(e^{-\rho t^\star(\hat{\psi};\eta)} - e^{-\rho(J+\tau)}\right).\end{aligned}$$

We wish to claim that this is larger than 0 for some value of η. Observe that the second line of the above inequality is larger than 0, as all objects in it are weakly positive. We therefore must bound only the first line for some value of η. Note that by the definition of sometimes-switchers and since the transition is instantaneous

as $\eta \to \infty$, there exists a value of η such that $t^\star(\hat{\psi};\eta) = 0$ and workers switch immediately. Define η_h to be the smallest value of η such that $t^\star(\hat{\psi};\eta) = 0$. Then for $\eta > \eta_h$, $\left(1 - e^{-\rho t^\star(\hat{\psi};\eta)}\right) = 0$. The first line therefore equals zero for $\eta > \eta_h$ so long as the absolute value of $\dfrac{\partial A_t^P(\eta)}{\partial \eta}$ grows slower than $1 - e^{-\rho t^\star}$ goes to zero. If $t^\star(\hat{\psi};\eta) = 0$, then $\inf_{0 \le t \le t^\star(\hat{\psi};\eta)} \partial A_t^P(\eta)/\partial\eta = \partial A_0^P(\eta)/\partial\eta$. Sending $\eta \to \infty$ we have that the operative part of the above equation becomes

$$\lim_{\eta \to \infty} \frac{\left(\dfrac{\partial A_0^P(\eta)}{\partial \eta}\right)}{\left(1 - e^{-\rho t^\star(\hat{\psi};\eta)}\right)^{-1}}.$$

Note that $e^{-\rho t^\star(\hat{\psi};\eta)} \to 1$ as $\eta \to \infty$. Applying L'Hopital's rule, we thus have

$$\lim_{\eta \to \infty} \frac{\left(\dfrac{\partial A_0^P(\eta)}{\partial \eta}\right)}{\left(1 - e^{-\rho t^\star(\hat{\psi};\eta)}\right)^{-1}} = \lim_{\eta \to \infty} -\frac{\dfrac{\partial_2 A_0^P(\eta)}{\partial \eta^2}}{\left(1 - e^{-\rho t^\star(\hat{\psi};\eta)}\right)^{-2} e^{-\rho t^\star(\hat{\psi};\eta)}}$$

We can continually apply L'Hopital's rule to have these limits involving progressively higher order derivatives of $A_0(t;\eta)$ with respect to η in the numerator, and something going to infinity on the denominator. Therefore if $\lim_{\eta\to\infty} \dfrac{\partial_n A_0(old;\eta)}{\partial \eta^n}$ is bounded for some n (item 4 of Assumption 1), this limit will equal 0, and $\dfrac{d\mathcal{W}(\tau,\hat{\psi};\eta)}{d\eta} \ge 0$. Therefore, there exists some η_h such that for all $\eta > \eta_h$, incumbent sometimes-switchers are made better off by a faster transition. Therefore, we have non-monotone micro welfare effects of a faster transition for any worker for whom there exists some finite $t^\star$ after which the worker would switch to the new sector.

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 relative skill $\hat{\psi}$ in the clean sector; and their employment state s (Section A.1). As shown in Appendix A.4, we do not need to include workers' overall skill ψ in our state space. To save on notation, we let $W_t\left(j,\hat{\psi},s\right)\equiv W_t^{\star}\left(j,\hat{\psi},s\right)$ denote workers' normalized values defined in Appendix A.4. We define the functions V_t, $\mathcal{O}_t$, θ_t, p_t, $\mathcal{F}$ and h and the constants δ_j^+, $\hat{\delta}_j$ and ρ similarly, dropping the $\star$ superscript relative to Appendices A.1 and A.4.

Workers. The value of an employed worker satisfies

$$\begin{aligned}\rho W_t\left(j,\hat{\psi},s\right) = & w\left(s\right)h\left(\hat{\psi},k\left(s\right)\right)\\ & +\lambda^E\sum_{s'}p_t\left(s';j,\hat{\psi},s\right)f\left(\theta_t\left(j,\hat{\psi},s'\right)\right)\left[W_t\left(j,\hat{\psi},s'\right)-W_t\left(j,\hat{\psi},s\right)\right]\\ & +\chi_0\mathcal{F}^{k(s)}\left(V_t\left(j,\hat{\psi},s\right)\right)\left[W_t\left(j,\hat{\psi},U\right)-W_t\left(j,\hat{\psi},s\right)\right]\\ & +\delta_j\left(k\left(s\right)\right)W_t\left(j,\hat{\psi},s\right)+\hat{\psi}\hat{\delta}_j\left(k\left(s\right)\right)\frac{\partial}{\partial\hat{\psi}}W_t\left(j,\hat{\psi},s\right)\\ & +\frac{\partial}{\partial j}W_t\left(j,\hat{\psi},s\right)+\frac{\partial}{\partial t}W_t\left(j,\hat{\psi},s\right)\end{aligned}\tag{B.1}$$

for all ages before retirement $j\in[0,J)$, relative productivity $\hat{\psi}$ in the clean sector, and markets $s\equiv(k,w)$. Employed workers search for jobs with intensity λ^E. The probability that a worker searches in market s' when they receive a search opportunity and are employed in sector s is

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

In turn, the value of a worker employed in the outside sector is

$$\begin{aligned}\rho W_t\left(j,\hat{\psi},O\right) = & \, h\left(\hat{\psi},O\right) \\ & + \lambda^E \sum_s p_t\left(s;j,\hat{\psi},O\right) f\left(\theta_t\left(j,\hat{\psi},s\right)\right)\left[W_t\left(j,\hat{\psi},s\right) - W_t\left(j,\hat{\psi},O\right)\right] \\ & + \chi_0 \bar{\mathcal{F}}\left[W_t\left(j,\hat{\psi},U\right) - W_t\left(j,\hat{\psi},O\right)\right] \\ & + \delta_j\left(O\right) W_t\left(j,\hat{\psi},O\right) + \frac{\partial}{\partial j} W_t\left(j,\hat{\psi},O\right) + \frac{\partial}{\partial t} W_t\left(j,\hat{\psi},O\right), \end{aligned} \tag{B.3}$$

where $\bar{\mathcal{F}}$ is the exogenous separation hazard in the outside sector. Finally, the value of an unemployed worker satisfies

$$\begin{aligned}\rho W_t\left(j,\hat{\psi},U\right) = & \, h\left(\hat{\psi},U\right) \\ & + \lambda^U \sum_s p_t\left(s;j,\hat{\psi},U\right) f\left(\theta_t\left(j,\hat{\psi},s\right)\right)\left[W_t\left(j,\hat{\psi},s\right) - W_t\left(j,\hat{\psi},U\right)\right] \\ & + \delta_j\left(U\right) W_t\left(j,\hat{\psi},U\right) + \frac{\partial}{\partial j} W_t\left(j,\hat{\psi},U\right) + \frac{\partial}{\partial t} W_t\left(j,\hat{\psi},U\right) \end{aligned} \tag{B.4}$$

The boundary conditions associated to the workers' values are

$$W_t\left(J,\hat{\psi},s\right) = W_t\left(J,\hat{\psi},O\right) = W_t\left(J,\hat{\psi},U\right) = 0 \tag{B.5}$$

for all workers $\left(\hat{\psi},s\right)$ when they retire at age $j = J$.

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

$$\begin{aligned} rV_t\left(j,\hat{\psi},s\right) = & \left(A_t^{k(s)} - w\left(s\right)\right) h\left(\hat{\psi},k\right) \\ & - \chi_0\left[\mathcal{F}^{k(s)}\left(V_t\left(j,\hat{\psi},s\right)\right) V_t\left(j,\hat{\psi},s\right) + \mathcal{O}_t\left(j,\hat{\psi},s\right)\right] \\ & - \lambda^E \sum_{s'} f\left(\theta_t\left(j,\hat{\psi},s'\right)\right) p_t\left(s';j,\hat{\psi},s\right) V_t\left(j,\hat{\psi},s\right) \\ & + \delta_j\left(k\left(s\right)\right) V_t\left(j,\hat{\psi},s\right) + \hat{\psi}\hat{\delta}_j\left(k\left(s\right)\right) \frac{\partial}{\partial\hat{\psi}} V_t\left(j,\hat{\psi},s\right) \\ & + \frac{\partial}{\partial j} V_t\left(j,\hat{\psi},s\right) + \frac{\partial}{\partial t} V_t\left(j,\hat{\psi},s\right), \end{aligned} \tag{B.6}$$

for all ages before retirement $j \in [0, J)$, relative productivity $\hat{\psi}$ in the clean sector, and markets $s \equiv (k, w)$, where $r \equiv \rho$ is the interest rate. The expression above

uses the fact that $\mathcal{P}_t^k = A_t^k$, as we have shown in Appendix A.7. 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, i.e., $\exp(\phi + \gamma\epsilon)\, h\left(\hat{\psi}, k(s)\right) \leq V_t\left(j, \hat{\psi}, s\right)$ where ϕ and γ denote the location and scale parameters of the distribution of operating costs, ϵ is drawn from the standard normal distribution Φ, and the $h\left(\hat{\psi}, k(s)\right)$ term reflects that operating costs are proportional to a worker's skill. Accordingly, the firm dissolves the match and fires the worker with probability

$$\mathcal{F}^{k(s)}\left(V_t\left(j, \hat{\psi}, s\right)\right) = 1 - \Phi\left(\frac{\log\left(V_t\left(j, \hat{\psi}, s\right) / h\left(\hat{\psi}, k(s)\right)\right) - \phi}{\gamma}\right) \tag{B.7}$$

In turn, the expected operating cost paid by the firm is

$$\mathcal{O}_t\left(j, \hat{\psi}, s\right) \equiv \exp\left(\phi + \frac{1}{2}\gamma\right) \Phi\left(\frac{\log\left(V_t\left(j, \hat{\psi}, s\right) / h\left(\hat{\psi}, k(s)\right)\right) - \phi - \gamma}{\gamma}\right) \tag{B.8}$$

when it continues operation.[53] In addition, the match dissolves if the worker searches on-the-job at rate λ^E and this search is successful. The boundary condition associated with (B.6) is

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

for all workers $\left(\hat{\psi}, s\right)$ when they retire at age $j = J$.

Free entry. The equilibrium tightnesses $\theta\left(j, \hat{\psi}, s\right)$ are pinned down by the firms' free entry condition

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

if this equation has a solution, and $\theta_t\left(j, \hat{\psi}, s\right) = 0$ otherwise, where the $h\left(\hat{\psi}, k(s)\right)$ term reflects that vacancy-posting costs are proportional to a worker's skill.

[53] Formally, the expression (B.8) is $\int_{-\infty}^{\bar{\epsilon}} \exp(\gamma\epsilon + \phi) \exp\left(-\frac{\epsilon^2}{2}\right) / \sqrt{2\pi} d\epsilon$ with $\bar{\epsilon} \equiv \left(\log\left(V_t\left(j, \hat{\psi}, s\right)\right) - \phi\right) / \gamma$.

B.2 Solving for Workers' and Firms' Values

Discretized system. We start by discretizing the differential equations of Appendix B.1. We let Δ denote the time step between periods t and ages j, and $\hat{\Delta}$ denote the distance between grid points for the relative skill $\hat{\psi}$. We let $\Delta \equiv 1/4$ so each period corresponds to a quarter. Our finite difference scheme is explicit, i.e., we evaluate continuation values in $t + \Delta$, which allows us to parallelize computation over the values for $\hat{\psi}$ to speed up our code.[54] As usual, the scheme is explicit in age j and time t.

After discretization, the value of being employed becomes

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

for all markets $s \equiv (k, w)$ excluding the outside sector and unemployment, where $\Delta > 0$ denotes the time step. In turn, the step $\hat{\Delta}$ for the relative skill $\hat{\psi}$ depends on which sector the worker is employed. With an abuse of notation, we let $\hat{\Delta}\left(k\left(s\right)\right) \equiv \hat{\Delta}$ when $k\left(s\right) = C$ and $\hat{\psi}$ increases and $\hat{\Delta}\left(k\left(s\right)\right) \equiv -\hat{\Delta}$ when $k\left(s\right) = P$ and $\hat{\psi}$ decreases.

[54] We have experimented with a hybrid scheme that is explicit over the relative skill $\hat{\psi}$ but implicit over the markets s. We obtained virtually identical results to our approach.

In turn, value of being employed in the outside sector O satisfies

$$\begin{aligned}\rho W_{t+\Delta}\left(j,\hat{\psi},O\right) = & \, h\left(\hat{\psi},O\right) \\ & + \lambda^{E}\sum_{s} p_{t+\Delta}\left(s;j+\Delta,\hat{\psi},O\right) f\left(\theta_{t+\Delta}\left(j+\Delta,\hat{\psi},s\right)\right) \\ & \qquad \times\left[W_{t+\Delta}\left(j,\hat{\psi},s\right)-W_{t+\Delta}\left(j,\hat{\psi},O\right)\right] \\ & + \chi_{0}\bar{\mathcal{F}}\left[W_{t+\Delta}\left(j,\hat{\psi},U\right)-W_{t+\Delta}\left(j,\hat{\psi},O\right)\right] \\ & + \delta_{j}\left(O\right)W_{t+\Delta}\left(j,\hat{\psi},O\right)+\frac{W_{t+\Delta}\left(j+\Delta,\hat{\psi},O\right)-W_{t}\left(j,\hat{\psi},O\right)}{\Delta}\end{aligned} \tag{B.12}$$

and the value of being unemployed satisfies

$$\begin{aligned}\rho W_{t+\Delta}\left(j,\hat{\psi},U\right) = & \, b^{U} \\ & + \lambda^{U}\sum_{s} p_{t+\Delta}\left(s;j+\Delta,\hat{\psi},U\right) f\left(\theta_{t+\Delta}\left(j+\Delta,\hat{\psi},s\right)\right) \\ & \qquad \times\left[W_{t+\Delta}\left(j,\hat{\psi},s\right)-W_{t+\Delta}\left(j,\hat{\psi},U\right)\right] \\ & + \delta_{j}\left(U\right)W_{t+\Delta}\left(j,\hat{\psi},U\right)+\frac{W_{t+\Delta}\left(j+\Delta,\hat{\psi},U\right)-W_{t}\left(j,\hat{\psi},U\right)}{\Delta}\end{aligned} \tag{B.13}$$

Finally, the value of a firm becomes

$$\begin{aligned}rV_{t+\Delta}\left(j,\hat{\psi},s\right) = & \left(A_{t}^{k(s)}-w\left(s\right)\right)h\left(\hat{\psi},k\left(s\right)\right) \\ & - \chi_{0}\left[\mathcal{F}^{k(s)}\left(V_{t+\Delta}\left(j,\hat{\psi},s\right)\right)V_{t+\Delta}\left(j,\hat{\psi},s\right)+\mathcal{O}_{t+\Delta}\left(j,\hat{\psi},s\right)\right] \\ & - \lambda^{E}\sum_{s'} f\left(\theta_{t+\Delta}\left(j+\Delta,\hat{\psi},s'\right)\right)p_{t+\Delta}\left(s';j+\Delta,\hat{\psi},s\right)V_{t+\Delta}\left(j,\hat{\psi},s\right) \\ & + \delta_{j}\left(k\left(s\right)\right)V_{t+\Delta}\left(j,\hat{\psi},s\right) \\ & + \hat{\psi}\hat{\delta}_{j}\left(k\left(s\right)\right)\frac{V_{t+\Delta}\left(j+\Delta,\hat{\psi}+\hat{\Delta}\left(k\left(s\right)\right),s\right)-V_{t+\Delta}\left(j+\Delta,\hat{\psi},s\right)}{\hat{\Delta}\left(k\left(s\right)\right)} \\ & + \frac{V_{t+\Delta}\left(j+\Delta,\hat{\psi},s\right)-V_{t}\left(j,\hat{\psi},s\right)}{\Delta},\end{aligned} \tag{B.14}$$

for all markets $s\equiv(k,w)$, with $\mathcal{O}_{t}\left(j,\hat{\psi},s\right)$ still defined by (B.8).

Workers' and firms' values are characterized by the system (B.11)–(B.14) together with the boundary conditions (B.5) and (B.9), the search probabilities (B.2),

the definition of $\mathcal{F}^{k(s)}$ (B.7), the definition of $\mathcal{O}_t$ (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. Solve for workers' and firms' values.

Step 0. Let the terminal values for workers $W_T\left(J,\hat{\psi},s\right)$, $W_T\left(J,\hat{\psi},O\right)$ and $W_T\left(J,\hat{\psi},U\right)$ and firms $V_T\left(J,\hat{\psi},s\right)$ satisfy the boundary conditions (B.5) and (B.9) at retirement at age J. Initiate the recursion by setting the time index to $t=T-\Delta$ and the age index to $j=J-\Delta$.

Step 1. Compute the search probabilities $p_{t+\Delta}\left(s';j+\Delta,\hat{\psi},s\right)$ using (B.2), the values $\mathcal{O}_{t+\Delta}\left(j+\Delta,\hat{\psi},s\right)$ using (B.8) and the tightnesses $\theta_{t+\Delta}\left(j+\Delta,\hat{\psi},s\right)$ using (B.10).

Step 2. Solve for workers' values:

Solve for the values

$$\mathbf{W}_t\left(j,\hat{\psi}\right)=\Delta\left\{\mathbf{B}_t\left(j,\hat{\psi}\right)+\left[\mathbf{M}_{t+\Delta}\left(j+\Delta,\hat{\psi}\right)+\mathbf{\Lambda}\right]\mathbf{W}_{t+\Delta}\left(j,\hat{\psi}\right)\right\}, \tag{B.15}$$

where the vector $\mathbf{W}_t\left(j,\hat{\psi}\right)$ contains workers' values, the matrix $\mathbf{M}_{t+\Delta}\left(j+\Delta,\hat{\psi}\right)$ captures workers' transitions across states that are part of the implicit scheme, the vector $\mathbf{B}_t\left(j,\hat{\psi}\right)$ contains workers' flow earnings and the transitions that are part of the explicit scheme, and the matrix $\mathbf{\Lambda}$ captures discounting and the evolution of the overall skill ψ which we do need keep track of in our state space. Formally, workers' values are

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

the transition matrix is

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

and the flows and discounting are

$$\mathbf{B}_t\left(j,\hat{\psi}\right) \equiv \begin{bmatrix} \mathbf{B}_{1,t}\left(j,\hat{\psi}\right) \\ B_{2,t}\left(j,\hat{\psi}\right) \\ B_{3,t}\left(j,\hat{\psi}\right) \end{bmatrix} \quad , \quad \mathbf{\Lambda} \equiv \begin{bmatrix} \mathbf{A}_1 & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & A_2 & 0 \\ \mathbf{0} & 0 & A_3 \end{bmatrix} \tag{B.18}$$

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

$$\begin{aligned} \mathbf{M}_{1,1,t}\left(j,\hat{\psi}\right)_{[s,s']} \equiv & \lambda^E p_{t+\Delta}\left(s';j+\Delta,\hat{\psi},s\right) f\left(\theta_{t+\Delta}\left(j+\Delta,\hat{\psi},s'\right)\right) \\ & + \mathbf{N}_t\left(j,\hat{\psi}\right)_{[s,s']} \end{aligned} \tag{B.19}$$

with

$$\mathbf{N}_t\left(j,\hat{\psi}\right)_{[s,s']} \equiv \begin{cases} -\lambda^E \sum_{\hat{s}} p_{t+\Delta}\left(\hat{s};j+\Delta,\hat{\psi},s\right) f\left(\theta_{t+\Delta}\left(j+\Delta,\hat{\psi},\hat{s}\right)\right) & \text{if } s'=s \\ \quad -\chi_0 \mathcal{F}^{k(s)}\left(V_{t+\Delta}\left(j+\Delta,\hat{\psi},s\right)\right) & \\ 0 & \text{otherwise} \end{cases},$$

and the column vectors

$$\mathbf{M}_{1,2,t}\left(j,\hat{\psi}\right)_{[s,1]} = \lambda^E p_{t+\Delta}\left(O;j+\Delta,\hat{\psi},s\right) \tag{B.20}$$

$$\begin{aligned} \mathbf{M}_{1,3,t}\left(j,\hat{\psi}\right)_{[s,1]} = & \lambda^E p_{t+\Delta}\left(U;j+\Delta,\hat{\psi},s\right) \\ & + \chi_0 \mathcal{F}^{k(s)}\left(V_{t+\Delta}\left(j+\Delta,\hat{\psi},s\right)\right) \end{aligned} \tag{B.21}$$

where we have used the fact that workers can transition instantaneously to the outside sector or unemployment if they are given the opportunity to search. We also define the column vectors

$$\begin{aligned} \mathbf{B}_{1,t}\left(j,\hat{\psi}\right)_{[s,1]} \equiv & w(s)\, h\left(\hat{\psi},k(s)\right) \\ & + \hat{\psi}\hat{\delta}\left(k(s)\right) \frac{W_{t+\Delta}\left(j+\Delta,\hat{\psi}+\hat{\Delta}\left(k(s)\right),s\right) - W_{t+\Delta}\left(j+\Delta,\hat{\psi},s\right)}{\hat{\Delta}\left(k(s)\right)}, \end{aligned} \tag{B.22}$$

and the diagonal matrix

$$\mathbf{\Lambda}_{1[s,s']} = \begin{cases} \frac{1}{\Delta} + \delta_j\left(k\left(s\right)\right) - \rho & \text{if } s' = s \\ 0 & \text{otherwise} \end{cases} \tag{B.23}$$

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

$$\mathbf{M}_{2,1,t}\left(j, \hat{\psi}\right)_{[1,s]} \equiv \lambda^E p_{t+\Delta}\left(s; j+\Delta, \hat{\psi}, O\right) f\left(\theta_{t+\Delta}\left(j+\Delta, \hat{\psi}, s\right)\right), \tag{B.24}$$

the scalar

$$\begin{aligned} M_{2,2,t}\left(j, \hat{\psi}\right) = \lambda^E & p_{t+\Delta}\left(O; j+\Delta, \hat{\psi}, O\right) \\ & - \lambda^E \sum_s p_{t+\Delta}\left(s; j+\Delta, \hat{\psi}, O\right) f\left(\theta_{t+\Delta}\left(j+\Delta, \hat{\psi}, s\right)\right) \\ & - \chi_0 \bar{\mathcal{F}} \end{aligned} \tag{B.25}$$

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

$$M_{2,3,t}\left(j, \hat{\psi}\right) \equiv \lambda^E p_{t+\Delta}\left(U; j+\Delta, \hat{\psi}, O\right) + \chi_0 \bar{\mathcal{F}}. \tag{B.26}$$

We also define the scalars

$$B_{2,t}\left(j, \hat{\psi}\right) \equiv h\left(\hat{\psi}, O\right) \tag{B.27}$$

and

$$\Lambda_2 \equiv \frac{1}{\Delta} + \delta_j\left(O\right) - \rho \tag{B.28}$$

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

$$\mathbf{M}_{3,1,t}\left(j, \hat{\psi}\right)_{[1,s]} \equiv \lambda^U p_{t+\Delta}\left(s; j+\Delta, \hat{\psi}, U\right) f\left(\theta_{t+\Delta}\left(j+\Delta, \hat{\psi}, s\right)\right), \tag{B.29}$$

the scalar

$$M_{3,2,t}\left(j, \hat{\psi}\right) = \lambda^U p_{t+\Delta}\left(O; j+\Delta, \hat{\psi}, U\right), \tag{B.30}$$

and the scalar

$$M_{3,3,t}\left(j,\hat{\psi}\right) \equiv \lambda^{U} p_{t+\Delta}\left(U; j+\Delta, \hat{\psi}, U\right) - \lambda^{U} \sum_{s} p_{t+\Delta}\left(s; j+\Delta, \hat{\psi}, U\right) f\left(\theta_{t+\Delta}\left(j+\Delta, \hat{\psi}, s\right)\right). \quad \text{(B.31)}$$

We also define the scalars

$$B_{3,t}\left(j,\hat{\psi}\right) \equiv b^{U} \quad \text{(B.32)}$$

and

$$\Lambda_3 \equiv \frac{1}{\Delta} + \delta_j\left(U\right) - \rho. \quad \text{(B.33)}$$

Step 3. Solve for the firms' values:

Solve for the values by inverting the system

$$\mathbf{V}_t\left(j,\hat{\psi}\right) = \Delta\left\{\mathbf{D}_t\left(j,\hat{\psi}\right) + \left[\mathbf{P}_{t+\Delta}\left(j+\Delta,\hat{\psi}\right) + C\right]\mathbf{V}_{t+\Delta}\left(j,\hat{\psi}\right)\right\}, \quad \text{(B.34)}$$

where the vector $\mathbf{V}_t\left(j,\hat{\psi}\right)$ contains firms' values, the matrix $\mathbf{P}_{t+\Delta}\left(j+\Delta,\hat{\psi}\right)$ captures workers' transitions across states that are part of the implicit scheme, the vector $\mathbf{D}_t\left(j,\hat{\psi}\right)$ contains firms' flow profits and the transitions that are part of the explicit scheme, and the scalar C captures discounting and the evolution of the overall skill ψ which we do need keep track of in our state space. Formally, the firms' values are

$$\mathbf{V}_t\left(j,\hat{\psi}\right)_{[s,1]} \equiv V_t\left(j,\hat{\psi},s\right), \quad \text{(B.35)}$$

with the square matrix

$$\mathbf{P}_t\left(j,\hat{\psi}\right)_{[s,s']} \equiv \begin{cases} -\lambda^{E}\sum_{\hat{s}} f\left(\theta_{t+\Delta}\left(j+\Delta,\hat{\psi},\hat{s}\right)\right) p_{t+\Delta}\left(\hat{s}; j+\Delta,\hat{\psi},s\right) & \text{if } s'=s \\ \quad -\chi_0 \mathcal{F}\left(V_{t+\Delta}\left(j+\Delta,\hat{\psi},s\right)\right) & \\ 0 & \text{otherwise} \end{cases},$$

the column vector

$$\mathbf{D}_t\left(j,\hat{\psi}\right)_{[s,1]} = \left(A_t^{k(s)} - w\left(s\right)\right) h\left(\hat{\psi}, k\left(s\right)\right) - \chi_0 \mathcal{O}_{t+\Delta}\left(j+\Delta,\hat{\psi},s\right) + \hat{\psi}\hat{\delta}\left(k\left(s\right)\right) \frac{V_{t+\Delta}\left(j,\hat{\psi}+\hat{\Delta}\left(k\left(s\right)\right),s\right) - V_{t+\Delta}\left(j,\hat{\psi},s\right)}{\hat{\Delta}\left(k\left(s\right)\right)}, \quad \text{(B.36)}$$

and the scalar

$$C_{[s,s']} = \begin{cases} \frac{1}{\Delta} + \delta_j\left(k\left(s\right)\right) - r & \text{if } s' = s \\ 0 & \text{otherwise} \end{cases}. \quad \text{(B.37)}$$

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 steady state values.

In principle, the finite difference scheme described above could become unstable if the diagonal elements of $\Delta \times \mathbf{M}_{t+\Delta}\left(j+\Delta,\hat{\psi}\right)$ and $\Delta \times \mathbf{P}_{t+\Delta}\left(j+\Delta,\hat{\psi}\right)$ exceed 1 in absolute value. This occurs, for instance, if the worker is fired with probability 1 but can also perform a job-to-job transition. To address this issue, we truncate the diagonal elements to ensure that they are bounded by 1 and re-scale the off-diagonal elements proportionately to make sure that the rows sum up to 0.

B.3 Distribution of Workers' States

We denote the density of workers' states by $\mu_t\left(\mathbf{x}\right)$. This density is a continuous function of age j and the relative productivity in the clean sector $\hat{\psi}$, 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 $\int f\left(s,\mathbf{x}_{-1}\right)\mu_t\left(ds,\mathbf{x}_{-1}\right)$ as a discrete sum over markets $s \equiv (k,w)$ with positive mass, where $\mathbf{x}_{-1}$ denotes the other states. As in Appendix B.1, we do not keep track of a worker's overall skill ψ when iterating over the distribution.

As usual, the law of motion of the distribution is closely related to the recur-

sive formulation of workers' values (Appendix B.2). In fact, the matrix $\mathbf{M}_t(j,\omega)$ encodes the information required to iterate on the distribution. This is intuitive: this matrix captures 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 the changes in the relative productivity in the clean sector $\hat{\psi}$ that are included in $\mathbf{B}_t\left(j,\hat{\psi}\right)$ as part of the explicit scheme.

Abstracting momentarily from changes in $\hat{\psi}$, the law of motion for the distribution is

$$\frac{d}{dt}\boldsymbol{\mu}_t\left(j,\hat{\psi}\right) = \mathbf{M}_t(j,\omega)'\,\boldsymbol{\mu}_t\left(j,\hat{\psi}\right) \tag{B.38}$$

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

$$\begin{gathered}\boldsymbol{\mu}_t\left(j,\hat{\psi}\right)_{[s,1]} \equiv \mu_t\left(j,\hat{\psi},s\right) \qquad \boldsymbol{\mu}_t\left(j,\hat{\psi}\right)_{[\text{end-1},1]} \equiv \mu_t\left(j,\hat{\psi},O\right) \\ \boldsymbol{\mu}_t\left(j,\hat{\psi}\right)_{[\text{end},1]} \equiv \mu_t\left(j,\hat{\psi},U\right)\end{gathered} \tag{B.39}$$

Integrating (B.38) over a short time interval Δ,

$$\boldsymbol{\mu}_{t+\Delta}\left(j,\hat{\psi}\right) = \boldsymbol{\mu}_t\left(j-\Delta,\hat{\psi}\right)\exp\left(\mathbf{M}_t\left(j,\hat{\psi}\right)'\Delta\right), \tag{B.40}$$

where $\exp(X) \equiv \sum_{k=0}^{\infty} 1/k!X^k$ is the matrix exponential. We iterate on (B.40) separately over consecutive intervals of length Δ over which the transition matrices are kept constant. The non-linear formulation (B.40) is computationally more intensive compared to a simple linear approximation of expression (B.38). However, it allows us to compute workers' values over relative long time intervals, e.g., quarterly $\Delta \equiv 1/4$, while still accounting for multiple, high-frequency changes in employment status that occur over these intervals or shorter ones. Doing so is important to ensure that our model-simulated moments (such as monthly job flows) are consistent with their empirical counterparts measured in the CPS (Appendix B.4).

As mentioned, the law of motion above does not account for changes in the relative productivity $\hat{\psi}$ in our explicit scheme. We adopt a simple approach to account for these transitions. We let

$$\boldsymbol{\mu}_{t+\Delta}\left(j,\hat{\psi}\right) = \sum_{\tilde{\psi}} \mathbf{Q}\left(\hat{\psi},\tilde{\psi}\right)\boldsymbol{\mu}_t\left(j-\Delta,\tilde{\psi}\right)\exp\left(\mathbf{M}_t\left(j,\tilde{\psi}\right)'\Delta\right), \tag{B.41}$$

where the sum is over the initial relative productivities $\tilde{\psi}$. The matrices $\mathbf{Q}\left(\hat{\psi},\tilde{\psi}\right)$

are diagonal and the elements $[s,s]$ indicate whether $\hat{\psi}$ changes or not depending on workers' current employment status s. If the worker is employed in the clean or polluting sectors, i.e., $k(s) = P, C$, then the relative productivity evolves deterministically by $\hat{\delta}(k(s))\Delta$ after a time step Δ. When this new value does not fall on a grid point for $\hat{\psi}$, we allocate the corresponding mass to the neighboring points following the non-stochastic simulation method of Young (2010). Accordingly, we set the diagonal elements to

$$\mathbf{Q}_t\left(\hat{\psi},\tilde{\psi}\right)_{[s,s]} \equiv \begin{cases} 1-q\left(\hat{\psi},\tilde{\psi},s\right) & \text{if } \hat{\psi}=\hat{\psi}_0\left(\tilde{\psi},s\right) \\ q\left(\hat{\psi},\tilde{\psi},s\right) & \text{if } \hat{\psi}=\hat{\psi}_1\left(\tilde{\psi},s\right), \\ 0 & \text{otherwise} \end{cases} \tag{B.42}$$

where $\hat{\psi}_0\left(\tilde{\psi},s\right)$ is the largest point on the grid for relative productivities that is smaller or equal to $\tilde{\psi}+\hat{\delta}(k(s))\Delta$ and $\hat{\psi}_1\left(\hat{\psi},\tilde{\psi},s\right) \equiv \hat{\psi}_0\left(\tilde{\psi},s\right)+\hat{\Delta}$ is the smaller point that is strictly larger than it, and $q\left(\hat{\psi},\tilde{\psi},s\right) \equiv \left(\hat{\psi}-\tilde{\psi}-\hat{\delta}(k(s))\right)/\hat{\Delta}$ assigns masses in inverse proportion to the distance between $\tilde{\psi}+\hat{\delta}(k(s))\Delta$ and the closest grid points. All the off-diagonal elements are zero.

An alternative approach would be to extend the law of motion (B.40) by stacking the vectors $\boldsymbol{\mu}_{t+\Delta}\left(j,\hat{\psi}\right)$ for all values of $\hat{\psi}$, and define a larger transition matrix that also accounts for flows between values of $\hat{\psi}$. This approach turns out to be computationally demanding since this new transition matrix is very large and the formulation prevents numerical parallelization. The only difference between our approach (B.41) and this alternative one is that we suppose that the state $\hat{\psi}$ evolves only once at the end of the time interval Δ, whereas the alternative approach accounts for its evolution over this interval.

Finally, the law of motion (B.41) has a boundary at age $j = J$ when workers retire. The flow of retirees, and hence newborns, is

$$\mu_t^R = \int\int \mu_{t-\Delta}\left(J, d\hat{\psi}, ds\right) \tag{B.43}$$

Newborn workers are endowed with an overall skill $\psi = 1$ and a relative skill $\hat{\psi} \sim G$. Accordingly, the distribution of workers' states among newborn workers

is

$$\mu_t\left(0,\hat{\psi},s\right)=\begin{cases}\mu_t^R\times G\left(d\hat{\psi}\right) & \text{if } s=U\\ 0 & \text{otherwise}\end{cases} \tag{B.44}$$

Stationary distribution and transition. The economy starts from a stationary distribution where the clean sector is absent, i.e., $A^C\equiv 0$. We normalize the stationary distribution so it has a unit mass.

B.4 Calibration

We discretize our continuous time model into short periods corresponding to a quarter, i.e., $\Delta\equiv 1/4$. We explain below how we compute the moments that we use in our steady state calibration (Section 6.2).

State space reduction in initial steady state. First off, it is useful to note that our initial steady state does not depend on the distribution G of relative skill $\hat{\psi}$ in the clean sector, since that sector is effectively absent with $A^C=0$ (Section 3.2). This property can easily be shown by guessing and verifying that $W_t\left(j,\hat{\psi},s\right)=W_t\left(j,s\right)$ and $V_t\left(j,\hat{\psi},s\right)=V_t\left(j,s\right)$ for any $\hat{\psi}$ and employment state s at the initial state, since the worker never supplies labor in the clean sector.[55] The derivation is similar to Appendix A.4, so we omit it here. Furthermore, the initial steady state does not depend on $\hat{\delta}_j$ directly, only on $\delta_j^+ + \hat{\delta}_j$ which we directly measure in the data (Section 6.2). When it comes to our steady state calibration, we can therefore normalize $\hat{\psi}=1$ and set $\hat{\delta}=0$, without loss of generality, as we discipline ten parameters internally. Once these parameters are calibrated, we can structurally estimate the distribution G and the rate $\hat{\delta}$ using reallocation flows over the transition. As we explain in Section 6.4, this structural estimation involves simulating the initial steady state, accounting for the endogenous evolution of $\hat{\psi}$ which is relevant for the subsequent transition, and then simulating workers forward over this transition.

Employment flows. We compute the EE, EU and UE probabilities over one month,

[55] When doing so, we use the fact that: $h\left(\hat{\psi},s\right)=h\left(s\right)$ does not depend on $\hat{\psi}$ whenever the worker is employed in the polluting sector or the outside sector, or is unemployed; $\frac{\partial}{\partial\hat{\psi}}W_t\left(j,\hat{\psi},s\right)=0$ for all employment states since $W_t\left(j,\hat{\psi},s\right)=W_t\left(j,s\right)$ under our guess; and $\theta_t\left(j,s\right)=0$ and hence $f\left(\theta_t\left(j,s\right)\right)=0$ in the clean sector since $A^C=0$.

i.e., $T \equiv 1/12$. When doing so, we account for the possibility that workers might experience multiple job transitions within the same month. For instance, a worker who first experiences an EU transition followed by an UE one during the same month will be counted in the EE probability, which ensures that our moment is comparable to the EE probability as measured in the CPS.

To compute the EU probability, we use the law of motion (B.40) since we do not account for changes in $\hat{\psi}$ within a month. We make two changes compared to this law of motion. First, we initialize it using the distribution of states conditional on employment $\boldsymbol{\mu}_t^E$ instead of the unconditional distribution $\boldsymbol{\mu}_t$. Second, we set the time step to $T = 1/12$ instead of $\Delta = 1/4$. We use this new law of motion for all ages j and productivities $\hat{\psi}$. The EU probability corresponds to the mass of workers with state $s = U$ after a month. We proceed analogously to compute the UE probability.

Similarly, we combine two moments to compute the EE probability over a month: the probability that an employed worker is again employed in a month in *any* market (computed in a way that is similar to the one described above); and the probability that the worker stays in their current job.[56] The EE probability is the difference between the these two quantities. To compute the second moment, we use the same law of motion as before, except with an alternative matrix $\widetilde{\mathbf{M}}_t\left(j, \hat{\psi}\right)$ in which all the *inflows*, i.e., the negative terms, are all zero. This matrix lets workers "flow out" of the system as they move out of their current job. The mass of workers who remain after a month is the probability that a worker stays in the current job.

Elasticity of the separation probability w.r.t. output change. We compute the elasticity of the separation probability following an idiosyncratic, 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 our empirical target (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 workers whose firms is subject to this change.

[56] A worker who leaves their current job for unemployment and then moves back to the same market (but a different job) is still counted in the EE probability to be consistent with the data.

The first step consists of computing alternative values for the workers $\widehat{W}_t\left(j,\hat{\psi},s\right)$ and firms $\widehat{V}_t\left(j,\hat{\psi},s\right)$ 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 $(1-\alpha)\,A_t^{k(s)}h\left(\hat{\psi},k\left(s\right)\right)$. Second, the continuation values $W_t\left(j,\hat{\psi},s\right)$ in *other markets* (or employment states) are treated as exogenous in expression (B.11) and evaluated at steady state since the outside options are unchanged.[57] The worker's job finding probabilities $f\left(\theta_t\left(j,\hat{\psi},s\right)\right)$ are also exogenous. In contrast, the search behavior of employed workers and $\hat{p}_t\left(s';j,\hat{\psi},s\right)$ and firms' firing decisions $\mathcal{F}\left(\hat{V}_t\left(j,\hat{\psi},s\right)\right)$ are endogenous. In our comparative statics, we consider a permanent productivity change of $\alpha=0.1$.

The second step consists of computing the average separation probability at the annual level ($T\equiv 1$) associated to these values. 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 probability is given by one minus the probability that a worker stays in their current job. This moment is computed as we described above, except that account for changes in the relative skill $\hat{\psi}$ over this longer period by using the law of motion (B.41). 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-

[57] However, the continuation values associated to changes in $\hat{\psi}$ are endogenous.

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"[58] 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

[58] 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

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.

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 9. 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.[59] 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.[60] All wages are deflated by the CPI-U. By focus-

[59] 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.

[60] 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

ing 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 being 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.[61] 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

the calibration and thus provides a conservative of the cost of the transition.

[61] 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-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.

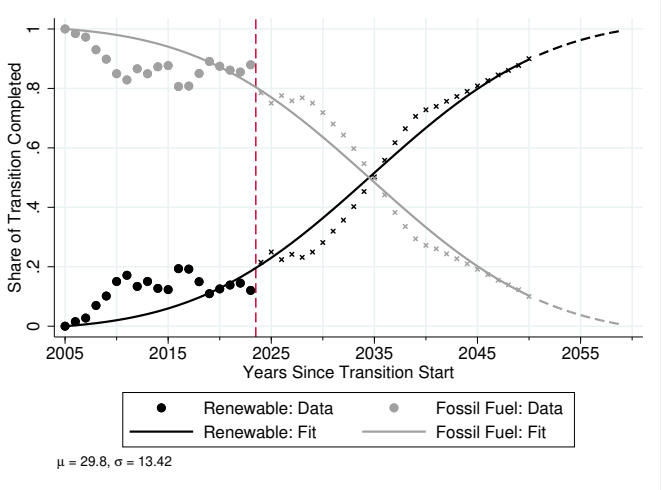
Table 4 reports the characteristics of probabilistically polluting-attached workers who hold jobs in polluting sectors and clean sectors as of 2006 and 2024. The workers holding polluting jobs are substantially less educated than those holding clean jobs in both periods, suggesting that high human capital workers join the clean sector. In addition, those working in clean sectors are younger than those in 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 polluting manufacturing employment to clean and polluting sectors.[62] We do so based on the share of cars sold that run on alternative fuel (hybrid, plug-in hybrid, electric, or biofuel).[63] This correction has the added benefit

[62] We maintain the following four manufacturing sectors as polluting over the full transition: Petroleum products (NAICS 3241), Petrochemical manufacturing (NAICS 3251), Oil and gas field machinery and equipment (NAICS 333132) and Motor vehicle gasoline engine and parts mfg (NAICS 336310). Other polluting manufacturing employment includes all motor vehicle manufacturing sectors.

[63] 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/

Figure 9: 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 (6.1). The dashed lines indicate years in which we use projections instead of realized data.

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 by taking the moving average over 12 quarters before and after a target date. 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 6.4.

Figure 9 shows the share of the transition completed as projected by the US Energy Information Administration and the fit of our truncated normal CDFs.

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

