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Clean job creation versus dirty job destruction: labor market dynamics and business cycles

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Abstract

Purpose – This paper studies how the green transition affects labor-market reallocation, business-cycle dynamics and distributional outcomes. It focuses on the distinction between clean job creation and dirty job destruction and how these adjustment margins affect high- and low-skilled workers differently.

Design/methodology/approach – We develop an environmental dynamic stochastic general equilibrium (DSGE) model with search-and-matching frictions, clean and dirty sectors, and high- and low-skilled workers. Transition risk is modeled through four skill-specific job-flow shocks, distinguishing clean job creation from dirty job destruction.

Findings – The paper finds that job creation and job destruction are asymmetric channels of adjustment. Clean job creation supports sectoral reallocation but generates limited aggregate fluctuations. By contrast, dirty job destruction produces larger business-cycle effects, especially when it affects low-skilled workers. Low-skilled dirty job destruction generates the largest output losses, stronger inflationary pressures and the most severe distributional effects, widening both consumption inequality and the wage premium.

Originality/value – The paper treats transition risk as a labor-market reallocation process rather than solely as a carbon-pricing shock. By separating creation and destruction margins and introducing skill heterogeneity within both sectors, it identifies the channels through which the green transition affects workers unevenly.

Keywords E-DSGE model, Labor market, Skill heterogeneity, Job separation, Job creation

Paper type Research article

1. Introduction

The transition to a low-carbon economy entails a profound reallocation of workers across sectors, occupations, and skill groups, with important implications for unemployment, wages, and inequality (ILO, 2019; Cedefop, 2023; Vandeplas *et al.*, 2022). By reducing labor demand in high-emission industries and reshaping job creation in expanding clean activities, decarbonization affects both unemployment inflows and job-finding prospects, making labor-market frictions central to the macroeconomic assessment of transition risk (Hafstead and Williams, 2018; Causa *et al.*, 2024a; Metcalf and Stock, 2023). These effects are heterogeneous across workers because green and transition-related jobs tend to be more skill-intensive than many carbon-intensive occupations (Consoli *et al.*, 2016; Vona *et al.*, 2018). Using EU-LFS data for 21 European countries, Causa *et al.* (2024b) find that highly educated workers have 2.1 times the odds of entering green occupations, implying approximately 52% lower odds for low-educated workers. As a result, low-skilled face weaker outside options, lower job-finding probabilities, and higher displacement risks (Marin and Vona, 2019; Curtis *et al.*, 2024; OECD, 2024). More broadly, this heterogeneity affects not only inequality and wage premia, but also unemployment, productivity, and business-cycle

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dynamics (Wu *et al.*, 2022; Dolado *et al.*, 2021; Abbritti and Consolo, 2024; Albanese *et al.*, 2025).

The timing of adjustment reinforces these mechanisms. The green transition affects the economy not only through implemented climate policy, but also through firms' anticipatory hiring, separation, vacancy-posting, and investment decisions (Meng *et al.*, 2024; Känzig, 2023). These decisions generate two job-flow margins: clean job creation and dirty job destruction. In frictional labor markets, the macroeconomic and welfare effects of reallocation depend on which margin prevails. A decline in dirty employment may differ sharply in its implications when driven by clean-sector hiring rather than dirty-sector separations (Kuo and Miyamoto, 2015; Zanetti, 2019). This channel remains relatively underexplored in environmental DSGE models.

In light of these considerations, this paper studies how worker heterogeneity and sectoral skill mismatch between clean and dirty sectors shape business-cycle dynamics under transition-related labor-market shocks. We develop an environmental DSGE (E-DSGE) model with Diamond–Mortensen–Pissarides search-and-matching (SAM hereafter) frictions, high- and low-skilled workers, and clean and dirty production sectors. The model builds on Abbritti and Consolo (2024), but introduces a clean–dirty structure and extends Albanese *et al.* (2025) by incorporating transition-related job-flow shocks. Heterogeneity operates through sectoral skill mismatch and skill-specific adjustment: the clean sector is relatively skill-intensive, the dirty sector employs more low-skilled workers, and worker types differ in matching probabilities, unemployment dynamics, and bargaining power. We isolate these mechanisms through four shocks: skill-specific clean job-creation shocks, modeled as reductions in clean-sector vacancy-posting costs, and skill-specific dirty job-destruction shocks, modeled as increases in dirty-sector separation rates. Clean shocks capture targeted policies supporting green hiring. On the dirty side, separation shocks capture transition-related labor-market disruptions that increase the probability of match destruction in carbon-intensive activities [1]. These disturbances should be interpreted as a parsimonious representation of regulatory tightening, policy-induced restructuring, technological displacement, or changes in the expected profitability of dirty production that make existing dirty-sector matches less viable. This framework disentangles labor-market adjustment margins that a standard carbon-tax shock cannot separately identify, clarifying how transition risk affects macroeconomic dynamics and distributional outcomes.

Our results deliver three main findings. First, labor reallocation toward the clean sector is strongly skill-dependent: high-skilled dirty job destruction leads to stronger clean employment gains, while low-skilled workers benefit more from clean job creation because they face weaker job-finding prospects and stronger skill mismatch. Second, the business-cycle effects of transition risk are mainly driven by the destruction margin, especially low-skilled dirty job destruction, which raises unemployment and makes the transition more recessionary and inflationary. Third, transition shocks generate asymmetric spillovers and distributional costs, with low-skilled dirty job destruction producing the largest increase in inequality and the wage premium.

This paper relates to three strands of the literature. First, it contributes to the macro-labor literature on labor-market frictions, job flows, and business-cycle dynamics (Sun *et al.*, 2023; El Ouazzani *et al.*, 2024; Mavrigiannakis *et al.*, 2025; Wesselbaum, 2015). This literature highlights the relevance of job-destruction shocks, job-creation subsidies, unemployment inflows and outflows, asymmetric job-finding dynamics, wage rigidity, firing costs, labor-adjustment margins, and the link between fiscal policy, corporate tax evasion, and job creation (Zanetti, 2011, 2019; Kuo and Miyamoto, 2015; Bryson, 2026; Kohlbrecher and Merkl, 2022; Uemura, 2024; Takano, 2025; Lisi and Castañeda-Rodríguez, 2025). We contribute by developing a two-sector clean–dirty framework with skill-specific transition-related job-flow shocks, which allows us to study how sectoral skill mismatch and heterogeneous matching conditions shape the transmission of job-creation and job-destruction shocks. Second, the paper relates to the literature on the macroeconomic and labor-market effects of climate policy.

Early DSGE contributions embed environmental policy into macroeconomic models, while recent studies emphasize employment, unemployment, heterogeneous workers, labor mobility, firm creation, green technology adoption, and the interaction between unemployment and environmental regulation (Heutel, 2012; Annicchiarico and Di Dio, 2015; Hafstead and Williams, 2018; Aubert and Chiroleu-Assouline, 2019; Castellanos and Heutel, 2019; Shapiro and Metcalf, 2023). Relative to this literature, we treat climate-related labor reallocation as a distinct source of macroeconomic fluctuations by separating clean job creation from dirty job destruction and by introducing skill heterogeneity within both sectors. Finally, the paper connects to the Beveridge-curve literature, which studies how aggregate-demand disturbances, wage shocks, liquidity shocks, technology shocks, matching-efficiency fluctuations, and homeownership generate movements along, or shifts in, the vacancy–unemployment relationship (Ellington *et al.*, 2021; Abbritti and Consolo, 2024; Kohlbrecher and Merkl, 2022; Lisi, 2024). We contribute by bringing sectoral reallocation and skill heterogeneity into the analysis of vacancy–unemployment dynamics during the green transition.

The remainder of the paper is organized as follows. Section 2 develops the model. Section 3 discusses the calibration. Section 4 presents the quantitative results. Section 5 presents a robustness analysis. Section 6 concludes.

2. The model

This paper develops an environmental DSGE model with SAM frictions, sectoral heterogeneity, and skill heterogeneity. The economy includes: high-skilled workers, low-skilled workers, entrepreneurs, final producing firms and intermediate clean and dirty firms, and a government.

2.1 Labor market and matching process

The economy is populated by three household types: entrepreneurs and two groups of workers, high-skilled and low-skilled. Each type has a constant population mass φ^s, with $s \in \{H, L, E\}$. On the production side, there are two sectors, indexed by $j \in \{C, D\}$, where C denotes the clean sector and D the carbon-intensive sector. For each worker type $s \in \{H, L\}$, the unit time endowment is allocated across employment in the clean sector, employment in the carbon-intensive sector, unemployment, and leisure:

$$1 = n^s_{C,t} + n^s_{D,t} + u^s_t + \ell^s_t, \qquad s \in \{H, L\}. \tag{1}$$

To allow for skill- and sector-specific matching, let $u^s_{j,t}$ denote the pool of unemployed workers of type s searching in sector j, so that:

$$u^s_t = \sum_{j \in \{C,D\}} u^s_{j,t}, \qquad s \in \{H, L\}. \tag{2}$$

New matches are generated by a constant-returns matching function combining unemployed workers $u^s_{j,t}$ and vacancies $v^s_{j,t}$:

$$M^s_{j,t} = \overline{m}^s_j \left(u^s_{j,t}\right)^{\mu^s_j} \left(v^s_{j,t}\right)^{1-\mu^s_j}, \qquad s \in \{H, L\},\ j \in \{C, D\}, \tag{3}$$

where $\overline{m}^s_j > 0$ measures matching efficiency and $\mu^s_j \in (0, 1)$ is the elasticity of matches with respect to unemployment. This specification follows the standard SAM approach and provides a parsimonious way to introduce labor-market frictions in a multisector environment. The constant-returns assumption implies that, within each segment, a proportional increase in unemployed searchers and vacancies generates a proportional increase in new matches. This rules out mechanical scale effects across labor-market segments and allows sectoral and skill heterogeneity to operate through matching efficiency, matching elasticities, job-finding probabilities, and vacancy-filling rates. This formulation is consistent with models of skill mismatch and heterogeneous search frictions, in which differences across labor-market groups are captured by segment-specific matching conditions rather than by aggregate matching externalities (Sun *et al.*, 2023; Abbritti and Consolo, 2024).

Aggregate employment, unemployment, and vacancies are obtained by scaling individual quantities by the corresponding population mass:

$$N^s_{j,t} \equiv \varphi^s n^s_{j,t}, \qquad U^s_{j,t} \equiv \varphi^s u^s_{j,t}, \qquad V^s_{j,t} \equiv \varphi^s v^s_{j,t}, \qquad s \in \{H, L\},\ j \in \{C, D\}. \tag{4}$$

Labor-market tightness is defined as the vacancy–unemployment ratio:

$$\theta^s_{j,t} \equiv \frac{v^s_{j,t}}{u^s_{j,t}} = \frac{V^s_{j,t}}{U^s_{j,t}}, \qquad s \in \{H, L\},\ j \in \{C, D\}. \tag{5}$$

The probability that a posted vacancy is filled is:

$$q^s_{j,t} \equiv \frac{M^s_{j,t}}{v^s_{j,t}} = \overline{m}^s_j \left(\theta^s_{j,t}\right)^{-\mu^s_j}, \qquad s \in \{H, L\},\ j \in \{C, D\}, \tag{6}$$

while the probability that an unemployed worker finds a job in sector j is:

$$f^s_{j,t} \equiv \frac{M^s_{j,t}}{u^s_{j,t}} = \overline{m}^s_j \left(\theta^s_{j,t}\right)^{1-\mu^s_j}, \qquad s \in \{H, L\},\ j \in \{C, D\}. \tag{7}$$

Timing and employment dynamics.

Timing within period t is standard. Firms in sector j enter the period with predetermined employment $n^s_{j,t-1}$, post vacancies $v^s_{j,t}$, and meet searching workers through the matching process. Matches $M^s_{j,t}$ are formed within the period, and a fraction ρ^s_j of existing jobs is destroyed at the end of the period. Employment therefore evolves according to:

$$N^s_{j,t} = \left(1 - \rho^s_j\right) N^s_{j,t-1} + M^s_{j,t}, \qquad s \in \{H, L\},\ j \in \{C, D\}, \tag{8}$$

where $M^s_{j,t} = v^s_{j,t} q^s_{j,t}$ and $q^s_{j,t}$ is given by (6).

2.2 Households

The model features three categories of households: entrepreneurs, low-skilled workers, and high-skilled workers. Each household type has a constant population mass φ^s, with $s \in \{H, L, E\}$.

2.2.1 Entrepreneurs. Entrepreneurs choose consumption c^E_t, sectoral investment $\{i^E_{j,t}\}_{j\in\{C,D\}}$, next-period capital stocks $\{k^E_{j,t}\}_{j\in\{C,D\}}$, and bond holdings b^E_t to maximize:

$$\max_{\{c^E_t, i^E_{j,t}, k^E_{j,t}, b^E_t\}} \mathbb{E}_0 \sum_{t=0}^{\infty} \left(\beta^E\right)^t \frac{\left(c^E_t\right)^{1-\sigma^E}}{1 - \sigma^E},$$

subject to the real flow budget constraint:

$$c_t^E + \sum_{j\in\{C,D\}} i_{j,t}^E + \frac{b_t^E}{P_t} = \sum_{j\in\{C,D\}} r_{j,t}^k k_{j,t}^E + r_{t-1}\frac{b_{t-1}^E}{P_t} + \sum_{j\in\{C,D\}} d_{j,t}, \tag{9}$$

and sector-specific capital accumulation with quadratic adjustment costs,

$$k_{j,t}^E = (1-\delta_j)k_{j,t-1}^E + \left[1 - \frac{\kappa_j^k}{2}\left(\frac{i_{j,t}^E}{i_{j,t-1}^E} - 1\right)^2\right] i_{j,t}^E, \qquad j\in\{C,D\}. \tag{10}$$

Here, $r_{j,t}^k$ denotes the rental rate of capital in sector j, r_t is the gross nominal risk-free rate, and P_t is the aggregate price level. Parameters β^E, σ^E, and h^E govern discounting, risk aversion, and external habits, respectively; δ_j is the depreciation rate and κ_j^k controls investment adjustment costs.

Let λ_t^E denote the multiplier on (9). Optimality with respect to consumption implies:

$$\left(c_t^E\right)^{-\sigma^E} = \lambda_t^E. \tag{11}$$

Optimal bond holdings satisfy the Euler equation:

$$\lambda_t^E = \beta^E \mathbb{E}_t\left(\lambda_{t+1}^E \frac{r_t}{\pi_{t+1}}\right), \tag{12}$$

where $\pi_{t+1} \equiv P_{t+1}/P_t$. Define $Q_{j,t}^E$ as the shadow value of installed capital in sector j (Tobin's q). The optimal investment condition is:

$$\begin{aligned} 1 \quad &= Q_{j,t}^E\left[1 - \frac{\kappa_j^k}{2}\left(\frac{i_{j,t}^E}{i_{j,t-1}^E} - 1\right)^2 - \kappa_j^k\left(\frac{i_{j,t}^E}{i_{j,t-1}^E} - 1\right)\frac{i_{j,t}^E}{i_{j,t-1}^E}\right] \\ &+\beta^E \mathbb{E}_t\left[\frac{\lambda_{t+1}^E}{\lambda_t^E} q_{j,t+1}^E \kappa_j^k \left(\frac{i_{j,t+1}^E}{i_{j,t}^E} - 1\right)\left(\frac{i_{j,t+1}^E}{i_{j,t}^E}\right)^2\right], \qquad j\in\{C,D\}, \end{aligned} \tag{13}$$

and Tobin's q satisfies:

$$Q_{j,t}^E = \beta^E \mathbb{E}_t\left[\frac{\lambda_{t+1}^E}{\lambda_t^E}\left(r_{j,t+1}^k + (1-\delta_j)q_{j,t+1}^E\right)\right], \qquad j\in\{C,D\}. \tag{14}$$

Equations (12)–(14) jointly characterize entrepreneurs' intertemporal allocation of savings and sectoral capital.

2.2.2 High- and low-skilled workers. Workers are indexed by skill $s \in \{H, L\}$. They choose consumption, savings in a one-period risk-free bond, and labor-force participation. Employment outcomes are not directly chosen, but evolve according to the matching process described in (3). In particular, search frictions generate sector-specific employment transition constraints.

A worker of type s maximizes:

$$\max_{\left\{c_t^s, b_t^s, u_t^s, n_{C,t+1}^s, n_{D,t+1}^s\right\}} \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{\left(c_t^s\right)^{1-\sigma^s}}{1-\sigma^s} + \phi^s \frac{\left(\ell_t^s\right)^{1-\psi^s}}{1-\psi^s} \right], \tag{15}$$

subject to the period budget constraint:

$$c_t^s + b_t^s = \sum_{j \in \{C,D\}} \left(1 - \tau_n^s\right) w_{j,t}^s n_{j,t}^s + \tau_u^s u_t^s + \frac{r_{t-1} b_{t-1}^s}{\pi_t}, \qquad s \in \{H, L\}, \tag{16}$$

and the sector-specific employment laws of motion:

$$n_{C,t}^s = \left(1 - \rho_C^s\right) n_{C,t-1}^s + f_{C,t}^s u_t^s, \qquad s \in \{H, L\}. \tag{17}$$

$$n_{D,t}^s = \left(1 - \rho_{D,t}^s\right) n_{D,t-1}^s + f_{D,t}^s u_t^s, \qquad s \in \{H, L\}. \tag{18}$$

Leisure is residual from the time-endowment constraint in (1). Parameters ϕ^s and ψ^s govern the weight and curvature of leisure, while h^s captures external habits. Workers receive after-tax labor income and unemployment benefits at rate τ_u^s.

Let λ_t^s denote the multiplier on (16) and $\chi_{j,t}^s$ the multiplier on (17) and (18). Optimality implies:

$$\left(c_t^s\right)^{-\sigma^s} = \lambda_t^s, \tag{19}$$

$$\lambda_t^s = \beta \, \mathbb{E}_t \left(\lambda_{t+1}^s \frac{r_t}{\pi_{t+1}} \right), \tag{20}$$

$$\sum_{j \in \{C,D\}} \chi_{j,t}^s f_{j,t}^s + \tau_u^s \lambda_t^s = \phi^s \left(\ell_t^s\right)^{-\psi^s}, \tag{21}$$

and

$$\chi_{C,t}^s = \lambda_t^s \left(1 - \tau_n^s\right) w_{C,t}^s - \phi^s \left(\ell_t^s\right)^{-\psi^s} + \beta \left(1 - \rho_C^s\right) \mathbb{E}_t \left[\chi_{C,t+1}^s \right]. \tag{22}$$

$$\chi_{D,t}^s = \lambda_t^s \left(1 - \tau_n^s\right) w_{D,t}^s - \phi^s \left(\ell_t^s\right)^{-\psi^s} + \beta \left(1 - \rho_{D,t+1}^s\right) \mathbb{E}_t \left[\chi_{D,t+1}^s \right]. \tag{23}$$

2.3 Production sector

The production side is organized in three layers: a representative final-good firm, a continuum of intermediate firms operating under monopolistic competition, and two sectors that produce clean and dirty inputs.

2.3.1 Final-good firm. A representative final-good firm produces the aggregate good by combining a continuum of intermediate varieties according to the CES aggregator:

$$y_t = \left(\int_0^1 y_t(i)^{\frac{\varepsilon-1}{\varepsilon}} \, di \right)^{\frac{\varepsilon}{\varepsilon-1}}, \tag{24}$$

where $y_t(i)$ denotes the quantity of variety $i \in [0, 1]$ supplied by intermediate firm i at price $P_t(i)$. Cost minimization implies the standard demand schedule

$$y_t(i) = \left(\frac{P_t(i)}{P_t}\right)^{-\varepsilon} y_t, \tag{25}$$

where $\varepsilon > 1$ is the elasticity of substitution across varieties and P_t is the corresponding aggregate price index.

2.3.2 Intermediate-good firms. A continuum of intermediate firms indexed by $i \in [0, 1]$ produces differentiated varieties $y_t(i)$ that are sold to the final-good firm. Variety-i output is a CES composite of clean and dirty inputs:

$$y_t(i) = y_{I,t}(i), \tag{26}$$

$$y_{I,t}(i) = \left[\omega_C^{\frac{1}{\xi}} y_{C,t}(i)^{\frac{\xi-1}{\xi}} + (1-\omega_C)^{\frac{1}{\xi}} y_{D,t}(i)^{\frac{\xi-1}{\xi}}\right]^{\frac{\xi}{\xi-1}}, \tag{27}$$

where $\xi > 1$ governs the elasticity of substitution between clean and dirty inputs and $\omega_C \in (0, 1)$ is the weight on clean inputs. Firms operate under monopolistic competition and set nominal prices $P_t(i)$ subject to the demand schedule of the final-good firm.

Price adjustment is subject to Rotemberg (1982) quadratic costs (in final-good units):

$$\Gamma_t^p(i) = \frac{\gamma^p}{2}(\pi_t(i) - \overline{\pi})^2 y_t(i), \qquad \pi_t(i) \equiv \frac{P_t(i)}{P_{t-1}(i)}, \tag{28}$$

where $\overline{\pi}$ is the inflation target and $\gamma^p > 0$ controls the degree of price rigidity.

Given $y_t(i)$, the firm chooses the cost-minimizing input mix. The associated demand functions for clean and dirty inputs are:

$$y_{C,t}(i) = \omega_C \left(\frac{p_{C,t}}{p_{I,t}}\right)^{-\xi} y_t(i), \qquad y_{D,t}(i) = (1-\omega_C)\left(\frac{p_{D,t}}{p_{I,t}}\right)^{-\xi} y_t(i), \tag{29}$$

where $p_{C,t}$ and $p_{D,t}$ are the CPI-deflated prices of the clean and dirty inputs, and $p_{I,t}$ denotes the unit cost (real marginal cost) of producing $y_t(i)$:

$$p_{I,t} = \left[\omega_C \left(p_{C,t}\right)^{1-\xi} + (1-\omega_C)\left(p_{D,t}\right)^{1-\xi}\right]^{\frac{1}{1-\xi}}. \tag{30}$$

The firm then sets $P_t(i)$ to maximize the present discounted value of profits, taking demand as given. Aggregating across firms yields the Rotemberg nonlinear New Keynesian Phillips Curve:

$$\pi_t\left(\pi_t - \overline{\pi}\right) = \beta\, \mathbb{E}_t\left[\frac{\lambda_{t+1}^E}{\lambda_t^E}\ \frac{y_{t+1}}{y_t}\ \pi_{t+1}\left(\pi_{t+1} - \overline{\pi}\right)\right] + \frac{\varepsilon}{\gamma^p}\left(p_{I,t} - \frac{\varepsilon-1}{\varepsilon}\right), \tag{31}$$

where λ_t^E denotes the marginal utility of consumption and $p_{I,t}$ is real marginal cost. For $\gamma^p > 0$, price adjustment is costly and inflation responds to movements in marginal costs.

2.3.3 Clean and carbon-intensive firms. The economy features two production sectors: a clean and a dirty sector. Sectoral heterogeneity reflects differences in emission intensity and energy use. Clean firms rely on low-emission technologies, whereas dirty firms operate technologies that are inherently emission-intensive [2].

Let $j \in \{C, D\}$ index the clean sector (C) and the dirty sector (D). Sector-j output is produced using capital and labor of two skill groups according to:

$$y_{j,t} = A_{j,t}\left(K_{j,t}\right)^{\alpha_j}\left(N_{j,t}^{H}\right)^{\alpha_j^H}\left(N_{j,t}^{L}\right)^{\alpha_j^L}, \qquad \alpha_j, \alpha_j^s \in (0,1), \tag{32}$$

where $K_{j,t} = \varphi^E k_{j,t}^E$ and $A_{j,t}$ denotes sector-specific TFP.

Only dirty production generates flow emissions according to:

$$e_t = (1 - \varpi_t)\,\phi_e\, y_{D,t}, \qquad \varpi_t \in [0,1], \tag{33}$$

and abatement costs are convex:

$$ac_t = \frac{\varphi_1}{1+\varphi_2}\,\varpi_t^{1+\varphi_2}\, y_{D,t}, \tag{34}$$

where $\phi_e > 0$ is emissions intensity and $\varphi_1, \varphi_2 > 0$ govern abatement technology.

Firms in each sector choose capital, employment, and vacancies to maximize real profits. In the clean sector, we allow for time-varying sector- and skill-specific vacancy posting costs, so that profits are:

$$\Gamma_{C,t} = p_{C,t}y_{C,t} - \sum_{s\in\{H,L\}} w_{C,t}^s n_{C,t}^s - \sum_{s\in\{H,L\}} \kappa_{C,t}^s\, v_{C,t}^s - r_{C,t}k_{C,t-1}, \tag{35}$$

where $\kappa_{C,t}^s$ denotes the per-vacancy posting cost faced by clean firms for skill group s.

In the dirty sector, profits additionally account for carbon-tax liabilities and abatement costs:

$$\Gamma_{D,t} = p_{D,t}^{net}y_{D,t} - \sum_{s\in\{H,L\}} w_{D,t}^s n_{D,t}^s - \sum_{s\in\{H,L\}} \kappa_D^s\, v_{D,t}^s - r_{D,t}k_{D,t-1}, \tag{36}$$

with the net output price defined as:

$$p_{D,t}^{net} \equiv p_{D,t} - \tau_t(1-\varpi_t)\phi_e - \frac{\varphi_1}{1+\varphi_2}\varpi_t^{1+\varphi_2}. \tag{37}$$

Let $J_{j,t}^s$ denote the multiplier on the employment transition constraint. The optimality condition for capital in each sector is:

$$r_{j,t} = p_{j,t}^{net}\,\alpha_j\left(\frac{y_{j,t}}{k_{j,t-1}}\right), \qquad j \in \{C,D\}, \tag{38}$$

where, by convention, $p_{C,t}^{net} \equiv p_{C,t}$.

Unlike the existing E-DSGE literature, we introduce two novel shocks affecting the separation rate in the dirty sector, $\rho_{D,t}^H$ and $\rho_{D,t}^L$. Accordingly, the first-order conditions for employment in the dirty sector are:

$$w_{D,t}^s = p_{D,t}^{net}\,\alpha_D^s \frac{y_{D,t}}{n_{D,t}^s} - J_{D,t}^s + \beta\left(1-\rho_{D,t+1}^s\right)\frac{\lambda_{t+1}^E}{\lambda_t^E}\,\xi_{D,t+1}^s, \qquad s \in \{H,L\}. \tag{39}$$

The corresponding optimality conditions in the clean sector are:

$$w^s_{C,t} = p_{C,t}\,\alpha^s_C \frac{y_{C,t}}{n^s_{C,t}} - J^s_{C,t} + \beta\left(1-\rho^s_C\right)\frac{\lambda^E_{t+1}}{\lambda^E_t}\,\xi^s_{C,t+1}, \qquad s\in\{H,L\}. \tag{40}$$

Vacancy posting satisfies, in the clean sector:

$$\kappa^s_{C,t} = q^s_{C,t}\,J^s_{C,t}, \qquad s\in\{H,L\}, \tag{41}$$

where $\kappa^s_{C,t}$ denotes the time-varying per-vacancy posting cost. In the dirty sector,

$$\kappa^s_D = q^s_{D,t}\,J^s_{D,t}, \qquad s\in\{H,L\}. \tag{42}$$

where $q^s_{j,t}$ is the vacancy-filling probability defined in (6).

Finally, abatement is chosen only in the dirty sector. For $j = D$,

$$\varpi_t = \left(\frac{\phi_e\,\tau_t}{\varphi_1}\right)^{\frac{1}{\varphi_2}}. \tag{43}$$

2.4 Wage setting

Wages are determined by Nash bargaining at the match level, separately for each sector j and skill group s, where $\eta^s_j \in (0,1)$ denotes the worker's bargaining power. For a given match, the bargained wage $w^s_{j,t}$ solves:

$$\max_{w^s_{j,t}} \left(\chi^s_{j,t}\right)^{\eta^s_j}\left(J^s_{j,t}\right)^{1-\eta^s_j}, \qquad s\in\{H,L\},\ j\in\{C,D\}. \tag{44}$$

Equivalently,

$$\max_{w^s_{j,t}} \eta^s_j \ln\left(\chi^s_{j,t}\right) + \left(1-\eta^s_j\right)\ln\left(J^s_{j,t}\right), \qquad s\in\{H,L\},\ j\in\{C,D\}. \tag{45}$$

Here, $\chi^s_{j,t}$ denotes the household's surplus from employment in sector j, while $J^s_{j,t}$ is the firm's surplus from a filled job. The Nash solution implies the following wage schedules for the clean and dirty sectors, respectively:

$$w^s_{C,t} = \eta^s_C\left[\underbrace{\alpha^s_C\frac{p_{C,t}y_{C,t}}{N^s_{C,t}}}_{\text{Marginal Productivity}} + \underbrace{(1-\rho^s_C)\frac{\kappa^s_{C,t}}{q^s_{C,t}}}_{\text{Hiring-Rent}}\right] + \frac{1-\eta^s_C}{(1-\tau^s_n)\lambda^s_t}\left[\underbrace{\phi^s\left(\ell^s_t\right)^{-\psi^s}}_{\text{Participation-Cost}} - \underbrace{(1-\rho^s_C)\chi^s_{C,t}}_{\text{Continuation Value}}\right], \tag{46}$$

$$w^s_{D,t} = \eta^s_D\left[\underbrace{\alpha^s_D\frac{p^{net}_{D,t}y_{D,t}}{N^s_{D,t}}}_{\text{Marginal Productivity}} + \underbrace{\left(1-\rho^s_{D,t}\right)\frac{\kappa^s_D}{q^s_{D,t}}}_{\text{Hiring-Rent}}\right] + \frac{1-\eta^s_D}{(1-\tau^s_n)\lambda^s_t}\left[\underbrace{\phi^s\left(\ell^s_t\right)^{-\psi^s}}_{\text{Participation-Cost}} - \underbrace{\left(1-\rho^s_{D,t}\right)\chi^s_{D,t}}_{\text{Continuation Value}}\right]. \tag{47}$$

Eqs. (46) and (47) show that wages are determined through Nash bargaining, as in Dolado *et al.* (2021), with the match surplus split between workers and firms according to their relative bargaining power. In particular, the parameter η^s_j, with $j \in \{C, D\}$ and $s \in \{H, L\}$, governs the sensitivity of wages to firm-side surplus components, while $1-\eta^s_j$ weights the worker-side outside-value components.

The Nash bargained wage reflects four components: the worker's marginal productivity, the firm's value of preserving the match, the worker's participation cost, and the continuation value of employment. In the dirty sector, the productivity component also captures environmental policy through its effect on firms' net profitability. Hiring rents matter because costly vacancy posting increases the value of existing matches, while participation and continuation terms capture the worker's outside option and future labor-market prospects.

2.5 Government

Government revenues are given by carbon-tax receipts. The government budget constraint reads as:

$$\tau_t e_t = g_t + \mathrm{Tr}_t, \tag{48}$$

where g_t denotes public spending and Tr_t denotes lump-sum transfers to households. We assume that public spending is an exogenous constant share of aggregate output.

Monetary policy sets the nominal interest rate according to a Taylor-type rule, as in Annicchiarico and Di Dio (2015):

$$\frac{r_t}{r_{ss}} = \left(\frac{\pi_t}{\pi_{ss}}\right)^{(1-\iota_r)\iota_\pi}, \tag{49}$$

where r_{ss} and π_{ss} denote the deterministic steady-state values of the nominal interest rate and inflation, respectively; $\iota_r \in [0, 1)$ captures interest-rate smoothing and $\iota_\pi > 0$ is the inflation feedback coefficient.

2.6 Market clearing and Aggregation

Combining households' and government budget constraints and imposing bond-market clearing yields the aggregate resource constraint:

$$y_t = c_t + i_t + g_t + \frac{\varphi_1}{1+\varphi_2} \varpi_t^{1+\varphi_2} y_{D,t} + \sum_{s\in\{H,L\}} \kappa^s_{C,t} v^s_{C,t} + \sum_{s\in\{H,L\}} \kappa^s_D v^s_{D,t}. \tag{50}$$

Aggregate consumption is the population-weighted sum across household types,

$$c_t = \sum_{s\in\{E,H,L\}} \varphi^s c^s_t, \tag{51}$$

and aggregate investment equals entrepreneurs' sectoral investment scaled by their population mass,

$$i_t = \varphi^E \left(i^E_{C,t} + i^E_{D,t}\right). \tag{52}$$

Bond-market clearing requires

$$\sum_{s\in\{E,H,L\}} b^s_t = 0. \tag{53}$$

2.7 Stochastic processes

The model economy is driven by four exogenous disturbances, each following an AR(1) process. Specifically, we consider two sector- and skill-specific vacancy-cost shocks in the clean sector and two sector- and skill-specific separation shocks in the dirty sector:

$$\ln \kappa^H_{C,t} = \left(1 - \phi^H_C\right) \ln \overline{\kappa}^H_C + \phi^H_C \ln \kappa^H_{C,t-1} + \varepsilon^H_{C,t}, \tag{54}$$

$$\ln \kappa^L_{C,t} = \left(1 - \phi^L_C\right) \ln \overline{\kappa}^L_C + \phi^L_C \ln \kappa^L_{C,t-1} + \varepsilon^L_{C,t}, \tag{55}$$

$$\ln \rho^H_{D,t} = \left(1 - \phi^H_D\right) \ln \overline{\rho}^H_D + \phi^H_D \ln \rho^H_{D,t-1} + \varepsilon^H_{D,t}, \tag{56}$$

$$\ln \rho^L_{D,t} = \left(1 - \phi^L_D\right) \ln \overline{\rho}^L_D + \phi^L_D \ln \rho^L_{D,t-1} + \varepsilon^L_{D,t}, \tag{57}$$

where $\overline{\kappa}^s_C$ and $\overline{\rho}^s_D$ denote deterministic steady-state values, $\phi^s_j \in [0,1)$ are persistence parameters, and innovations $\varepsilon^s_{j,t}$ are i.i.d. with $\varepsilon^s_{j,t} \sim \mathcal{N}(0, \sigma^2_{j,s})$. The two disturbances separately identify the creation and destruction margins of transition risk within the SAM framework. Clean-sector vacancy-cost shocks capture exogenous changes in green job-creation incentives. Dirty-sector separation shocks capture exogenous increases in skill-specific match destruction in carbon-intensive activities. This specification isolates the business-cycle implications of each shock and allows a direct comparison between clean job creation and dirty job destruction within the same SAM framework [3].

2.8 Inequality measures

We measure inequality using the clean-sector wage premium, the dirty-sector wage premium, the total wage premium, and the high-versus low-skilled consumption inequality:

$$\tilde{w}^{H,L}_{C,t} = \frac{w^H_{C,t}}{w^L_{C,t}}, \tag{58}$$

$$\tilde{w}^{H,L}_{D,t} = \frac{w^H_{D,t}}{w^L_{D,t}}, \tag{59}$$

$$\tilde{w}^{H,L}_{t} = \frac{w^H_{C,t} + w^H_{D,t}}{w^L_{C,t} + w^L_{D,t}}, \tag{60}$$

$$\tilde{c}^{H,L}_{t} = \frac{c^H_t}{c^L_t}. \tag{61}$$

3. Calibration

This section presents the quarterly calibration of the model for the euro area, as summarized in Table 1.

Preferences and production. We set the discount factor to $\beta = 0.99$, the inverse Frisch elasticity to 2, and relative risk aversion to 1.2, in line with the standard DSGE literature. Leisure preference parameters are calibrated to match participation rates and steady-state labor supply across skill groups. Following Ferrari and Nispi Landi (2023), the price adjustment cost is set to 71.20 and the elasticity of substitution between differentiated goods to 3.8571. Capital shares in the clean and dirty sectors are 0.33. The clean-sector size is set to 0.2, while the elasticity of substitution between clean and dirty production is 2. Sector-specific productivity levels reproduce the steady-state allocation between clean and dirty production. The investment adjustment costs are set to 10.78 and the depreciation rate is 0.025 in both sectors.

Labor market and skill heterogeneity. The weaker outside options faced by low-skilled workers during the green transition are captured by calibrating two aspects of labor-market

Table 1. Calibrated parameters

Parameter	Symbol	Value	Parameter	Symbol	Value
Panel A: Preferences and production					
Discount factor	β	0.99	Risk aversion	σ	1.20
Inverse Frisch elasticity	ψ	2.00	Leisure weight	ϕ^H, ϕ^L	0.04, 0.44
Price adjustment cost	γ^p	71.20	Elast. substitution, goods	ε	3.857
Clean–dirty substitution	ξ	2.00	Clean sector size	ω_C	0.20
Capital share	α_C, α_D	0.33	Capital depreciation	δ_C, δ_D	0.025
Investment adj. cost	κ_C^k, κ_D^k	10.78	TFP	A_C, A_D	1.30, 1.29
Skill intensity, clean H	α_C^H	0.37	Skill intensity, dirty H	α_D^H	0.31
Panel B: Labor market and skill heterogeneity					
High-skilled pop. share	φ^H	0.30	Low-skilled pop. share	φ^L	0.60
Entrepreneurs' share	φ^E	0.10	Bargaining power ratio	η_j^H/η_j^L	1.50
Unemployment rate, H	$\overline{u}^H$	0.05	Unemployment rate, L	$\overline{u}^L$	0.11
Participation rate, H	p^H	0.81	Participation rate, L	p^L	0.55
Bargaining power, H	η_j^H	0.60	Bargaining power, L	η_j^L	0.40
Separation rate, H	ρ_j^H	0.03	Separation rate, L	ρ_j^L	0.06
Matching elasticity, H	μ_j^H	0.60	Matching elasticity, L	μ_j^L	0.40
Job-finding rate, H	f_C^H, f_D^H	0.172, 0.588	Job-finding rate, L	f_C^L, f_D^L	0.085, 0.400
Vacancy posting cost, H	κ_C^H, κ_D^H	0.098, 0.093	Vacancy posting cost, L	κ_C^L, κ_D^L	0.503, 0.494
Matching efficiency, H	$\overline{m}_C^H, \overline{m}_D^H$	0.147, 0.306	Matching efficiency, L	$\overline{m}_C^L, \overline{m}_D^L$	0.163, 0.303
Vacancy rate, H	v_C^H, v_D^H	0.018, 0.061	Vacancy rate, L	v_C^L, v_D^L	0.012, 0.058
Panel C: Environmental, policy, and shock parameters					
Emission intensity	ϕ_e	0.38	Abatement parameter	ϕ_1	0.19
Abatement curvature	ϕ_2	2.80	Shock persistence	ϕ_j^s	0.90
Public spending/GDP	g/y	0.215	Investment/GDP	i/y	0.210
Taylor coefficient	ι_π	2.74	Interest-rate smoothing	ι_r	0.93

Source(s): Authors' own work

heterogeneity: sectoral skill mismatch and skill-specific labor-market conditions. The first refers to the mismatch between skill demand, driven by sector-specific production technologies, and skill supply, determined by population shares. The second is modeled through asymmetric labor-market parameters, whereby low-skilled workers have lower bargaining power, higher separation rates, and less favorable matching conditions. As a result, dirty-sector job destruction translates into weaker fallback opportunities and more limited reallocation prospects for low-skilled workers. Accordingly, the labor-market calibration matches key institutional and empirical features of the European labor market. Low-skilled unemployment is set to 11% and high-skilled unemployment to 5.07%, based on quarterly Eurostat data [4]. Participation rates are set to 81% for high-skilled workers and 55% for low-skilled workers [5]. Population shares are 0.60 for low-skilled workers, 0.30 for high-skilled workers, and 0.10 for entrepreneurs, following Abbritti and Consolo (2024). Separation rates are 0.03 for high-skilled workers and 0.06 for low-skilled workers, consistent with Dolado *et al.* (2021). Following the SAM literature, the matching elasticity with respect to unemployment is 0.6 for high-skilled workers and 0.4 for low-skilled workers (Petrongolo and Pissarides, 2001; Oikonomou, 2023). Bargaining powers are set equal to matching elasticities, according to the Hosios condition (Hosios, 1990). Employment is allocated across sectors according to sector size and relative skill intensity [6].

The implied production elasticities with respect to high-skilled labor are $\alpha_C^H = 0.37$ in the clean sector and $\alpha_D^H = 0.31$ in the dirty sector, consistent with evidence that green occupations are more skill-intensive (Consoli *et al.*, 2016; OECD, 2024). Vacancy rates are set to 8% for high-skilled workers and 7% for low-skilled workers, on average, following Cedefop (2023). This implies steady-state vacancies of 0.061 and 0.018 for high-skilled workers, and 0.058 and 0.012 for low-skilled workers, in the dirty and clean sectors, respectively (see Table 1). To match these European labor-market targets, job-finding probabilities are calibrated heterogeneously across skills and sectors. The calibration implies higher job-finding rates for high-skilled workers in both sectors $(f_j^H > f_j^L)$ and, therefore, higher labor-market tightness $(\theta_j^H > \theta_j^L)$, consistent with stronger demand pressures for skilled labor in Europe (Abbritti and Consolo, 2024). Vacancy posting costs are then obtained endogenously from steady-state targets. They are higher for low-skilled than for high-skilled workers in both sectors $(\kappa_j^L > \kappa_j^H)$, in line with Oikonomou (2023). Matching efficiency parameters are calibrated residually to reproduce sector- and skill-specific job-finding rates.

Environmental, policy, and shock parameters. Public spending is expressed as 21.15% of GDP and investment as 21% of GDP. Following Ferrari and Nispi Landi (2023), the Taylor-rule coefficients are $\iota_\pi = 2.74$ and $\iota_r = 0.93$, while the environmental parameters are set to $\phi_e = 0.38$, $\phi_1 = 0.19$, and $\phi_2 = 2.80$. All transition-related labor-market shocks follow persistent AR(1) processes with persistence equal to 0.90, in line with Kuo and Miyamoto (2015).

4. Results

4.1 Impulse response functions

Figure 1 reports labor-market responses to creation and destruction shocks: high-skilled dirty job destruction (solid blue line), low-skilled dirty job destruction (dash-dotted blue line), high-skilled clean job creation (dashed red line), and low-skilled clean job creation (dotted red line). Clean job-creation shocks (columns 1 and 3) mainly operate through the vacancy-posting margin (Kuo and Miyamoto, 2015). Lower clean-sector vacancy costs raise vacancies, labor-market tightness, and job-finding probabilities, increasing clean employment. The effect is stronger and more front-loaded for low-skilled workers, while high-skilled clean job creation generates a smoother employment response. Both shocks generate limited displacement from the dirty sector, suggesting that clean job creation mainly works through net employment gains rather than large crowding-out effects. Wage dynamics reinforce this interpretation: in the targeted clean segment, employment expansion is accompanied by wage compression, especially after low-skilled clean job creation.

A second result concerns dirty job-destruction shocks (columns 2 and 4), which are quantitatively stronger than clean job-creation shocks. Consistent with the SAM literature (e.g. Zanetti, 2019), higher dirty-sector separation rates generate an immediate and persistent contraction in employment in the affected segment. Firms increase vacancy posting, but not enough to offset the stronger destruction margin, so unemployment rises (see Figure 2). This raises the marginal product of labor and puts upward pressure on wages. The effects are strongly skill-specific. Employment losses are larger for low-skilled workers, showing that destruction is more disruptive at the lower end of the skill distribution. Wage responses also differ. After high-skilled dirty job destruction, dirty-sector wages rise persistently, supported by higher vacancies and job-finding rates. After low-skilled dirty job destruction, wages rise only on impact and then fall sharply, as vacancy posting and job-finding probabilities adjust weakly. Thus, dirty job destruction generates asymmetric adjustment paths, with low-skilled workers bearing a disproportionate share of transition costs.

A third insight from Figure 1 is that transition-related shocks propagate beyond the directly affected segment. Spillovers operate along three dimensions: *(1) skill-based*, *(2) sector-based*, and *(3) skill–sector-based* spillovers. Skill-based spillovers capture transmission across worker groups within the same sector. High-skilled clean job creation produces limited spillovers to low-skilled workers in the clean sector (column 3, red dashed line), reflecting the

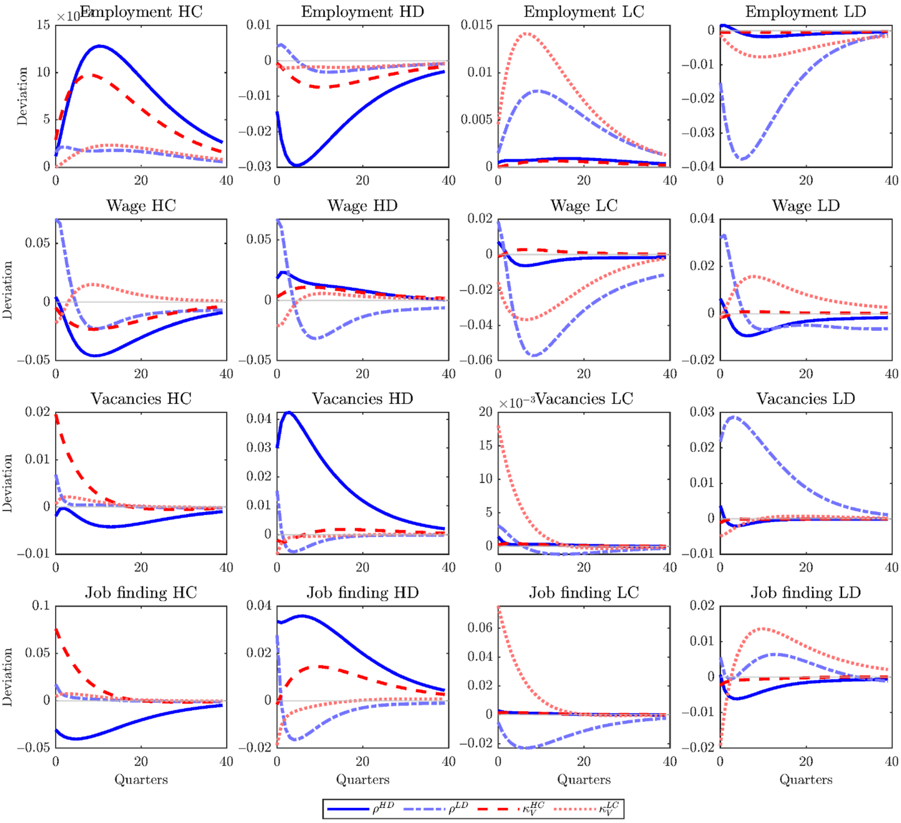


Figure 1. Impulse response functions to one-percent transition-related labor-market shocks. *Labor Market Variables*. **Source:** Authors' own work

high-skill intensity of clean production. Low-skilled clean job creation (red dotted line, column 3 to 1) generates stronger, though still moderate, spillovers, raising high-skilled clean employment slightly and reducing high-skilled wages in the short run. Dirty job-destruction shocks are more asymmetric. High-skilled dirty destruction (blue solid line, columns 2 to 4) has limited effects on low-skilled workers in the same sector, except for wages, which rise on impact and then decline. By contrast, low-skilled dirty destruction (blue solid-dashed lines, columns 2 and 4) raises high-skilled wages and stimulates high-skilled vacancy creation in the dirty sector. Hence, the transmission of dirty job destruction depends crucially on which skill group is affected.

Sectoral spillovers capture the effects of a shock originating in one sector for a given skill group on the same skill group employed in the other sector. Clean job-creation shocks targeting high-skilled workers generate limited spillovers to high-skilled workers in the dirty sector (red dashed line, columns 1 and 2). High-skilled dirty employment declines only marginally and with delay, while dirty-sector wages increase modestly, reflecting firms' incentives to retain skilled workers in carbon-intensive activities. A similar mechanism operates after low-skilled clean job creation (red dotted line, columns 3 and 4), although the adjustment is stronger: dirty-sector job-finding rates fall more sharply, and low-skilled dirty wages increase only gradually. Thus, spillovers are stronger when shocks originate in the low-skilled segment. Spillovers from dirty job destruction to the clean sector are quantitatively stronger. High-skilled dirty

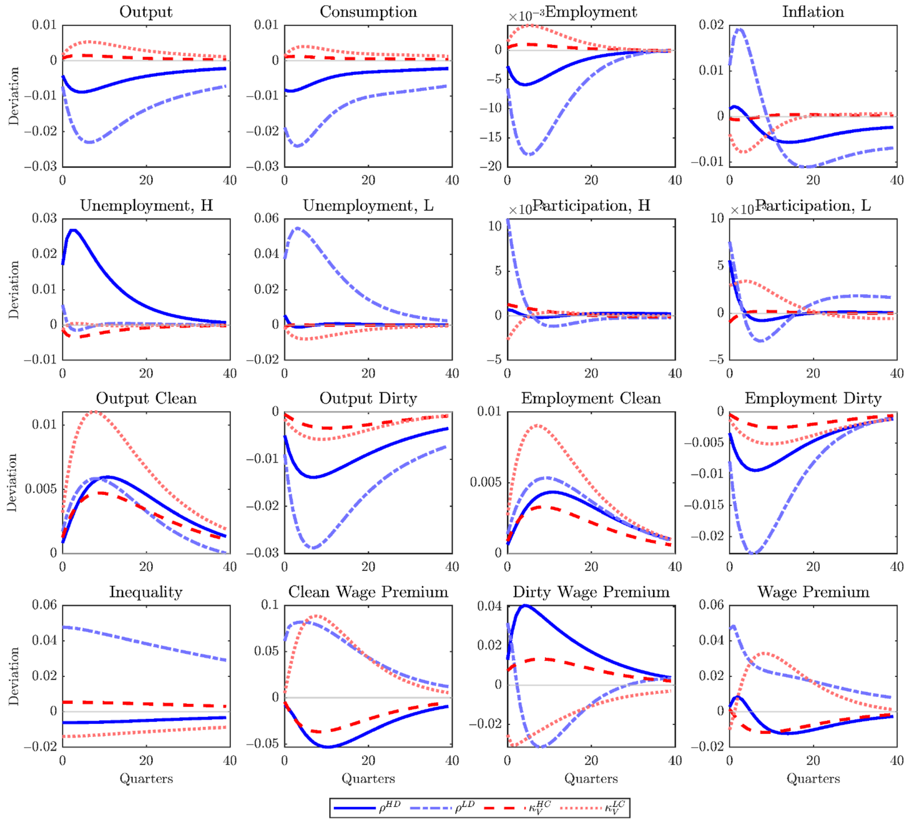


Figure 2. Impulse Response Functions to one-percent transition-related labor-market shocks. *Aggregate Variables*. **Source:** Authors' own work

destruction (blue solid line, columns 2 to 1) generates a sizeable increase in clean employment, reflecting the reallocation of displaced workers toward green activities. Over time, however, congestion in the clean labor market lowers wages and job-finding rates. A similar but weaker employment response follows low-skilled dirty destruction (blue solid-dashed line, columns 4 to 3), together with stronger wage compression.

Skill-sector-based spillovers capture how shocks affecting a specific skill group in one sector transmit to workers with different skills in the other sector. Job-creation shocks generate moderate sector–skill spillovers, especially when clean jobs are created for high-skilled workers (columns 1 and 4, dashed red line). By contrast, low-skilled clean job creation (columns 3 and 2, dotted red line) lowers the probability that high-skilled workers find a job in the dirty sector, weakening bargaining power and reducing wages. High-skilled dirty destruction (columns 2 and 3, blue solid line) slightly raises low-skilled clean employment and modestly reduces wages. Low-skilled dirty destruction (columns 4 and 1, dashed-dotted blue line) generates stronger spillovers for high-skilled clean workers by increasing vacancies, wages, and employment. These patterns indicate that low-skilled dirty job destruction triggers stronger sector–skill spillovers.

To interpret wage dynamics, we decompose clean-sector wages using Eqs. 46 and 47 into productivity, hiring-rent, participation-cost, and continuation-value components (see Appendix for details). Clean job-creation shocks reduce the wage of the targeted skill group mainly through lower hiring rents: lower vacancy costs stimulate job creation but reduce the rent from a filled match. Non-targeted workers may instead experience wage gains, as clean-sector expansion raises the value of complementary labor without directly reducing their vacancy-posting cost. For dirty job-destruction shocks, wage responses depend on the displaced skill group. High-skilled dirty destruction lowers high-skilled clean wages by reducing their relative scarcity, while low-skilled clean wages rise on impact and then fall as continuation-value and participation-cost effects dominate. Low-skilled dirty destruction depresses low-skilled clean wages through productivity, hiring-rent, and participation-cost channels, reflecting limited clean-sector absorption. High-skilled clean wages rise on impact, but the effect fades as productivity and participation-cost channels turn negative.

Figure 2 shows the aggregate macroeconomic responses. Job-creation shocks raise clean output and employment, with low-skilled vacancy creation generating stronger effects than high-skilled job creation. This reflects the fact that the clean sector is relatively saturated with high-skilled workers, who also have stronger bargaining power and face greater competition. By contrast, dirty job-destruction shocks have larger aggregate effects. Dirty output and employment fall sharply, especially after low-skilled job destruction. These shocks also generate positive spillovers to the clean sector by increasing clean employment and output; in particular, low-skilled dirty job destruction raises clean production more than high-skilled clean job creation. Overall, clean job-creation shocks produce modest increases in output, consumption, and aggregate employment, whereas dirty job-destruction shocks, especially those affecting low-skilled workers, lead to large and persistent declines in output, consumption, and employment, together with strong increases in unemployment.

The low-skilled dirty job-destruction shock emerges as the most disruptive transition-risk shock because it combines a large destruction effect in the polluting sector with weak absorption capacity in the clean sector. The shock directly reduces dirty employment and increases unemployment among low-skilled workers. However, displaced workers do not move smoothly into green employment because matching efficiency for low-skilled workers in the clean sector is relatively low. This creates a reallocation bottleneck: low-skilled workers exit dirty jobs faster than they can be matched with clean-sector vacancies. This reflects the interaction between sectoral reallocation and skill mismatch. Even when the clean sector expands, displaced low-skilled workers face weaker transition prospects because their skills are less transferable to green jobs and the matching process is less efficient for this group. This mechanism is consistent with evidence showing that dirty-to-green job transitions are limited, especially for less-educated workers, and that workers displaced from high-emission sectors face sizeable adjustment costs (Vona *et al.*, 2018; Curtis *et al.*, 2024; OECD, 2024). The same mechanism also makes the low-skilled dirty job-destruction shock the main driver of green inflation pressures in the model. By reducing dirty-sector production while delaying reallocation toward clean employment, the shock creates a supply-side bottleneck that amplifies upward pressure on prices.

Finally, these shocks generate sizable distributional effects. Low-skilled dirty job destruction widens the consumption gap the most, while high-skilled job destruction and low-skilled job creation slightly reduce consumption-based inequality. Wage-premium dynamics differ across sectors: in the clean sector, the premium rises after shocks affecting low-skilled workers and falls after shocks affecting high-skilled workers; in the dirty sector, it increases on impact in all cases except after low-skilled clean job creation, when dirty firms raise low-skilled wages to retain workers. At the aggregate level, the wage premium rises sharply after low-skilled dirty job destruction, with smaller and more delayed effects in the other cases.

4.2 Shocks contribution

Tables 2 and 3 report the contribution of each shock to the variance of macroeconomic and labor-market variables. Job-destruction shocks dominate job-creation shocks in explaining business-cycle fluctuations, especially skill-specific unemployment, consistently with the literature (e.g. Zanetti, 2019). Skill-specific destruction shocks mainly affect the corresponding worker group. Low-skilled dirty job destruction is the dominant source of fluctuations, driving output, consumption, sectoral activity, inflation, and both wage and consumption inequality (accounting for more than 88% of output variance). High-skilled dirty job destruction plays a smaller aggregate role but is central for high-skilled employment dynamics, especially in the dirty and clean sectors. Clean-sector job-creation shocks have a limited impact on aggregate fluctuations and generate weak spillovers to the dirty sector; only low-skilled clean job creation contributes meaningfully to low-skilled clean employment fluctuations.

Table 4 shows that volatility differs markedly across shocks. Clean-sector job creation generates limited aggregate fluctuations, whereas dirty-sector job destruction produces larger effects, especially when it affects low-skilled workers. Clean output displays similar volatility across shocks, suggesting that its fluctuations are not strongly driven by the specific labor-market disturbance. By contrast, total employment volatility under low-skilled dirty destruction is nearly twice that under high-skilled dirty destruction, reflecting the larger role of low-skilled workers in dirty employment and their weaker outside options in the clean sector. Distributional volatility is lowest under clean job creation, moderate under high-skilled dirty destruction, and highest under low-skilled dirty destruction.

We then examine comovement with aggregate output. The transition-risk literature suggests that brown-sector variables are procyclical, while green-sector variables are often countercyclical (Ferrari and Nispi Landi, 2023; Le *et al.*, 2024). Table 5 shows that this pattern depends on the shock. Clean output is procyclical after clean-sector shocks but becomes countercyclical under dirty-sector destruction shocks, as displaced workers are partly reabsorbed by the clean sector during downturns. Total employment remains procyclical,

Table 2. Variance decomposition – macroeconomic variables (40 quarters in %)

Variables	$\varepsilon_{\kappa_{lc}}$	$\varepsilon_{\kappa_{hc}}$	$\varepsilon_{\rho_{hd}}$	$\varepsilon_{\rho_{ld}}$
Output and prices				
Output (y)	3.86	0.29	10.52	85.32
Clean Output (y_c)	55.29	11.67	18.33	14.72
Dirty Output (y_d)	3.05	1.22	18.95	76.77
Clean Price (p_c)	24.00	3.84	12.55	59.62
Dirty Price (p_d)	7.40	0.48	4.64	87.49
Inflation (π)	6.60	0.10	10.46	82.84
Consumption				
Aggregate (c)	2.62	0.23	9.38	87.77
Entrepreneurs (c_e)	0.86	0.16	7.76	91.21
High-Skilled (c_h)	2.05	2.89	27.59	67.47
Low-Skilled (c_l)	5.90	0.04	3.62	90.45
Investment and capital				
Aggregate Investment (I)	3.31	0.18	7.61	88.90
Clean Investment (i_{ec})	34.07	6.07	1.18	58.68
Dirty Investment (i_{ed})	0.91	0.01	10.19	88.88
Clean Capital (k_c)	23.68	4.12	1.28	70.92
Dirty Capital (k_d)	0.96	0.02	9.40	89.62

Note(s): Variance decomposition computed applying HP filter ($\lambda = 1600$)

Source(s): Authors' own work

Table 3. Variance decomposition – labor market variables (40 quarters in %)

Variables	$\varepsilon_{\kappa_{lc}}$	$\varepsilon_{\kappa_{hc}}$	$\varepsilon_{\rho_{hd}}$	$\varepsilon_{\rho_{ld}}$
Employment and unemployment				
Total Employment (n)	4.96	0.28	8.95	85.81
Empl. High-Dirty (N_{hd})	0.75	7.46	90.16	1.63
Empl. High-Clean (N_{hc})	2.38	34.18	61.53	1.91
Empl. Low-Dirty (N_{ld})	6.00	0.04	0.28	93.68
Empl. Low-Clean (N_{lc})	71.80	0.23	0.53	27.44
Unempl. Rate H (u_h)	0.05	1.54	97.63	0.78
Unempl. Rate L (u_l)	1.86	0.00	0.17	97.97
Participation Rate H	5.41	3.58	1.29	89.73
Participation Rate L	29.83	0.37	11.51	58.29
Market tightness				
Tightness HD (θ_{hd})	2.13	11.99	75.92	9.97
Tightness HC (θ_{hc})	1.00	42.93	55.03	1.05
Tightness LD (θ_{ld})	76.29	0.34	8.49	14.88
Tightness LC (θ_{lc})	70.34	0.09	0.12	29.46
Wages				
Wage HD (w_{hd})	5.46	6.64	16.54	71.37
Wage HC (w_{hc})	4.47	14.13	52.49	28.91
Wage LD (w_{ld})	35.63	0.14	10.28	53.95
Wage LC (w_{lc})	29.83	0.13	0.73	69.30
Inequality and wage premium				
Inequality (c_h/c_l)	8.44	1.06	1.47	89.03
Wage Premium H/L	36.57	5.70	6.72	51.01

Note(s): Variance decomposition computed applying HP filter ($\lambda = 1600$)

Source(s): Authors' own work

Table 4. Standard deviations by shock

Variables	$\varepsilon_{\kappa_{lc}}$	$\varepsilon_{\kappa_{hc}}$	$\varepsilon_{\rho_{hd}}$	$\varepsilon_{\rho_{ld}}$
Macroeconomic				
Output (y)	0.625	0.657	1.287	2.933
Consumption (c)	0.509	0.532	1.327	3.575
Inflation (π)	1.179	1.165	1.400	3.838
Clean Output (y_c)	1.215	1.331	1.408	1.555
Dirty Output (y_d)	0.601	0.702	1.663	3.662
Labor market				
Total Employment (n)	0.561	0.580	0.992	2.556
Empl. HD (N_{hd})	0.072	0.229	1.121	1.176
Empl. HC (N_{hc})	0.060	0.323	0.480	0.496
Empl. LD (N_{ld})	0.456	0.464	0.504	2.886
Empl. LC (N_{lc})	0.994	0.998	0.997	1.129
Inequality and wage premium				
Inequality (c_h/c_l)	1.870	1.965	2.135	6.598
Wage Premium H/L	4.435	4.558	5.085	8.001

Note(s): The standard deviations of variables for each shock are generated by the model for 200 realizations of shock sequences of size 10,000, dropping the first 100 observations. We apply HP filter $\lambda = 1.600$ to the simulated series

Source(s): Authors' own work

Table 5. Correlations with output by shock (%)

Variables	$\varepsilon_{\kappa_{lc}}$	$\varepsilon_{\kappa_{hc}}$	$\varepsilon_{\rho_{hd}}$	$\varepsilon_{\rho_{ld}}$
Macroeconomic				
Consumption (c)	97.1	96.5	88.9	85.0
Inflation (π)	−85.5	−83.1	−51.6	−61.8
Clean Output (y_c)	99.1	97.7	24.1	−26.2
Dirty Output (y_d)	−96.2	−91.7	57.0	91.2
Labor market				
Total Employment (n)	99.1	99.0	99.0	98.7
Empl. HD (N_{hd})	−78.6	−47.0	79.6	35.8
Empl. HC (N_{hc})	61.7	42.3	−30.3	−26.8
Empl. LD (N_{ld})	−91.1	−88.6	−46.6	83.6
Empl. LC (N_{lc})	99.8	95.9	47.1	−15.8
Inequality and wage premium				
Inequality (c_h/c_l)	−78.5	−60.9	−0.4	−66.4
Wage Premium H/L	72.1	60.1	13.5	−32.2

Note(s): Correlations with aggregate output y are computed under each structural shock and are generated by the model for 200 realizations of shock sequences of size 10,000, dropping the first 100 observations. We apply HP filter $\lambda = 1.600$ to the simulated series

Source(s): Authors' own work

whereas skill-sectoral employment responses are more heterogeneous. Clean job-creation shocks strengthen the clean employment-output correlation and weaken the dirty one, while dirty-sector shocks generate countercyclical responses in selected skill-sectoral employment categories.

For distributional variables, the model reproduces the countercyclical behavior of income-based inequality documented by Bilbiie *et al.* (2023), except after high-skilled dirty job-destruction shocks. The wage premium is generally procyclical, consistent with Boeing-Reicher and Caponi (2024) and Gu (2023), except after low-skilled job-destruction shocks. Hence, the brown–green cyclical dichotomy is shock-dependent, making it essential to disentangle labor-market disturbances when assessing transition-risk exposure over the business cycle.

4.3 A skill-based beveridge curve

To assess clean-sector reallocation, we examine whether transition shocks generate a skill-specific Beveridge curve, using the clean-vacancy share as a measure of green hiring intensity. Figure 3 shows that the relationship is shock-dependent. A clear Beveridge-type pattern emerges after dirty job-destruction shocks, while it breaks down under clean job-creation shocks. After a low-skilled dirty job-destruction shock, clean vacancies initially fall and low-skilled unemployment rises, tracing a movement along the curve. During the recovery, vacancies rebound faster than unemployment declines, producing an apparent outward shift. A similar, although milder and faster-reverting, pattern emerges for high-skilled workers after a high-skilled separation-rate shock. Overall, dirty job-destruction shocks generate stronger unemployment responses for low-skilled workers and larger clean-vacancy fluctuations for high-skilled workers. This confirms that transition costs are unevenly distributed and that policy design should account for both skill and sectoral heterogeneity.

4.4 Welfare analysis

This section evaluates the welfare effects of labor-market shocks for high- and low-skilled workers. Following Annicchiarico and Diluiso (2019), welfare $\mathcal{W}$ is measured as the unconditional expectation of lifetime utility:

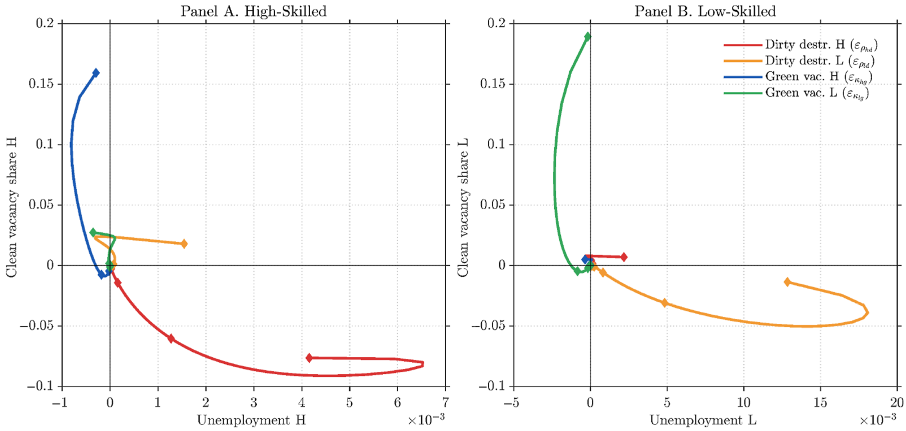


Figure 3. Clean Vacancy Share and Unemployment. *Note:* The figure reports model-implied clean-sector vacancy-share curves after a one-standard-deviation structural shock. The horizontal axis shows deviations of unemployment from steady state; the vertical axis shows deviations of the clean vacancy share, $s_c^H = v_{hc}/(v_{hd} + v_{hc})$ and $s_c^L = v_{lc}/(v_{ld} + v_{lc})$, from steady state. **Source:** Authors' own work

$$\mathcal{W}^i = \mathbb{E}\sum_{t=0}^{\infty}\beta^i\left[\frac{\left(c_t^i\right)^{1-\sigma^i}}{1-\sigma^i} + \phi^i\frac{\left(\ell_t^i\right)^{1-\psi^i}}{1-\psi^i}\right] \tag{62}$$

where $i = H, L$ denotes high- and low-skilled workers. Table 6 reports mean welfare, deviations from the deterministic steady state, and welfare volatility for each shock. The steady-state values, equal to -551.3279 for high-skilled workers and -713.3987 for low-skilled workers, reveal a persistent welfare gap.

Clean vacancy shocks leave mean welfare broadly unchanged and generate limited volatility, especially for high-skilled workers. Dirty separation-rate shocks instead produce stronger welfare effects. A high-skilled job-destruction shock raises welfare for high-skilled workers but reduces it for low-skilled workers, whereas a low-skilled job-destruction shock increases welfare for both groups and generates the largest welfare volatility. These results suggest that green job-creation policies support reallocation at low welfare cost, while dirty

Table 6. Welfare analysis

Shock	High-skilled ($\mathcal{W}_H$) Mean	Std. Dev.	Low-skilled ($\mathcal{W}_L$) Mean	Std. Dev.
Clean sector — job creation				
Low-Skilled Vacancy ($\varepsilon_{\kappa_{lc}}$)	$-551.3290(-0.0011)$	0.0915	-713.4009 (-0.0022)	0.5301
High-Skilled Vacancy ($\varepsilon_{\kappa_{hc}}$)	-551.2287 ($+0.0992$)	0.1801	-713.2973 ($+0.1014$)	0.5255
Dirty sector — job destruction				
Low-Skilled Destruction ($\varepsilon_{\rho_{ld}}$)	-551.2586 ($+0.0693$)	0.7254	-712.8891 ($+0.5096$)	2.2682
High-Skilled Destruction ($\varepsilon_{\rho_{hd}}$)	-551.1890 ($+0.1389$)	0.5002	-713.9203 (-0.5216)	0.6249

Note(s): Mean and standard deviation are computed under each shock in isolation over 200 simulations of length 10,000 periods, discarding the first 100 observations of each replication. Values in parentheses denote deviations of mean welfare from the deterministic steady-state level

Source(s): Authors' own work

job-destruction shocks may widen welfare gaps when displaced high-skilled workers have stronger clean-sector reallocation prospects and lower adjustment costs.

5. The role of labor market heterogeneity

This section performs a sensitivity analysis to isolate the contribution of skill heterogeneity by comparing the baseline model against a symmetric specification. In detail, we eliminate the following sources of heterogeneity: (1) the composition of skill supply ($\varphi^H/\varphi^L = 1$), (2) sectoral skill intensity in labor demand ($\xi_C^H/\xi_C^L = 1$), and (3) workers' bargaining power ($\eta_C^H/\eta_C^L = 1$). Table 7 reports the resulting parameterization.

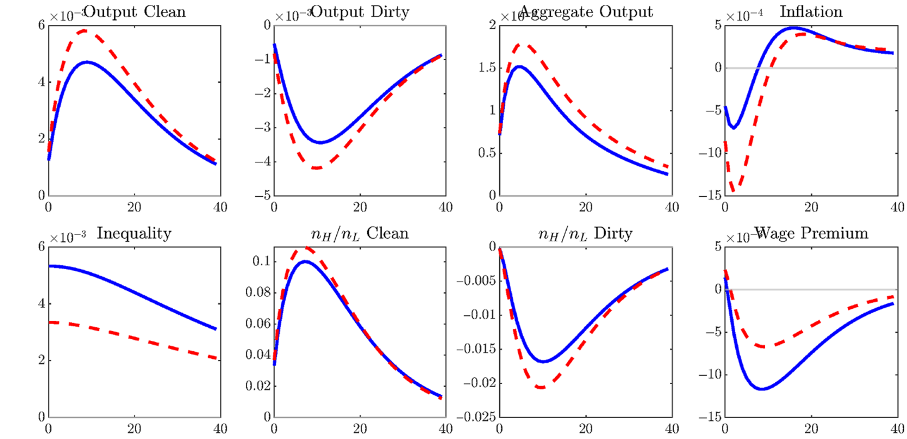
Figures 4 and 5 show the impulse response functions to the four labor-market shocks under the heterogeneous and symmetric calibrations. In each figure, panel (a) refers to high-skilled workers and panel (b) to low-skilled workers. The results confirm that the main findings from the previous section remain robust, although labor-market symmetry changes the magnitude and propagation of the shocks.

Clean job-creation shocks remain less disruptive than dirty job-destruction shocks, though symmetry alters the magnitude of responses. For high-skilled clean job creation, the symmetric model yields larger output gains by removing high-skilled labor scarcity and asymmetric matching frictions, which in the heterogeneous model constrain clean employment and make skill mismatch more persistent. Low-skilled clean job creation, instead, produces stronger clean-output gains in the heterogeneous economy, since higher initial vacancy-posting costs imply a larger response when they fall; it also reduces inequality, though it may worsen sectoral skill allocation by raising low-skilled absorption into the clean sector.

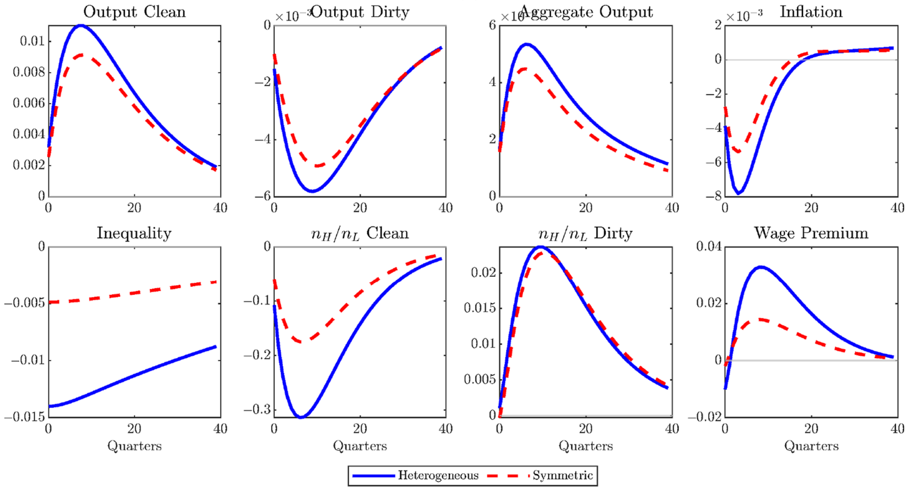
Table 7. Steady-state values: heterogeneous vs. Symmetric model

Description	Symbol	Heterogeneous	Symmetric
Features of the models			
Relative supply of skills	φ^H/φ^L	0.5	1
Sectoral rel. supply of skills (Clean)	φ_C^H/φ_C^L	1.29	1
Sectoral rel. supply of skills (Dirty)	φ_D^H/φ_D^L	0.94	1
Sectoral skills intensity (Clean)	$\mu_c/(1-\mu_c)$	1.22	1
Sectoral skills intensity (Dirty)	$\mu_d/(1-\mu_d)$	0.88	1
Bargaining power (ratio)	η_H/η_L	1.50	1
Steady-state values			
Employment ratio (Clean)	n_C^H/n_C^L	1.02	1.57
Employment ratio (Dirty)	n_D^H/n_D^L	0.74	1.57
Vacancy posting costs, H (Clean, Dirty)	κ_C^H, κ_D^H	0.098, 0.093	0.148, 0.142
Vacancy posting costs, L (Clean, Dirty)	κ_C^L, κ_D^L	0.503, 0.494	0.345, 0.337
Efficiency of matching, H (Clean, Dirty)	$\overline{\Omega}_C^H, \overline{\Omega}_D^H$	0.147, 0.306	0.162, 0.324
Efficiency of matching, L (Clean, Dirty)	$\overline{\Omega}_C^L, \overline{\Omega}_D^L$	0.163, 0.303	0.135, 0.270
Vacancies, H (Clean, Dirty)	v_C^H, v_D^H	0.018, 0.061	0.016, 0.064
Vacancies, L (Clean, Dirty)	v_C^L, v_D^L	0.012, 0.058	0.014, 0.056
Job finding rate, H (Clean, Dirty)	f_C^H, f_D^H	0.172, 0.588	0.152, 0.608
Job finding rate, L (Clean, Dirty)	f_C^L, f_D^L	0.085, 0.400	0.097, 0.388
Wage premium		1.37	0.67
Inequality		2.16	1.06

Source(s): Authors' own work



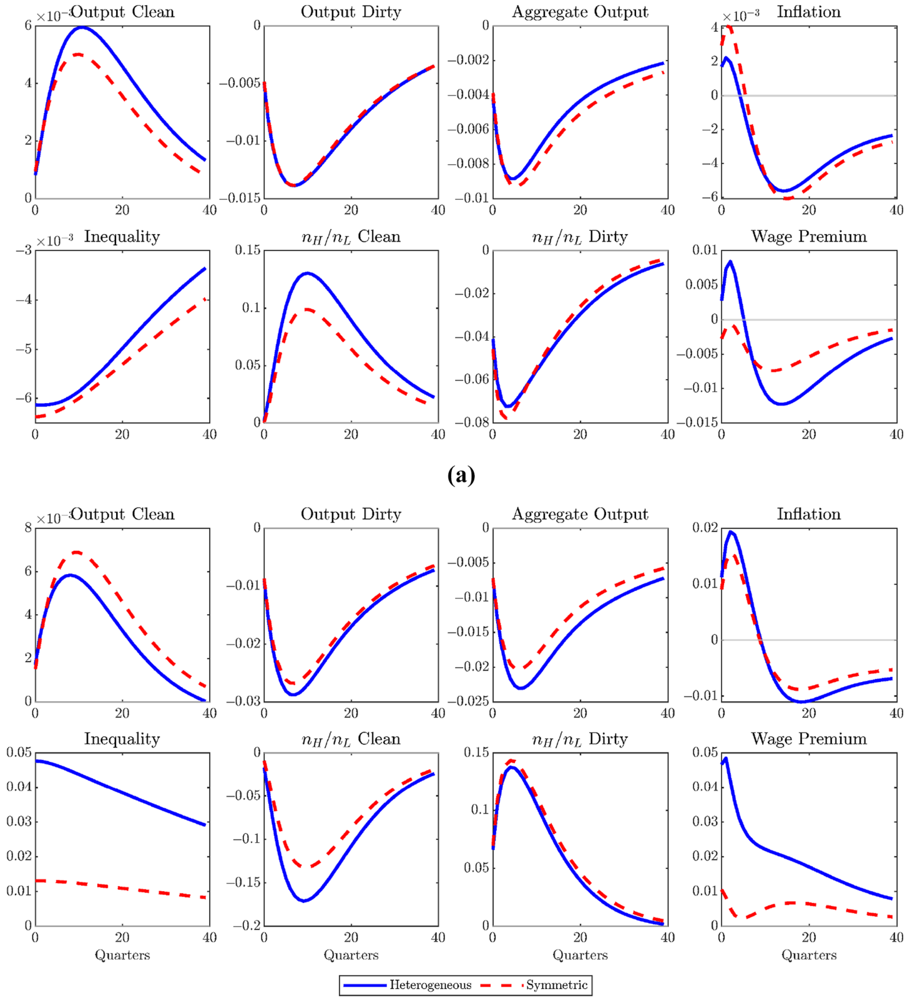
(a)



(b)

Figure 4. Impulse response functions to clean job-creation shocks. **Source:** Authors' own work

Dirty job-destruction shocks remain larger and more persistent, confirming the dominant role of the destruction margin. Under high-skilled dirty job destruction, clean output rises more in the heterogeneous economy as displaced skilled workers partially shift to clean activities; yet reallocation is incomplete, aggregate output falls, and the wage premium and inequality increase more persistently. Low-skilled dirty job destruction is the most disruptive shock: weaker outside options and lower bargaining power limit clean-sector absorption, so output, employment, and consumption decline more strongly than in the symmetric model. When matching conditions are more symmetric across skill groups, displaced low-skilled workers are absorbed more rapidly into clean employment, reducing unemployment and attenuating the disruptive effects of dirty job destruction. This highlights the policy relevance of upskilling and reskilling measures, which can ease labor reallocation, reduce distributional costs, and mitigate the macroeconomic effects of transition-risk shocks.



(b)

Figure 5. Impulse response functions to dirty job-destruction shocks. **Source:** Authors' own work

Overall, the robustness exercise confirms the results hold, while showing that ignoring heterogeneity compresses distributional responses and understates the macroeconomic costs of dirty job destruction.

6. Conclusions

This paper has studied the short-term labor-market implications of the green transition through an environmental DSGE model with SAM frictions, clean and dirty sectors, and skill heterogeneity.

The results show that transition-risk shocks generate asymmetric labor-market effects across skill groups. Clean job-creation shocks raise vacancies and job-finding rates, but their aggregate effects remain limited when targeted workers are not easily matched with clean-sector labor demand. This suggests that green hiring policies should be complemented by measures that improve the compatibility between workers' skills and clean-sector requirements. By contrast, dirty job-destruction shocks, especially those affecting low-skilled workers, generate stronger recessionary and inflationary effects and larger distributional costs. Policies that accelerate the destruction of carbon-intensive jobs without facilitating worker reallocation may therefore amplify macroeconomic instability and widen inequality.

Skill heterogeneity is thus central to the design of a just transition. Low-skilled workers face larger job losses, weaker absorption by the clean sector, and stronger adverse effects on consumption inequality and the wage premium. Our results point to the importance of reducing skill bottlenecks and improving workers' transferability across sectors. Upskilling, reskilling, vocational training, apprenticeships, and targeted active labor-market policies can increase matching efficiency, ease the transition into green employment, and reduce the burden on vulnerable workers. By relaxing these constraints, policy can mitigate both the distributional and macroeconomic costs of the green transition, including price pressures. Future research could extend this framework by incorporating endogenous education, reskilling, and a richer role for fiscal policy.

(The Appendix follows overleaf)

Appendix

Wage decomposition

Figure A1 shows the wage-decomposition responses presented in Appendix and used to support the discussion in Section 4.1.

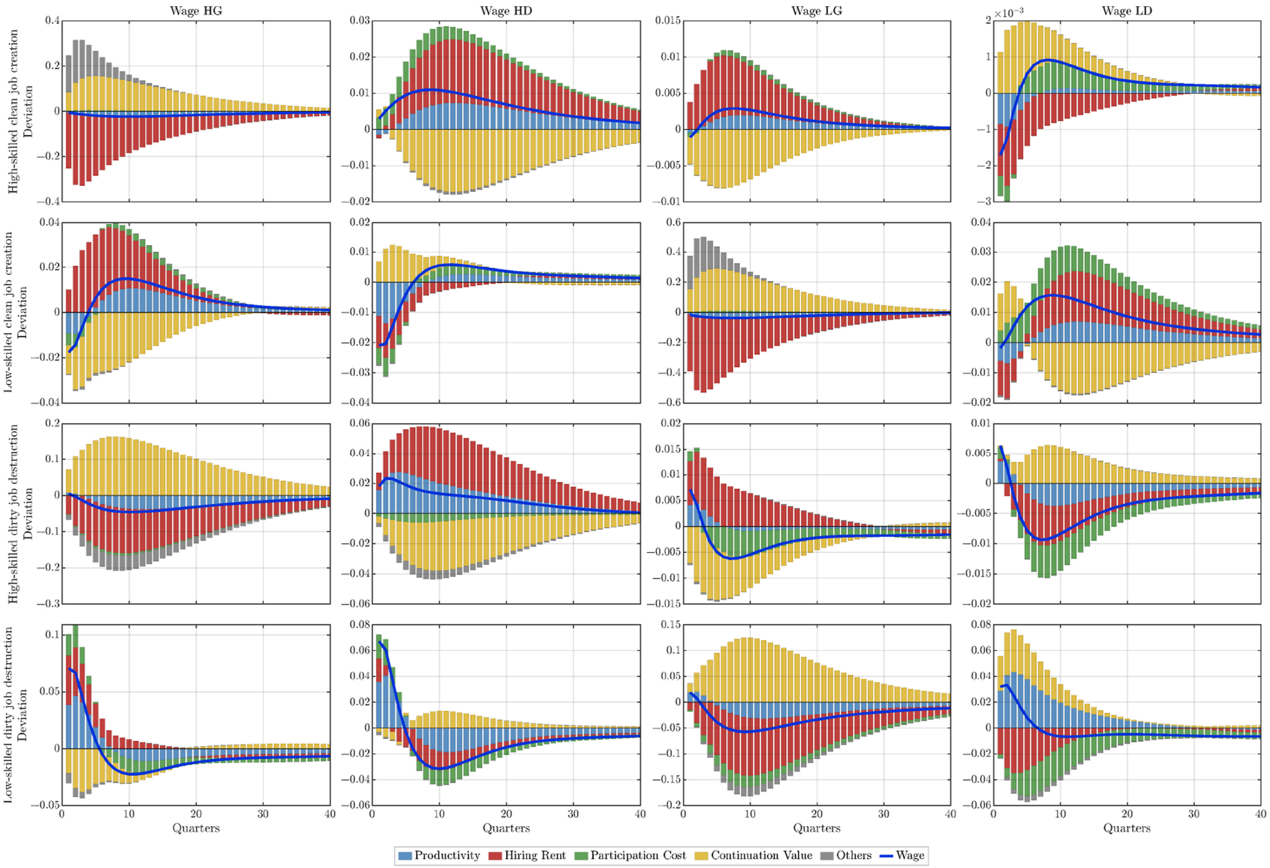


Figure A1. Wage decomposition responses presented in Appendix. **Source:** Authors' own work

Notes

1. We do not introduce a pre-announcement stage because modelling the expectation-formation process behind future climate-policy changes is not the objective of the paper. The usual rational expectations mechanism applies.
2. Following Ferrari and Nispi Landi (2023), we consider clean and dirty sectors as renewable and fossil-fuel sectors.
3. We abstract from firms' expectations and endogenous separations in order to isolate the destruction margin and compare it directly with clean-sector job creation. In the spirit of Zanetti (2019), treating job-destruction shocks as exogenous allows us to assess their business-cycle consequences and their contribution to labor-market fluctuations.
4. Data are drawn from Eurostat, *Unemployment rates by educational attainment level*, quarterly data, dataset code: une_educ_q, https://ec.europa.eu/eurostat/databrowser/view/lfsq_urgaed/default/table?lang=en
5. Data are drawn from Eurostat, *Labour force participation rates by educational attainment level*, quarterly data, dataset code: lfsq_argaed, https://ec.europa.eu/eurostat/databrowser/view/lfsq_argaed/default/table?lang=en
6. We follow Albanese *et al.* (2025), who document that approximately 55% of workers in the clean sector are high-skilled, and Abbritti and Consolo (2024) for the dirty-sector parametrization.

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