Aging and Labor Market Dynamics

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Abstract

We explore the macroeconomic impact of population aging on labor market dynamics. Empirical evidence suggests that aging reduces the aggregate unemployment rate while amplifying its cyclical volatility. We account for this feature using a life-cycle Roy model with directed search frictions and human capital accumulation. Quantitative analysis suggests that an aging economy faces rigid sectoral labor reallocation, which amplifies and prolongs unemployment fluctuations as reduced labor mobility weakens endogenous macroeconomic stabilization. Policy analysis indicates that hiring subsidies are more effective than vocational training in an aging economy.

Keywords: *Aging, Unemployment, Business Cycle, Occupational mobility*
JEL classification: E32, J11, J62, J64

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1 Introduction

In most advanced economies, fertility rates have fallen well below replacement levels while life expectancy continues to rise, shifting the age distribution of the labor force toward older workers. This structural shift raises a fundamental economic question: How does an older workforce alter labor market dynamics? Since individuals at different life-cycle stages face distinct incentives and opportunities, shifts in the age structure can generate non-trivial aggregate consequences. Building on this idea, we explore how an aging labor force affects aggregate unemployment and its sensitivity to macroeconomic disturbances.

We begin by documenting salient facts regarding distinct labor market dynamics across age cohorts using four decades of U.S. Current Population Survey (CPS) data. We find marked differences in labor market outcomes depending on life-cycle stages: unemployment, separation, job-finding, and occupational transition rates consistently and considerably decrease with age. Given these heterogeneities, we investigate how these cohort-level differences cumulate to affect aggregate labor market dynamics. To this end, we decompose aggregate unemployment and its cyclical volatility into a weighted sum of age-specific components. A counterfactual decomposition of the Great Recession suggests that, had the U.S. labor force retained the younger demographic structure of the early 1980s, the unemployment rate would have peaked roughly one percentage point higher, but its cyclical amplitude would have been consistently smaller throughout the recession. We formalize these findings by estimating a dynamic factor model, which suggests that labor market hazards are relatively more sensitive among older cohorts. Consequently, the aggregate unemployment fluctuations are amplified as old workers account for a larger share of the workforce.

Why does aging lead to this 'low-level, high-volatility' equilibrium? We argue that sector-specific human capital accumulation and its consequent lock-in effect are the key drivers underlying this phenomenon. Intuitively, individuals accumulate specialized human capital in particular sectors through work experience over time. This comparative skill advantage raises their productivity and job security within their primary sector but, at the same time, narrows their reallocation options. When productivity shocks hit, older workers cannot adjust as flexibly as young workers do. Instead of reallocating across sectors, they either remain matched to their current sector or face prolonged unemployment once displaced. In contrast, young workers possess limited comparative skill advantages while holding longer work horizons over which to recoup switching costs. This induces them to react to varying labor market conditions more flexibly by adapting their occupations temporarily or permanently. Since labor reallocation helps the economy absorb exogenous shocks, demographic aging undermines this endogenous stabilization mechanism and leads to amplified unemployment fluctuations.

To formalize and quantify this mechanism, we develop a multi-sector, life-cycle model that integrates a Roy-type selection mechanism with endogenous human capital development and directed search frictions in the labor market. The model is estimated using CPS data through the Simulated Method of Moments (SMM), targeting age-specific unemployment rates, transition hazards, and

occupational mobility between cognitive and manual occupations. The estimated model accounts for the distinct life-cycle labor market profiles through the interactions among work horizons, human capital, and search frictions. Young workers are more vulnerable to layoff risks due to their limited skill specialization, while also exhibiting stronger incentives to voluntarily quit in search of better matches given their longer remaining work horizons. As a result, the separation rate decreases monotonically with age. Job-finding rates exhibit a non-monotonic age profile: initial fluctuations reflect the trade-off between productivity and separation risks, followed by a sharp decline near retirement as the shortening time horizon erodes the expected match surplus. Finally, the formation of a stronger dynamic comparative advantage over time, coupled with diminished labor demand for senior labor due to shortening remaining tenures, increasingly curtails sectoral transition incentives, thereby reinforcing the lock-in effect for older workers.

To explore the macroeconomic impact of aging, we first examine steady-state transitions driven by demographic aging. Calibrated to the observed aging pace in the U.S., we incorporate aging into the model as a transition from a square to an inverted-triangular population pyramid led by declining labor market entrants. This structural shift gradually increases the relative share of senior workers, allowing us to examine the age composition effect. Consistent with empirical evidence, our model shows that an aging economy exhibits reduced aggregate separation, job-finding, and transition rates, resulting in a lower steady-state unemployment rate. We then investigate labor market responses to aggregate productivity shocks. As predicted, the aging economy exhibits amplified aggregate unemployment fluctuations in response to TFP innovations. Intuitively, sectoral labor reallocation over the business cycle serves as an endogenous stabilizer. As older workers exhibit higher sectoral attachment, they respond to shocks with amplified fluctuations in job-finding rates rather than smooth reallocation across sectors. This rigid sectoral mobility effectively leads to higher aggregate unemployment volatility.

Given the importance of sectoral labor mobility, we further explore reallocation dynamics through counterfactual experiments involving sector-specific shocks. A shock that reduces labor demand in the manual sector raises unemployment across all age groups without much sectoral reallocation because only a limited volume of displaced manual workers can transition to the cognitive sector due to its stringent skill requirements and higher entry barriers. The age structure exerts a limited influence on aggregate outcomes in this case, as mobility is structurally constrained for all cohorts. On the other hand, a shock that reduces labor demand in the cognitive sector generates reallocation to the manual sector, particularly among young and middle-aged workers. Older workers, nonetheless, remain unemployed for extended periods due to strong sectoral attachment. Consequently, an aging economy shows sluggish adjustments in response to this type of shock.

Importantly, we highlight that senior workers, by remaining in their primary sectors despite adverse market conditions, effectively exhibit behavior that mirrors 'rest' unemployment. While rest unemployment is widely explored in the literature through explicit search disutility (Alvarez and Shimer, 2011) or reallocation costs (Carrillo-Tudela and Visschers, 2023), our framework endogenously generates a similar pattern driven by comparative skill advantages and diminishing returns

from sectoral mobility as age increases. Moreover, our analysis provides important implications regarding recent technological progress: when cognitive labor demand falls, an aging economy is more prone to a sluggish economic transition because a considerable share of the workforce tends to be more passive in adapting to shifting market conditions.

Our quantitative findings raise direct policy questions regarding labor market stabilization. Should policy measures incentivize workers to acquire skills aligned with changing labor market conditions or encourage firms to create jobs providing opportunities for skill development? We address this question by evaluating two active labor market policies (ALMPs): vocational training and hiring subsidies. The former allows unemployed workers to build sector-specific skills at the cost of foregone job searches, while the latter directly stimulates firm-side labor demand. Numerical analysis suggests that vocational training yields negligible aggregate benefits and becomes increasingly less effective as the workforce ages. This is because many workers who already possess comparative skill advantages in a particular sector have little incentive to leverage training opportunities. Furthermore, the incentive to develop new skills is concentrated among younger workers with sufficiently long career horizons to recoup the associated human capital investment costs. In contrast, hiring subsidies appear consistently more effective in reducing unemployment and stimulating sectoral reallocation by bolstering labor demand across all skill and age levels. These findings suggest that stimulating demand-side incentives is more effective for achieving a stable labor market than inducing voluntary human capital development on the supply side.

Related Literature

The current study builds on several strands of the literature. The first body of work documents the demographic transition and its macroeconomic implications. Jaimovich and Siu (2009), Jaimovich et al. (2013), and Maestas et al. (2023) examine how population aging affects macroeconomic outcomes and highlight the heterogeneity in labor market dynamics and productivity across different age groups of workers. On the other hand, studies using firm-level data highlight potential discrepancies between wages and productivity at older ages (Cardoso et al., 2011; Skirbekk, 2004), while others emphasize complementarities in team production that mitigate the productivity decline associated with aging (Börsch-Supan and Weiss, 2016). At the macroeconomic level, aging has also been linked to the pace of technological adoption, with demographic change driving faster automation and robot adoption in some economies (Acemoglu and Restrepo, 2018, 2022).

A second line of work builds on search-theoretic frameworks to analyze how aging interacts with labor market frictions. Chéron et al. (2011, 2013) study labor market dynamics over the life cycle within a random-matching framework. Hairault et al. (2010) examines how the *distance to retirement* shapes workers' job search behavior. These studies show that labor market behavior varies systematically over the life cycle, implying that demographic changes may have important implications for aggregate labor market outcomes. Nonetheless, one major shortcoming of this body of work is that the random-matching framework is not well suited to studying the nonstationary

equilibrium dynamics associated with a time-varying labor force. For tractability, this literature typically assumes a fixed labor force size, which limits its applicability to analyzing interactions between population changes and labor market frictions. Recent advances in the directed search literature (Menzio et al., 2016; Guo, 2018; Carrillo-Tudela and Visschers, 2023) provide one way to explore nonstationary dynamics by exploiting the block-recursive property of labor market equilibrium under certain conditions. We build on this approach to incorporate structural changes in the size and composition of the labor force into a frictional labor market environment. It is particularly worth noting that Hairault et al. (2019) documents similar age-dependent heterogeneity in labor market dynamics and attributes it to life-cycle variations in workers' outside options. As age increases, outside options tend to be less responsive to aggregate shocks, leading to more rigid wage adjustments and consequently amplified (un)employment fluctuations. We complement this view by proposing a distinct mechanism: we emphasize sector-specific human capital accumulation and the resulting lock-in effect. As older workers account for an increasing share of the labor force, the endogenous stabilization mechanism is gradually weakened through rigid sectoral reallocation rather than rigid wage adjustments.

Another related literature combines search frictions with sectoral sorting. On the sorting side, Roy-type models emphasize heterogeneity in comparative advantage across sectors and the endogenous accumulation of human capital (Heckman and Honoré, 1990; Dvorkin and Monge-Naranjo, 2019). In parallel, the search-friction literature shows how wage posting and market segmentation generate equilibrium unemployment and sorting by worker and firm types (Acemoglu and Shimer, 1999; Shimer, 2005). More recent contributions incorporate endogenous sorting through occupational or sectoral choice within search-theoretic frameworks (Menzio and Shi, 2011; Lentz and Mortensen, 2010; Lise and Robin, 2017; Lise and Postel-Vinay, 2020). We extend this line of work by combining a Roy model with endogenous human capital accumulation and directed search frictions both across and within sectors. This integrated framework allows us to capture the rich heterogeneity in labor market dynamics occurring over the life cycle.

A final strand of aging research focuses on the labor market interactions across age groups. In particular, labor market spillover effects arising from adjustments to the retirement age have received considerable attention. Yet, the issue remains open. Gruber and Wise (2010), Munnell and Wu (2012), and Staubli and Zweimüller (2013) examine the effects of raising the statutory retirement age on employment across different age groups, finding little evidence that older workers crowd out younger ones. In contrast, European evidence (e.g., Martins et al., 2009 for Portugal and Boeri et al., 2022 for Italy) suggests that delayed retirement reduces employment among younger cohorts. Turning to the occupational aspects of employment effects, recent empirical studies (Bianchi et al., 2023; Mohnen, 2025) indicate that retirement slowdowns alter sectoral labor demand for youth, which in turn affects their career opportunities. These findings highlight the general equilibrium interactions between the retirement decisions of senior workers and the early-career choices of younger cohorts.

Although labor market interactions across age groups and, more broadly, general-equilibrium

feedback through the distribution of labor force may be empirically relevant, the mixed evidence in the literature regarding the strength and direction of these channels leaves it unclear whether incorporating them is essential for a quantitative investigation of how demographic aging shapes aggregate labor market dynamics. This paper adopts a block-recursive labor market structure, arguably the only practical approach to address nonstationary dynamics in search-frictional environments. This modeling approach, however, abstracts from distributional effects in general equilibrium that arise from the time-varying composition of heterogeneous agents. While acknowledging this limitation, our framework provides a distinguished analytical advantage in studying heterogeneous life-cycle behavior and the nonstationary aggregate dynamics induced by demographic changes, thereby serving as a useful benchmark for future extensions.

2 Empirical Motivation

2.1 Data

This section documents stylized facts regarding the disparities across age groups in labor market transition patterns within the U.S. economy. The empirical analysis is based on the Current Population Survey (CPS henceforth), a monthly household survey that collects information on a wide range of labor market topics. We exploit its rolling panel structure, in which selected households are interviewed for four consecutive months, then rotated out for eight months, and finally rotated back in for another four months before permanently leaving the sample. This design is particularly valuable for estimating labor market transitions because the same individuals can be matched across adjacent months, allowing researchers to observe changes in their employment status in a monthly time interval: whether they moved from employed to unemployed, exited or entered the labor force, or remained in the same state.

We use CPS monthly surveys ranging from January 1978 to December 2019. The sample is restricted to the working-age population (ages 16 to 64), excluding nonfarm business sectors and armed forces. It is acknowledged that the rotating panel structure of the CPS survey may suffer from non-random attrition or rotation group bias (Fallick and Fleischman, 2004; Nagypál, 2008). To address this, we restrict our analysis to the first four waves of the survey and compute worker flows across employment, unemployment, and non-participation. To control for potential reporting errors, we *iron out* the reported labor market status, following Elsby et al. (2015) and Choi et al. (2015). As in Shimer (2012), we seasonally adjust the monthly time series using the ratio-to-moving-average method with a one-year window and then smooth high-frequency fluctuations based on a five-month moving average. To alleviate time-aggregation bias, each monthly transition rate is converted into its continuous-time hazard equivalent through the standard transformation; the resulting monthly hazard rates are then aggregated to a quarterly frequency by averaging within each quarter. CPS person-level weights (WTFINL) are applied to all flow calculations.

2.2 Age-dependent labor market characteristics

In 1980, the average age of workers was about 35 years; by 2019, it was around 40 years. Figure 1 shows that individuals under 30 years of age accounted for about 40 percent of the labor force in 1980. This share has steadily declined over time, reaching 29 percent in recent years. Meanwhile, individuals aged 50 and older now account for 28 percent of the labor force, nearly 10 percentage points higher than in 1980.

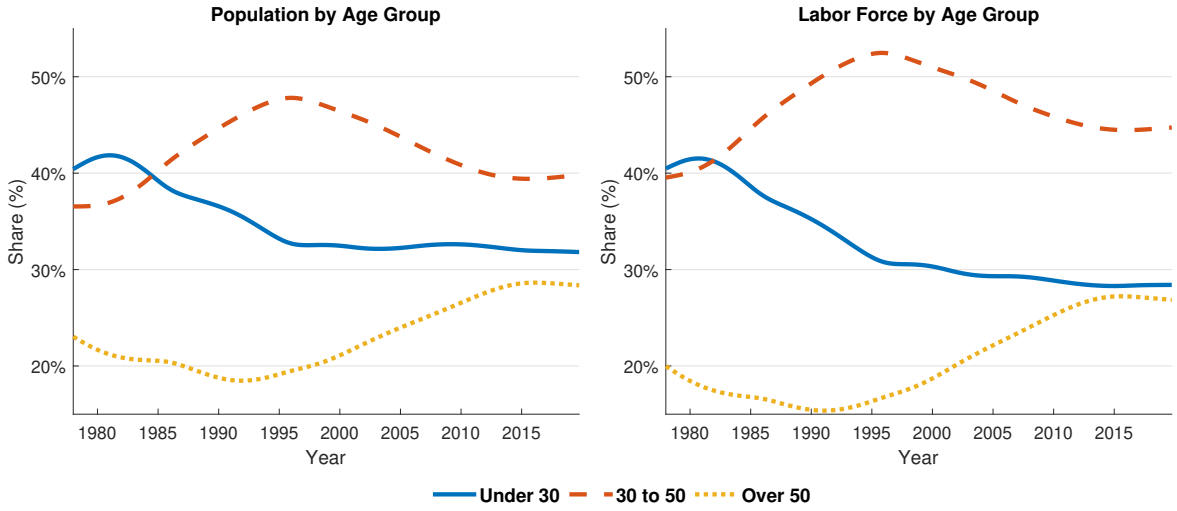


Figure 1: Population structure transition in the U.S

The left panel of Figure 2 shows the unemployment rates of the young and old cohorts, together with the aggregate rate. The unemployment rate of the young cohort is consistently about 6 to 10 percentage points higher than that of the old cohort. As older workers make up a larger share of the labor force, the aggregate unemployment rate tends to decline. The right panel plots the aggregate unemployment rate and its low-frequency trend extracted using the HP filter with a smoothing parameter of 10^5. The trend shows that the average unemployment rate fell from 7.8 percent in the first five years of the sample period to 5.6 percent in the last five years.

Figure 3 displays the job separation and job-finding hazard rates by age group, along with their aggregate counterparts. The figure shows that the young cohort exhibits notably higher job-separation and job-finding rates [1]. These patterns are consistent with well-documented evidence of declining labor market dynamism with age and suggest that younger individuals have lower job attachment but face greater (re)employment opportunities during unemployment.

Figure 4 shows that young workers exhibit significantly higher rates of occupational mobility. The left panel presents the job-finding rate (from unemployment or non-participation to employment) via occupation changes across major occupational groups defined by the 2018 Standard Occupational Classification (SOC) system. For younger workers, these rates are approximately 25

[1]The separation hazard encompasses all transitions from employment to unemployment or non-participation, including voluntary quits, layoffs, and dismissals.

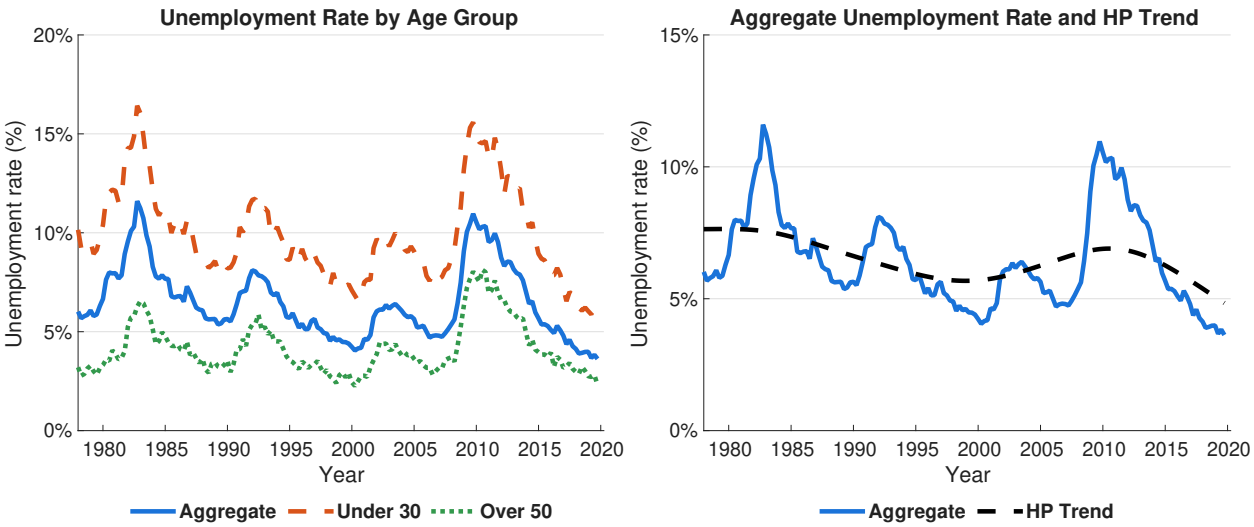


Figure 2: Unemployment Rates by Age Group and HP-Trend Decomposition

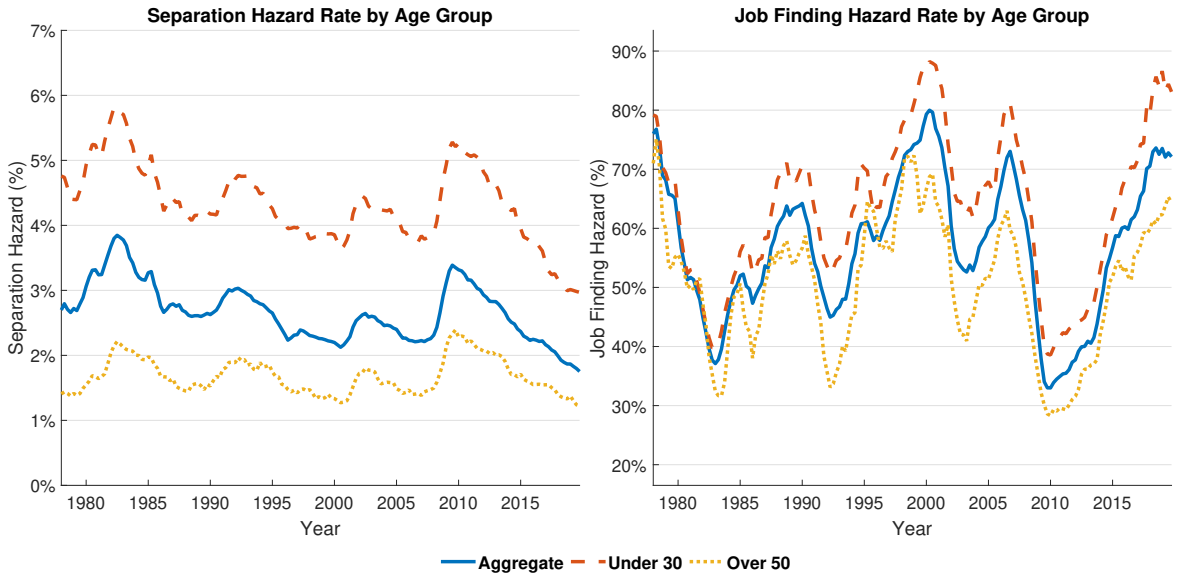


Figure 3: Job separation and finding hazards by age groups

percentage points higher than those of their older counterparts. This pattern is robust regardless of the granularity of the occupational classification. For instance, the remaining panels in Figure 4 display transition rates between manual and cognitive occupations, which are classified according to the task-based approach of Autor et al. (2003) (see Table 2). These task-specific transition rates are roughly twice as high for young workers as for those aged over 50. We also observe consistent patterns for industry-level or joint industry-occupation transition rates, which are omitted for brevity.

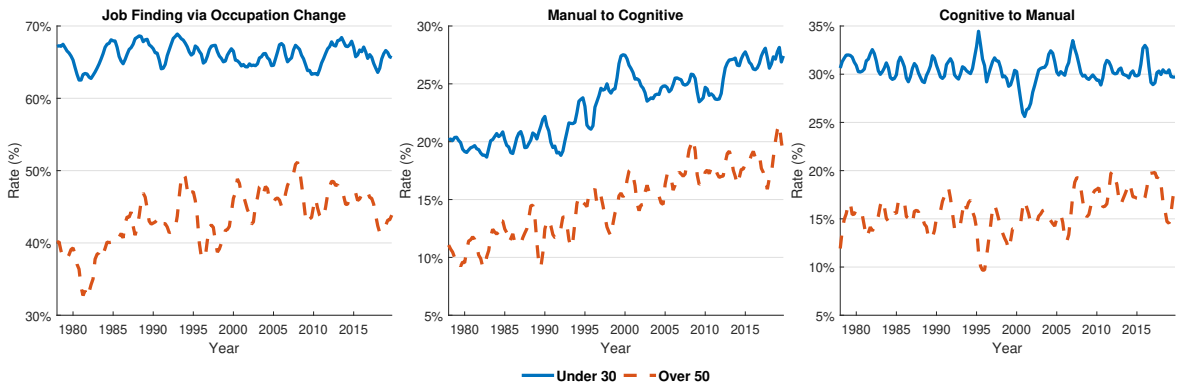


Figure 4: Job-finding rates through occupation changes

2.3 Unemployment dynamics: Business cycle analysis

2.3.1 Unemployment Decomposition

The aggregate unemployment rate can be expressed as a weighted average of unemployment rates across age groups, as in Equation 1: Y refers to individuals below age 30, O refers to those aged 50 and above, while M refers to individuals between these two age ranges.

$$u_t = \lambda_t^Y u_t^Y + \lambda_t^M u_t^M + \lambda_t^O u_t^O \tag{1}$$

For the age group $Z \in \{Y, M, O\}$, $\lambda_t^Z \equiv \frac{L_t^Z}{L_t}$ denotes the fraction of each age group in the total working-age population, and $u_t^Z \equiv \frac{U_t^Z}{L_t^Z}$ indicates the unemployment rate for each age group. Similarly, we can also decompose fluctuations in the aggregate unemployment rate into age-dependent contributions from separation and job-finding hazards across age groups. Building on Elsby et al. (2009) and Petrongolo and Pissarides (2001), we develop a three-state model for steady-state unemployment with three age groups, yielding the following identity (see Appendix A.1 for details):

$$d\log u_t \approx \sum_{Z\in\{Y,M,O\}} \Phi_t^Z (1-\tilde{u}_t^Z)\Big(d\log s_t^Z - d\log f_t^Z\Big) \tag{2}$$

where $\Phi_t^Z = \frac{U_t^Z}{U_t}$ indicates the fraction of unemployed individuals in each age group with respect to total unemployment, i.e., $\sum_Z \Phi_t^Z = 1$. The term $\tilde{u}_t^Z \equiv s_t^Z/(s_t^Z + f_t^Z)$ denotes the approximate unemployment rate conditional on the counterfactual steady-state, where s_t^Z and f_t^Z represent the effective separation and job-finding hazards, respectively.

Equations 1 and 2 provide a framework for examining how the age composition of the labor force shapes unemployment dynamics. Specifically, we can analyze cyclical unemployment under counterfactual demographic scenarios by applying alternative series of λ_t^Z and Φ_t^Z to these equations. This approach allows us to isolate the impact of population structure by comparing actual and counterfactual economies. To formalize this analysis, we focus on the labor market surround-

ing the Great Recession, spanning from the second quarter of 2007 to the second quarter of 2017 [2]. We then construct a counterfactual scenario in which the time series of λ_t^Z and Φ_t^Z are replaced with their counterparts from the early 1980s recession [3], which is often called the twin recession of the Great Recession. As shown in Figure 1, the counterfactual period features a substantially younger demographic structure [4].

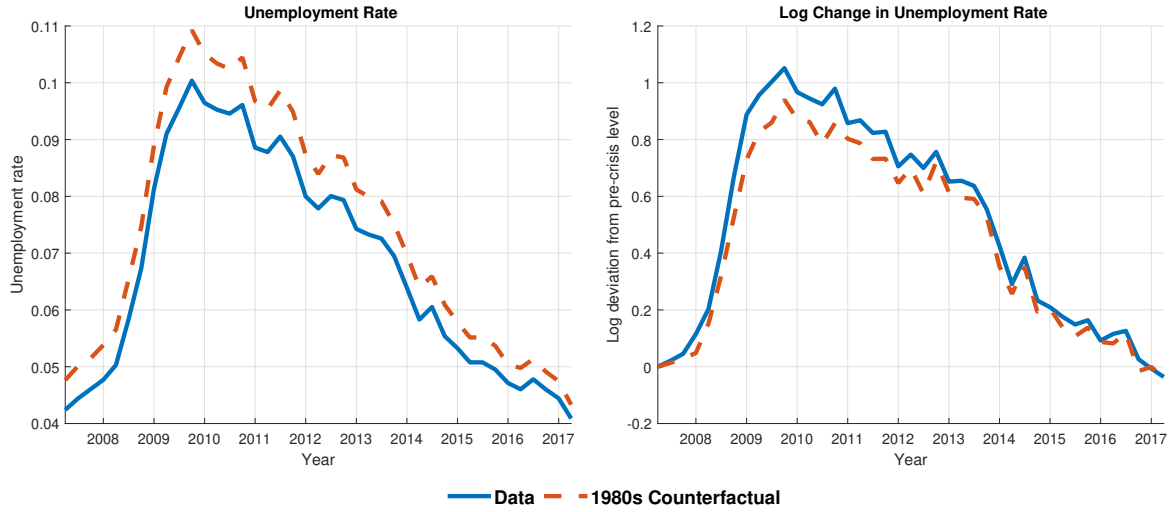


Figure 5: Unemployment decomposition

In Figure 5, the blue solid line indicates the Great Recession baseline, while the red dashed line denotes the counterfactual based on the 1980s population structure. We present the results for both the unemployment level (left panel) and the relative log-point change, normalized to zero at the onset of the recession (right panel). In terms of levels, the baseline case exhibits a lower unemployment rate throughout the period; at the peak of the recession in 2009 Q4, the actual unemployment rate is approximately one percentage point lower compared to the one in the younger counterfactual. In contrast, the counterfactual displays smaller log-point changes throughout the recession (right panel), indicating dampened cyclical fluctuations and a more rapid return to the pre-crisis unemployment level. In the extreme case, we observe that the recession could have concluded four to six quarters sooner had the entire workforce been under the age of 30, compared to the actual baseline economy.

[2]Following the NBER recession indicators and the methodology of Elsby et al. (2009), we define the start date as the quarter when the unemployment rate reaches its local minimum near the onset of the recession, and the end date as the quarter when it first returns to its pre-crisis level.

[3]Following the same approach based on NBER recession indicators and the local minimum of the unemployment rate, we identify the early 1980s recessionary period as spanning from the second quarter of 1979 to the second quarter of 1988. Given that this duration is shorter than that of the Great Recession, we include four additional quarters beyond the second quarter of 1988, ensuring a comparable timeframe for the analysis.

[4]During the Great Recession, the young and old groups each accounted for approximately 25 percent of the labor force. In the early 1980s counterfactual scenario, the young group represented roughly 35 percent, while the old group accounted for less than 20 percent.

2.3.2 A Dynamic Factor Model

We further investigate the origin of the increased unemployment volatility in an aging economy by examining cyclical fluctuations in labor market transition rates across different age groups in a more systematic manner. Specifically, we estimate the following dynamic factor model using quarterly data:

$$\mathbf{Y}_t = \boldsymbol{\alpha} + \boldsymbol{\Lambda} F_t + \boldsymbol{\eta}_t \quad \textit{and} \quad F_t = A(L)F_{t-1} + \epsilon_t$$

where $\mathbf{Y}_t$ is a 6×1 vector containing the logarithms of separation and job-finding hazards for young (Y), middle-aged (M), and old (O) workers. The factor loading matrix $\boldsymbol{\Lambda}$ maps the common latent factor F_t to the observed series. The latent factor is a scalar time series that simultaneously affects the separation and job-finding hazards across all age groups. We specify the latent factor to follow an AR(2) process based on the Bayesian Information Criterion test. The idiosyncratic disturbance vector $\boldsymbol{\eta}_t$ is a 6×1 vector and captures measurement errors and other idiosyncratic fluctuations. Finally, the scalar series ϵ_t denotes innovations to the latent factor. The idiosyncratic disturbances are assumed to be uncorrelated and orthogonal to the common factor F_t, while ϵ_t is assumed to follow an *i.i.d* standard normal distribution. We estimate the above dynamic factor model using data covering the entire sample period (1978 Q1 - 2019 Q4). The parameters $\boldsymbol{\alpha}$, $\boldsymbol{\Lambda}$, $A(L)$, the latent factor F_t, and the variance-covariance matrix of the idiosyncratic disturbances are estimated by maximum likelihood using the Kalman filter and smoothing (KFS).

Table 1: Dynamic Factor Model Estimates

	F_t	$\log(s_t^Y)$	$\log(s_t^M)$	$\log(s_t^O)$	$\log(f_t^Y)$	$\log(f_t^M)$	$\log(f_t^O)$
$\boldsymbol{\Lambda}$	–	-0.0115***	-0.0153***	-0.0147***	0.0209***	0.0219***	0.0218***
		(0.00186)	(0.00234)	(0.00227)	(0.00316)	(0.00331)	(0.00336)
$\boldsymbol{\alpha}$	–	-3.212***	-4.072***	-4.230***	-0.497***	-0.708***	-0.745***
		(0.0330)	(0.0431)	(0.0415)	(0.0587)	(0.0615)	(0.0617)
F_{t-1}	1.794***	–	–	–	–	–	–
	(0.0603)						
F_{t-2}	-0.822***	–	–	–	–	–	–
	(0.0599)						

Table 1 reports the estimation results. The first block presents the estimated factor loadings $(\boldsymbol{\Lambda})$ and intercepts $(\boldsymbol{\alpha})$ associated with each observed variable, while the second block shows the autoregressive coefficients of the latent factor equation. The factor loading parameters can be interpreted as the sensitivity of each variable to marginal changes in the common aggregate labor market driver F_t. As shown in the table, the absolute values of the factor loadings are smaller for the young group compared to the other groups, suggesting that job separation and job-finding hazards for young workers are less responsive to fluctuations in F_t. Figure A1 presents the impulse responses of age-dependent separation and job-finding hazard rates to a marginal decline in F_t.

Throughout the period, the young group shows more attenuated responses in both hazard rates.

The estimation results shed light on the sources of amplified unemployment volatility in an aging economy. The magnitude of fluctuations in separation and job-finding hazards in response to aggregate shocks tends to increase with age. This amplifies counter-cyclical unemployment fluctuations within those age groups and, consequently, aggregate volatility. While the sensitivity of these hazard rates varies by age, the disparities appear relatively modest. That is, the shifting age structure of the labor force raises aggregate unemployment volatility, but its overall impact appears to be relatively limited. To explore the structural mechanisms of the observed patterns, the following section presents a life-cycle Roy model with labor market friction. As shown below, numerical analysis reveals that aging fundamentally alters the endogenous adjustment mechanisms to shocks, notwithstanding the modest impact observed in macroeconomic aggregates.

3 The model

In this section, we develop a multi-sector overlapping generations model where the labor market is subject to competitive search frictions, as in Moen (1997). The model also features a Roy-type structure in which individuals choose a sector based on their skill sets that evolve endogenously through (un)employment experience. On the production side, sectors differ in their productivity levels and structural frictions.

3.1 Environment

Time is discrete and goes on forever. The economy is populated by risk-neutral individuals who live for T periods. At each point in time t, a cohort with weight Π_t is born and enters the economy, while the cohort of individuals born T periods earlier (with the size of Π_{t-T}) exits the economy. The size of each population cohort changes over time at rate ψ:

$$\Pi_t = (1+\psi)\Pi_{t-1} \tag{3}$$

The economy consists of N productive sectors and is subject to an aggregate total factor productivity (TFP) shock A_t that follows an AR(1) process:

$$A_t = \rho_A A_{t-1} + e_t \quad \text{where} \quad e_t \sim N(0, \sigma_A)$$

Individuals derive utility solely from consumption and do not experience disutility from working. Labor earnings depend on match productivity, aggregate technology shocks, and human capital (HC) levels (henceforth we use the terms skill and human capital interchangeably). Each individual's HC at calendar time t is represented by an N-dimensional vector $\mathbf{X}_t = \{x_t^1, x_t^2, \ldots, x_t^N\}$, where each element denotes the HC level in the corresponding sector in period t and ranges from 0 to 1. Skills are sector-specific and non-transferable; skills in one sector do not affect an individual's

productivity in other sectors. Each individual is born with an initial HC endowment, which may evolve or depreciate over the course of their working life. To be specific, individuals are endowed with initial sector-specific skills. The initial HC for each sector is drawn from Beta distributions, jointly distributed via a Copula ($\mathbf{C}$) with a correlation ρ_{hc}:

$$x^j \sim \textbf{Beta}(\beta_1, \beta_2) \quad \forall\, j \in N$$
$$F(x^1, x^2, ..., x^n) = \mathbf{C}\Big(F_1(x^1), F_2(x^2), ..., F_n(x^n); \rho_{hc}\Big)$$

Individual human capital depreciates at a rate δ^u while unemployed:

$$\mathbf{X}_{t+1} = (1 - \delta^u)\mathbf{X}_t \tag{4}$$

In contrast, when an individual is employed in a sector j, HC evolves as follows:

$$\begin{aligned} x^j_{t+1} &= \min\{(1 + \rho(x^j_t))x^j_t, 1\} \\ x^i_{t+1} &= \max\{0, (1 - \delta^e)x^i_t\} \quad \forall\, i \neq j \end{aligned} \tag{5}$$

The above equations suggest that an agent can improve their skill level in the sector where they are employed. This can be interpreted as learning-by-doing skill acquisition. In contrast, skills in the other sectors depreciate at a rate δ^e. This depreciation rate may differ from the rate experienced during unemployment. The rate of HC accumulation is governed by a concave function $\rho(\cdot)$:

$$\rho(x) = \rho \times (1 - x)^{\rho_x}$$

where ρ represents the baseline skill growth rate, and ρ_x governs how the growth rate declines with skill level. The concavity of the HC accumulation function implies diminishing returns to skill development: as individuals possess higher levels of HC within a sector, acquiring additional skills in that sector becomes increasingly difficult.

Given both idiosyncratic and aggregate states, job seekers choose a sector at the beginning of each period. Their employment status is then determined probabilistically. Following Menzio et al. (2016), we assume that the economy consists of numerous submarkets indexed by workers' skills, age, sector, and the aggregate state, where agents direct their search to a specific submarket based on their idiosyncratic states. Once a match is formed, an exogenous match-specific productivity z is drawn from a Beta distribution. Combined with the worker's sector-specific skills and the aggregate state, this match-specific productivity determines the total output of the match.

3.2 The unemployed

At the beginning of period t (after the aggregate TFP shock is realized), unemployed individuals choose a sector in which to search for a job. The value of searching for a job in sector j for an

individual of age a with HC $\mathbf{X}_t$ can be written as:

$$\widehat{\mathbf{U}}_j^a(\mathbf{X}_t, A_t) \equiv \Big(1 - \tilde{p}_j^a(\mathbf{X}_t, A_t)\Big)\mathbf{U}^a(\mathbf{X}_t, A_t) + \tilde{p}_j^a\big(\mathbf{X}_t, A_t\big)E_z\Big[\mathbf{W}_j^a(z, \mathbf{X}_t, A_t)|z \geq z_h^a(\mathbf{X}_t, A_t)\Big]$$

where $\tilde{p}_j^a(\mathbf{X}_t, A_t)$ denotes the effective job-finding probability in a submarket indexed by age a, sector j, and skills $\mathbf{X}_t$, given the aggregate TFP shock A_t. The effective job-finding probability is expressed as:

$$\tilde{p}_j^a(\mathbf{X}_t, A_t) \equiv p_j^a(\mathbf{X}_t, A_t)\Big[1 - F^z\big(z_h^a(\mathbf{X}_t, A_t)\big)\Big].$$

where p_j^a is the probability of receiving a job offer given idiosyncratic and aggregate states $\{X_t, A_t, a\}$. With probability $1 - \tilde{p}_j^a(\mathbf{X}_t, A_t)$, an agent fails to secure employment and obtains the ex-post welfare of $\mathbf{U}^a(\mathbf{X}_t, A_t)$. Otherwise, the agent finds a job and attains value $E_z\big[\mathbf{W}_j^a(z, \mathbf{X}_t, A_t) \mid z \geq z_h^a(\mathbf{X}_t, A_t)\big]$, where $z_h^a(\mathbf{X}_t, A_t)$ represents the minimum match productivity required for hiring (the hiring threshold), and $E_z[\cdot]$ denotes the expectation operator with respect to the match productivity distribution.

Agents choose the sector that yields the highest welfare:

$$j^* = argmax_{j \in \mathbf{N}}\Big[\widehat{\mathbf{U}}_j^a(\mathbf{X}_t, A_t) - sc^a + \epsilon_j^a\Big]$$

Given age a, individual skill sets $\mathbf{X}_t$, and the aggregate state A_t, the ex-ante welfare term captures the job-finding probabilities across sectors and the expected value associated with each potential employment outcome. Hence, the occupational choice primarily depends on both individual skills and aggregate labor market conditions. Since individual labor market decisions may be influenced by other factors such as liquidity or liquid asset positions (Herkenhoff, 2019; Eeckhout and Sepahsalari, 2024; Jung and Lee, 2025), mobility costs (Pilossoph, 2012), household constraints (Costa and Kahn, 2000), and other sociodemographic characteristics (Bayer et al., 2008), we include a sector-specific exogenous preference shock ϵ_j^a, assumed to follow a Type I extreme value (**Gumbel**) distribution:

$$\epsilon_j^a \overset{i.i.d.}{\sim} \mathbf{Gumbel}(0, \sigma_P^a) \quad \forall\, j \in N$$

We allow the size of the preference shock to vary over the life cycle. Specifically, the standard deviation of the sector preference shock may decrease with age:

$$\sigma_P^a = \sigma_P \times \Big(1 + \lambda_P \times \frac{T - a}{T}\Big)$$

where a denotes age, σ_P is the standard deviation of the preference shock for the oldest cohort (age T), and λ_P determines the slope of its age dependence. Because the scale of the lifetime value function declines with age due to a shorter remaining horizon, applying preference shocks of the same magnitude across all age cohorts would exert a disproportionately larger impact on older

groups. The age-dependent specification is required to correct for this scale effect. On the other hand, the optimal sector choice decision also depends on an age-dependent job search cost sc^a. We assume that sc^a equals the expected value of the preference shock, $sc^a = \sigma_P^a \times \gamma^E$, where γ^E denotes the Euler–Mascheroni constant.

Given the Type I Extreme Value distribution and the optimal sector choice condition, we can derive a closed-form expression for the probability of choosing sector j as follows:

$$s_{j,t}^a = \frac{exp\big(\widehat{\mathbf{U}}_j^a(\mathbf{X}_t, A_t)/\sigma_P^a\big)}{\sum_{j'} exp\big(\widehat{\mathbf{U}}_{j'}^a(\mathbf{X}_t, A_t)/\sigma_P^a\big)}$$

and the ex-post value function of an unemployed individual is written as

$$\begin{aligned}(6) \qquad \mathbf{U}^a(\mathbf{X}_t, A_t) &= b + \beta E_t\Big[\underbrace{\sum_j s_{j,t+1}^{a+1}\widehat{\mathbf{U}}_j^{a+1}(\mathbf{X}_{t+1}, A_{t+1})}_{\equiv \mathbf{R}^{a+1}(\mathbf{X}_{t+1}, A_{t+1})}\Big] + \beta E_t\Big[\sum_j s_{j,t+1}^{a+1}(E_\epsilon[\epsilon_j^a] - sc^a)\Big] \\ &= b + \beta E_t\Big[\mathbf{R}^{a+1}(\mathbf{X}_{t+1}, A_{t+1})\Big]\end{aligned}$$

where b denotes home production during unemployment. The last term in the first equation cancels out because, by construction, $E_\epsilon[\epsilon_j^a] = sc^a$.

3.3 The Worker–Firm Match

3.3.1 Workers

The value function of a worker aged a with skill $\mathbf{X}_t$ employed in a sector j with the match productivity z can be written as follows:

$$\mathbf{W}_j^a(z, \mathbf{X}_t, A_t) = w_j^a(z, \mathbf{X}_t, A_t) + \beta E_t\Big[\Big(\lambda^z E_{z'}[\mathbf{Z}_j^{w,a+1}(z', \mathbf{X}_{t+1}, A_{t+1})] + (1-\lambda^z)\mathbf{Z}_j^{w,a+1}(z, \mathbf{X}_{t+1}, A_{t+1})\Big)\Big]$$

In the above expression, λ_z denotes the Poisson arrival rate of the exogenous match-productivity shock: with probability λ_z, the match draws a new productivity shock, whereas with probability $(1-\lambda_z)$, the current productivity level persists. While employed, the worker receives labor earnings $w_j^a(z, \mathbf{X}_t, A_t)$. The value function $\mathbf{Z}_j^{w,a}(z, \mathbf{X}_t, A_t)$ represents the expected welfare of a worker at the beginning of the next period, which is given by:

$$\mathbf{Z}_j^{w,a}(z, \mathbf{X}_t, A_t) = d_j^a(z, \mathbf{X}_t, A_t)\mathbf{R}^a(\mathbf{X}_t, A_t) + \Big(1 - d_j^a(z, \mathbf{X}_t, A_t)\Big)\mathbf{W}_j^a(z, \mathbf{X}_t, A_t)$$

where $d_j^a(z, \mathbf{X}_t, A_t)$ denotes the job-separation indicator function, which we elaborate below. Notably, individuals who separate from their current positions immediately re-enter the job-search process, including the sector-choice decision [5].

[5] It is worth noting that the model deliberately abstracts from explicit on-the-job (OTJ) transitions, as incorporating them would add little value to the current framework. Indeed, OTJ dynamics are indirectly incorporated: the timing

3.3.2 Firms

The surplus of a firm in sector j can be written as:

$$\mathbf{V}_j^a(z, \mathbf{X}_t, A_t) = \pi_j^a(z, \mathbf{X_t}, A_t) + \beta E_t\Big[\Big(\lambda^z E_{z'}[\mathbf{Z}_j^{f,a+1}(z', \mathbf{X}_{t+1}, A_{t+1})] + (1-\lambda^z)\mathbf{Z}_j^{f,a+1}(z, \mathbf{X}_{t+1}, A_{t+1})\Big)\Big]$$

with

$$\mathbf{Z}_j^{f,a}(z, \mathbf{X}_t, A_t) = \Big(1 - d_j^a\big(z, \mathbf{X}_t, A_t\big)\Big)\mathbf{V}_j^a(z, \mathbf{X}_t, A_t)$$

where $\pi_j^a(z, \mathbf{X}_t, A_t) \equiv y^j(z, x_t^j, A_t) - w_j^a(z, \mathbf{X}_t, A_t) - oc_j$ denotes the firm's net profit. The parameter oc_j represents a sector-specific operating cost of production, which is essential for generating endogenous layoffs. We further assume that firms are subject to a non-negative periodic profit constraint:

$$\pi_j^a(z, \mathbf{X}_t, A_t) \geq 0$$

This restriction captures a form of cash flow or liquidity constraint that firms may face, which prevents them from maintaining matches that yield persistent losses. Match output is defined as:

$$y^j(z, x_t^j, A_t) = \Phi^j \times e^{A_t} \times x_t^j \times z$$

where Φ^j denotes a sector-specific productivity scale.

3.3.3 Wage determination

Firms and workers split the generated output according to a fixed *piece-rate* rule, governed by the parameter $\zeta \in (0, 1)$:

$$\begin{aligned} w_j^a(z, \mathbf{X}_t, A_t) &= (1-\zeta) \times y^j(z, x_t^j, A_t) \\ \pi_j^a(z, \mathbf{X}_t, A_t) &= y^j(z, x_t^j, A_t) - w_j^a(z, \mathbf{X}_t, A_t) - oc_j = \zeta \times y^j(z, x_t^j, A_t) - oc_j \end{aligned}$$

Under this rule, labor earnings and firm profits depend on (i) match-specific productivity, (ii) HC in the corresponding sector, and (iii) the aggregate TFP shock. By construction, they are unaffected by workers' age or their HC in other sectors.

The piece-rate rule implies that firms compensate workers based on their current match-specific productivity. Specifically, our wage rule posits that skills not utilized in the current sector are largely inconsequential for labor compensation. The degree to which wages reflect experience unrelated to a worker's current role depends on the cross-sectoral transferability of those skills.

assumption allows workers to voluntarily separate from their current match and immediately search for a new position within the same period. Furthermore, the exogenous arrival of new productivity shocks captures the potential for improved match quality. These two mechanisms account for OTJ movements in an implicit yet comprehensive manner.

Our wage specification is consistent with empirical evidence suggesting limited skill transferability across sectors (e.g., Kambourov and Manovskii, 2009b; Gathmann and Schönberg, 2010; Fujita, 2018; Baley et al., 2022).

3.3.4 Job separation

At the beginning of each period, job separation may occur due to voluntary quits, endogenous layoffs, exogenous separations, or retirement. Specifically, the separation indicator function $d_j^a(z, \mathbf{X}_t, A_t)$ can be written by:

$$d_j^a(z, \mathbf{X}_t, A_t) = \begin{cases} s & \text{if} \quad \pi_j^a(z, \mathbf{X_t}, A_t) \geq 0 \quad \textit{and} \quad \mathbf{W}_j^a(z, \mathbf{X}_t, A_t) \geq \mathbf{R}^a(\mathbf{X}_t, A_t) \\ 1 & \text{if} \quad \text{Otherwise} \quad \text{or} \quad a \geq T+1 \end{cases}$$

Workers may voluntarily quit their current jobs if they expect higher returns from job searching than from maintaining the current match, i.e., $\mathbf{R}^a(\mathbf{X}_t, A_t) > \mathbf{W}_j^a(z, \mathbf{X}_t, A_t)$. Similarly, firms terminate the match if current net profits become negative [6]. Otherwise, the match is subject to exogenous separation with probability s. The above condition determines the separation threshold $z_s^a(\mathbf{X}_t, A_t)$ accordingly:

$$z_s^a(\mathbf{X}_t, A_t) = \min\{z \in [0,1] \mid \pi_j^a(z, \mathbf{X_t}, A_t) \geq 0 \quad \textit{and} \quad \mathbf{W}_j^a(z, \mathbf{X}_t, A_t) \geq \mathbf{R}^a(\mathbf{X}_t, A_t)\}$$

All else being equal, the firm's match surplus increases with the worker's sector-specific skill, x_t^j, as the match becomes more productive. In contrast, it declines with age (as the remaining job tenure shortens) and with higher skills in other sectors, as workers with stronger outside options are more likely to quit. Consequently, the expected duration of a match decreases with both age and skill levels in other sectors.

In the model, older workers tend to possess higher skills in a specific sector due to endogenous skill accumulation in a primary sector as well as the depreciation of unused human capital (HC). Consequently, they typically exhibit lower job separation rates than younger workers. However, this pattern is not trivial, as the match surplus does not monotonically increase with age or experience. Specifically, the remaining job tenure shortens as workers age, which reduces the match value. Thus, firms do not necessarily value matches with older, seasoned workers more highly. To reproduce the empirical regularity of separation rates over the life cycle, the non-negative profit constraint plays a key role. Since younger workers typically possess lower skills due to their shorter

[6] Precisely, a firm maintains a match as long as it generates positive contemporaneous profits and a positive surplus, where the latter corresponds to the discounted sum of current and future profits. That is, firms retain matches if:

$$\min \mathbf{V}_j^a(z, \mathbf{X}_t, A_t), \pi_j^a(z, \mathbf{X}_t, A_t) \geq 0$$

Since the non-negative profit constraint is imposed for both current and future periods, the discounted sum of profits, $\mathbf{V}_j^a(z, \mathbf{X}_t, A_t)$, is necessarily non-negative. Consequently, given the period-by-period profit constraint, the positive surplus restriction becomes redundant in determining firms' layoff decisions.

work histories, their matches are more likely to be bound by this constraint when facing adverse aggregate or match-specific shocks, making them more prone to endogenous layoffs.

3.4 Labor market: Directed-search

The labor market is characterized by directed search frictions. Conditional on A_t, there are numerous sector-specific labor sub-markets segmented by (i) age, (ii) occupation type, and (iii) HC.

When there exist $v_j^a(\mathbf{X}_t, A_t)$ vacancies posted by firms and $u_j^a(\mathbf{X}_t, A_t)$ job seekers in this sub-market, the number of matches is determined by the constant-returns-to-scale matching technology $M_j^a(\mathbf{X}_t, A_t)$, and the vacancy-filling and match-finding rates are accordingly determined as follows:

$$q_j^a\big(\mathbf{X}_t, A_t\big) = M_j^a(\mathbf{X}_t, A_t)/v_j^a(\mathbf{X}_t, A_t)$$
$$p_j^a(\mathbf{X}_t, A_t) = M_j^a(\mathbf{X}_t, A_t)/u_j^a(\mathbf{X}_t, A_t)$$

The sub-market tightness can be written as $\theta_j^a(\mathbf{X}_t, A_t) = v_j^a(\mathbf{X}_t, A_t)/u_j^a(\mathbf{X}_t, A_t)$. We assume that the matching process follows the functional form in den Haan et al. (2000):

$$M_j^a(\mathbf{X}_t, A_t) = \left(\frac{(v_j^a(\mathbf{X}_t, A_t))^\gamma (u_j^a(\mathbf{X}_t, A_t))^\gamma}{(v_j^a(\mathbf{X}_t, A_t))^\gamma + (u_j^a(\mathbf{X}_t, A_t))^\gamma} \right)^{\frac{1}{\gamma}}$$

Each sub-market is cleared by the free-entry condition (with complementary slackness):

$$\kappa \geq q_j^a\big(\mathbf{X}_t, A_t\big) E_z \Big[\mathbf{V}_j^a(z, \mathbf{X}_t, A_t) | z \geq z_h^a(\mathbf{X}_t, A_t) \Big]$$

where $z_h^a(\mathbf{X}_t, A_t)$ denotes the hiring threshold, which can be written as:

$$z_h^a(\mathbf{X}_t, A_t) = \min\{z \in [0,1] \mid \pi_j^a(z, \mathbf{X_t}, A_t) \geq 0 \quad \textit{and} \quad \mathbf{W}_j^a(z, \mathbf{X}_t, A_t) \geq \mathbf{U}^a(\mathbf{X}_t, A_t)\}$$

As the above expression suggests, not all matches proceed to production. When an employer and an employee meet, they draw a match-specific productivity level. If the realized productivity is too low, the match is immediately dissolved before production takes place, with the worker returning to unemployment and the firm earning no surplus. Notably, given the possibility of voluntary quits and the absence of disutility from working, the worker's participation condition, $\mathbf{W}_j^a(z, \mathbf{X}_t, A_t) \geq \mathbf{U}^a(\mathbf{X}_t, A_t)$, becomes irrelevant in practice. That is, workers always prefer to maintain a match for at least one period once it is formed. In contrast, firms may immediately dissolve a match if the realized productivity is not high enough to cover operating costs. Hence, the hiring productivity threshold is determined solely by the firms' non-negative profit constraint.

We close this section by discussing the advantages and limitations of the directed search approach to labor market frictions. As documented in Menzio and Shi (2011), segmenting the labor market into myriad sub-markets, combined with firms' free-entry conditions, yields *block recursiv-*

ity, where aggregate distributions do not directly affect agents' decision-making. This property enables the model to incorporate rich heterogeneity among both workers and firms and to analyze non-stationary structural transition dynamics without losing tractability. Nonetheless, it should be acknowledged that the block-recursive structure inherently rules out certain labor market interactions in general equilibrium (e.g., labor demand spillovers across age groups) as well as broader distributional feedback mechanisms (e.g., demand-side effects in product markets associated with a shrinking population). This methodological trade-off is common in models with search frictions, regardless of whether one adopts random search frameworks with tractable decision rules (Lise and Robin, 2017) or the directed search approach used here. Despite these limitations, the directed search approach is particularly advantageous for incorporating demographic aging into a structural analysis of labor market dynamics within a tractable setting. Our quantitative analysis focuses on the core mechanism of labor force composition effects driven by population aging, while leaving general equilibrium interactions across labor markets beyond our scope. As discussed earlier, the effects of these distributional channels remain empirically ambiguous, as does their quantitative impact at the aggregate level. Therefore, this study centers on the direct channels through which demographic aging affects aggregate labor market dynamics.

4 Quantitative analysis

4.1 Parameterization

The time period is a quarter. Individuals live for 160 periods ($T = 160$), which is equivalent to a 40-year working life. For expositional convenience, we refer to agents as entering the labor market at age 20 and exiting at age 60. Quantitative analysis considers a two-sector economy: one corresponds to manual occupations (manual routine and manual non-routine), and the other to cognitive occupations (cognitive routine and cognitive non-routine). Table 2 documents the occupation classification. Along with its significant numerical convenience, a two-sector framework based on a broad sectoral definition aligns well with our model environment, which postulates sector-specific and non-transferable human capital. Table 3 summarizes the parameter values, which are either externally calibrated or internally estimated.

4.1.1 External calibration

Consistent with the quarterly time unit, we set the time discount rate at 0.99, which corresponds to an annual interest rate of 4 percent. Home production (b) is set to zero. Hence, regardless of sector, individual skill levels, match productivity, or aggregate conditions, labor compensation is always no smaller than the earnings received while unemployed. Therefore, all unemployment is involuntary. The matching function elasticity γ is set to 0.5, which falls within the estimation range in Petrongolo and Pissarides (2001). The piece-rate ζ is set at 0.35 so that the labor income share accounts for 65 percent of aggregate output. Following the estimates in Kambourov and

Table 2: Task-based occupation classification

Task	Major Occupation Group	Occupation code
Cognitive Non-Routine	Management, business, and financial occupations	0010 - 0950
	Professional and related occupations	1000 - 3540
Manual Non-Routine	Service occupations	3600 - 4650
Cognitive Routine	Sales and related occupations	4700 - 4965
	Office and administrative support occupations	5000 - 5940
Manual Routine	Farming, fishing, and forestry occupations	6000 - 6130
	Construction and extraction occupations	6200 - 6940
	Installation, maintenance, and repair occupations	7000 - 7630
	Production occupations	7700 - 8965
	Transportation and material moving occupations	9000 - 9750
N/A	Armed Forces	9840

Manovskii (2009a), we set the quarterly human capital depreciation rate during unemployment and the growth rate while employed to 0.015 and 0.006, respectively. These values fall within the empirical range of related estimates reported in other studies (e.g., Topel, 1991; Dustmann and Meghir, 2005; Pavan, 2011; Buhai et al., 2014; Jung and Kuhn, 2019). The productivity scale of the manual sector is normalized to unity. The exogenous quarterly job destruction rate s is set at 1.25 percent, indicating that 5 percent of total employment is dissolved exogenously on an annual basis. Because the model features endogenous separations, this exogenous rate represents a lower bound for the gross job separation rate. The autoregressive process of the TFP shock is discretized into a three-state Markov process using the Rouwenhorst method. We calibrate the autocorrelation of the TFP shock to 0.9, following the standard calibration in the Real Business Cycle literature. The standard deviation of the shock is set to 0.1 so that a one-standard-deviation negative TFP shock increases the aggregate unemployment rate by roughly 5 percentage points, comparable to the rise observed at the onset of the Great Recession.

4.1.2 Parameter estimation

The remaining 16 parameters are estimated to match 18 data moments using the simulated method of moments (SMM). The estimation strategy proceeds as follows. We first compute the average age-dependent labor market statistics based on CPS data from the first quarter of 2000 to the fourth quarter of 2015 and then estimate the parameters that minimize the discrepancy between model-generated and empirical moments. In line with empirical evidence, the model economy classifies individuals into three age groups: young ($a \in [1, 40]$), middle-aged ($a \in [41, 120]$), and old ($a \in [121, 160]$) [7]. The targeted moments include (by age group) the unemployment rate, the Employment to Unemployment (E-to-U) rate, the Unemployment to Employment (U-to-E) rate, the sector transition rate, the share of cognitive occupations in total employment, and the median

[7] These correspond to real ages of 20 to 30 for the young, 30 to 50 for middle-aged, and above 50 for older workers.

Table 3: Parameter calibration

Parameter	Value	Description
External Calibration		
β	0.99	Time discount factor
b	0	Home production
γ	0.50	Matching function elasticity
ζ	0.35	Piece-rate in wage determination
s	0.0125	Exogenous job separation rate
δ_u	0.015	HC depreciation while unemployed
ρ	0.006	Baseline HC growth while employed
Φ_M	1.000	Manual sector productivity scale
ρ_A	0.90	TFP persistence
σ_A	0.10	TFP innovation standard deviation
ψ	0	Population growth rate
SMM Estimation		
Φ_C	1.5039	Cognitive sector productivity scale
oc_C	0.0897	Operating cost in cognitive sector
oc_M	0	Operating cost in manual sector
κ	0.2339	Vacancy posting cost
δ_e	2.06×10^{-4}	Depreciation of unused HC while employed
ρ_x	0.9223	Concavity of HC accumulation
λ_z	0.3785	Poisson arrival rate of match-specific shocks
z_1	3.9659	Match productivity parameter 1
z_2	2.3264	Match productivity parameter 2
β_1^M	4.9725	Manual skill distribution parameter 1
β_2^M	2.9820	Manual skill distribution parameter 2
β_1^C	4.5535	Cognitive skill distribution parameter 1
β_2^C	3.5132	Cognitive skill distribution parameter 2
ρ_{HC}	0.7494	Correlation between initial HC
σ_P	7.9453	Std. dev. of preference shock
λ_P	16.3541	Age-slope of preference shock

wage ratio between sectors. To capture the distributional features of human capital, particularly its initial heterogeneity, we also include moments related to the wage distribution of the young cohort. Because the monthly CPS does not contain individual earnings information, we use the CPS Annual Social and Economic Supplement (CPS-ASEC), conducted each March for a subsample of

CPS respondents [8], to obtain the wage-related moments.

It is worth noting that the E-to-U rate differs from the job separation rate. The latter measures the fraction of individuals who were employed in the previous period but lost their jobs at the beginning of the current period, whereas the E-to-U rate further requires that they fail to find new employment within the same period. The U-to-E rate also differs from the match-finding rate because some workers who are matched in the labor market may undergo immediate match dissolution if the realized match productivity does not reach the hiring threshold. The sector stay rate measures the share of newly employed individuals who remain in the same occupation among all newly employed individuals. For example, the cognitive sector stay rate is calculated as the number of newly employed individuals moving from cognitive to cognitive occupations divided by the total number of newly employed individuals who previously held cognitive occupations before becoming unemployed.

The estimation is designed to match the steady-state labor market moments. To this end, we turn off the aggregate TFP shock during the estimation process. The TFP shock is allowed for the impulse response analysis presented later. In each simulation, the model runs for 260 periods, with the first 160 periods discarded as burn-in. The model moments are computed as the average values of the targeted moments over the remaining periods. The baseline estimation assumes a constant population size ($\psi = 0$), which we refer to as a square demographic structure where all cohorts are of equal size. The population is set to 10,000 per cohort, yielding a total population of 1.6 million. We find that the model-generated moments are robust to sample size variations, remaining largely unchanged once the cohort size exceeds 5,000. The aging counterfactual allows the cohort size to decline over time, causing the demographic structure to take on an inverted-triangular shape and thereby increasing the relative weight of older workers in the aggregate labor force.

Tables 3 and 4 report the estimation results and the goodness-of-fit to the targeted moments, respectively. Some remarks are in order. First, the cognitive sector productivity scale (Φ_C) is approximately 50 percent higher compared to the manual sector. Given the initial HC distribution, this parameter influences the employment share of cognitive occupations as well as the wage inequality between sectors. The operating cost in the manual sector (oc_M) is estimated to be zero, whereas that in the cognitive sector (oc_C) is strictly positive. This implies that all endogenous separations in the manual sector arise from voluntary quits by workers. Moreover, the positive operating cost indicates that firms in the cognitive sector impose a minimum hiring skill threshold, whereas individuals can, in principle, find employment in the manual sector even with relatively low human capital in that sector. The estimated operating cost implies that individuals of any age are effectively excluded from employment opportunities in the cognitive sector if they lack a certain skill level. The minimum skill levels required in cognitive occupations align with empirical evidence indicating that more than half of workers in cognitive occupations hold a college degree, whereas less than one-fifth of workers in manual occupations are college graduates.

[8]Similarly, we restrict the sample to full-time workers employed in the private sector and apply the CPS-ASEC individual weights (ASECWT).

Table 4: Target Moments: Data vs. Model

Moment	**Data**	**Model**
Labor market flow rates by age group		
Unemployment rate — Young	0.1033	0.0991
Unemployment rate — Middle	0.0557	0.0456
Unemployment rate — Old	0.0478	0.0578
U-to-E rate — Young	0.2687	0.3089
U-to-E rate — Middle	0.2605	0.2865
U-to-E rate — Old	0.2228	0.1952
E-to-U rate — Young	0.0239	0.0167
E-to-U rate — Middle	0.0136	0.0137
E-to-U rate — Old	0.0105	0.0136
Occupation stay rate — Young	0.7301	0.7397
Occupation stay rate — Middle	0.8147	0.8712
Occupation stay rate — Old	0.8403	0.8422
Cognitive employment share	0.6084	0.6350
Wage distribution moments		
Median wage ratio (Cognitive / Manual)	1.6154	1.8682
Manual sector, Young: P_{25}/P_{50}	0.7058	0.7199
Manual sector, Young: P_{75}/P_{50}	1.3971	1.3133
Cognitive sector, Young: P_{25}/P_{50}	0.6986	0.7816
Cognitive sector, Young: P_{75}/P_{50}	1.4341	1.2341

The estimation indicates that the depreciation rate of unused skills while employed (δ_e) is nearly zero, implying that skill loss is largely offset by the accumulation of general human capital. The estimate for ρ_x, which governs the concavity of human capital (HC) accumulation, suggests that skill growth during employment is almost linear. The Poisson arrival rate of match-specific productivity shocks implies that a given match typically lasts about 2.6 quarters. The estimated parameters for match productivity (z) and the initial HC distributions indicate that the average match productivity is 0.63, while the average skill endowments in the manual and cognitive sectors are 0.63 and 0.56, respectively. Finally, the estimation suggests a positive correlation between the initial sector-specific HC [9].

[9]If initial sectoral HC is negatively correlated across sectors, individuals are born with a strong comparative advantage in a specific sector. Consequently, the model struggles to replicate empirical moments related to occupational transitions and job-finding rates. While exogenous preference shocks can induce individuals to search for jobs in sectors where they lack a comparative advantage, a negative initial HC correlation combined with endogenous skill depreciation results in a low job-finding probability in those sectors, thereby generating excessively low U-to-E and sectoral transition rates.

Sector-choice preference shocks are essential for generating realistic sectoral transition dynamics in the steady state. In the absence of exogenous aggregate or sector-specific shocks, the steady-state economy abstracts from disturbances that could trigger temporary or persistent reversals in occupational preferences. Consequently, without these preference shocks, sector preference would be strictly stylized, as individuals would simply prefer the sector in which they hold a comparative advantage. Our estimation indicates that the standard deviation of these shocks decreases with age. This greater dispersion of idiosyncratic preferences among younger individuals not only mitigates the welfare scale effects inherent in the life-cycle framework but also suggests that early-career occupational choices are more influenced by non-market factors, independent of labor market conditions and idiosyncratic human capital. As observed, the model successfully replicates the age profile of sectoral transition rates. Importantly, this is not merely a result of the decreasing dispersion in preference shocks with age. Job-finding probabilities tend to decline with age and with lower skill levels in a given sector. Therefore, while preference shocks primarily induce individuals to seek employment in sectors where they do not have a comparative advantage, younger workers are more able to convert their job searches into employment at higher rates, leading to more sectoral mobility.

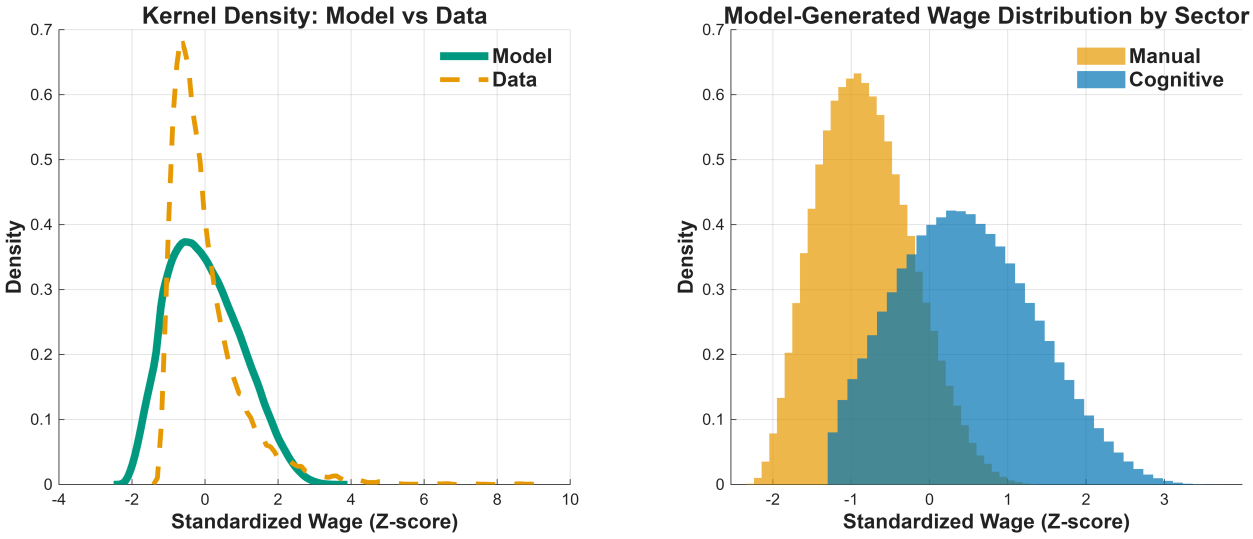


Figure 6: Wage Distribution: Model vs. Data

The model shows some limitations in reproducing the observed wage distribution. The left panel in Figure 6 presents the kernel density of the standardized wage distributions from the model and the data, respectively, while the right panel decomposes the model-generated wage distribution by sectors[10]. We observe that the empirical wage distribution exhibits much starker right skewness than the model-generated one. The simulated wage distribution has a skewness of 0.36 and a Gini coefficient of 0.25, whereas the corresponding values in the data are 2.3 and 0.38. This discrepancy may arise from the stylized structure of wage determination. We assume linear

[10]Wages are standardized using the Z-score formula to facilitate comparison, and the top and bottom 1 percent of wages in the data are trimmed to minimize the influence of outliers

wage growth with respect to skills, whereas the empirical wage distribution exhibits a long right tail that likely reflects convex returns to skills in certain occupations, a phenomenon commonly referred to as a *superstar effect* (e.g., Rosen, 1981; Koenig, 2023).

4.2 Exploring model mechanisms

In this section, we examine the policy functions to highlight the mechanisms generating heterogeneous labor market dynamics across different age groups. Our main finding is that both aging and human capital accumulation create strong incentives either to remain in or to transition between sectors. Sectoral characteristics, such as differences in productivity and hiring standards, interact in non-trivial ways, leading to a dynamic selection process in which individuals optimally choose sectors conditional on their idiosyncratic human capital and prevailing labor market conditions. The resulting endogenous sorting and human capital evolution, in turn, shape workers' life-cycle mobility decisions.

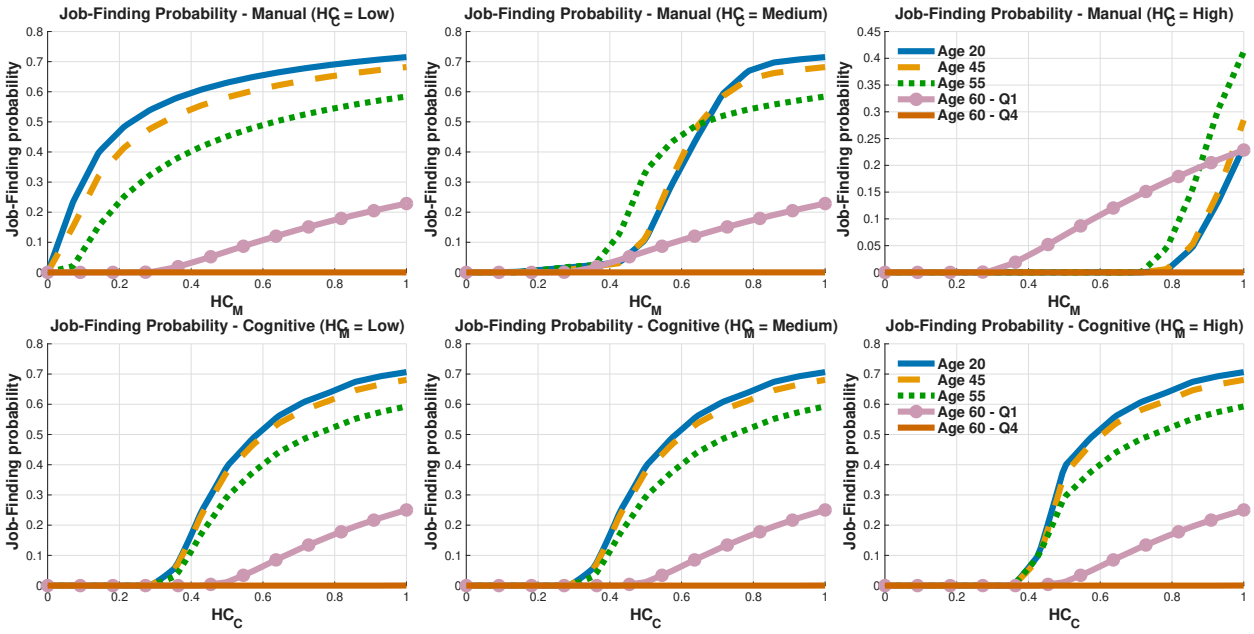


Figure 7: Job-Finding Probability of Heterogeneous Individuals

Figure 7 illustrates job-finding probabilities, conditional on the steady-state level of TFP. The upper panels show probabilities in the manual sector for workers with low, medium, and high skill levels in the cognitive sector (set to 0.25, 0.5, and 0.75, respectively). The lower panels present the corresponding probabilities for the cognitive sector [11]. Labor demand for heterogeneous workers exhibits several key patterns. The employer surplus from employment relationships increases with both worker skill and expected match duration. While a longer remaining career horizon makes younger workers attractive to firms, their stronger incentive for job turnover, driven by the

[11] See the Appendix for complementary figures on the firm's expected match surplus, hiring match-productivity thresholds, and separation match-productivity thresholds.

greater potential gains from searching for better matches, also shortens expected match durations. These countervailing forces result in non-monotonic variations in job-finding probabilities across age groups. The age penalty, a decline in the job-finding probability as workers age, remains modest throughout most of the working life but intensifies sharply after age 55, with job-finding probabilities approaching zero near retirement regardless of skill level.

Interestingly, job-finding probabilities in the manual sector exhibit substantial cross-sector skill dependencies. For instance, a 20-year-old worker with high manual-sector human capital faces a job-finding probability of 0.7 when their cognitive skills are low (northwest panel of Figure 7), compared to only 0.2 when their cognitive skills are high (northeast panel). This pattern reflects how cognitive-sector skill levels influence the quit incentives of workers employed in the manual sector. Higher cognitive skills stimulate quit incentives in the manual sector for cross-sector job turnover. This, in turn, reduces expected match durations and, consequently, employer surplus in the manual sector. This cross-sector interdependence becomes even more pronounced during recessions. Since elevated hiring thresholds in the cognitive sector weaken the quit incentives of manual-sector workers, particularly those with moderate cognitive skills, firms may anticipate longer match durations for these workers, which potentially offsets the cyclical decline in manual-sector labor demand (see Figure A3). Overall, job-finding probabilities decline significantly when a match fails to generate a surplus exceeding vacancy posting costs, which could arise when productivity is exceptionally low (due to low human capital) or when workers have short expected match durations (due to short remaining tenures or strong quit incentives).

In contrast, cognitive-sector job-finding probabilities remain largely independent of manual-sector skills (Figure 7, bottom panels). Both higher productivity and superior long-run earnings prospects in cognitive work confine the incentives for sectoral transitions, even among workers with high manual skills. While within-sector turnover incentives among younger workers mitigate age penalties, the dominance of shortened remaining tenures after age 55 leads to sharp declines in job-finding probabilities near retirement. Furthermore, the cognitive sector requires minimum skill thresholds for employment across all age groups. Consequently, we observe very low job-finding rates at low HC levels, with these thresholds rising with age. As the expected match surplus declines with age, higher initial productivity is required to justify initiating a match.

As noted above, labor market dynamics hinge critically on the distribution of human capital. Figure 8 depicts the cross-sectional distribution of initial human capital and its subsequent evolution. The figure highlights endogenous HC evolution and the consequent occupational sorting: workers in the cognitive sector progressively shift northwest relative to the initial distribution, while those in the manual sector shift southeast, reflecting sector-specific skill accumulation and depreciation and the formation of dynamic comparative skill advantages.

Younger workers tend to possess lower skill specialization in a particular sector, making them more likely to be bound by firms' non-negative profit constraints. Combined with their stronger incentives for voluntary quits in search of better employment opportunities, this accounts for the higher separation rates among young workers. In contrast, senior workers possess significant skill

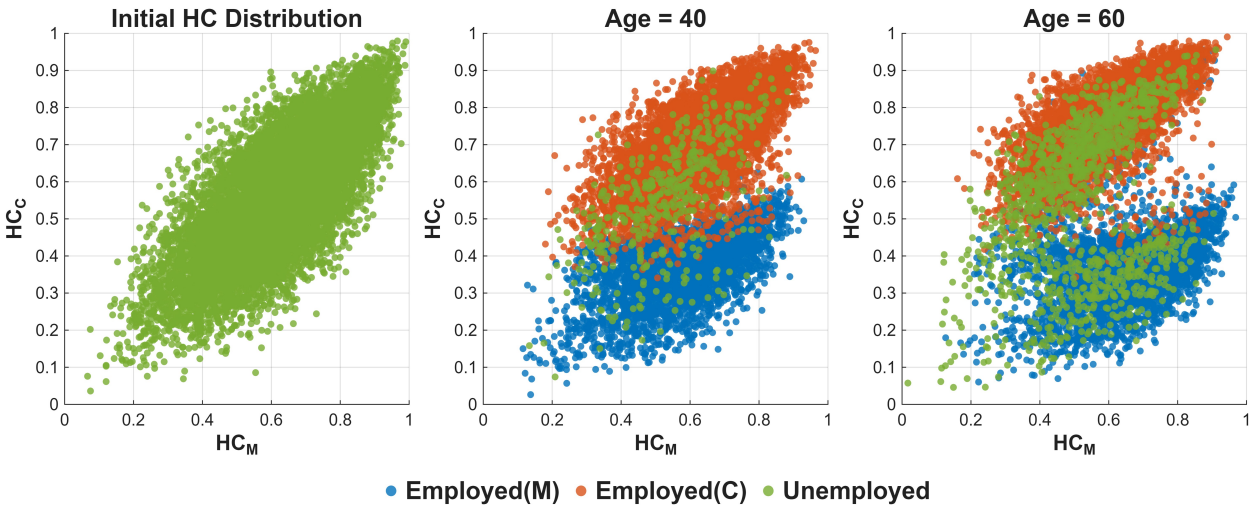


Figure 8: Human Capital Distribution

advantages in specific sectors, which shield them from layoffs during adverse productivity or labor demand shocks. This high specialization, in principle, raises their job-finding probabilities within their specialized sector, not only due to higher human capital but also because they exhibit fewer incentives to quit. However, this positive labor demand effect is offset by direct age penalties in hiring, which yields non-trivial job-finding dynamics among senior workers. Finally, skill specialization can result in a lock-in effect within a particular sector. By increasing the opportunity cost of sectoral transitions and reducing labor demand in non-primary sectors, it leads to rigid sectoral adjustments, particularly among older workers. This phenomenon suggests that as workers accumulate sector-specific human capital, the barriers to sectoral reallocation rise endogenously, rendering the labor market less responsive to exogenous disturbances.

4.3 Numerical Exploration of Labor Market Dynamics

We now investigate how the labor market responds to temporary and permanent economic disturbances, both with and without demographic aging. For the latter, we assume that the population declines by 0.5 percent per quarter (Ψ=-0.005), which is consistent with an increase in the fraction of workers above 50 years old from approximately 25 percent in 2005 to 28 percent in 2020 [12]. In the model, the share of the old cohort rises from 25 percent to 33 percent in the aging scenario over one generation (40 years). The simulation proceeds in two steps. First, we simulate the model for 160 periods without aging to generate a baseline cross-sectional distribution for 1.6 million indi-

[12]Given a constant population growth rate and assuming that this phase lasts for at least one generation (160 quarters), the fraction of the old cohort can be calculated as $\frac{1-(1+\psi)^{40}}{1-(1+\psi)^{160}}$. In the baseline case without aging, the old cohort represents about 25 percent of the labor force. In the aging scenario with a constant population decline rate of Ψ=-0.005, the share gradually increases and converges to about 33 percent after 40 years. It is worth noting that although the total population continues to decline, the relative shares of each age group converge to a stable composition after one generation under a constant population growth rate. Consequently, the steady-state values of aggregate labor market variables remain unchanged thereafter, despite the ongoing population decline.

viduals. In the second stage, the economy is simulated for an additional 160 periods during which aging progresses. Temporary or permanent shocks are introduced at period 100, when the share of the older cohort reaches approximately 28 percent, aligning with the recent share of the older workforce in the United States. All economic disturbances are assumed to be MIT-type shocks. The entire simulation is repeated 100 times, and our analysis focuses on the mean responses across these iterations.

4.3.1 Aging and Labor Market Transitions

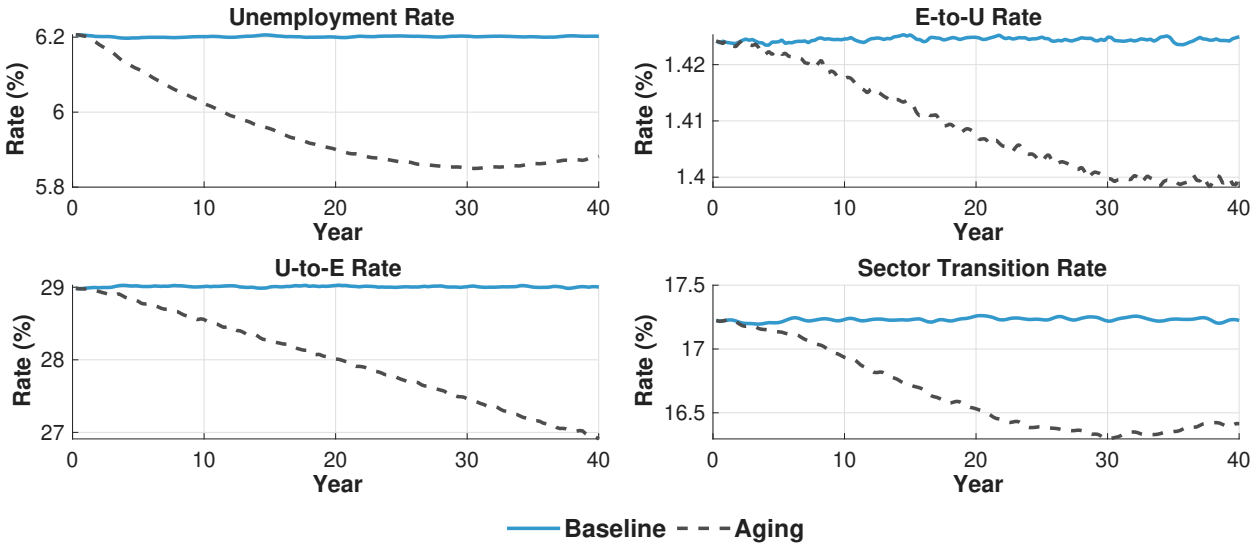


Figure 9: Long-run Changes in the Labor Market due to Aging

Figure 9 displays the long-run changes in the labor market as it tilts toward older generations. Consistent with empirical evidence, the unemployment rate declines as the share of the older cohort increases. The older generation exhibits a lower E-to-U rate due to their skill accumulation. On the other hand, they also show a lower U-to-E rate once unemployed, which can be attributed to the age penalty arising from shorter remaining job tenure. The old generation also shows reduced sectoral transition rates, reflecting their strong skill advantage in a particular sector, as well as the reduced labor demand toward them. As a result, the aggregate E-to-U, U-to-E, and sectoral reallocation rates all decline as aging progresses. Figure 10 exhibits the impulse response dynamics to a one-standard-deviation negative TFP shock, with Figure A7 in the Appendix providing the impulse responses of additional variables. We observe that the aging economy exhibits a pre-shock unemployment rate approximately 0.4 percentage points lower than the baseline and remains lower throughout the recession. However, when expressed as log deviations from steady states, the aging economy exhibits more amplified fluctuations, albeit the magnitude remains modest given the calibrated pace of aging. These quantitative dynamics closely resemble the counterfactual exercise of the Great Recession presented in Figure 5.

While the magnitude of the aging composition effect appears limited, the result provides a new

interpretation of the secular decline in U.S. labor market dynamism (Davis and Haltiwanger, 2014; Molloy et al., 2016; Fujita, 2018): While aging leads to reduced labor market fluidity characterized by lower separation, job-finding, and occupational transition rates in levels, it simultaneously results in increased cyclical volatility. While the aggregate composition effect remains modest at the current pace of U.S. aging, population aging has qualitatively important implications for macroeconomic adjustment mechanisms over the business cycle. Furthermore, as the aging process intensifies, these shifts could exert a considerable impact on the resilience of the economy to business cycle shocks.

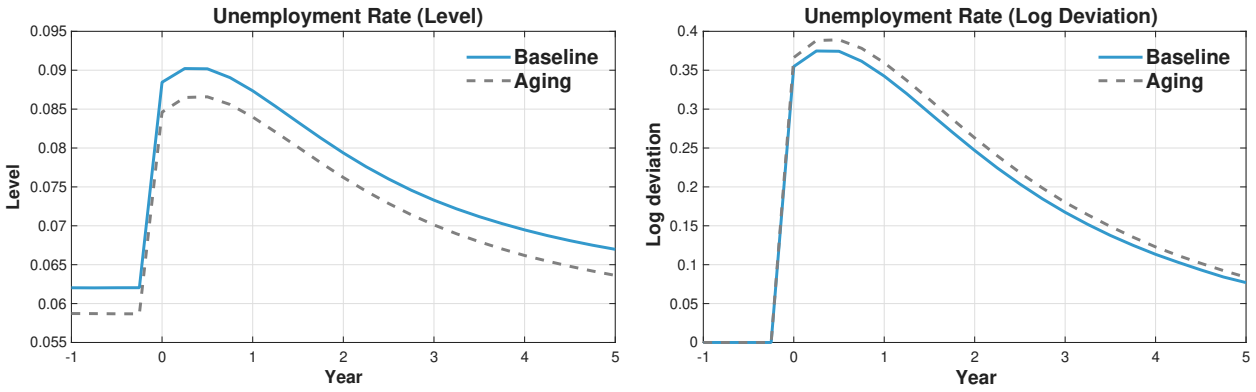


Figure 10: Impulse-Response of Unemployment to a Negative TFP shock

Figure 11 displays the labor market dynamics of different age cohorts in the baseline economy. The blue solid line indicates the dynamics of the young cohort, whereas the red dashed and yellow dotted lines correspond to the middle-aged and old cohorts, respectively. Consistent with empricial evidence from the dynamic factor model analysis, the fluctuations in E-to-U and U-to-E rates are more dampened for the young cohort than for older groups. A negative TFP shock reduces firms' match surplus and attenuates labor demand across all sectors, leading to a decline in job-finding probabilities. Nonetheless, the shock exerts a disproportionately stronger effect on the cognitive sector due to its higher operating costs, which triggers the destruction of marginally profitable firms in this sector. This is reflected in the declining share of cognitive occupations across all age groups in response to the shock, alongside an increase in transitions from the cognitive to the manual sector. Conversely, as workers have weaker incentives to quit voluntarily during recessions, the separation rate in the manual sector decreases due to reduced voluntary quits for cross-sector job turnover, while it increases in the cognitive sector due to rising layoffs by firms (see Figure A7). Some displaced workers from the cognitive sector transition to the manual sector, which partially absorbs the surge in unemployment. Older workers, however, exhibit greater rigidity in occupational adjustment, particularly when moving from cognitive to manual jobs. This rigidity results in larger and more persistent deviations in their unemployment rates, thereby amplifying aggregate fluctuations in the aging economy. In contrast, younger workers exhibit greater flexibility in sectoral reallocation, which endogenously stabilizes unemployment within this cohort.

As shown in Figure A7, although all aggregate variables exhibit clear differences in their steady-

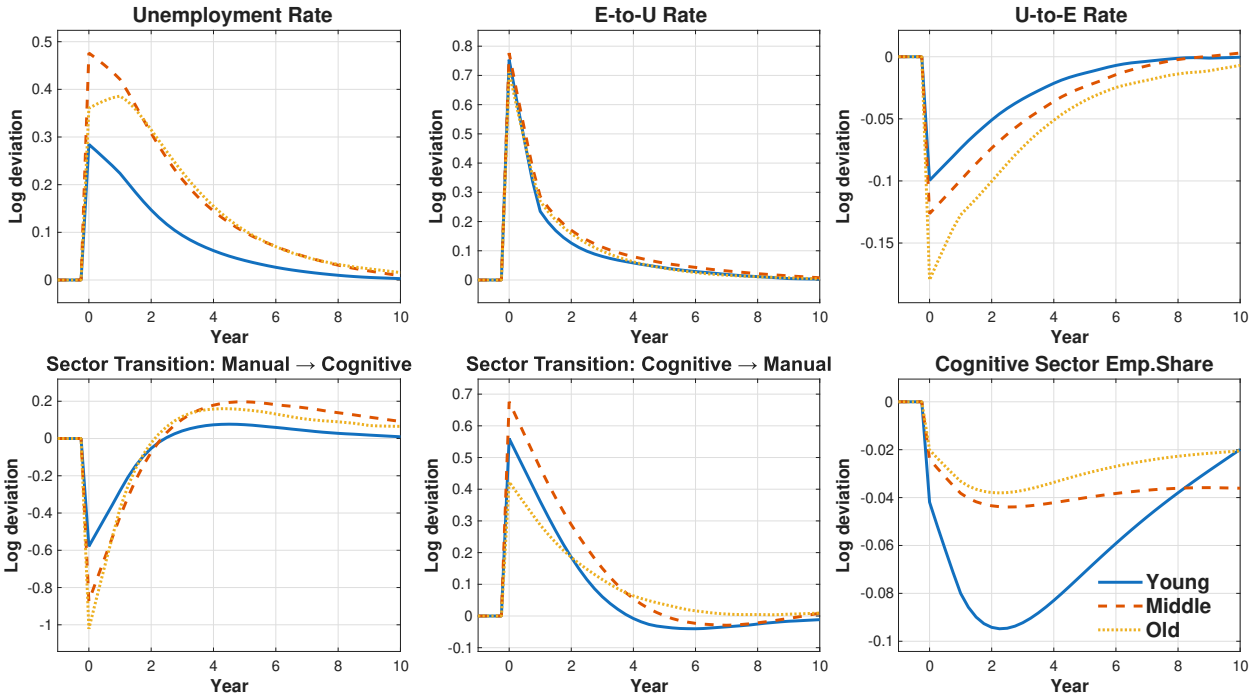


Figure 11: Impulse-Response to a Negative TFP shock by Age Groups

state levels, these disparities are nearly neutralized when expressed as log deviations from their respective steady states. We refer to this as an aging aggregation effect, where compositional changes associated with aging effectively offset the scale differences in steady states between the baseline and aging economies. It should be noted that certain occupational choices become hard-to-reverse career decisions due to the minimum skill requirements in the cognitive sector, combined with the endogenous skill evolution over time. Specifically, workers who previously held only a marginal comparative advantage in the cognitive sector may transition to the manual sector during a recession. Over time, their cognitive skills depreciate while their manual-sector skills increase. This eventually reverses their comparative advantage if manual employment persists long enough. Since these workers do not, or cannot, return to the cognitive sector later, the cognitive occupation share remains persistently below its pre-shock level even after the aggregate unemployment rate has recovered to its pre-crisis level.

4.3.2 Temporary hiring freeze

The preceding exercise shows that heterogeneous sectoral reallocation dynamics across age groups are central to the endogenous stabilizing mechanisms. To further illustrate these dynamics, we conduct thought experiments using temporary and permanent sector-specific shocks and examine the labor market adjustment dynamics in response to those shocks. In this section, we begin with temporary sector-specific labor market disturbances. Specifically, we consider scenarios in which the vacancy posting cost in one sector rises tenfold over the course of one year, increasing gradually

over four quarters before returning to its pre-shock level. This temporary increase in vacancy costs makes job creation in the corresponding sector temporarily more costly, generating a hiring freeze during the shock period and temporary sectoral labor demand shifts.

Hiring Freeze in the Cognitive Sector

When a hiring freeze occurs in the cognitive sector, the job-finding probability in that sector falls, while finding jobs in the manual sector temporarily becomes relatively easier. In particular, we observe during the hiring freeze that the cognitive-to-manual transition rate rises temporarily but falls sharply once the freeze ends. This pattern occurs because workers who temporarily moved to the manual sector during the hiring freeze voluntarily return to cognitive jobs once these jobs become available again. Interestingly, during the hiring freeze in the cognitive sector, the unemployment rate particularly rises for the older cohort while it declines for the younger groups. Furthermore, a sharp hike in unemployment is observed across all age groups immediately after the hiring freeze ends. The E-to-U rates decline for young and middle-aged workers during the freeze, and, interestingly, the U-to-E rates also appear to increase for these groups. In contrast, the old cohort shows an increase in the E-to-U rate, along with a decline in the U-to-E rate. These patterns highlight heterogeneous labor market transition incentives across age groups.

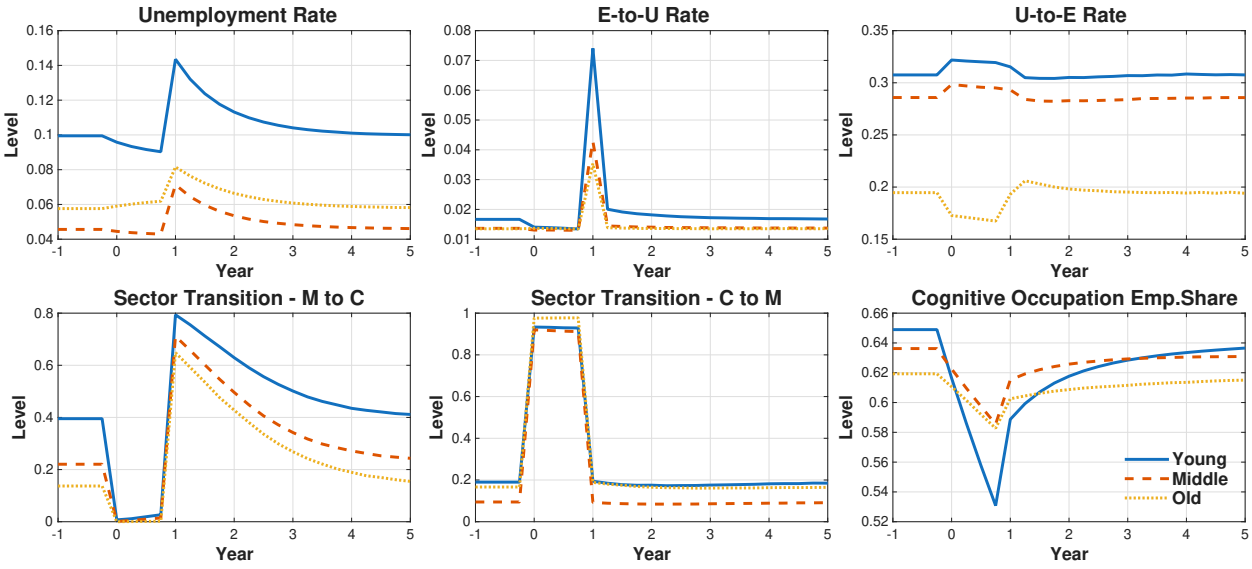


Figure 12: Hiring Freeze in the Cognitive Sector

The increases in the U-to-E rates for young and middle-aged workers arise from their flexibility in adjusting their job search direction. When cognitive-sector employment opportunities drop, young individuals who were previously seeking jobs in the cognitive sector direct their search toward manual jobs. The E-to-U and U-to-E rate dynamics underscore the flexibility of young workers in shifting from cognitive to manual occupations. Because they temporarily change their occupation, the E-to-U transition rate can even decline, as they may be separated from the cognitive

sector but immediately secure a job in the manual sector. Similarly, the U-to-E rate increases for the same reason. Consequently, the share of cognitive employment among young workers drops noticeably during the freeze but quickly returns to its steady-state level after the freeze ends. In contrast, sectoral transition is weaker for older workers, who hold a relatively stronger comparative advantage in the cognitive sector. Since their manual-sector human capital is relatively low due to skill depreciation over time, and they face lower job-finding probabilities due to their age, the old cohort exhibits a lock-in effect in the cognitive sector during the hiring freeze and experiences a pronounced decline in the U-to-E rates.

Hiring Freeze in the Manual Sector

The adjustment dynamics in response to a hiring freeze in the manual sector are notably different. In this case, unemployment rates rise across all age groups. Unlike the case of a hiring freeze in the cognitive sector, all age groups experience lower job-finding rates and an increase in unemployment. Reallocation from the manual to the cognitive sector is relatively limited because employment in the cognitive sector requires a minimum skill level. Many unemployed workers with strong comparative advantages in the manual sector do not meet this requirement and, therefore, continue searching for jobs in manual occupations. While the relative employment share of the cognitive sector appears to increase, this primarily reflects the stagnation in manual hiring rather than active reallocation toward the cognitive sector.

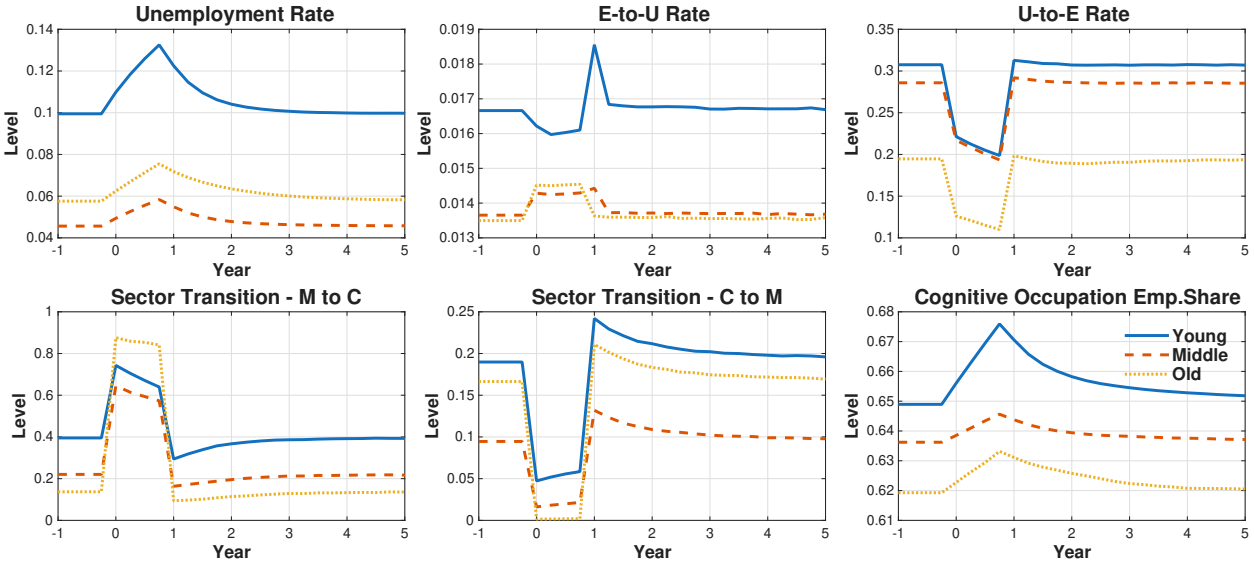


Figure 13: Hiring Freeze in the Manual Sector

During the freeze, the old and middle-aged groups exhibit higher E-to-U rates, whereas the young group shows a decline. As noted earlier, the manual sector does not feature endogenous layoffs. Namely, all separations in this sector are either exogenous or voluntary quits. Thus, the observed changes in the E-to-U rates arise from the varying reemployment rates of workers who

were either exogenously dismissed or quit voluntarily. Workers in the manual sector across all age groups have weaker incentives to leave their current jobs during the hiring freeze, as reemployment becomes more challenging. The increase in the E-to-U rate among older workers reflects the lower job-finding probabilities they face after dismissals in the manual sector, causing them to remain unemployed for longer periods. In contrast, the decrease in E-to-U rates among young workers reflects their reduced voluntary quits combined with relatively higher chances of reemployment compared to older workers.

4.3.3 Permanent Technological Change and Labor Market Transition

We now turn to labor market dynamics in response to permanent changes in production technologies. Specifically, we consider two distinct scenarios of permanent labor demand shifts driven by unexpected technological changes. The first case is Skill-Biased Technological Change (SBTC), which is formalized by a permanent 20 percent increase in the cognitive sector productivity scale factor. This shift raises the labor surplus from forming cognitive occupations, thereby increasing labor demand for these occupations and reinforcing workers' incentives to choose this type of occupation. On the other hand, we also examine the scenario in which labor demand for cognitive occupations declines, a concern that has recently gained attention with the advent of artificial intelligence technologies. To incorporate the permanent decline in labor demand for cognitive occupations, we consider a permanent 20 percent decrease in the productivity scale factor in this sector, which we refer to as Task-Displacing Technological Change (TDTC).

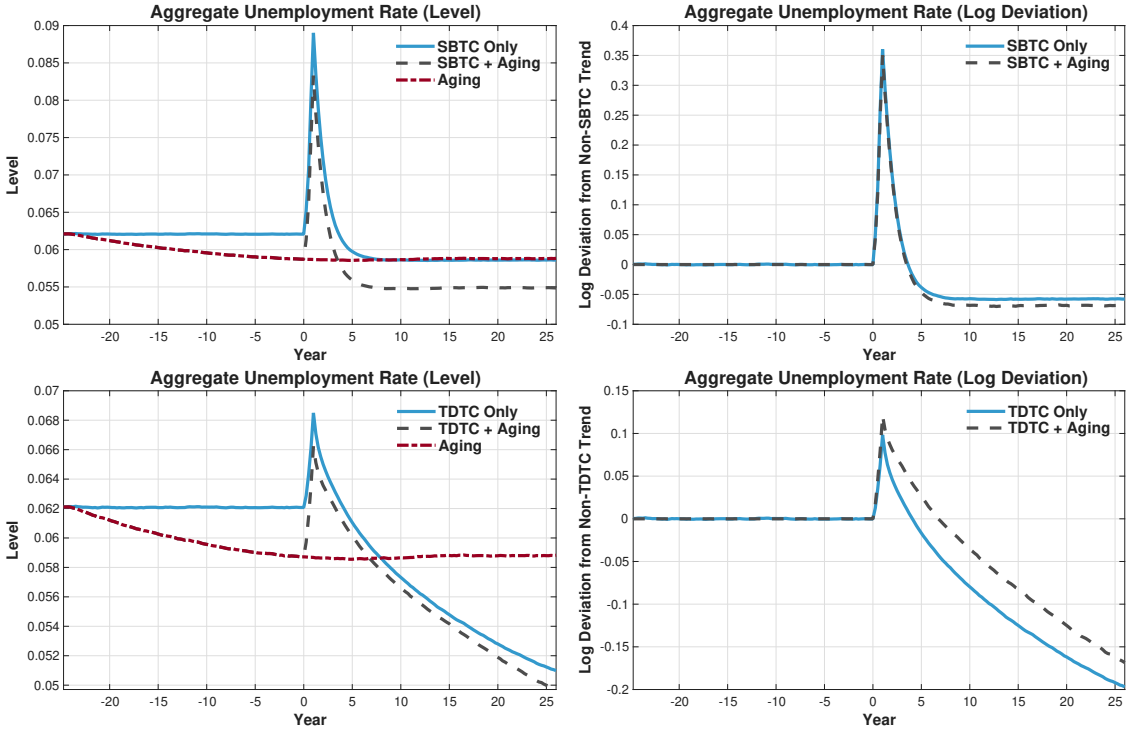


Figure 14: Structural Changes and Aggregate Unemployment Dynamics

Figure 14 displays the aggregate unemployment changes, both in levels and log points, in response to the SBTC (first row) and TDTC (second row), respectively. Both technological changes result in a decline in the unemployment rate in the long run. In the TDTC case, however, aging amplifies deviations from the non-shock trend and prolongs the transition period, whereas it makes little difference under SBTC.

SBTC and Labor Market Transitions

When SBTC occurs, unemployment initially rises but gradually declines as workers reallocate to the cognitive sector over time. The model predicts that the employment share of cognitive jobs increases by 20 percent in the long run. The aggregate unemployment rate declines because the cognitive sector exhibits higher job-finding probabilities. As shown in Figure 14, the transition brought about by SBTC is completed within a relatively short interval; the unemployment rate reaches its new steady-state level approximately five years after the shock.

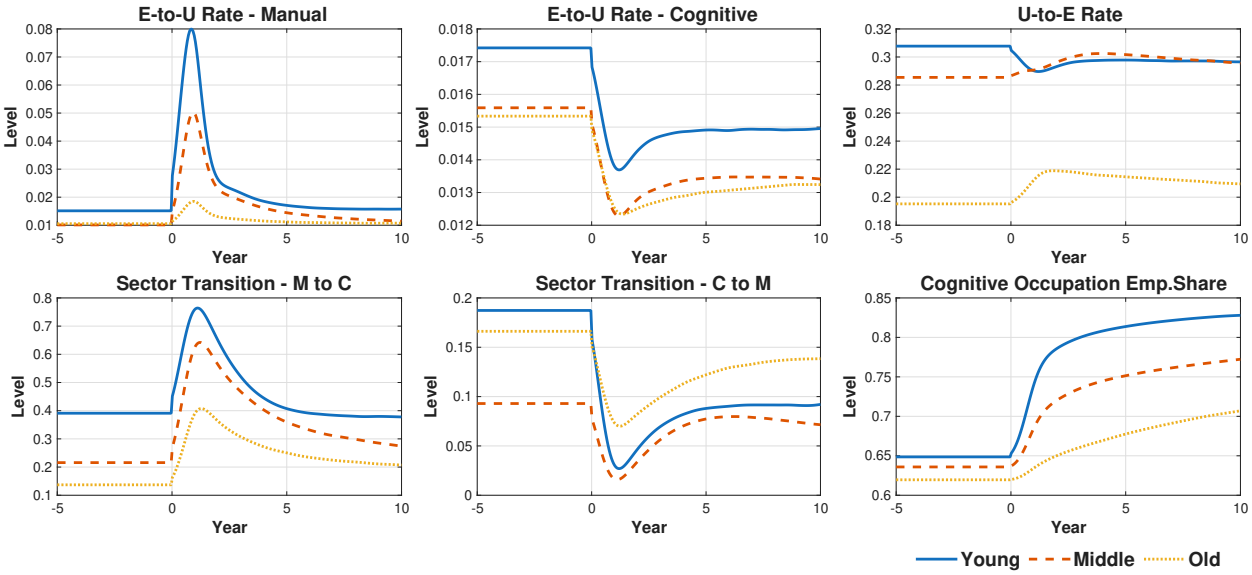


Figure 15: SBTC and Labor Market Dynamics across Age Groups

Figure 15 illustrates the dynamics. In response to the SBTC, the E-to-U rates in the manual sector increase across all age groups, as some workers find it advantageous to move to the cognitive sector. Many occupation switchers voluntarily quit their manual jobs to seek opportunities in the expanding cognitive sector. In particular, the temporary rise in the E-to-U rate among young workers reflects a surge in voluntary quits in this group as they shift their career paths toward cognitive occupations. In contrast, the E-to-U rate in the cognitive sector declines permanently because firms reduce separations and workers are less likely to quit. In contrast, the U-to-E rate exhibits an opposite pattern, decreasing for young workers but increasing for older workers. Among the young, total hiring declines as many opt for cognitive jobs despite possessing relatively low human capital in that sector. These occupational transitions effectively lower the reemployment probability for

labor market entrants, as job-finding probabilities are positively correlated with skill levels. For older workers, by contrast, the U-to-E rate rises because they are less likely to change occupations regardless of market conditions. Their shorter remaining work horizon diminishes the expected returns on switching sectors. Consequently, most job seekers in this group remain within their sector of comparative advantage. Therefore, the improved job-finding probability in the cognitive sector primarily benefits workers already attached to that sector, whereas manual workers remain less affected, leading to an overall increase in hiring rates for the older cohort.

While SBTC shifts labor demand toward the cognitive sector, labor reallocation to this sector remains constrained. As in the previous manual-sector hiring freeze exercise, only a limited share of workers can move from manual to cognitive jobs due to the required minimum skill level. Although SBTC lowers this threshold, only a small fraction of workers across all age groups effectively adjust their occupations. Consequently, the extent to which the aggregate unemployment rate deviates from its trend remains nearly identical across economies, regardless of aging.

TDTC and Labor Market Transitions

TDTC also reduces the aggregate unemployment rate in the long run, albeit through a different mechanism. Figure 16 illustrates this distinction. TDTC induces a reallocation of workers toward the manual sector. As technological change, which permanently reduces productivity in the cognitive sector, progresses, job-finding rates in the cognitive sector decline. This prompts workers to increasingly seek employment in the manual sector. This shift is reflected in the increased transition rate from cognitive to manual occupations. Consequently, the employment share of the cognitive sector steadily declines.

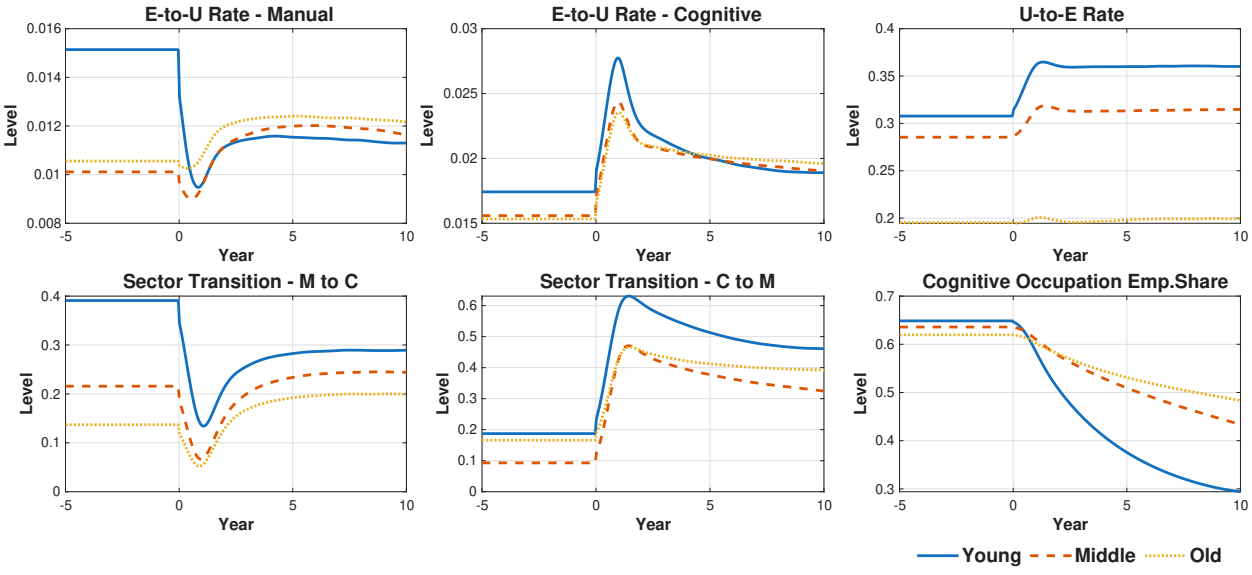


Figure 16: TDTC and Labor Market Dynamics across Age Groups

As shown in Figure 14, TDTC leads to a persistent decline in the unemployment rate that con-

tinues for more than 25 years after the structural change. This persistence highlights the lock-in effect among older workers, who are more reluctant to switch from cognitive to manual occupations. Despite the permanent decline in labor demand within the cognitive sector, older workers with accumulated human capital in that field struggle to switch occupations. This difficulty stems from the high opportunity cost of sectoral transitions, exacerbated by the lower labor demand toward them in the manual sector. Consequently, the aging economy exhibits a more pronounced and persistent deviation in the log unemployment rate from its non-TDTC trend throughout the transition phase compared with the baseline economy.

5 Policy Extension: Active Labor Market Policy

This section incorporates active labor market policies (ALMPs) into the baseline framework. ALMPs broadly encompass government programs designed to facilitate employment and improve labor market outcomes through measures such as job search assistance, vocational training, and hiring incentives. In this study, we particularly evaluate the effects of two specific policy interventions: vocational training (VT) and hiring subsidies (HS).

5.1 Incorporating ALMPs into the Model

Unemployed workers choose whether to participate in sector-specific vocational training. Those who enroll in training are unable to search for jobs during the training period, but they can improve their skills in the corresponding sector at a rate equivalent to the human capital development achievable through employment. Meanwhile, their skills in the non-trained sector depreciate due to unemployment. Formally, if an individual takes vocational training for sector i, the value function can be expressed as follows:

$$\begin{aligned}
&\mathbf{U}^a_{VT}(\mathbf{X}_t, A_t) \equiv \max_i \{\mathbf{U}^a_{VT,i}(\mathbf{X}_t, A_t)\}) \\
&\mathbf{U}^a_{VT,i}(\mathbf{X}_t, A_t) = b + \beta E_t\Big[\mathbf{\Omega}^{a+1}(\mathbf{X}'_{t+1}, A_{t+1})\Big]
\end{aligned}$$

where $\mathbf{\Omega}^a(\mathbf{X}_t, A_t) \equiv \max\Big\{\mathbf{R}^a(\mathbf{X}_t, A_t), \mathbf{U}^a_{VT}(\mathbf{X}_t, A_t)\Big\}$ and $\mathbf{U}^a_{VT,i}(\mathbf{X}_t, A_t)$ indicates the value function of an individual who participates in vocational training for the sector i. The HC of a vocational trainee for the sector i evolves as follows:

$$\mathbf{X}'_{t+1} = \begin{cases} x^i_{t+1} = \min\{(1+\rho(x^i_t))x^i_t, 1\} \\ x^j_{t+1} = \max\{0, (1-\delta^u)x^j_t\} \quad \forall\, j \neq\ i \end{cases}$$

The value function of the unemployed is similar:

$$\mathbf{U}^a(\mathbf{X}_t, A_t) = b + \beta E_t\Big[\mathbf{\Omega}^{a+1}(\mathbf{X}_{t+1}, A_{t+1})\Big]$$

where $\mathbf{X}_{t+1} = (1 - \delta^u)\mathbf{X}_t$. We assume that individuals who are employed at the beginning of the period but become separated for any reason can search for a new job but do not have access to vocational training during that period. Vocational training influences labor supply by enabling individuals to acquire skills relevant to their preferred sectors in response to changing labor market conditions. To facilitate comparison across different policy regimes, we count individuals attending vocational training as unemployed.

On the other hand, we consider an ALMP designated to stimulate labor demand. Specifically, we assume that the government provides a hiring subsidy, which alters firms' job creation condition as follows:

$$\kappa \geq q_j^a\left(\mathbf{X}_t, A_t\right)\left(E_z\left[\mathbf{V}_j^a(z, \mathbf{X}_t, A_t)|z \geq z_h^a(\mathbf{X}_t, A_t)\right] + \tau\right)$$

where τ indicates a front-loaded hiring subsidy upon job creation. To preserve tractability, we assume that the government has deep pockets and finances the hiring subsidy without relying on taxation or debt issuance. We calibrate τ to the average annual wage. All other equilibrium conditions remain the same.

The vocational training described in our framework represents the relatively least restrictive form of this policy. For instance, we do not assume any costs or disutility associated with attending or providing vocational training, and the skill growth rate through training matches the rate achievable through work experience, regardless of the skill levels. In reality, however, vocational training typically focuses on entry-level skill acquisition and requires nontrivial time and effort. The only cost of vocational training in our model is that individuals are unable to search for jobs during the training period. As discussed below, even in this most optimistic environment, vocational training appears less effective than commonly expected and primarily benefits young workers. On the other hand, while the hiring subsidy is modeled in a straightforward way, this specification does not take into account potential costs associated with providing the subsidy, such as the fiscal burden of such spending. This stylized formulation aims to maintain model tractability, but we acknowledge that the hiring subsidy effects likely understate the accompanying inefficiency costs [13].

5.2 ALMPs and Steady-State Labor Market Dynamics

Table 5 reports the steady-state values of key labor market variables across four distinct scenarios: economies without ALMPs, with hiring subsidies, with vocational training, and with both policies implemented simultaneously. All results are based on the baseline economy without aging.

[13] We do not impose productivity restrictions for hiring subsidies, which could inefficiently subsidize unproductive matches that would otherwise be unable to survive. A productivity restriction could be easily introduced by assuming that subsidies are provided only to matches expected to yield a surplus above a certain level. This restriction would likely benefit older workers, as they tend to possess higher human capital in their primary sectors. That is, the productivity restriction yields a disproportionate effect toward productive matches, which would likely target seasoned (i.e., older) workers. We find that the main lessons of our ALMPs analysis remain largely robust even with this form of productivity restrictions. Our quantitative analysis employs a more general specification for the sake of clarity and ease of exposition.

Table 5: Steady-state labor market outcomes across different ALMP scenarios

	Baseline	HS only	VT only	HS + VT
Aggregate statistics				
Cognitive sector emp. share (%)	63.5	74.4	63.5	74.5
Aggregate unemp. rate (%)	5.9%	4.5%	6.2%	4.6%
Output (relative to the baseline)	1	1.065	0.99	1.065
Unemployment rate (%)				
Young	9.8	7.5	9.9	7.5
Middle	4.5	3.5	4.6	3.6
Old	5.8	3.6	5.8	3.7
U-to-E transition rate (%)				
Young	30.7	46.4	30.4	46.3
Middle	28.6	46.1	28.3	46.0
Old	19.5	42.6	19.3	42.5
E-to-U transition rate (%)				
Young	1.7	2.5	1.7	2.5
Middle	1.4	1.7	1.4	1.7
Old	1.4	1.6	1.4	1.6
Sector transition rate (%)				
Young	17.1	47.2	17.1	47.2
Middle	16.4	46.9	16.4	46.9
Old	16.4	46.9	16.4	46.9
VT composition (%)				
Total VT participation rate	–	–	0.76	0.13
Share: Young	–	–	35.0	54.8
Share: Middle	–	–	40.9	43.6
Share: Old	–	–	24.1	1.6

Compared with the economy without ALMPs, the one with only a hiring subsidy shows the largest reduction in the unemployment rate. The hiring subsidy stimulates labor demand across all sectors, skill levels, and age groups, which leads to a lower unemployment rate and higher U-to-E transition rates for all age cohorts. The rise in job-finding probabilities also increases sectoral transition rates uniformly across age groups. In the baseline economy, preference shocks may lead some workers to seek employment in a sector where they lack comparative skill advantages. Workers in this case generally face relatively low job-finding probabilities, yielding a low realized sectoral transition rate. When the hiring subsidy is introduced, however, it raises job-finding probabilities uniformly for all types of workers, enabling workers to move more easily to sectors where they lack comparative advantages. As a result, more workers are matched to jobs that are inconsistent with their human capital attributes, which subsequently leads to higher separation rates. Consequently, both the sectoral transition rates and the overall E-to-U rates increase. Furthermore, as reemployment becomes easier, individuals, particularly young workers with low match productivity, have stronger incentives to quit voluntarily for within- or across-sector job changes, further contributing to higher E-to-U rates. Given the existing human capital distribution, jobs in the cognitive sector

become more accessible as firms lower both hiring and separation thresholds, which raises the cognitive sector employment share. In the economy with the hiring subsidy, aggregate output rises by 6.5 percent relative to the economy without ALMPs.

When vocational training is introduced, the economy shows slightly higher unemployment rates across all age groups because individuals remain unemployed while training, leading to a 0.1 percent decline in output compared with the baseline economy. It should be noted that only a limited share of the unemployed make use of vocational training: Less than one percent of unemployed workers choose to take vocational training, and most participants (around 75 percent) are young and middle-aged individuals. In addition, nearly 95 percent of vocational trainees participate in training for cognitive occupations. Because the manual sector does not impose a minimum skill requirement, individuals prefer to seek employment directly rather than spending time unemployed training. The low vocational training participation rate among old workers reflects their relatively higher cost (or lower benefits) of vocational training: because they have a shorter remaining work tenure, (i) the marginal benefit of skill acquisition is smaller, (ii) the opportunity cost of postponing job search is relatively higher, and (iii) firms' labor demand for these workers is limited even after skill training. When the government provides a hiring subsidy, the effect of vocational training attenuates further. Specifically, hiring subsidies partially substitute for vocational training. As the hiring subsidy raises the job-finding probability across all skill levels and age groups, individuals who might otherwise participate in vocational training choose to search for jobs directly. Compared with an economy implementing vocational training alone, the overall training participation rate decreases by one-fifth when the hiring subsidy is added on, with a particularly sharp decline observed in the older group.

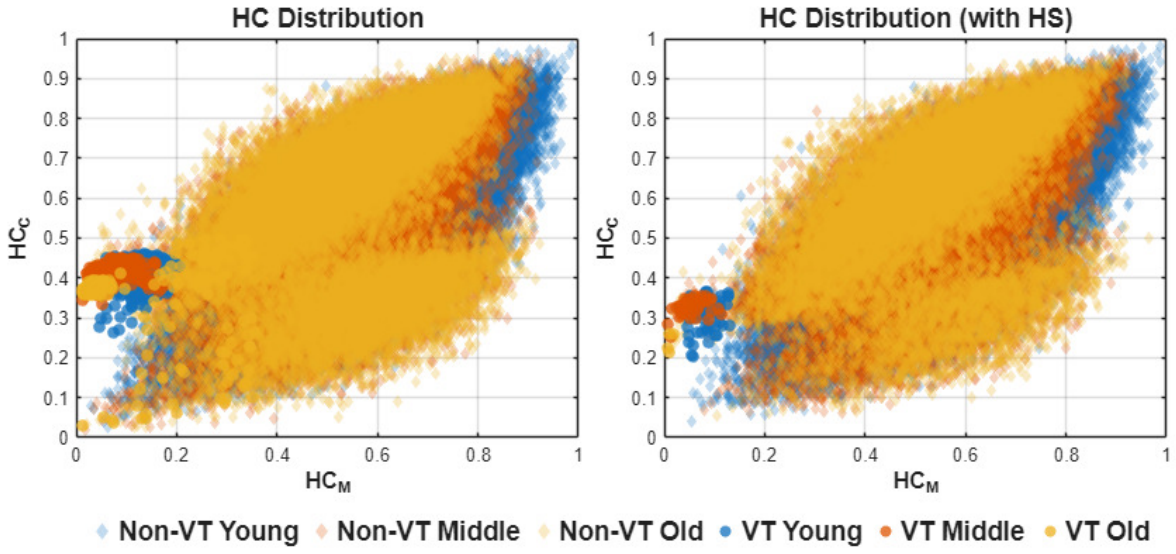


Figure 17: Human capital distribution of vocational trainees and non-trainees

Figure 17 shows the cross-sectional HC distribution of unemployed individuals across age

groups, illustrating the human capital characteristics of those who participate in vocational training and those who do not. The darker cluster located in the southwest represents unemployed workers who choose to take vocational training, while the dispersed points across the graph correspond to those who do not participate in the training program. We observe that individuals whose cognitive skill levels lie close to the minimum skill threshold required in the cognitive sector utilize vocational training. Two cases are relevant. First, individuals who have a comparative advantage in the cognitive sector but possess relatively low skills within it undergo training to raise their job-finding probabilities. Otherwise, their human capital would depreciate while unemployed, and their chances of reemployment in cognitive jobs would decline sharply. On the other hand, some workers whose cognitive skills are below the threshold level but who have only a weak comparative advantage in the manual sector use vocational training to become qualified for cognitive jobs and switch from manual to cognitive occupations. However, most individuals possess a strong comparative skill advantage in a particular sector, and therefore, the benefit of vocational training falls short of the opportunity cost of foregoing job search opportunities.

The welfare benefit of vocational training decreases with age. Most vocational training participants are young or middle-aged workers, implying that such training becomes increasingly less relevant as the labor force ages. As the proportion of older workers increases, fewer individuals participate in training. In fact, as the share of older individuals in the labor force increases from 25 percent in the baseline to 33 percent in the aging counterpart, the vocational training participation rate declines by one-third. In contrast, the hiring subsidy, which directly stimulates labor demand across all age groups and skill levels, remains effective irrespective of demographic composition. For instance, introducing a hiring subsidy calibrated to the average annual wage reduces the aggregate unemployment rate by 1.5 percentage points in both the baseline and aging economies.

5.3 Technological Changes and the ALMPs

One might expect vocational training to be particularly effective during economic transitions driven by technological change, as it helps workers adapt and acquire relevant skills in response to structural shifts in labor demand. Since older workers face greater difficulty adjusting to technological transitions, ALMPs could be more effective in an aging economy. To examine this possibility, we analyze the effects of ALMPs during SBTC and TDTC. We follow a similar numerical strategy. The population gradually declines over time as aging progresses, and the permanent technological change unfolds over one year when the share of the old group in the labor force reaches 28 percent. No policy is implemented before the technological shock, and the government begins implementing ALMPs at the onset of the technological changes and continues thereafter.

Figure 18 illustrates the transition paths of the aggregate unemployment rate in response to SBTC (left panel) and TDTC (right panel). We compare two policy environments: one providing vocational training (VT) only and another implementing the full ALMP package (HS + VT). The hiring subsidy appears to be a more effective policy intervention in response to permanent tech-

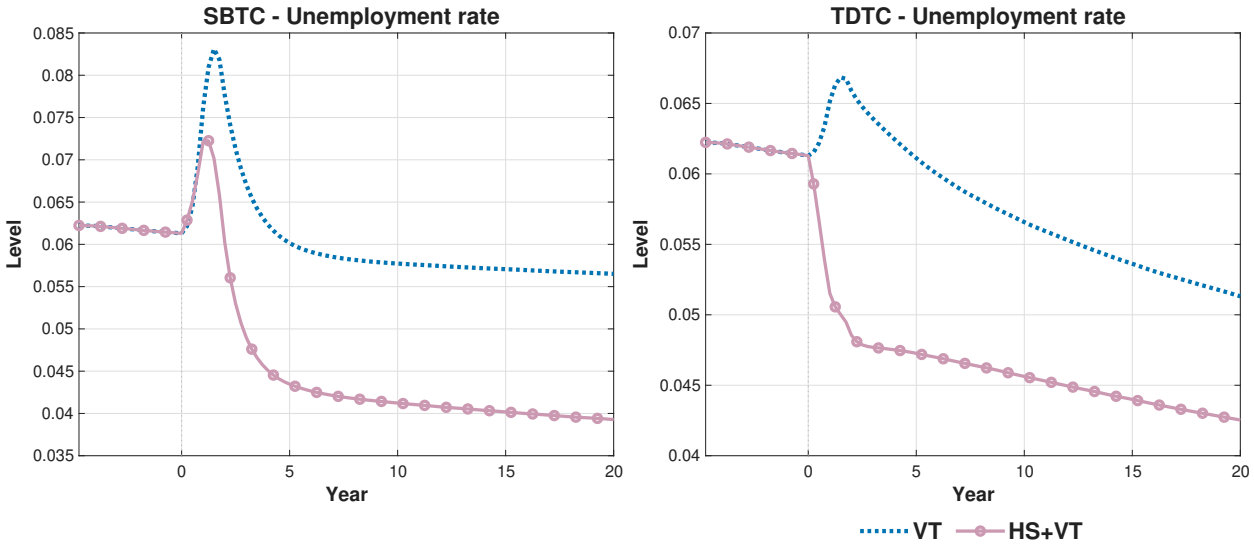


Figure 18: Permanent Technological Changes and ALMPs

nological changes. Under SBTC, the economy with hiring subsidies exhibits a smaller increase in unemployment compared to the VT-only case and converges to a lower steady-state unemployment rate. Under TDTC, the hiring subsidy prevents a rise in unemployment, whereas vocational training leads to an additional increase in unemployment. These results suggest that, during transitions driven by permanent technological shifts, providing employment opportunities that allow HC development through work experience is more effective at mitigating the unemployment increase than inducing individuals to develop appropriate skills through vocational training.

Figures A8 and A9 in the appendix display the impulse responses of aggregate labor market variables to SBTC and TDTC, respectively. When SBTC occurs, vocational training tends to raise the unemployment rate among young workers. This is because, given an initial human capital endowment distribution that is invariant to technological changes, more young individuals who would otherwise pursue jobs in the manual sector now choose to undergo vocational training to pursue careers in the cognitive sector. Under these circumstances, the hiring subsidy mitigates the increase in unemployment by making all jobs more accessible to individuals who would otherwise be unqualified or face very low hiring probabilities. This effect is reflected in the increased U-to-E rates and cognitive employment shares across all age groups.

During TDTC, which reduces labor demand in the cognitive sector, individuals without a strong comparative advantage in that sector tend to switch to the manual sector. However, because jobs in the manual sector do not require minimum skill levels, vocational training tends to be redundant for many workers. As a result, the vocational training participation rate barely changes. On the other hand, workers with strong cognitive skills are often reluctant to change occupations and remain unemployed for extended periods. Under these circumstances, the hiring subsidy provides incentives for firms in the cognitive sector to open vacancies. As a result, some workers are still able to find jobs in the declining sector, albeit at the cost of longer unemployment duration and lagging

sectoral reallocation. Consequently, the economy with the hiring subsidy exhibits an attenuated decline in the cognitive employment share.

It is beneficial to close this section with possible policy concerns. In particular, one may be concerned that hiring subsidies could yield non-trivial efficiency costs by overly protecting non-productive firms. Nonetheless, one should note that the counterfactual outcome of not implementing this policy could be a considerable surge in unemployment, thereby rendering the net welfare effect ambiguous. Moreover, our findings imply that policymakers can stimulate productive labor reallocation by targeting subsidies toward more productive sectors, as the policy raises labor demand across all skill and age levels.

6 Conclusion

This paper studies (i) the micro-foundation of heterogeneous labor market dynamics across age groups and (ii) the quantitative impact of demographic aging on aggregate labor market dynamics. Using CPS data, we find that separation, job-finding, and occupational transition rates all decline as age increases. The unemployment decomposition and dynamic factor analysis further show that population aging reduces the natural rate of unemployment while amplifying its cyclical volatility.

To interpret these empirical findings, we develop a life-cycle OLG model with directed search frictions, endogenous job destruction, endogenous human capital evolution, and sectoral reallocation. The model replicates the observed age-dependent labor market transition patterns. Numerical analysis accounts for distinct labor market dynamics across age groups through general equilibrium interactions among human capital, work horizons, and search frictions. Quantitative results suggest that as the labor force ages, aggregate unemployment fluctuations become more pronounced due to rigid sectoral labor reallocation. As a policy extension, we incorporate active labor market policies consisting of vocational training and hiring subsidies into the model economy. We find that vocational training is less effective in reducing unemployment and promoting sectoral labor reallocation, with its efficiency further diminishing for older workers. In contrast, hiring subsidies remain effective for all age groups in reducing unemployment during both the steady-state and transition phases driven by permanent technological changes.

Although this study provides new insights into age-specific labor market dynamics and their aggregate effects, it likely sheds light on only a part of the mechanisms operating in an aging economy. In reality, demographic aging interacts with various structural forces that may amplify or offset its effects, such as changes in aggregate demand and industrial reorganization (e.g., Cutler et al., 1990; Cravino et al., 2022), labor demand spillovers (e.g., Bound and Holzer, 2000; Bianchi et al., 2023; Mohnen, 2025), automation and capital deepening (e.g., Irmen, 2021; Acemoglu and Restrepo, 2022), and fiscal or institutional reforms (e.g., Attanasio et al., 2010; Cooley and Henriksen, 2018). Extending the current study to include these additional factors would be essential for a deeper understanding of the implications of ongoing demographic changes. We leave this for future research.

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A Appendix

A.1 Derivation of the unemployment decomposition identity

Let U_t^Z and L_t^Z denote the number of unemployed individuals and the labor force in the age group $Z \in \{Y, M, O\}$. Define $\lambda_t^Z \equiv \frac{L_t^Z}{L_t}$ as the share of the age group $Z \in \{Y, M, O\}$ in the total labor force and $u_t^Z \equiv \frac{U_t^Z}{L_t^Z}$ as the unemployment rate for that age group. Likewise, $u_t = \frac{U_t}{L_t}$ represents the aggregate unemployment rate. The total number of unemployed workers can be decomposed as follows:

$$U_t = U_t^Y + U_t^M + U_t^O.$$

Accordingly, the aggregate unemployment rate is given by

$$u_t = \lambda_t^Y u_t^Y + \lambda_t^M u_t^M + \lambda_t^O u_t^O. \tag{A.1}$$

Taking the logarithm and applying time differentiation to Equation A.1 yields

$$d\log u_t = \sum_{Z=\{Y,M,O\}} \Phi_t^Z \left(d\log u_t^Z + d\log \lambda_t^Z \right) \approx \sum_{Z=\{Y,M,O\}} \Phi_t^Z \left(d\log u_t^Z \right) \tag{A.2}$$

where $\Phi_t^Z = \frac{U_t^Z}{U_t}$ denotes the share of each age group in total unemployment, and $\sum_Z \Phi_t^Z = 1$. We impose the approximation $d\log \lambda_t^Z = \frac{dL_t^Z}{L_t^Z} - \frac{dL_t}{L_t} \approx 0$. Here, $\frac{dL_t^Z}{L_t^Z}$ and $\frac{dL_t}{L_t}$ represent the growth rates of the labor force for a specific age group and for the total labor force, respectively. Their difference reflects changes in the labor force composition. Both terms, as well as their difference, are typically very close to zero over a reasonably short time interval, such as the monthly or quarterly frequency considered in this paper.

We now decompose $d\log u_t^Z$ for $Z \in \{Y, M, O\}$. The three-state (Employed, Unemployed, and Inactive) law of motion for individuals in each age group can be expressed as follows:

$$\begin{aligned}
\Delta U_t^Z &= p_t^{Z,EU} E_{t-1}^Z + p_t^{Z,IU} I_{t-1}^Z - (p_t^{Z,UE} + p_t^{Z,UI}) U_{t-1}^Z \\
\Delta E_t^Z &= p_t^{Z,UE} U_{t-1}^Z + p_t^{Z,IE} I_{t-1}^Z - (p_t^{Z,EU} + p_t^{Z,EI}) E_{t-1}^Z \\
\Delta I_t^Z &= p_t^{Z,UI} U_{t-1}^Z + p_t^{Z,EI} E_{t-1}^Z - (p_t^{Z,IU} + p_t^{Z,IE}) I_{t-1}^Z
\end{aligned}$$

where the superscripts E, U, and I indicate the employed, unemployed, and inactive states, respectively, and $p_t^{Z,XY}$ denotes the transition rate from state X to state Y for individuals in the age cohort Z over the time interval between $t-1$ and t. Conditional on the steady-state where

$\Delta U_t^Z = \Delta E_t^Z = 0$ holds, we can solve the above equations and obtain:

$$u_t^Z \approx \tilde{u}_t^Z = \frac{p_t^{Z,EU} + \frac{p_t^{Z,EI} p_t^{Z,IU}}{p_t^{Z,IU} + p_t^{Z,IE}}}{p_t^{Z,EU} + \frac{p_t^{Z,EI} p_t^{Z,IU}}{p_t^{Z,IU} + p_t^{Z,IE}} + p_t^{Z,UE} + \frac{p_t^{Z,UI} p_t^{Z,IE}}{p_t^{Z,IU} + p_t^{Z,IE}}} = \frac{s_t^Z}{s_t^Z + f_t^Z} \tag{A.3}$$

where s_t^z and f_t^z denote the effective separation and job-finding hazards, respectively, and are defined as follows:

$$s_t^z \equiv p_t^{Z,EU} + \frac{p_t^{Z,EI} p_t^{Z,IU}}{p_t^{Z,IU} + p_t^{Z,IE}}$$
$$f_t^z \equiv p_t^{Z,UE} + \frac{p_t^{Z,UI} p_t^{Z,IE}}{p_t^{Z,IU} + p_t^{Z,IE}}$$

Log-differentiating Equation A.3 gives

$$d \log u_t^Z \approx d \log \tilde{u}_t^Z = (1 - \tilde{u}_t^Z) \Big(d \log s_t^Z - d \log f_t^Z \Big)$$

Replacing $d \log u_t^Z$ in Equation A.2 with the above expression yields

$$d \log u_t \approx \sum_{Z=\{Y,M,O\}} \Phi_t^Z (1 - \tilde{u}_t^Z) \Big(d \log s_t^Z - d \log f_t^Z \Big) \qquad \square$$

A.2 Figures

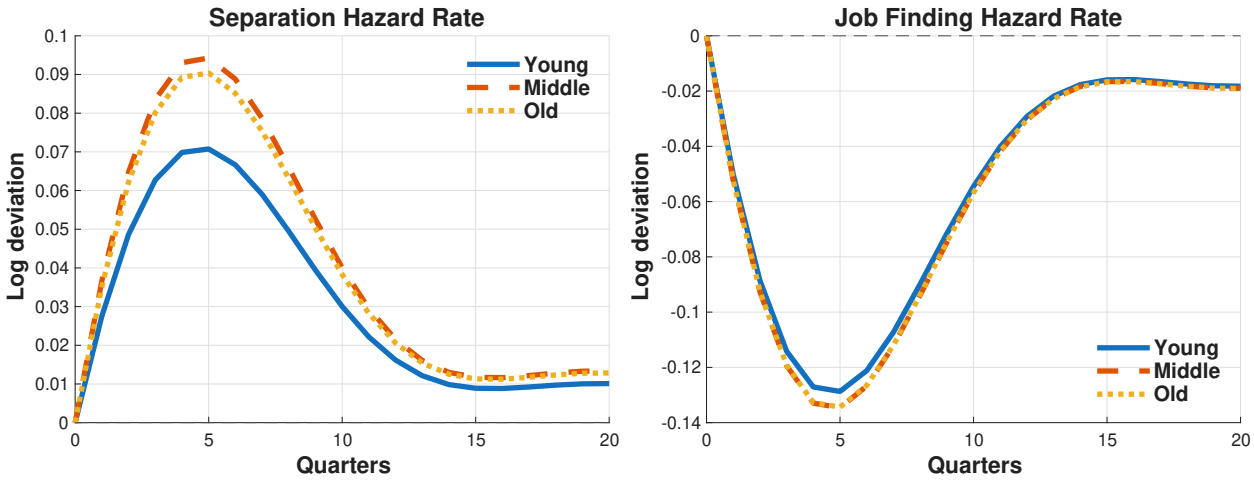


Figure A1: DFM Impulse-Response Analysis

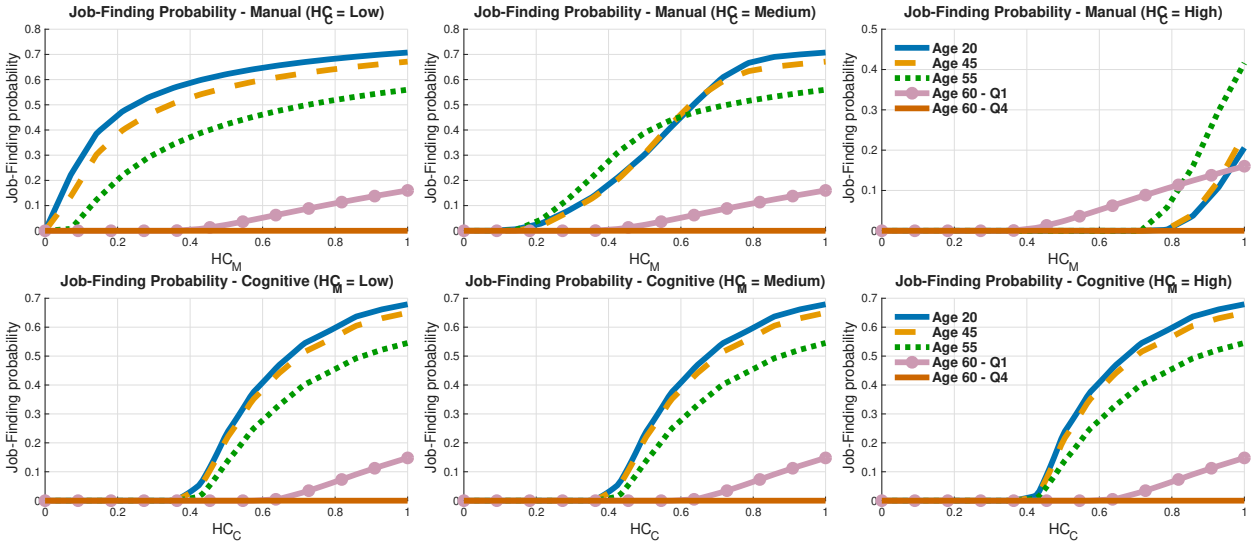


Figure A2: Job-Finding Probability of Heterogeneous Individuals during Recession

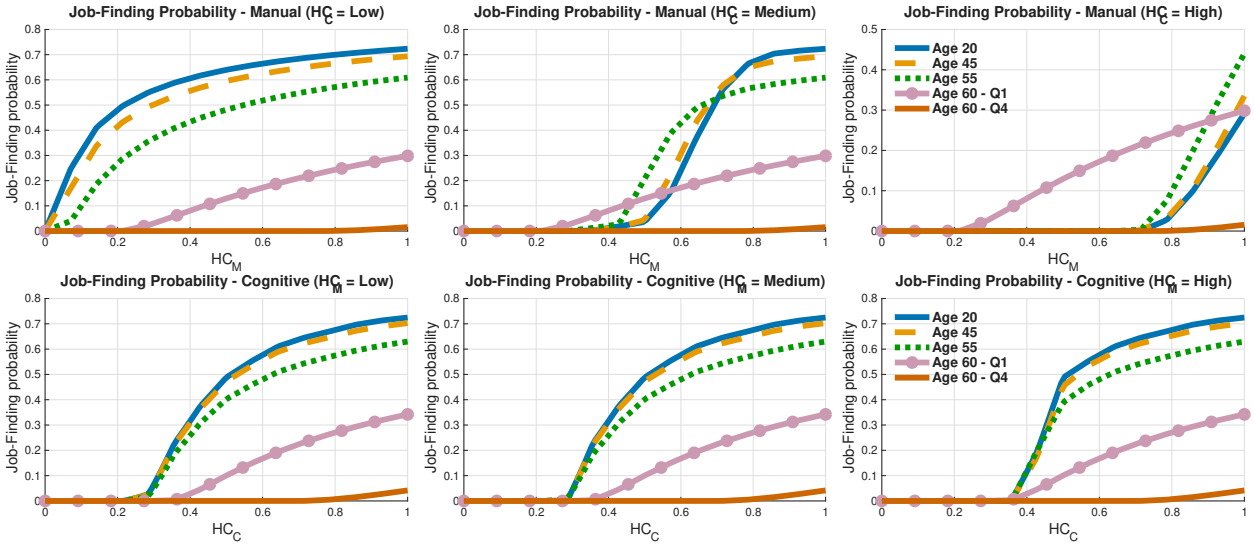


Figure A3: Job-Finding Probability of Heterogeneous Individuals during expansion

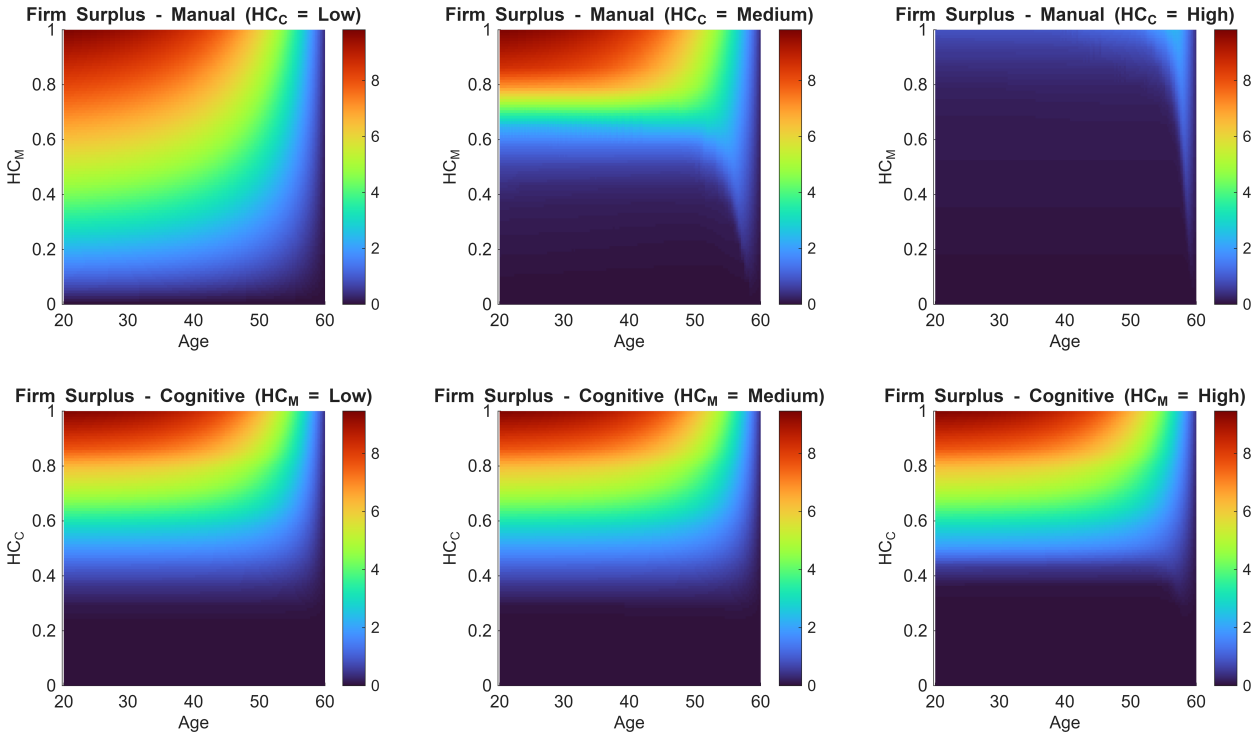


Figure A4: Firms' Expected Match Surplus

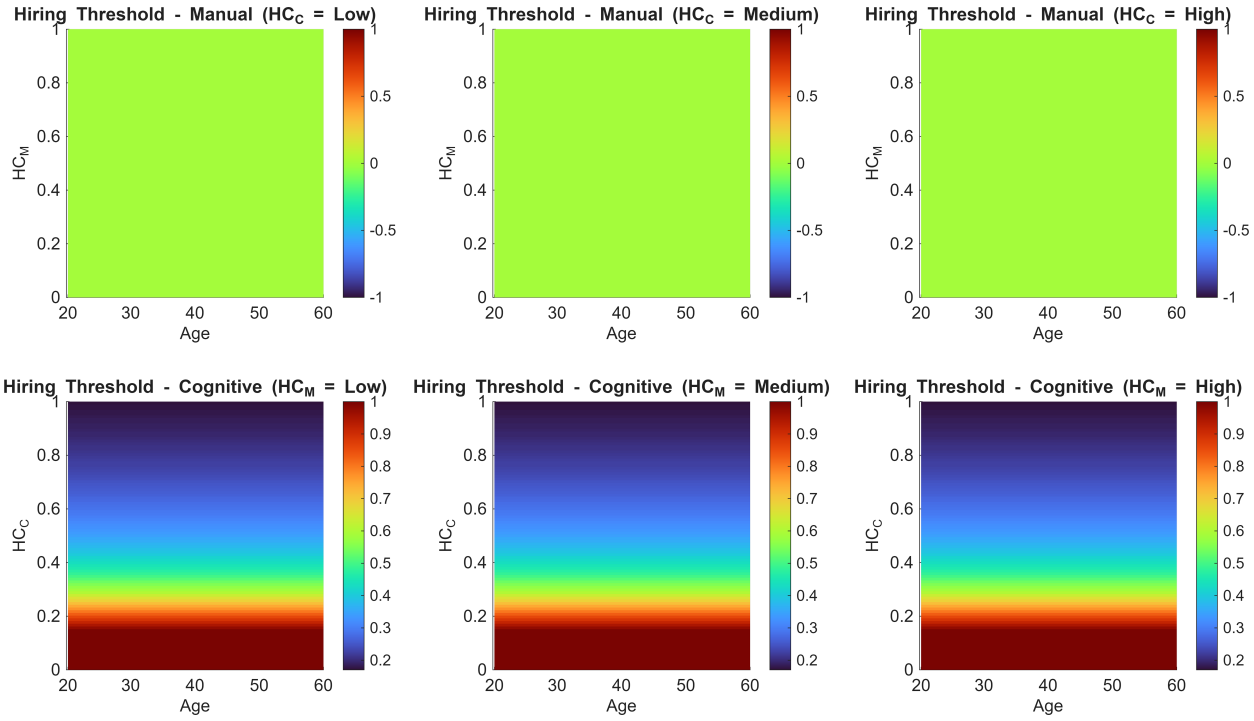


Figure A5: Hiring Match Productivity

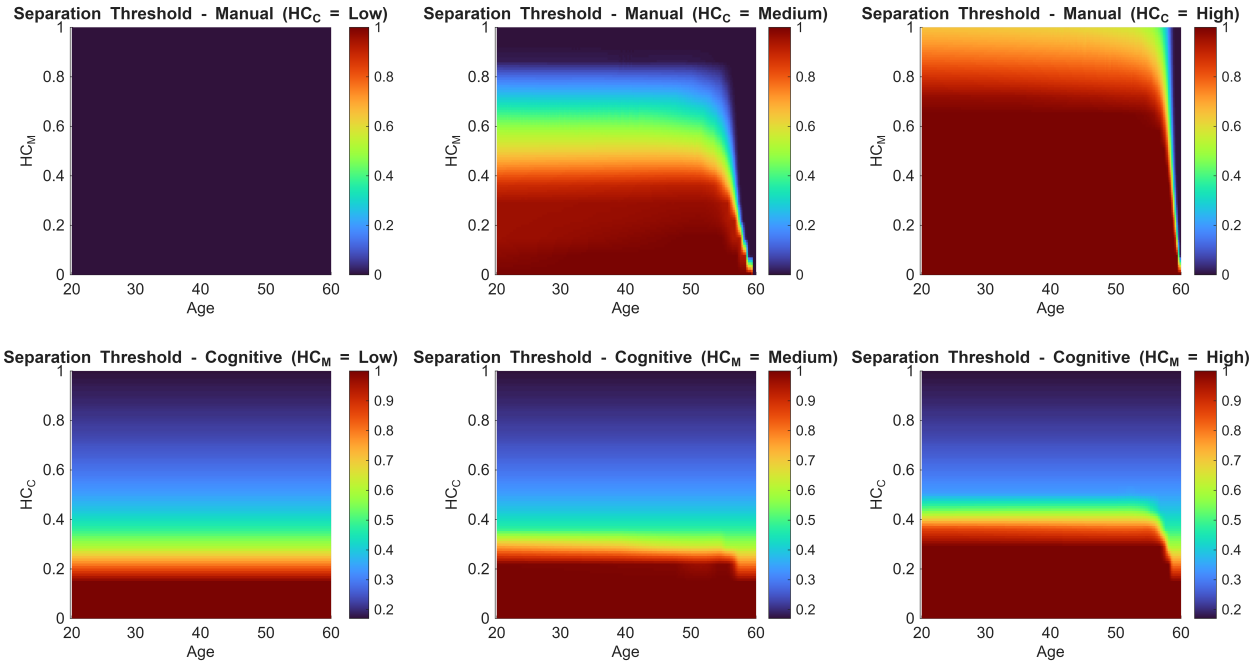


Figure A6: Separation Match Productivity

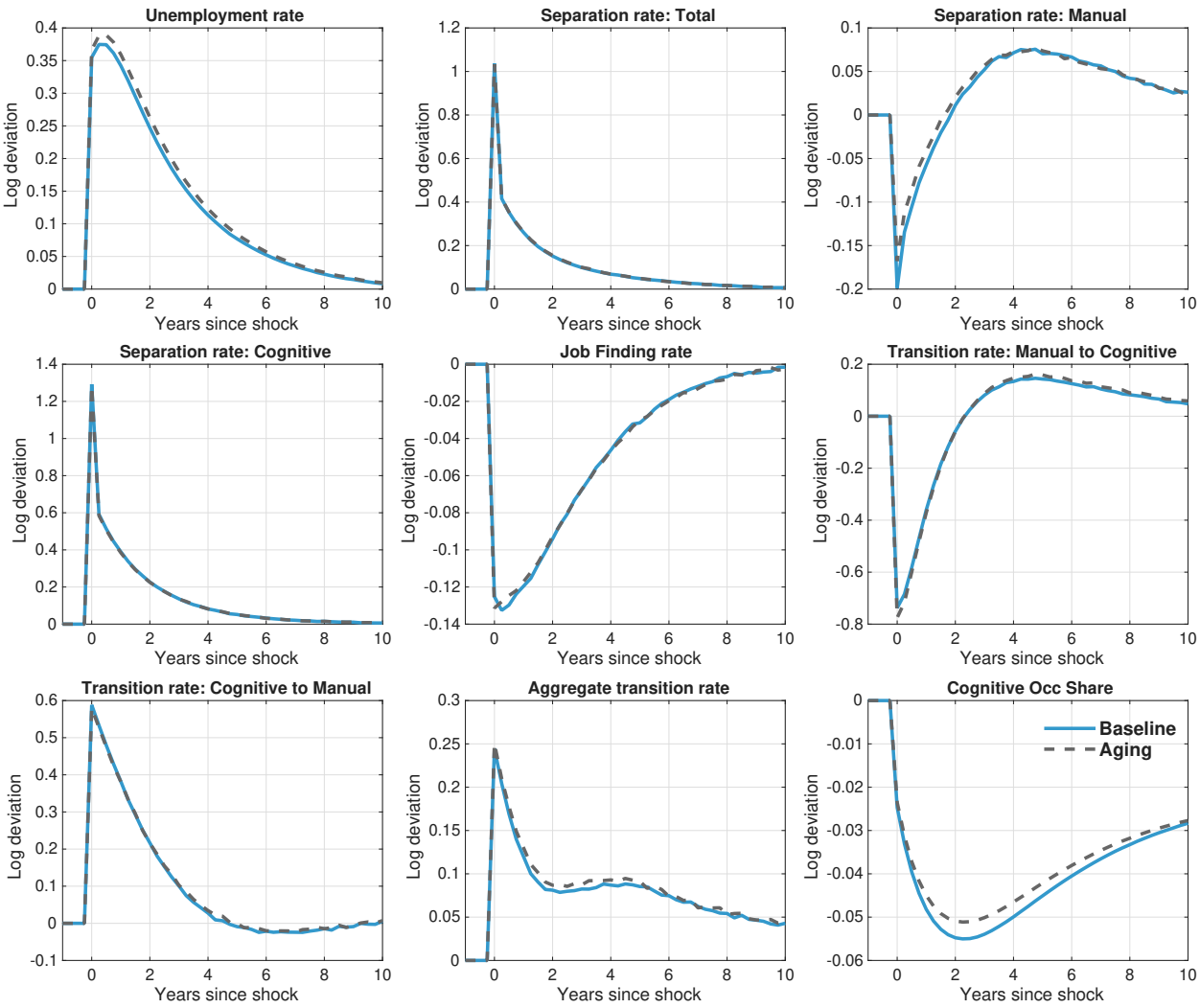


Figure A7: Impulse-Response to a Negative TFP Shock

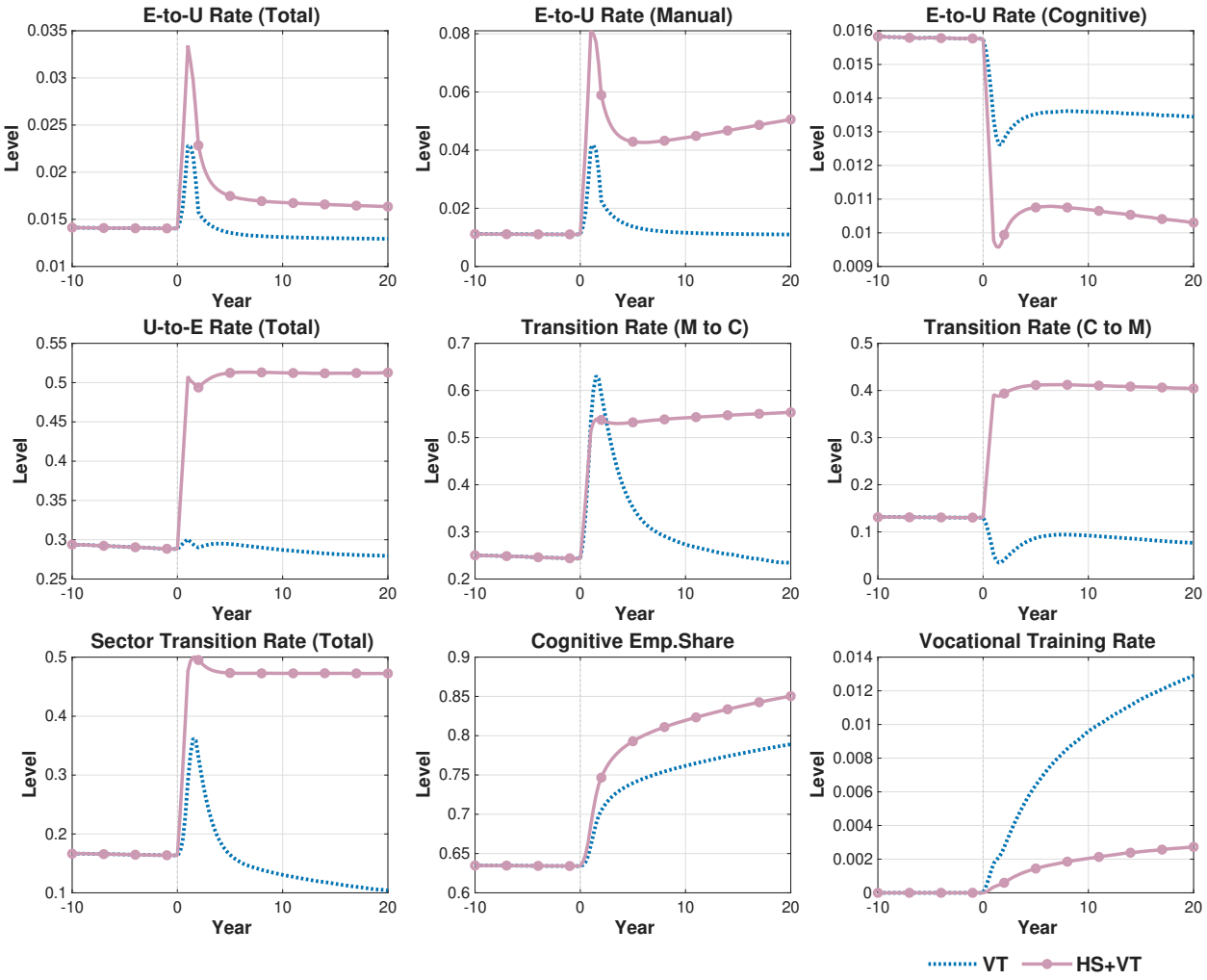


Figure A8: SBTC transition and ALMPs

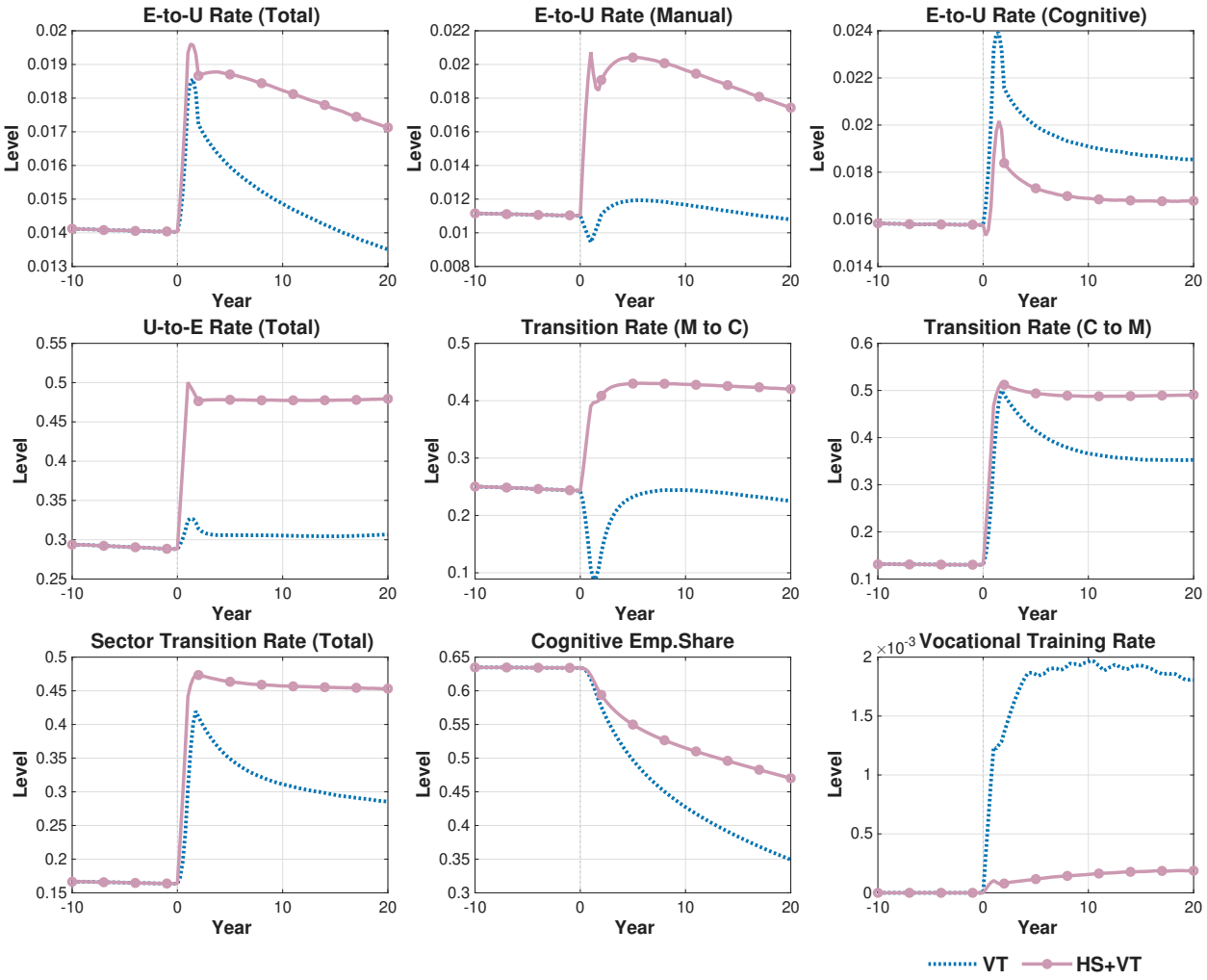


Figure A9: TDTC transition and ALMPs

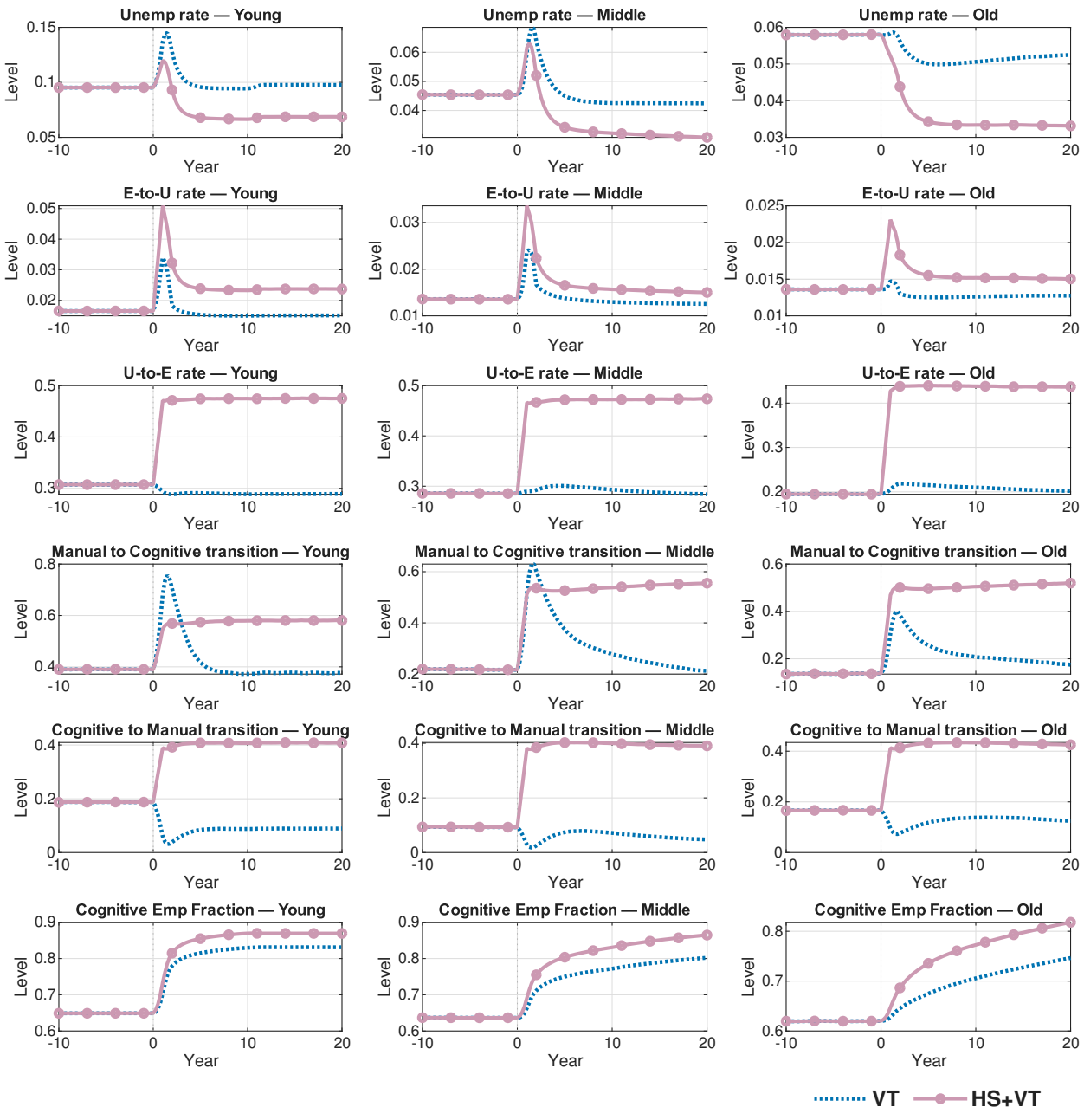


Figure A10: SBTC transition and ALMP

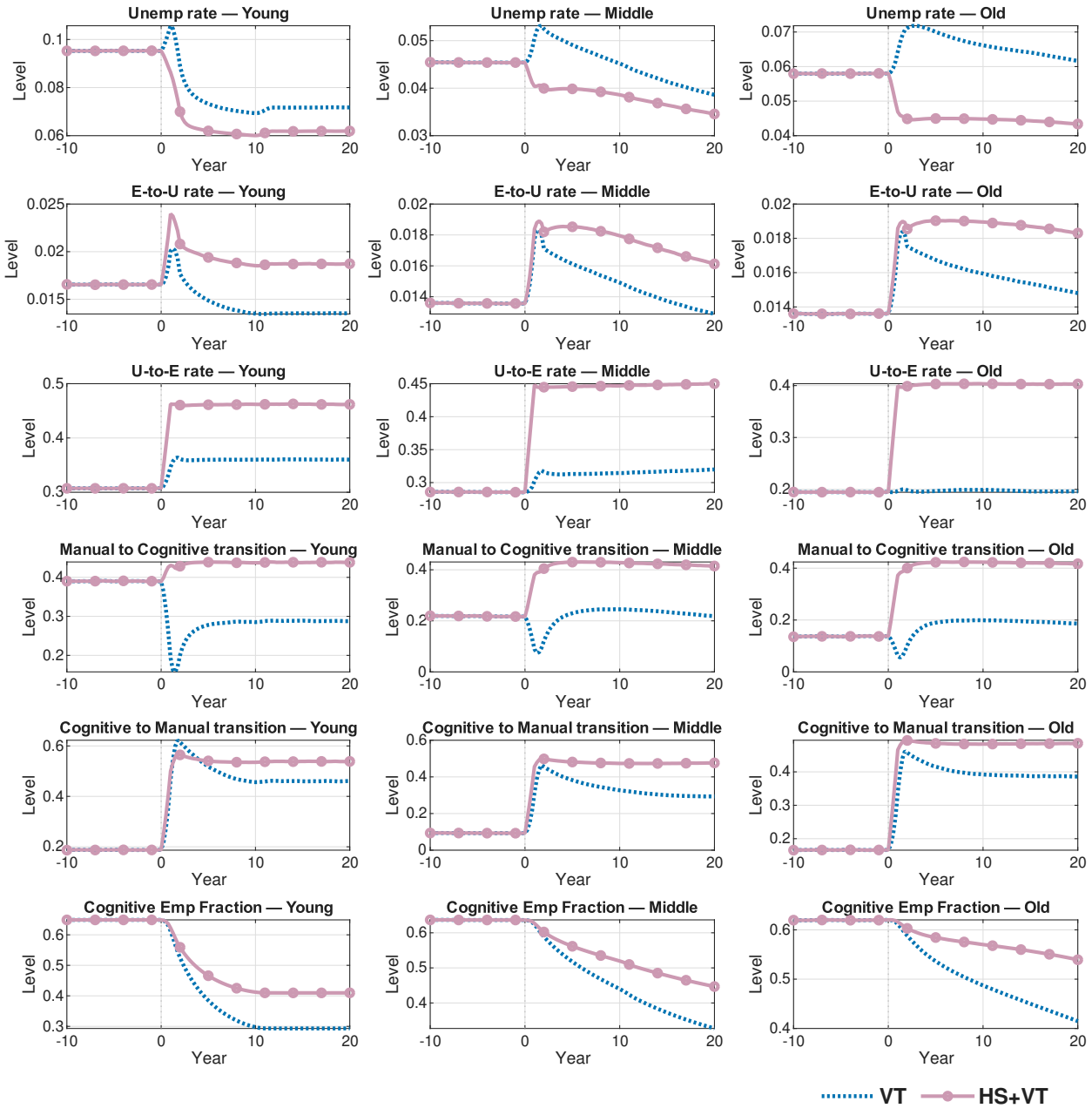


Figure A11: TDTC transition and ALMP