Assignment 3: Skill-Biased Technological Changes and Job Training Subsidies

Household Behavior over the Life Cycle

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Abstract

In this paper, I investigate the impact of Skill-Biased Technological Changes (SBTC) on human capital accumulation for low-skilled and high-skilled workers. My contribution is a structural life cycle model akin to Imai and Keane, 2004 and Keane and Wasi, 2016 augmented with SBTC that influences both skills and productivity. The model reveals a widening productivity and wage disparity due to SBTC. Through counterfactual simulations, I explore how job training subsidies targeted at low-skilled workers can increase productivity among low-skilled workers and potentially mitigate adverse effects from SBTC.

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1 Research Question

How does skill-biased technological changes affect human capital accumulation for low- and high-skilled workers? And how can targeted job training subsidies assist low-skilled workers in leveraging the benefits of these technological changes?

2 Motivation

Technological progress has been instrumental in shaping the global economy in the last decades. However, recent research suggests that ideas have become more challenging to find, reducing technological growth (Bloom et al., 2020). Nevertheless, the emergence of Artificial Intelligence (AI) technology could disrupt this trend by accelerating innovation and productivity growth.[1] Yet, the rise of AI also embodies a potential Skill-Biased Technological Change (SBTC). The skill-bias arises because AI technologies might replace (some of) the work done by low-skilled and, at the same time, increase the productivity of the high-skilled. Such a change fosters greater productivity dispersion and widens the wage gap between low- and high-skilled workers. In the existing literature the wage gap between low- and high-skilled has been represented by the term "college wage premium" (Katz and Murphy, 1992). Thus, the impact of SBTC could further enlarge this wage disparity. This calls for attention to how policies such as job training programs can become an incentive for low-skilled workers to use and reap the benefits of AI's possibilities.

3 Model Framework

Often models capturing SBTC take a "macroeconomic" approach (see for example Acemoglu and Autor, 2010). Contrarily, my intent is to model the SBTC from a "microeconomic" perspective, within a household life cycle and partial equilibrium setting.
As a point of departure, I employ a simple structural model akin to those used in Imai and Keane, 2004 and Keane and Wasi, 2016. In this life cycle setting, the individual's choice is the amount of consumption $c_t > 0$, hours of labor supplied $h_t \geq 0$, and a binary job training decision variable $j_t \in \{0, 1\}$. The resources available to the individual are a Mincerian wage conditional on being low-skilled (L) or high-skilled (H). The state variables are liquid savings a_t, human capital k_t and the skill-type $s_t \in \{L, H\}$. Moreover, the market of particular interest is a labor market. There exist two labor markets, one for low- and high-skilled workers. For simplicity, I model an imperfect capital market (i.e., no insurance or borrowing) since it is not of central interest and let there be no bequest motive.

To credibly address the research question in Section 1, I introduce several key features that will be elaborated as I unfold the complete model setup.

[1] See e.g. PricewaterhouseCoopers, 2018.

Human capital accumulation is

$$k_{t+1,s} = k_{t,s} + h_t + \delta_s j_t, \quad k_{0,s} = 0, \quad s \in \{L, H\}. \tag{3.1}$$

Here, k_{t+1} represents the human capital accumulated at time $t+1$, and δ_s is the return to job training that depends on the individual's skill level s reflecting that high-skilled workers gain more from job training.

A key mechanism will be mapping skill-biased technological changes to skill-types. To do so, I define a productivity factor $\alpha_{t,s}$, which depends on the skill-type s and time t. The type-specific productivity factor is modeled as a random walk with a drift[2]

$$\alpha_{t,s} = \begin{cases} \kappa + \alpha_{t-1,s} + \varepsilon_{t+1} & \text{if } s = H \\ -\kappa + \alpha_{t-1,s} - \varepsilon_{t+1} & \text{if } s = L \end{cases}, \tag{3.2}$$

where $\log \varepsilon_{t+1} \sim \mathcal{N}\left(\mu_\varepsilon, \sigma_\varepsilon^2\right)$ and κ captures the trend growth in skill-biased technical change.

The next critical mechanism involves mapping the skill-type onto human capital accumulation and wages. To do so, I model a Mincerian wage process as follows

$$w_{t,s} = w_0 \left(1 + \alpha_{t,s} \sum_{i=1}^{t-1} (h_i + \delta_s j_i)\right), \quad s \in \{L, H\}, \tag{3.3}$$

where $\alpha_{t,s}$ is the parameter that maps work experience to human capital for skill. Since w_0 is a baseline skill-endowment, it is possible to introduce additional (ex-ante) worker heterogeneity by initializing workers with different levels of skill-endowment.

The policy experiments I wish to explore involve job training targeted at low-skilled workers. Thus, I introduce a subsidy ϕ that is provided for job training and targeted at low-skilled workers who choose to undergo job training ($j_t = 1$) in period t. The intertemporal budget constraint then becomes

$$a_{t+1} = (1+r)\left(a_t + (1-\tau)\, w_{t,s} h_t - c_t - \psi j_t + \mathbb{1}_{s=L} \phi j_t\right), \quad a_0 = 0, \quad s \in \{L, H\}, \tag{3.4}$$

where $\tau \in (0,1)$ is a fixed tax rate. Furthermore, ψ represents an economic cost of job training for the individuals (for example to reflect foregone wages) irrespective of the skill-type.

[2] The form takes inspiration from Guvenen and Kuruscu, 2007, pp. 10.

The Bellman equation is

$$V_t\left(a_t, k_t, s_t\right) = \max_{c_t, h_t, j_t \in \{0,1\}} \left[\frac{c_t^{1+\eta}}{1+\eta} - \beta \frac{h_t^{1+\gamma}}{1+\gamma} - \lambda_t j_t + \rho \mathbb{E}\left[V_{t+1}\left(a_{t+1}, k_{t+1}, s_{t+1}\right)\right] \right]. \quad (3.5)$$

Notice I add an age-dependent preference for job training λ_t. The model choice captures that older individuals might derive more disutility from job training than younger ones, reflecting a lower preference for job training among the elderly.

To solve the model, I discretize the state space, solve by backward recursion (e.g. Value Function Iteration) and employ a method to interpolate off-grid solutions. To "integrate out" the stochastic skill-biased technology shock, I use a Gauss-Hermite quadrature method since the shock is (log-) normally distributed. The terminal condition assuming no bequest is

$$V_T\left(a_T, k_T, s_T\right) = \max_{h_T, j_T \in \{0,1\}} \left[\frac{c_T^{1+\eta}}{1+\eta} - \beta \frac{h_T^{1+\gamma}}{1+\gamma} - \lambda_T j_T \right]$$

$$\text{s.t.}$$

$$c_T = a_T + (1-\tau)\, w_{T,s} h_T - \psi j_T + \mathbb{1}_{s=L} \phi j_T, \quad s \in \{L, H\}.$$

4 Answering the Research Question Through the Model

One of the significant reasons to conduct structural estimation is that it allows us to use structural models for policy experiments. In my model, I first seek to explore how Skill-Biased Technological Change (SBTC), captured by $\alpha_{t,s}$, affects the two groups of workers. Following this, my interest lies in predicting the impacts of job training policies aimed at low-skilled workers to mitigate these effects.

A key variable representing policy within this model is the job training subsidy, ϕ. This subsidy is designed specifically for low-skilled workers who opt for job training ($j_t = 1$). By varying the level of this subsidy, I can simulate varying degrees of policy support for job training. This enables me to assess how these changes influence the choices individuals make within the model, particularly their decision to undergo job training, denoted as j_t.

Another mechanism to incorporate job training policies into this model involves adjusting the economic cost of job training, defined by ψ. A decrease in this cost can simulate policies intended to reduce barriers to job training, such as programs that compensate for lost wages or cover the financial costs associated with job training. Ultimately, this counterfactual simulation will affect both type of workers.

Finally, the age-dependent preference for job training, λ_t, allows for examination of policies targeting different age groups. By varying λ_t across age, I can model the relative disadvantage that various age groups may encounter with job training, reflecting the potentially lower adaptability of older workers to new technologies.

5 Data and Estimation

The first step in the process would be to set the parameters that can be directly drawn from the literature. For instance, the return to job training that depends on the individual's skill level δ_s and skill-biased technological growth κ.

I would need to estimate the remaining key parameters that cannot be set directly from the data. This would include parameters like the baseline skill-endowment w_0 and the age-dependent preference for job training λ_t. These parameters could be estimated using a Simulated Method of Moments (SMM) approach. Here, I need to select informative moments from the data. For instance, to estimate human capital parameters I need wage distribution across skill levels and time. I could use data on the groups "ufaglærte" (and perhaps "MVU") for low-skilled workers and "LVU" for high-skilled workers. The participation rate in job training across different age groups could provide information about λ_t. Here I would probably rely on some form of survey data.

6 Model Limitations and Potential Extensions

My current model relies on the assumption that high-skilled workers are not negatively affected by Skill-Biased Technological Change. However, this assumption is open to question. For instance, AI could render significant portions of jobs in professions like law redundant due to the repetitive nature of some of the tasks involved. A potential extension would be to include a state variable capturing job tasks, similar to the approach in Adda et al., 2017. This would allow for technological shifts to have differential impacts on distinct tasks.

Another limitation of the current model lies in its representation of skill sets. At present, individuals begin their "economic life" with a given skill-type that remains unchanged throughout their life cycle. This could be modified to allow for the possibility of skill transitions. For example, individuals might transition from low- to high-skilled via some stochastic process. This modification better captures the evolution of skills over the course of an individual's life cycle.

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