Complementarity and Transition to Modern Economic Growth

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Abstract

In developing countries, aggregate labor productivity typically remains stagnant for long periods before taking-off. We study this as the outcome of a *gradual* transition of the workforce from traditional to modern sectors. While exogenous productivity growth is present in the modern sector only, modern transition is gradual because labor and *sector-specific* experience are complements within each sector. We measure the theory using nationally representative micro data from Thailand (1976-1996). The technology parameters are estimated using a cross-sectional earnings equation implied by the model. We find the model simulated at these estimates captures well the nonlinear dynamics of aggregate earnings growth and inequality in Thailand.

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1 Introduction

In developing countries, aggregate labor productivity typically remains stagnant for long periods before it takes off, and then followed by sustained growth. We study these phenomena as an outcome of a process of modernization, measured as a transition of the workforce from traditional to modern technology sectors. The identifying assumption of the modern sector is the existence of exogenous productivity growth, which is not present in the traditional sector.

Transition to the modern sector is gradual because of a particular adjustment cost. As in Chari and Hopenhayn (1991), we assume labor and *sector-specific* experience are complements in each sector. Under this complementarity, entry into the modern sector among young agents who supply labor is limited by the stock of old agents who supply experience. Meanwhile, today's young entrants in turn determine tomorrow's stock of experience. Thus, the transition to the exclusive use of modern-sector technology occurs gradually, despite the productivity growth gap between the two sectors. As the workforce shifts from the traditional to the modern sector, the labor-experience ratios change in both sectors. Due to the complementarity, this causes the within-sector experience-earnings profiles and the between-sector earnings gap to vary over time. By linking the aggregate growth path to these dimensions of inequality, we highlight a novel nexus of growth and inequality.

We find strong evidence in favor of the model. First, transition in Thailand indeed occurred out of a group of occupations with no labor productivity growth into a group of occupations with positive and stable labor productivity growth. This transition has been gradual and the two sectors have coexisted not only among old cohorts but also among the youngest cohorts entering the workforce. Second, we observe that experience-earnings profiles differ across sectors, and sector-specific experience-earnings profiles vary substantially over time. In particular, for each sector, the experience premium rises when experience becomes scarce relative to labor, consistent with the sector-specific complementarity between labor and experience.

The speed and shape of the transition depend on the initial distribution of experience across sectors and the magnitudes of the complementarity. We measure the theory using nationally representative micro data from the Socio-Economic Survey of Thailand (1976-1996). Specifically, the *parameters* of the model as well as the *partition* of economy into traditional and modern sectors (which is not directly measured in the data) are identified by estimating a cross-sectional earnings equation as implied by the model. We then simulate the model to assess its quantitative importance. At these micro estimates of parameters, the model simulates well the nonlinear dynamics of aggregate earnings growth and inequality, together with the gradual transition of the labor force from the traditional to the modern sectors. Specifically, the model captures an S-shaped path (remaining stagnant initially, taking off with acceleration, and then decelerating) of earnings growth, the rise and fall of intra-sectoral experience premium, and the converging and then diverging inter-sectoral earnings gap during transition.

The paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the model. Section 4 discusses the data. Section 5 discusses estimation. Simulation results are compared to data in Section 6. Section 7 concludes.

2 Literature

A theoretical contribution of this paper is to show that a dual-economy model combined with the idea of labor-experience complementarity can generate long periods of stagnation followed by take-off to sustained growth (an *S-shaped growth*), the speed and slope of which depend on the *distribution of experience* across the two sectors when exogenous productivity growth became available only in modern sector. Chari and Hopenhayn (1991) consider the role of technology-specific complementarity between labor and experience (vintage human capital) in a steady state framework, implying *linear* growth. In a multi-sector economy, Kremer and Thomson (1998) show when labor and *skill* are complements (where the level of skill is a decision variable), the aggregate transition path to steady states is *concave*.[1] We show when labor and *experience* are complements, the transition path will be convex before becoming concave in a dual economy. This generates the S-shaped transition as we observe in the data. This is a key to our analysis.

Jeong and Kim (2006) show that the S-shaped growth is a salient feature of the long term growth not only among developing countries but also among today's rich countries, and calibrate a version of the model to explain the differences in growth and the evolution of inequality *across countries* since 1820. This paper focuses on rich measurement of the theory by explicitly implementing structural estimation using micro data and assesses the quantitative importance of the model in explaining the *within-country* (Thailand) dynamics of aggregate growth and various dimensions of inequality. Conley and Udry (2005) study the process of technology diffusion using micro data for villages in Ghana. They focus on the micro mechanism of social learning for diffusion rather than its impact on macroeconomic dynamics, which is our focus.

Models featuring transition from a stagnant traditional sector to a growing modern sector were pioneered by Lewis (1954) and Ranis and Fei (1961). Unlike the assumptions

[1] Beaudry and Francois (2005) show how labor-experience complemantarities can generate multiple steady states in a two-sector model.

of these early models, we consider all inputs to be priced at competitive margins in both traditional and modern sectors. Despite this and the constant returns to scale production technologies, we still generate the essential take-off dynamics.

Household or firm surveys do not directly collect data on the partition of economy according to the use of traditional and modern technologies. Thus, the literature of dual-economy models approximates the traditional or modern sector by product or industry types (agriculture versus manufacturing) or by community type (rural versus urban). An empirical innovation of this paper is to identify the modern and traditional sectors together with their technology parameters from estimation on micro earnings equations tightly linked to theory.

Aggregate growth in the model is driven by the endogenous evolution of experience across sectors, combined with exogenous productivity growth in the modern sector. In conventional growth accounting, both sources of aggregate output growth would enter into total factor productivity (TFP) growth. Moreover, Klenow and Rodríguez-Clare (1997) and Caselli (2005) show that adding *aggregate* experience in measuring human capital plays virtually no role in accounting for differences in levels and growth rates of income across countries. Our model suggests that the relevant variable for explaining income differences is the *distribution* of *sector-specific* experience rather than aggregate experience. Incorporating this variable in measuring human capital will reduce the size of TFP and magnify the importance of human capital.[2]

The importance of structural change in understanding growth process is emphasized by Kuznets (1966), Lucas (2000) and Galor (2005) among others. Gollin, Parente and Rogerson (2002), and Hansen and Prescott (2002) highlight the importance of transition from agriculture to non-agriculture. In this literature, either Stone-Geary type non-homothetic preferences, the existence of a fixed input such as land, or some external barriers play a key role in making the transition gradual. We show that gradual transformation is also possible without these factors and that the speed and shape of transition can differ from differences in initial conditions alone. Another important aspect of structural change is rural-urban migration, emphasized by Todaro (1969) and recently by Lucas (2004), illuminating the role of human capital. We also emphasize the role of human capital in the transition from traditional to modern technology, but focus on human capital acquired through work experience rather than schooling.

The demographic composition of the workforce is a key aggregate state variable in explaining changes in earnings inequality in the model. The significance of cohort composition across industries and occupations in explaining the change in U.S. wage structure

[2] Manuelli and Seshadri (2005) pursue a different approach to reducing the size of TFP in relation to human capital, by endogenizing schooling decisions and quality of human capital.

has been documented by Welch (1979) and Katz and Murphy (1992) who emphasize relative cohort size, and more recently by Kambourov and Manovskii (2005) who emphasize occupation-specific experience. In contrast, our model emphasizes the relative ratio between labor (cohort size) and sector-specific experience in accounting for the changes in earnings profile over time. These effects can be identified by incorporating the time-series variation of the sectoral distribution of work experience in earnings equations. Here we highlight how these effects are more pronounced in developing countries undergoing transition between two sectors. Jeong, Kim and Manovskii (2006) consider a one sector model with labor-experience complementarity to explain changes in U.S. earnings inequality since the late 1960's. That analysis of one-sector model for U.S. is consistent with the current two-sector model for Thailand, under the view that the U.S. is considered to have completed the transition to modern sector.

3 Model

3.1 Two-period Model

Consider a two-period overlapping generations economy with constant population. Lifetime preferences of agents who are born at date t are

$$U(c_{0t}, c_{1t+1}) = c_{0t} + \beta c_{1t+1}, \tag{1}$$

where $\beta \in (0,1)$ is the time-discount factor, c_{0t} denotes the consumption of the young, and c_{1t+1} the consumption of the old. The lifetime budget constraint is given by

$$c_{0t} + \frac{1}{R_{t+1}} c_{1t+1} = y_{0t} + \frac{1}{R_{t+1}} y_{1t+1}, \tag{2}$$

where R_t is the interest factor. y_{0t} denotes the earnings of the young and y_{1t+1} the earnings of the old. Linear preferences imply $\beta = \frac{1}{R_t}$, $\forall t$.

There are two sectors, traditional and modern, associated with different technologies that produce a homogenous good. Each young agent is endowed with one unit of raw labor that is inelastically supplied to either sector. When old, this agent acquires a skill from the work experience specific to the sector he worked in when young. Old agents supply both this sector-specific experience and raw labor,[3] the effective units of which are subject to change by a factor λ ("depreciation" if $\lambda < 1$ or "appreciation" if $\lambda > 1$).

[3]Note that we split up the inputs into labor and experience for each agent unlike Chari and Hopenhayn (1991) who assume young and old agents supply different inputs. Our specification provides a more natural characterization of complementarity between young and old workers so that the two-period model can be easily generalized into a multi-period model, which we use for estimation and simulation later.

Let N_t and M_t denote the cohort shares of young agents who enter the traditional and modern sectors respectively in period t. Then, the aggregate measures of labor $L_{k,t}$ and experience $E_{k,t}$ of sector k ($k = T$ for traditional sector and $k = M$ for modern sector) are given by

$$\begin{aligned} L_{T,t} &= N_t + \lambda N_{t-1},\ E_{T,t} = \lambda N_{t-1} \\ L_{M,t} &= M_t + \lambda M_{t-1},\ E_{M,t} = \lambda M_{t-1} \end{aligned}$$

where

$$N_t + M_t = 1,$$

which determine the resource constraints. These can be simplified into a first-order difference equation system of single state variable M_t such that

$$\begin{aligned} L_{T,t} &= 1 - M_t + \lambda(1 - M_{t-1}),\ E_{T,t} = \lambda\left(1 - M_{t-1}\right), \\ L_{M,t} &= M_t + \lambda M_{t-1},\ E_{M,t} = \lambda M_{t-1}, \end{aligned} \tag{3}$$

given the initial state M_{-1}.

Let $G\left(L_{T,t}, E_{T,t}\right)$ and $\gamma^t X F\left(L_{M,t}, E_{M,t}\right)$ denote efficiency units of output contributed from the raw labor and experience in the traditional sector and the modern sector, respectively. $\gamma > 1$ is the exogenous growth factor available only in the modern sector and X denotes the productivity level of the modern sector relative to the traditional sector.[4] We assume $\beta\gamma < 1$. Aggregate labor earnings at date t is given by

$$LY_t = G\left(L_{T,t}, E_{T,t}\right) + \gamma^t X F\left(L_{M,t}, E_{M,t}\right). \tag{4}$$ [5]

The functions G and F represent sector-specific technologies combining labor and experience subject to constant returns to scale. In each sector, labor and experience are complements in a sense that

$$\frac{\partial^2 G\left(L_{T,t}, E_{T,t}\right)}{\partial L_{T,t}\partial E_{T,t}} \geq 0 \text{ and } \frac{\partial^2 F\left(L_{M,t}, E_{M,t}\right)}{\partial L_{M,t}\partial E_{M,t}} \geq 0.$$

Thus, experience does not simply add to raw labor in contributing to efficiency units of output.

Define $g\left(\frac{L_{T,t}}{E_{T,t}}\right) \equiv \frac{G\left(L_{T,t},E_{T,t}\right)}{E_{T,t}}$. Then $g'\left(\frac{L_{T,t}}{E_{T,t}}\right)$ measures the marginal product of raw labor, and $\phi\left(\frac{L_{T,t}}{E_{T,t}}\right) \equiv g\left(\frac{L_{T,t}}{E_{T,t}}\right) - g'\left(\frac{L_{T,t}}{E_{T,t}}\right)\frac{L_{T,t}}{E_{T,t}}$ measures the marginal product of experience in the traditional sector. Similarly, define $f\left(\frac{L_{M,t}}{E_{M,t}}\right) \equiv \frac{F\left(L_{M,t},E_{M,t}\right)}{E_{M,t}}$ and $\pi\left(\frac{L_{M,t}}{E_{M,t}}\right) \equiv$

[4] The growth factor γ may come from pure productivity changes or from relative price changes, which we do not distinguish.

[5] In Appendix A.2, we show how this aggregate earnings function can be derived from a general aggregate production function with physical capital, when the interest factor is constant (as implied by our assumption of linear perferences).

$f\left(\frac{L_{M,t}}{E_{M,t}}\right) - f'\left(\frac{L_{M,t}}{E_{M,t}}\right)\frac{L_{M,t}}{E_{M,t}}$. Then, the earnings of young workers $y_{k,0t}$ in sector k at date t are

$$\begin{aligned} \widetilde{y}_{T,0t} &= g'\left(\frac{L_{T,t}}{E_{T,t}}\right) \text{ for traditional sector,} \\ \widetilde{y}_{M,0t} &= \gamma^t X f'\left(\frac{L_{M,t}}{E_{M,t}}\right) \text{ for modern sector,} \end{aligned}$$

and the earnings of old workers $y_{k,1t}$ in sector k at date t are

$$\begin{aligned} \widetilde{y}_{T,1t} &= \lambda\left[g'\left(\frac{L_{T,t}}{E_{T,t}}\right) + \phi\left(\frac{L_{T,t}}{E_{T,t}}\right)\right] \text{ for traditional sector,} \\ \widetilde{y}_{M,1t} &= \lambda\gamma^t X\left[f'\left(\frac{L_{M,t}}{E_{M,t}}\right) + \pi\left(\frac{L_{M,t}}{E_{M,t}}\right)\right] \text{ for modern sector.} \end{aligned}$$

The cross-sectional experience premia, measured as the ratio of experienced worker earnings to inexperienced worker earnings, for a given period t are given by

$$\begin{aligned} \frac{y_{T,1t}}{y_{T,0t}} &= \lambda\left(1 + \frac{\phi\left(\frac{L_{T,t}}{E_{T,t}}\right)}{g'\left(\frac{L_{T,t}}{E_{T,t}}\right)}\right) \text{ for the traditional sector,} \\ \frac{y_{M,1t}}{y_{M,0t}} &= \lambda\left(1 + \frac{\pi\left(\frac{L_{M,t}}{E_{M,t}}\right)}{f'\left(\frac{L_{M,t}}{E_{M,t}}\right)}\right) \text{ for the modern sector.} \end{aligned}$$

Labor-experience complementarity implies that g' and f' are decreasing and ϕ and π are increasing in sector-specific labor-experience ratios. Thus, the experience premium is positively correlated with labor-experience ratios within each sector.

The lifetime earnings of an agent born at date t entering each sector are

$$\begin{aligned} & g'\left(\frac{L_{T,t}}{E_{T,t}}\right) + \beta\lambda\left[g'\left(\frac{L_{T,t+1}}{E_{T,t+1}}\right) + \phi\left(\frac{L_{T,t+1}}{E_{T,t+1}}\right)\right] \text{ for traditional sector} \\ & \gamma^t X\left\{f'\left(\frac{L_{M,t}}{E_{M,t}}\right) + \beta\lambda\gamma\left[f'\left(\frac{L_{M,t+1}}{E_{M,t+1}}\right) + \pi\left(\frac{L_{M,t+1}}{E_{M,t+1}}\right)\right]\right\} \text{ for modern sector.} \end{aligned}$$

If there is no sectoral reallocation of workers (i.e. when N_t, M_t are constant over time), which defines a steady state, we have

$$\frac{L_{T,t}}{E_{T,t}} = \frac{L_{M,t}}{E_{M,t}} = 1 + \frac{1}{\lambda}.$$

We assume that the lifetime earnings of an agent working in the traditional sector is weakly lower than that in the modern sector when there is no sectoral reallocation of workers

$$g'\left(1+\frac{1}{\lambda}\right)+\beta\lambda\left[g'\left(1+\frac{1}{\lambda}\right)+\phi\left(1+\frac{1}{\lambda}\right)\right] \tag{5}$$
$$\leq \gamma^t X\left\{f'\left(1+\frac{1}{\lambda}\right)+\beta\lambda(1+\gamma)\left[f'\left(1+\frac{1}{\lambda}\right)+\pi\left(1+\frac{1}{\lambda}\right)\right]\right\},$$

which we will call "pivotal condition."

Transition is generated by the arrival of positive productivity growth in the modern sector. In the absence of such growth, there is a level X_{IR} for X such that the steady state sectoral distribution of agents is indeterminate, where

$$g'\left(1+\frac{1}{\lambda}\right)+\beta\lambda\left[g'\left(1+\frac{1}{\lambda}\right)+\phi\left(1+\frac{1}{\lambda}\right)\right] \tag{6}$$
$$= X_{IR}\left\{f'\left(1+\frac{1}{\lambda}\right)+\beta\lambda\left[f'\left(1+\frac{1}{\lambda}\right)+\pi\left(1+\frac{1}{\lambda}\right)\right]\right\}.$$

Note that $X = X_{IR}$ is a sufficient condition for pivotal condition.

3.2 Equilibrium

A *competitive equilibrium* consists of a of sequence of modern cohort shares $\{M_t\}_{t=0}^{\infty}$ and interest factor R such that

1. every agent earns his marginal product;

2. young agents decide which sector to work in and how much to consume to maximize their lifetime utility (1) subject to the budget constraint (2), and lifetime earnings given by

$$\max\left\{\begin{array}{c} g'\left(\frac{L_{T,t}}{E_{T,t}}\right)+\frac{1}{R_{t+1}}\lambda\left[g'\left(\frac{L_{T,t+1}}{E_{T,t+1}}\right)+\phi\left(\frac{L_{T,t+1}}{E_{T,t+1}}\right)\right], \\ \gamma^t X\left[f'\left(\frac{L_{M,t}}{E_{M,t}}\right)+\frac{1}{R_{t+1}}\lambda\gamma\left[f'\left(\frac{L_{M,t+1}}{E_{M,t+1}}\right)+\pi\left(\frac{L_{M,t+1}}{E_{M,t+1}}\right)\right]\right] \end{array}\right\}; \tag{7}$$

3. the resource constraints in (3) are satisfied, and

4. the credit market clears in every period. (Linear preferences imply the credit market clearing condition is $\frac{1}{R_t} = \beta \ \forall t$.)

If young agents enter both sectors in period t, i.e. $M_t \in (0,1)$, the following "participation constraint" should be satisfied during transition

$$g'\left(1+\frac{1-M_t}{\lambda(1-M_{t-1})}\right)+\beta\lambda\left[g'\left(1+\frac{1-M_{t+1}}{\lambda(1-M_t)}\right)+\phi\left(1+\frac{1-M_{t+1}}{\lambda(1-M_t)}\right)\right] \tag{8}$$
$$=\gamma^t X\left\{f'\left(1+\frac{M_t}{\lambda M_{t-1}}\right)+\beta\lambda\gamma\left[f'\left(1+\frac{M_{t+1}}{\lambda M_t}\right)+\pi\left(1+\frac{M_{t+1}}{\lambda M_t}\right)\right]\right\}.$$

Lemma 1 *Let $\widehat{T}$ denote the first period at which an entire cohort works in the modern sector. Then, $M_{\widehat{T}} = 1$ implies $M_{\widehat{T}+s} = 1$ $\forall s \geq 1$.* Proof is in Appendix A.1.

Combining Lemma 1 with the participation constraint (8), we get

$$\begin{aligned} (9) \qquad & g'(1) + \beta\lambda\left[g'(1) + \phi(1)\right] \\ \leq \; & \gamma^t X\left\{f'\left(1 + \frac{1}{\lambda M_{t-1}}\right) + \beta\lambda\gamma\left[f'\left(1+\frac{1}{\lambda}\right) + \pi\left(1+\frac{1}{\lambda}\right)\right]\right\}, \ \forall t \geq \widehat{T}. \end{aligned}$$

Equations (8) and (9) define a second-order difference equation system in M_t, which characterizes the equilibrium transition dynamics of the model.[6]

Proposition 1 *For a given initial state M_{-1}, (i) there exists a unique equilibrium transition path with $\widehat{T} < \infty$; (ii) $M_{t-1} \leq M_t$ $\forall t \geq 1$; (iii) M_t increases in M_{-1}, $\forall t \geq 0$; (iv) $\widehat{T}$ decreases in M_{-1}.* Proof is in Appendix A.1.

Proposition 1.(i) and 1.(ii) state that transition follows a unique path ending in finite time, and the modern population share does not decrease over time. Proposition 1.(iii) and 1.(iv) state that transition occurs faster if the initial modern share is higher. In other words, transition can be very slow, and the economy may seem trapped for a long while, when the initial modern share is very low.

We observe from our simulations that lifetime earnings display an S-shaped path. When transition is complete, everyone is in the modern sector and the economy will follow a constant steady-state growth path at a rate γ. During transition, lifetime earnings increase at a rate slower than γ and then faster than γ. Two extreme cases provide intuition for this result. First, suppose there is no complementarity in the traditional sector, $\frac{\partial^2 G\left(L_{T,t}, E_{T,t}\right)}{\partial L_{T,t} \partial E_{T,t}} = 0$. Then, the lifetime earnings of the traditional sector should be constant regardless of changes in labor-experience ratios during transition, and the participation constraint (8) implies the modern lifetime earnings is constant as well. Despite modern productivity growth, lifetime earnings are constant during transition up to period $\widehat{T} - 1$ (one period before all young agents enter the modern sector), then converge to the steady-state lifetime earnings path by period $\widehat{T} + 1$, generating a kink shaped path.

Second, suppose there is no complementarity in the modern sector, $\frac{\partial^2 F\left(L_{M,t}, E_{M,t}\right)}{\partial L_{M,t} \partial E_{M,t}} = 0$.Then, the labor-experience ratios do not affect modern lifetime earnings, which simply grow at the rate γ. Again, participation constraint (8) implies traditional lifetime earnings must grow at the same rate. Here, lifetime earnings grow linearly at rate γ during and after

[6] Note that this competitive equilibrium allocation of workers across technologies coincides with the allocation of the following social planner's problem:

$$\max_{\{M_t\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \beta^t L Y_t \text{ s.t. (3) and (4).}$$

transition. In general, when there exist complementarities in both sectors, we observe the S-shaped path of lifetime earnings.

Proposition 2 *During transition, (i) if lifetime earnings are rising over time, the population of the traditional sector is falling at a faster rate,* $\frac{1-M_t}{1-M_{t-1}} > \frac{1-M_{t+1}}{1-M_t}$*; (ii) if lifetime earnings are first rising slower than* γ*, then rising faster than* γ*, the population growth of the modern sector is single peaked, i.e., there exists unique period* $S < \widehat{T}$ *such that* $\frac{M_t}{M_{t-1}} < \frac{M_{t+1}}{M_t}$ *for all* $t < S$ *and* $\frac{M_t}{M_{t-1}} \geq \frac{M_{t+1}}{M_t}$ *for all* $t \geq S$*.*Proof is in Appendix A.1.

The result that the population growth of the modern sector is single peaked, implies that the modern sector population first accelerates then decelerates, generating an S-shaped pattern. The curvature of the S-shaped paths depend on functional forms and the parameter space of F and G. This makes quantitative analysis based on explicit estimation and simulation important, which we conduct later. We first perform some comparative statics analysis to illustrate key features of the model. Then, we extend the model to a general multi-period overlapping generations framework to bring the model to data.

3.3 Comparative Statics

The transition dynamics of the model crucially hinge on the degree of sectoral complementarity between labor and experience and the initial cohort share of the modern sector. We parameterize the sectoral production functions G and F by the following CES forms

$$G\left(L_{T,t}, E_{T,t}\right) = \left[\alpha_T L_{T,t}^{\rho_T} + (1-\alpha_T) E_{T,t}^{\rho_T}\right]^{\frac{1}{\rho_T}} \tag{10}$$

$$F\left(L_{M,t}, E_{M,t}\right) = \left[\alpha_M L_{M,t}^{\rho_M} + (1-\alpha_M) E_{M,t}^{\rho_M}\right]^{\frac{1}{\rho_M}} \tag{11}$$

where $\rho_k \leq 1$ and $0 < \alpha_k < 1$, for $k = T$ and M.[7] We demonstrate the properties of the model by varying the complementarity parameters ρ_k's, and the initial modern cohort share M_{-1} over the 5 cases reported in Table 1.[8]

Table 1. Parameter Values for Comparative Statics

	Case 1	Case 2	Case 3	Case 4	Case 5
ρ_T	1	-1	-0.5	-0.5	-0.5
ρ_M	-1	1	-0.5	-0.5	-0.5
M_{-1}	0.001	0.001	0.001	0.00001	0.1

[7] The elasticity of substitution between labor and experience in sector k is measured by $\frac{1}{1-\rho_k}$. The lower the value of ρ_k, the greater the complementarity between labor and experience in sector k. At the limit value of ρ_k at unity, labor and experience are perfect substitutes and the premium for an additional unit of experience is determined by $(1-\alpha_k)$ alone.

[8] We assume people work for 60 years and adjust the parameter values to the 2-period OLG framework. The values of the common parameters used for this exercise are $\beta = 0.8^{30}$, $\gamma = 1.022^{30}$, $\lambda = 0.98^{30}$ and $\alpha_T = \alpha_M = 0.8$. To satisfy the pivotal condition, we set $X = X_{IR}$ as in (6), which varies as the parameter configuration changes. Specifically, X_{IR} is 1.77 for Case 1, 0.56 for Case 2 and 1 for Cases 3 to 5.

In Case 1, there is no labor-experience complementarity in the traditional sector ($\rho_T = 1$). In Case 2, there is no complementarity in the modern sector ($\rho_M = 1$). In Case 3, there exists complementarity in both sectors ($\rho_T = \rho_M < 1$) at intermediate levels. The three Cases 1, 2, and 3 share the same initial modern cohort share $M_{-1} = 0.001$. Comparison over these three cases illustrates how transition dynamics depend on complementarities. Lower ρ_k means stronger complementarity, and hence higher elasticity of earnings to labor-experience ratios in sector k.[9] For the participation constraint (8) to be satisfied, we expect faster transition as the complementarity of the entry sector becomes weaker (higher ρ_M), or the complementarity of the exit sector becomes stronger (lower ρ_T). This is confirmed in Figures 1.1 and 1.2. Population transition is fastest for Case 2 and slowest for Case 1. The slower the transition, the longer it takes for aggregate earnings to approach the steady-state growth path.[10] We observe S-shaped transition paths both in terms of population share and aggregate earnings. The curvature becomes stronger as ρ_M becomes lower or ρ_T becomes higher.

Case 4 and Case 5 keep the technology parameters the same as Case 3, but allow the initial modern cohort share to vary such that $M_{-1} = 0.00001$ for Case 4 and $M_{-1} = 0.1$ for Case 5. Figure 1.3 shows that the lower the initial modern cohort share, the later the acceleration in population share and the faster the increase in population share once acceleration takes place. Figure 1.4 shows similar patterns for aggregate earnings dynamics. Thus, among economies with otherwise identical characteristics, diverse patterns of growth, from stagnation to miracles, can be generated from differences in the initial modern cohort share.

3.4 General J-period Model

We now generalize the model into a J-period overlapping-generations model for $2 \leq J < \infty$, which will be used in our estimation and simulation. Lifetime preferences of agents who are born at date t are

$$U_t = \sum_{j=0}^{J-1} \beta^j c_{j,t+j}. \tag{12}$$

[9] Changes in ρ_k affect the degrees of sectoral complementarities and also the levels of lifetime earnings that in turn affect the participation constraint. One way of filtering out the second effect is to vary X_{IR} across Cases 1 to 3 while varying ρ_k as in (6).

[10] For a consistent comparison over the steady states across cases, the aggregate earnings are normalized by the level of initial-period earnings of a full-transition economy, where transition is completed. This generates the gap in initial earnings across the three cases.

As before, linear preferences imply $\frac{1}{R_t} = \beta, \forall t$ and the lifetime budget constraint is

$$\sum_{j=0}^{J-1} \beta^j c_{j,t+j} = \sum_{j=0}^{J-1} \beta^j y_{j,t+j}. \tag{13}$$

Each agent who has worked for j periods in sector k is endowed with $\lambda_k(j)$ units of labor and $j\lambda_k(j)$ units of sector-specific experience, where $\lambda_k(j)$ reflects the change in effective units of labor and experience across experience j's.[11] The aggregate measures of sectoral labor and experience at date t are given by

$$L_{T,t} = \sum_{j=0}^{J-1} \lambda_T(j) D_{jt} N_{t-j}, \tag{14}$$

$$E_{T,t} = \sum_{j=0}^{J-1} j\lambda_T(j) D_{jt} N_{t-j}, \tag{15}$$

$$L_{M,t} = \sum_{j=0}^{J-1} \lambda_M(j) D_{jt} M_{jt-j}, \tag{16}$$

$$E_{M,t} = \sum_{j=0}^{J-1} j\lambda_M(j) D_{jt} M_{t-j}, \tag{17}$$

$$N_{t-j} + M_{t-j} = 1, \tag{18}$$

where D_{jt} denotes the total measure of agents with j periods of experience at date t. When workforce participation rates are constant across experience groups and over time, D_{jt} is constant over j and t. We allow D_{jt} to exogenously vary over j and t to capture the observed asymmetry in labor force participation rates across experience groups, which also fluctuates over time. The key state variable that endogenously evolves over time is $\{M_t\}_{t=0}^{\hat{T}-1}$ given the initial condition $\{M_{-j}\}_{j=1}^{J-1}$.

The cross-sectional earnings $\widetilde{y}_{k,t}(j)$ of workers with j periods of experience in sector k at date t are

$$\widetilde{y}_{T,t}(j) = \lambda_T(j)\left[g'\left(\frac{L_{T,t}}{E_{T,t}}\right) + \phi\left(\frac{L_{T,t}}{E_{T,t}}\right) j\right] \text{ for traditional sector,} \tag{19}$$

$$\widetilde{y}_{M,t}(j) = \lambda_M(j)\gamma^t X\left[f'\left(\frac{L_{M,t}}{E_{M,t}}\right) + \pi\left(\frac{L_{M,t}}{E_{M,t}}\right) j\right] \text{ for modern sector.} \tag{20}$$

The implied experience premia of workers with j periods of experience relative to zero-

[11]In the absence of $\lambda_k(j)$, the cross-sectional experience-earnings profile would be linear in j, whereas it is typically concave in j in the data. The $\lambda_k(j)$ factor is to capture this feature of the data.

experienced workers are

$$\frac{\widetilde{y}_{T,t}(j)}{\widetilde{y}_{T,t}(0)} = \frac{\lambda_T(j)}{\lambda_T(0)}\left[1+\frac{\phi\left(\frac{L_{T,t}}{E_{T,t}}\right)}{g'\left(\frac{L_{T,t}}{E_{T,t}}\right)}j\right] \text{ for traditional sector,} \tag{21}$$

$$\frac{\widetilde{y}_{M,t}(j)}{\widetilde{y}_{M,t}(0)} = \frac{\lambda_M(j)}{\lambda_M(0)}\left[1+\frac{\pi\left(\frac{L_{M,t}}{E_{M,t}}\right)}{f'\left(\frac{L_{M,t}}{E_{M,t}}\right)}j\right] \text{ for modern sector,} \tag{22}$$

which increase with the respective sectoral labor-experience ratios due to the complementarity.[12]

The lifetime earnings of a cohort born at date t entering sector k are given by

$$\sum_{j=0}^{J-1}\beta^j\lambda_T(j)\left[g'\left(\frac{L_{T,t+j}}{E_{T,t+j}}\right)+\phi\left(\frac{L_{T,t+j}}{E_{T,t+j}}\right)j\right] \text{ for traditional sector,}$$

$$\gamma^t X\sum_{j=0}^{J-1}\beta^j\lambda_M(j)\gamma^j\left[f'\left(\frac{L_{M,t+j}}{E_{M,t+j}}\right)+\pi\left(\frac{L_{M,t+j}}{E_{M,t+j}}\right)j\right] \text{ for modern sector.}$$

The pivotal condition becomes

$$\sum_{j=0}^{J-1}\beta^j\lambda(j)\left[g'\left(l_T^*\right)+\phi\left(l_T^*\right)j\right] \leq \gamma^t X\sum_{j=0}^{J-1}\beta^j\lambda(j)\gamma^j\left[f'\left(l_M^*\right)+\pi\left(l_M^*\right)j\right], \tag{23}$$

where l_k^* denotes the labor-experience ratio of sector k with no sectoral reallocation of workers, i.e. $l_T^* = \frac{\sum_{j=0}^{J-1}\lambda_T(j)}{\sum_{j=0}^{J-1}j\lambda_T(j)}$ and $l_M^* = \frac{\sum_{i=0}^{J-1}\lambda_M(j)}{\sum_{j=0}^{J-1}j\lambda_M(j)}$. In Appendix A.3, we outline the equilibrium construction procedure for this general model.

4 Data

We use a nationally representative household survey from Thailand, the Socio-Economic Survey (SES), for the 1976-1996 period. Eight rounds (1976, 1981, 1986, 1988, 1990,

[12]Note that the more distant the cohorts are separated in time, the more complementary they are at a given date. Taking modern sector, for example,

$$\begin{aligned}\frac{\partial^2 F}{\partial M_{t-i}\partial M_{t-j}} &= \frac{\partial}{\partial M_{t-j}}\lambda_M(i)\left[f'(\frac{L_{M,t}}{E_{M,t}})+i\pi(\frac{L_{M,t}}{E_{M,t}})\right] \\ &= f''(\frac{L_{M,t}}{E_{M,t}})\lambda_M(i)\left[1-i\frac{L_{M,t}}{E_{M,t}}\right]\frac{d\left(\frac{L_{M,t}}{E_{M,t}}\right)}{dM_{t-j}} \\ &= \left\{\frac{f''(\frac{L_{M,t}}{E_{M,t}})}{E_{M,t}}\lambda_M(i)\lambda_M(j)\right\}\left[1-i\frac{L_{M,t}}{E_{M,t}}\right]\left[1-j\frac{L_{M,t}}{E_{M,t}}\right]\end{aligned}$$

where $\left\{\frac{f''(\frac{L_{M,t}}{E_{M,t}})}{E_{M,t}}\lambda_M(i)\lambda_M(j)\right\} < 0$.

1992, 1994, and 1996) of repeated cross-sections were collected during this period, using clustered random sampling, stratified by geographic regions (Bangkok and its Metropolitan vicinity region, Central region, Northern region, Northeast region, and South region). The SES categorizes total income into wage, profits, property income, and transfer income.[13] The SES reports working status as employer, self-employed, employee, family worker, unemployed, or inactive.

Combining the disaggregated income and work status data, we sort out earned income (i.e. wages for the employed workers and profits for the self-employed) from total income to construct the earnings variable that we analyze. We include only economically active people, (neither unemployed nor inactive people) who indeed report positive earnings. The components of income from property income, rental income and transfer income are all excluded. People who live only these sources of income are also excluded. Given this selection rule, the size of the selected sample is 178,428 individuals over all sample years.

A basic feature of transition is entry and exit across occupational activities. The SES provides us with detailed, three-digit occupational categories, which we arrange by their growth in labor force share, and partition into an entry group and an exit group. Note, however, that we are not identifying the traditional versus modern sectors by the changes in employment share. We identify the sectors by absence (for "traditional sector") or presence (for "modern sector") of exogenous productivity growth. Details of this partition will be discussed in the Estimation Section.

We first estimate the following reduced-form log-earnings equation to describe the dynamics of sectoral earnings profiles in the data free of models:

$$\ln y_{it} = \sum_{k \in \{T,M\}} d_{k,it} \left[u_k t + \sum_{t=1981}^{1994} b_{kt} d_t + \sum_{t=1976}^{1996} \sum_{j=1}^{19} a_{kjt} d_{j,it} d_t + C_k \chi_{it} \right] + \nu_{it}. \tag{24}$$

The indices i, t, and k are for individual, date, and sector, respectively. The variable d_k denotes the sector dummy for sector k, u_k the linear trend of earnings for sector k, d_t the year dummy for date t, d_j the experience dummy for experience j, χ the income-generating socioeconomic characteristics (such as years of schooling, geographic region, community type, and gender), and ν the unobservable residuals. The SES does not provide direct information for actual work experience. We follow the convention of the labor literature, measuring experience by (age - years of schooling - 6), ranging from 0 to 59.[14] Then, the

[13] The nominal income values are converted into real terms in 1990 baht value using the CPI indices differentiated by the regions.

[14] If occupational switches occurred *within* each sector only, this is a precise measure of sectoral work experience, ignoring unemployment. One of the findings of Kim and Topel (1995) for Korea is that the reallocation of workers across sectors during industrialization is realized through new cohorts who stay in their sectors after entry. This seems to apply to Thailand as well, which we will verify in Figure 2.

experience groups are sorted into three-year intervals for the experience dummies d_j's.[15] This earnings equation includes the cross-sectional control variables of a typical Mincerian earnings regression, but it also controls for aggregate effects by allowing sector-specific and time-varying experience premia and sector-specific trend terms, and by including a set of identifiable year dummies.[16] We also avoid assuming any functional form on the experience-earnings profiles and the aggregate effects (except the sorting out of linear trend terms).

We identify sector-specific productivity growth by u_k, the trend term obtained after filtering out the effects of sector-specific cross-sectional variation due to experience, years of schooling, geographic regions, community types and gender, and also the effects due to time-series aggregate fluctuation. The estimates are $u_T = -0.00038$ and $u_M = 0.04656$ (p-values are 0.927 and 0.000, respectively for u_T and u_M). This indicates that there are two groups in the population with a clear gap in productivity growth, one with virtually zero growth ("traditional" sector) and the other with positive growth ("modern" sector), as our model assumes.

Despite this productivity growth gap, both sectors have coexisted over the sample period, not only among old cohorts, but also among the youngest cohorts entering the workforce. Figure 2 plots the series of cohort shares of the modern sector population from each of the eight rounds of the SES data.[17] If every cohort does not switch sectors after their initial entry decision, the cohort share series should overlap precisely over the eight rounds of sample years. We do observe some disparity in the cohort share series across sample years. The cohort share series has shifted up over time. This implies that net entry to modern sector has happened among workers in the middle of their career within cohorts. This within-cohort increase in modern sector was 11.6% between 1976 and 1996, i.e. a 0.6% average annual increase. However, a much larger expansion of modern sector happened due to the transition across cohorts, a 40% increase between 1976 and 1996, i.e. a 2% average annual increase. Furthermore, the cohort share series for each sample year displays a common pattern of transition, which is initially very gradual, then takes off with acceleration. We focus on this across-cohort transition dynamics and attempt to capture this as an equilibrium outcome.

Using a nonparametric method of local polynomial fitting, we estimate a trend of

[15] That is, the experience group dummy $d_0 = 1$ for the workers with experience 0 to 2, $d_1 = 1$ for the workers with experience 3 to 5, and so on. The least experience group is taken as a reference group and d_0 is omitted.

[16] The initial year 1976 is taken as a reference year and the year dummy d_{1976} is omitted. The year dummy for final year d_{1996} is also omitted to identify the sector-specific linear trends u_k's.

[17] A cohort is identified by experience, and the earliest cohort (the highest-experienced workers in 1976) entered the labor force in 1919 while the latest cohort (zero-experienced workers in 1996) in 1996.

modern cohort share.[18] This is labelled "Trend" in Figure 2, which we consider as representing the path of Thai transition to modern growth. Thai modern cohort share increased substantially from 18 percent for the 1919 cohort to 58 percent for the 1996 cohort. The transition was slow for the first thirty years and then accelerated rapidly around the early 1950's. The aggregate population share of the modern sector increased from 19 percent in 1976 to 40 percent in 1996.

The experience-earnings profile (normalized by the earnings level of the zero-experience group) for sector k at date t can be constructed from the estimates of $\{a_{kjt}\}_{j=1}^{19}$. Sample profiles for each sector are plotted in Figures 3.1 and 3.2, for 1976, 1996, and 1988 (the sample year when experience profiles peak). The experience premia are very large, in particular for traditional sector. Experience premia peak in 1988 at 4.90 and 8.63 for modern and traditional sectors respectively. The shapes of the profiles differ across sectors for a given year. While modern profiles are hump-shaped as is typically observed in developed countries, traditional profiles do not seem to decline with experience. Within each sector, the shape and slope of earnings profiles vary substantially over time. The profiles shift up and get steeper between 1976 and 1988, and then shift down and flatten between 1988 and 1996. The movements are much more pronounced in the traditional sector.

Figures 3.3 and 3.4 show that aggregate labor and experience increased in the modern sector while they decreased in the traditional sector throughout the sample period.[19] Thus, neither cohort size nor experience size alone are able to explain the rise and fall of the experience premium in each sector. However, for each sector, the *ratio* of labor to experience shown in Figures 3.5 and 3.6, mirrors the rise and fall of the experience

[18] Given the observed cohort share series $\{N_t\}_{t=1}^{T}$, averaged over the eight sample years, the smoothed value $\widehat{N}_t$ at each date t is estimated as follows:

$$\widehat{N}_t = \sum_{s=\max(1,s-k)}^{\min(s+k,T)} \varpi_s N_s,$$

where

$$\begin{aligned} k &= [(0.8T - 0.5)/2], \\ \varpi_s &= \left[1 - \left(\frac{|N_t - N_s|}{1.0001\max(N_{\min(s+k,T)} - N_t, N_t - N_{\max(1,s-k)})}\right)^3\right]^3. \end{aligned}$$

Note that k governs the bandwidth of the neighborhood values and ϖ_s is the tricubic weight for the neighborhood values within the bandwidth. The optimal bandwidth parameter and the weighting function are chosen from the Lowess procedure in Stata Technical Bulletin Vol. 3: 7-9.

[19] Sectoral labor is measured by the number of workers within each sector normalized to total population size at each year. Sectoral experience is measured by the sum of experience levels weighted by population shares of experience groups within sector. Depreciation factors to effective units of labor and experience are not considered here. Later incorporating depreciation factors (estimated from our structural estimation) does not change these patterns of movements of sectoral labor and experience.

premium. This positive correlation between the labor-experience ratio and experience premium within each sector, is consistent with the presence of sector-specific complementarity between labor and experience.

In sum, the documented (i) coexistence of two sectors with substantial gap in productivity growth, and (ii) the existence of sector-specific complementarity between labor and experience, are the key specifications of our model.

Figure 4.1 shows that average earnings grew with acceleration during the second decade, following a decade of stagnation, while earnings inequality, measured by the Theil-L entropy index, shows an inverted-U path.[20] When we filter out the effects from the control variables χ_{it} and the residual ν_{it} (which are not our model is about), the growth and inequality features becomes different, as shown in Figure 4.2. Despite the high modern-sector productivity growth, aggregate labor productivity (i.e., aggregate earnings after filtering out the effects of control variables) remained virtually constant due to the dominance of the stagnant traditional sector. The inverted-U shape of the earnings inequality path becomes more pronounced. In the following sections, we estimate the technology parameters of our model using a cross-sectional log-earnings relationship of the model and simulate the model at these estimates to assess its quantitative importance in explaining the transition dynamics of population shift and the growth and inequality of earnings as observed above.

5 Estimation

5.1 Sector Partitioning

Partitioning the workforce into traditional and modern sectors is a key measurement for the model. However, unlike other dual economy partitions (e.g. rural versus urban or agriculture versus non-agriculture), our partition does not have a direct counterpart in the data. Although possibly correlated, the "modern" sector in our model does not necessarily correspond to urban areas or non-agriculture.

We construct the partition following a *guess-and-verify* strategy by using an entry-exit criterion implied by the model. We disaggregate the workforce using three-digit occupational data, compute the rates of change in workforce shares between 1976-1996 for each occupational category, and order the occupational categories by the rates of net entry. The model predicts that occupations with positive net entry rates are likely to be in the modern sector in the model. So, we guess a threshold level of rate of net entry

[20] These inequality dynamics are robust to the choice of other inequality indices. Here, we use the Theil-L entropy index due to its decomposability that we use later.

around zero, occupational categories above which we assign to the modern sector.[21] It is important to note that we use the employment share growth data to get an initial guess for the sector partitioning, and not for the final identification of the modern sector.

Given the guessed partition, we estimate sectoral exogenous growth rates using an earnings function derived from the model and *verify* if the estimated exogenous growth rates are consistent with the model, i.e., positive only for the modern sector and zero for the traditional sector. If the estimates of the exogenous growth rates agree with the model, we take the partition in the data as the one corresponding to the model. If not, we choose another guess, and verify again. This loop of guess-and-verify is iterated until we find the right partition.

The use of disaggregated occupational categories is helpful in identifying the sectors for two reasons. First, this helps group people by homogeneous skills, and hence the presumed complementarity between labor and experience is likely to be captured. Second, if the workforce is grouped too coarsely, the compositional changes among the sub-groups belonging to different sectors may offset each other and we may not form an informative initial guess for the partition.[22]

At the chosen sectoral partition, we find that the Thai economy underwent transition slowly for the first thirty years since 1919, with rapid acceleration thereafter, as already shown in Figure 2. We find that traditional and modern sectors coexist in both rural and urban areas although the modern population share is higher in urban areas (53 percent on average) than rural areas (22 percent on average). Furthermore, the process of modernization, as shown in Figure 5.1, is similar between rural and urban areas. This suggests that there exists a driving force of modernization independent from urbanization. Figure 5.2 shows that transition to modern growth is present within agriculture, manufacturing, and services, although the magnitudes of modernization differ across them, 13 percent for agriculture, 35 percent in services, and 78 percent in manufacturing on average.

[21] The level and change of the population shares of occupational categories in the data are likely to be subject to sampling errors, and hence we vary the threshold level around zero rather than pinning it down at zero.

[22] There is also a caveat to using disaggregated occupational data. With too much disaggregation, we may lose consistency in grouping people in terms of relevant experience. In the model, sector-specific experience is defined by technology, not directly by occupation. In the data, however, the composition among employees, employers, and self-employed may change over time within a sector using the same technology. The model is silent about this kind of compositional change. Thus, the exclusive use of net entry rates for the initial guess may lead us to an error. When this kind of disaggregation problem is clear, we re-aggregate them into the same group. For example, the fastest and largest declining occupational group in Thailand is rice farmers. So, it is assigned to the traditional sector. However, the population share of rice-farm workers increased over time. The net-entry criterion suggests that the rice-farm workers be assigned to the modern sector but we assign them to the traditional sector for the purposes of consistency. Still, we verify if this re-assignment is consistent with the model in terms of estimated gap in productivity growth rates between the sectors.

Table 2 lists examples of three-digit occupations from traditional and modern sectors by industry, illustrating that traditional and modern sectors coexist within apparently similar types of activities.[23] This suggests what determines being traditional or modern is *the way* that workers organize their activities rather than *the objects* that they produce.

Table 2. Examples of Occupations of Each Sector

	Traditional Sector	Modern Sector
Agriculture	rice farming, field-crop farming	fishery, fruit farming
Manufacturing	metal caster, blacksmith	sheet metal maker, mechanic
	grain miller, tobacco maker	food and beverage processor
	tailor	pattern maker, embroider
	wood-paper-rubber product maker	electric/electronic engineer
Service	street and waterway vendor	insurance, real estate salesman
	midwife, occupational therapist	doctor, nurse
	legislative and government administrator	lawyer, judge
	journalist	physical/life scientist
	cook, cleaner, hairdresser, driver	accountant
	primary/secondary school teacher	pre-school/university teacher
	policeman, armed force	fireman

5.2 Earnings Function

Applying the CES specifications in (10) and (11) respectively to the J-period earnings functions (19) and (20), the cross-sectional earnings function $\widetilde{y}_{k,t}(j)$ of an agent with j periods of experience in sector k (for $k = T$ and M) at date t is given by

$$\widetilde{y}_{k,t}(j) = \lambda_k(j){\gamma_k}^t \left[\alpha_k \left(\frac{L_{k,t}}{E_{k,t}}\right)^{\rho_k} + (1-\alpha_k)\right]^{\frac{1}{\rho_k}-1} \left[\alpha_k \left(\frac{L_{k,t}}{E_{k,t}}\right)^{\rho_k - 1} + j(1-\alpha_k)\right]$$

In a typical aggregate production function, raw labor and experience are treated as perfect substitutes and experience simply adds to effective units of labor. This is a special limit case of the CES technology in our earnings function at $\rho_T = \rho_M = 1$. We take $J = 20$ and experience cohorts are formed in three year intervals as was done in the reduced-form earnings equation (24). The sectoral labor and experience variables $L_{T,t}$, $E_{T,t}$, $L_{M,t}$, and

[23] For example, among teachers, pre-school teachers are modern while primary school teachers are traditional. Among protective service workers, firemen are modern while policemen and armed forces are traditional. Among medical service workers, doctors and nurses belong to the modern sector while midwives and occupational therapists to the traditional sector. These kinds of examples are found also in manufacturing. Both blacksmiths and sheet metal workers work on metal materials, but blacksmiths belong to the traditional sector while sheet metal workers to the modern sector. Both tailors and embroiders work in the textile industry, but the former belong to the traditional sector while the latter to the modern sector.

$E_{M,t}$ are measured as in equations (14) to (17). Note that we allow both γ_T and γ_M to take any values in our estimation although the model presumes $\gamma_M > \gamma_T = 1$. This is our verifying device in identifying the traditional and modern sectors from the data. If the partitioning is correct, the estimated γ_T and γ_M should agree with the presumption of the model.

In applying the earnings equation to the data, we allow for exogenous variation in effective units of productivity z_k across individuals in each sector k to minimize omitted-variable bias. z_k depends on observable productive attributes χ_{it} and unobservable attributes ϵ_{it} for individual i at date t. Thus, the observed earnings $y_{k,it}(j)$ of individual i at date t with experience j in sector k is

$$y_{k,it}(j) = z_k(\chi_{it}, \epsilon_{it})\widetilde{y}_{k,t}(j), \text{ for } k \in \{T, M\}.$$

We include years of schooling, gender, community type, geographic region, and constant terms in χ_{it}, assuming $z_k(\chi_{it}, \epsilon_{it})$ to take the following exponential form

$$z_k(\chi_{it}, \epsilon_{it}) = \exp\left[C_k \chi_{it} + \epsilon_{it}\right],$$

and ϵ_{it} are drawn from a mean-zero $i.i.d$ normal distribution over i and t.

In sum, we estimate the following log-earnings equation for individual i at date t,

$$\ln y_{it} = \sum_{k \in \{T,M\}} d_{k,it}\left[t\ln(1+g_k) + \ln\lambda_k(j) + \Psi_k\left(\frac{L_{k,t}}{E_{k,t}}, j\right) + C_k\chi_{it}\right] + \epsilon_{it}, \tag{25}$$

where $d_{k,it}$ is an indicator variable for sector k, i.e. $d_{k,it} = 1$ if an individual i belongs to sector k at date t and 0 otherwise, and

$$\Psi_k\left(\frac{L_{k,t}}{E_{k,t}}, j\right) \equiv \left(\frac{1}{\rho_k} - 1\right)\ln\left[\alpha_k\left(\frac{L_{T,t}}{E_{T,t}}\right)^{\rho_k} + (1-\alpha_k)\right] + \ln\left[\alpha_k\left(\frac{L_{k,t}}{E_{k,t}}\right)^{\rho_k - 1} + j(1-\alpha_k)\right]. \tag{26}$$

We normalize years setting $t = 0$ for 1976. Note the growth factor γ_k is replaced with $(1 + g_k)$ in order to facilitate the statistical significance test in identifying sectors. We test if g_T is estimated to be statistically insignificant and g_M is statistically different from zero and positive. The sector-specific depreciation schedule $\lambda_k(j)$ is approximated by the fifth-order polynomial (rather than the typical quadratic form) to capture the more flexible depreciation schedules observed in the data[24]

$$\lambda_k(j) = 1 + \lambda_{k1} j + \lambda_{k2} j^2 + \lambda_{k3} j^3 + \lambda_{k4} j^4 + \lambda_{k5} j^5.$$

[24] We experimented over the order of the polynomial from one to ten and found that the cubic to fifth-order terms are essential in capturing the sectoral differences in the shapes of earnings profiles, but increasing the order of the polynomial beyond five plays virtually no role.

In typical Mincerian earnings regressions, only cross-sectional variations of individual income-generating attributes determine earnings. In our earnings equation (25), the time-series variation of aggregate state variables (sectoral labor-experience ratios) also affect individual earnings due to the sector-specific complementarity between labor and experience. The labor-experience ratio determines the market value of experience. The ratios change during transition causing the experience premium to change also.[25] Thus, excluding the sectoral labor-experience ratios in earnings equation may bias the size and change of the experience premium, particularly for economies undergoing transition to modern growth.

5.3 Identification

The technology parameters can be measured by estimating the cross-sectional earnings equation (25) using a sample pooled over time. This micro estimation strategy has two kinds of merit. First, no national income statistics exist to calibrate the complementarity parameters of production functions in our model distinguishing traditional and modern sectors. Furthermore, even if such data were available, it is well-known that identification of technology parameters from time series relationships between aggregate inputs and outputs suffers from endogeneity bias problems. Our micro estimation helps us avoid these problems. The standard errors from the structural estimation helps us to infer the parameter space of the model that conforms to the data. This is particularly helpful in finding the relevant range of parameters for sensitivity analysis.

Second, by not using the full data (such as aggregate dynamics) in parameter selection, and saving them for the model evaluation stage, the potential over-fitting problem can be avoided.[26] In this sense, we follow the original spirit of calibration, i.e. separation between parameter selection and model evaluation.

The parameters of the additively separable terms, i.e. $\{\gamma_k, \lambda_{k1}, \lambda_{k2}, \lambda_{k3}, \lambda_{k4}, \lambda_{k5}, C_k\}$ are easily identified. The remaining parameters α_k and ρ_k are identified from the non-linear terms in the function Ψ_k in (26). Note that the experience-earnings profile is time-invariant, and hence $(1-\alpha_k)$ can be identified from the cross-sectional variation of experience through the second term, $\ln\left[\alpha_k \left(\frac{L_{k,t}}{E_{k,t}}\right)^{\rho_k - 1} + j(1-\alpha_k)\right]$ in Ψ_k (note that at a given date t, the first term $\left(\frac{1}{\rho_k} - 1\right) \ln\left[\alpha_k \left(\frac{L_{k,t}}{E_{k,t}}\right)^{\rho_k} + (1-\alpha_k)\right]$ and $\alpha_k \left(\frac{L_{k,t}}{E_{k,t}}\right)^{\rho_k - 1}$ are constant). Given α_k, the complementarity parameter ρ_k can be identified from the

[25] Note that with ρ_k at the limit value of unity, the sectoral labor-experience ratio $\frac{L_{k,t}}{E_{k,t}}$ drops from the earnings equation (25).

[26] See Granger (1999) for a discussion of the over-fitting issue in model evaluation.

time-series variation of $\frac{L_{k,t}}{E_{k,t}}$ through the first term $\left(\frac{1}{\rho_k} - 1\right) \ln \left[\alpha_k \left(\frac{L_{k,t}}{E_{k,t}}\right)^{\rho_k} + (1-\alpha_k)\right]$.[27]

5.4 Estimates

We use *nonlinear-least-squares* estimation to estimate the earnings equation in (25), using the Gauss-Newton method. The estimates are reported in Table 3 with standard errors in parentheses. The estimates confirm that there coexist two sectors partitioning the economy, with a substantial gap in exogenous productivity growth. The estimate for g_T is close to zero at -0.005, and the estimate for g_M is 0.025.[28]

The estimates of ρ_T at -10.95 and ρ_M at -1.36 suggest that labor and experience are far from perfect substitutes. The implied elasticity of substitution between labor and experience $\frac{1}{1-\rho_k}$ is 0.084 for the traditional sector, and 0.424 for the modern sector. Given that $\rho_T < \rho_M$, experience complements labor more in the traditional sector than the modern sector.

The estimates for $\alpha_T = 7.68 * 10^{-11}$ and $\alpha_M = 0.033$ are apparently small, although both are statistically significantly different from zero. The α_k's are the weights on raw labor in the CES production functions (10) and (11). However, these estimates do not imply a tiny labor share. The raw labor share of sector k earnings is

$$\frac{\left(\partial Y_{k,t}/\partial L_{k,t}\right) L_{k,t}}{Y_{k,t}} = \left[1 + \frac{1-\alpha_k}{\alpha_k}\left(\frac{L_{k,t}}{E_{k,t}}\right)^{-\rho_k}\right]^{-1}.$$

This is determined by the combination of α_k and ρ_k, and also depends on the labor-experience ratio. The average implied labor shares at the above estimates are 0.18 and 0.24 for the traditional and modern sector respectively.[29] Thus, our low estimates of α_k's do not imply an odd configuration for the CES production function. Still, we see that a major part of earnings is attributed to experience.

Note that the depreciation schedules $\lambda_k(j)$'s affect the sectoral labor and experience measures as shown in equations (14) to (17). Thus, the estimated depreciation schedules should be consistent with those used in constructing the sectoral labor and experience measures. To obtain such consistent estimates, we use an iterative guess-and-verify

[27] Given that ρ_k is identified by time series variation, the presence of aggregate shocks may affect the estimates of ρ_k. However, as long as the aggregate shocks are independent of $\frac{L_{k,t}}{E_{k,t}}$, our estimates of ρ_k (and other estimates) are not biased. Thus, whether we include sector specific aggregate shocks (in the form of year dummies) or not, does not affect our estimates.

[28] The gap in productivity growth from the reduced-form earnings estimation in (24) was larger, which is now reduced by controlling explicitly for sectoral labor-experience ratios.

[29] Note that the labor share moves over time as the labor-experience ratio evolves and its time-series elasticity is determined by α_k and ρ_k. We found that traditional labor share fluctuates widely over time, decreasing from 0.28 in 1976 to 0.10 in 1988 and then increasing to 0.36 in 1996, averaging at 0.18. The modern labor share is more or less stable over time around 0.24. Thus, a constant labor share seems a good approximation for the modern sector but not for the traditional sector.

procedure. We first measure the sectoral labor and experience at an arbitrary initial depreciation schedule $\widetilde{\lambda}_{0,k}(j)$ and then estimate depreciation schedule $\widetilde{\lambda}_{1,k}(j)$, which is used in updating labor and experience measures, which in turn is used in estimating a new depreciation schedule $\widetilde{\lambda}_{2,k}(j)$, and so on. We iterate this estimation series until the $\left\|\widetilde{\lambda}_{r,k}-\widetilde{\lambda}_{r-1,k}\right\| \to 0$ under the l_2 norm.

At these estimated depreciation schedule parameters, the shapes of earnings profiles turn out to be very different between the two sectors. Modern earnings profiles display a clear hump-shape (as is typically observed in developed countries), peaking at experience interval 33-35 (displayed in Figure 7.2). Traditional profiles are concave but without a hump (displayed in Figure 7.6). This suggests that the premium to modern experience is not only smaller in size, but also it decays faster over the life cycle than traditional experience.

The estimated coefficients of the control variables provide us with further interesting information. These coefficients can be interpreted as the "returns" to productive attributes such as more schooling, being male, and living in better endowed regions or community type. The "returns" turn out to be higher in the traditional sector than the modern sector. For example, the rate of return to schooling is 13 percent for the modern sector but 16 per cent in the traditional sector.

The parameter estimates may depend on the specification of the control variables. In particular, Heckman, Lochner, and Todd (2003) recently document that the shape of the experience-earnings profiles are different across schooling groups, which in turn affects the estimate for returns to schooling. In principle, this may affect our estimates of the technology parameters. We experimented on the control-variable specification by allowing for the interaction between schooling and experience. We found that the coefficient of the interaction term turns out to be negative, i.e. the slope of the experience-earnings profiles are steeper for lower than higher education groups, consistent with the findings of Heckman, Lochner, and Todd (2003). We also find that this indeed changes the returns to schooling to 15% and 21%, respectively for the modern and traditional sectors. However, the estimates of the technology parameters of the model turn out to be robust to this specification change.[30]

[30] The estimation results are reported Table A.1 in Appendix A.4.

Table 3. Nonlinear Least-Squares Estimates

Sector	Traditional	Modern
g_k	-0.005 (0.0005)	0.025 (0.0009)
α_k	7.68e-11 (4.36e-11)	0.033 (0.0197)
ρ_k	-10.95 (0.286)	-1.36 (0.376)
λ_{1k}	-0.2200 (0.0186)	-0.1594 (0.0386)
λ_{2k}	0.0586 (0.0046)	0.0248 (0.0095)
λ_{3k}	-0.0064 (0.0006)	-0.0018 (0.0011)
λ_{4k}	0.0003 (0.00003)	0.00004 (0.00006)
λ_{5k}	-5.19e-6 (6.83e-7)	-7.07e-10 (1.14e-6)
Schooling	0.160 (0.0012)	0.130 (0.0012)
Male	0.644 (0.0062)	0.409 (0.0096)
Urban	0.709 (0.0114)	0.320 (0.0123)
North	0.197 (0.0077)	0.028 (0.0172)
Central	0.575 (0.0085)	0.326 (0.0158)
South	0.557 (0.0115)	0.245 (0.0162)
Bangkok	0.943 (0.0133)	0.612 (0.0168)
Constant	3.883 (0.0478)	4.900 (0.0849)

Note: Number of observations = 178,428, $RMSE = 1.043711$.

6 Simulation

We simulate a 20-period overlapping generations model at the estimated technology parameters of $\{\alpha_k, \rho_k, \gamma_k, \lambda_{k1}, \lambda_{k2}, \lambda_{k3}, \lambda_{k4}, \lambda_{k5}\}$ for $k = T$ and M, as reported in Table 3, setting the year 1976 as $t = 0$ for the model, as is done in estimation. Here, we put $\gamma_T = 1$ ignoring the negligible negative growth in the traditional sector. There remain two free parameters X (the relative productivity level gap between sectors in 1976) and β (time-discount factor).[31] They are calibrated at $X = 1.035$ and $\beta = 0.52$ (i.e. annual discount factor at 0.8) to match the modern cohort share for the periods 1976-96.[32] Given these selected parameters, we verify if pivotal condition is satisfied at the selected parameter values.

[31] Given that there are categorical variables in χ_{it}, the estimated constant includes both X and the average income of the reference group in the modern sector. Thus, a simple comparison between the estimated sectoral constant terms does not identify X and it remains as a free parameter. The time-discount factor β does not enter the earnings function.

[32] The chosen value for annual discount factor 0.8 seems lower than typical values which range between 0.9 and 0.99. This is due to the presumed linear preferences. Introducing concave utility function allows us to increase the discount factor into the typical range to match the same modern cohort share data. For example, simulating the model with constant-relative-risk-aversion utility function at a relative risk aversion coefficient of 3 increases the annual discount factor to 0.95. Still we keep the linear preferences rather than introducing concave utility function in our analysis to isolate the effects of technology on earnings dynamics from the combined effects of consumption smoothing. Calibrating β at the low value is a consistent restriction to this chosen specification.

The initial state $(M_{-j})_{j=1}^{J-1}$ is set to the modern cohort shares from the "Trend" data in Figure 2, dating back to the cohort who entered the workforce in calender year 1919. Given the chosen parameters and the initial state, the series of modern cohort shares $\{M_t\}_{t=0}^{\widehat{T}}$ is simulated, where $\widehat{T}$ is the first period when an entire cohort enters into the modern sector. Sectoral labor and experience and individual earnings are constructed in accordance with the simulated modern cohort shares. Here, the constructed labor and experience measures depend on the relative size of the labor force of each experience group, i.e. $\{D_{jt}\}_{j=0}^{J-1}$ in equation (18). We exogenously embed $\{D_{jt}\}_{j=0}^{J-1}$ using the labor force participation rates, as observed in the SES data, reported in Table A.2 in Appendix A.4. Our benchmark simulation (labeled "Sim1") assumes the participation rates vary across experience groups but ignores the time-series variation by taking the average participation rates of each experience group. We also simulate the model reflecting yearly deviations from the average participation rates (labeled "Sim2"). By comparing the two simulations, we can sort the effects of deterministic trends and from those of dynamic fluctuation due to exogenous changes in the demographic composition of experience groups.

6.1 In-Sample Comparison

Here we compare the simulated transition dynamics with data for the sample period. To make the comparison compatible, we filter out the effects of the observable (control variables χ_{it}) and unobservable (residual ϵ_{it}) income-generating attributes from the raw earnings data. That is, our filtered earnings y_{it}^F to be compared with simulation are

$$y_{it}^F \equiv \exp\left(\ln y_{it} - \sum_{k\in\{T,M\}} d_{k,it} C_k \chi_{it} - \epsilon_{it}\right). \tag{27}$$

We first compare the simulation results from Sim1 to isolate the performance of the model in explaining the trends (rather than fluctuation) of modernization and earnings, which are endogenously generated by the model. The trend of modernization, measured by the increase in the modern cohort share, is captured well by the model, as shown in Figure 6.1.[33] Figure 6.2 displays the aggregate share of the modern population (aggregated over the distribution of cohorts at each given year), which the simulation predicts as slightly higher than in the data.

Aggregate earnings, indexed to initial year, are compared in Figure 6.3. After filtering the income-generating attributes as in (27), aggregate earnings in Thailand were more or less stagnant, slightly increasing during 1988-1996, following a mild recession during 1976-1988. On average, aggregate filtered earnings grew by only 0.24% per year. Note that this

[33] The modern cohort shares before 1976 are common between the model and the data because we took the initial state of the cohort shares of the model from the data.

aggregate earnings growth can be interpreted as *aggregate labor productivity growth* from the perspective of the typical aggregate production function, entering as a component of TFP growth.[34] The model does not predict the mild recession, but does capture the stagnation of aggregate earnings (growing only by 0.45% per year).

Figure 6.4 shows that the stagnation of aggregate earnings is due to the stagnation in the traditional sector in both model and data. In contrast, the earnings of the modern sector (Figure 6.5) grew rapidly both in Thai data (at an annual rate of 2.5%) and simulation (at an annual rate of 2.1%).

The simulated ratio of modern average earnings to traditional average earnings increases from 0.56 in 1976 to 0.81 in 1996, shown in Figure 6.6. The ratio for Thai filtered earnings increases from 0.53 in 1976 to 0.86 in 1996 as well.[35] Note that *average* earnings are lower in the *modern* sector for the entire two-decade sample period in both model and data, although the productivity gap parameter $X = 1.035$ exceeds one. This is because the proportion of rich experienced workers is lower in the modern sector than in the traditional sector. Due to the higher modern productivity growth, and transition (i.e. accumulation of experience in the modern sector), this sectoral earnings gap narrows over time.

Figure 7.1 displays the evolution of modern labor-experience ratios. In the benchmark simulation (Sim1), the simulated modern labor-experience ratio moves around the levels in the data but increases monotonically, which does not capture the inverted-U shaped movement observed in the data. However, in Sim2, which adjusts for the yearly variation of experience-group composition, the simulation captures the fluctuation very well.

Capturing the inverted-U dynamics of the modern labor-experience ratio is important in explaining the rise and fall of the experience-earnings profiles in the data. Figure 7.2 displays the modern experience-earnings profiles (normalized to the zero-experience group) in Thailand for three years 1976, 1988, and 1996. The profiles are hump-shaped in each year. The experience premium increases until experience 33-35 (peaking at 3.2 in 1976, 3.9 in 1988 and 3.5 in 1996), and then decreases afterward (1.9 in 1976, 2.3 in 1988 and 2.0 in 1996 for the oldest group). The shape of the profiles changes over time: first shifting up and getting steeper between 1976 and 1988, and then shifting down and flattening between 1988 and 1996. In simulation Sim1, the monotone increase in the modern labor-experience ratio implies that profiles continue to shift up over time (Figure 7.3), which is different from the data. However, simulation Sim2 captures the

[34] This does not mean the aggregate TFP did not grow in Thailand during the sample period. In fact, the Thai aggregate TFP did grow at the rate of 2.3 percent per year on average but the major source of this TFP growth was *financial deepening* as Jeong and Townsend (2005) find.

[35] In the *raw earnings* data, the ratio of modern average earnings to traditional average earnings is greater than one and increases from 1.6 to 2.0 between 1976 and 1996.

non-monotonic movements of the modern earnings profiles in the data (Figure 7.4), as the simulated labor-experience ratio in Sim2 tracks the data.

Figure 7.5 displays the evolution of traditional labor-experience ratios. Again, Sim1 captures the level of the ratio in the data but not the fluctuation, which is captured by Sim2. The earnings profiles of the traditional sector are very different from the modern profiles. First, the traditional profiles are not hump-shaped in the data (Figure 7.6). That is, the experience premium does not decrease over experience in the traditional sector. Second, both the size and change of the experience premium are much larger in the traditional sector than modern sector. However, we still observe a positive correlation between the labor-experience ratio and the experience premium in the traditional sector. The earnings profile shifts up as the labor-experience ratio increases between 1976 and 1988, and flattens as the ratio decreases between 1988 and 1996. Accordingly, the maximum experience premium increases from 3.2 in 1976 to 12.0 in 1988, and then decreases to 2.4 in 1996. Again, simulation Sim2 mimics both the size and the dynamics of the traditional earnings profiles in the data (Figure 7.8).

These earnings dynamics imply an inverted-U shaped path of *within-sector inequality* for each sector over the sample period. The monotonically narrowing sectoral earnings gap (Figure 6.6) implies that *between-sector inequality* decreases over the same period. Overall, we expect non-monotonic inequality dynamics.

The Theil-L entropy index allows us to decompose the overall inequality into within-sector inequality and between-sector inequality.[36] This decomposition for the Thai filtered earnings y_{it}^F is shown in Figure 8.1. Movements of the overall inequality are driven by within-sector inequality, which in turn is mainly driven by traditional-sector inequality. Thus, despite the monotone decrease of between-sector inequality, overall earnings inequality follows an inverted-U shape. Recall that the inequality of raw earnings in Figure 1 is also inverted-U shaped. Thus, the inverted-U dynamics of earnings inequality in Thailand is in part driven by changes in sectoral labor-experience ratios during transition.

In Sim1, the labor-experience ratio increases in the modern sector while it decreases in the traditional sector, inducing an increase in modern inequality and decrease in tradi-

[36] Shorrocks (1984) shows that Theil-L index is the unique inequality measure that the overall inequality I_t is additively decomposed into within-sector inequality WI_t and between-sector inequality BI_t consistently with population shares of sectors such that:

$$\begin{aligned} I_t &= WI_t + BI_t, \\ WI_t &\equiv \sum_{k\in\{T,M\}} p_{kt} I_{kt}, \quad \textit{and} \quad BI_t \equiv \sum_{k\in\{T,M\}} p_{kt} \ln \frac{\mu_t}{\mu_{kt}}, \end{aligned}$$

where n_t denotes the sample size, μ_t the overall mean earnings, p_{kt} the population fraction of sector k, I_{kt} the sectoral inequality (measured by the same Theil-L entropy index) within sector k, and μ_{kt} the sectoral mean earnings of sector k at date t.

tional inequality. Between-sector inequality decreases from the reduced sectoral earnings gap. The overall inequality turns out to be decreasing (Figure 8.2). After correcting for exogenous compositional changes of experience groups over time, Sim2 mimics both the overall and decomposed features of the Thai earnings inequality (Figure 8.3). Thus, the source of the inverted-U shape of the filtered earnings inequality over the sample period is exogenous compositional changes in workforce participation, rather than the endogenous trends of transition.

We perform a sensitivity analysis by varying the technology parameters $\{\alpha_T, \rho_T, \alpha_M, \rho_M, \gamma_M\}$ within 95% confidence intervals using the standard errors of the estimates in Table 3, and check the robustness of the simulation results. We focus on the robustness of the modern cohort share, the building block of the simulation. For the calibrated parameters β and X, we experiment with $\pm 10\%$ deviations. We find that both the trend and level of the modern cohort shares remain robust to all these perturbations.[37]

6.2 Long-run Forecast

We simulate the model beyond the sample period until the transition is complete in the benchmark simulation Sim1. The model predicts that the entire 2036 cohort will enter into the modern sector, and the entire workforce will be in the modern sector by 2096, as shown in Figures 9.1 and 9.2. The figures illustrate an S-shaped process of modernization in terms of workforce share.

Figure 9.3 shows that the ratio of modern average earnings to traditional average earnings is initially lower than one but keeps increasing to eventually exceed one from the year 2006. Thus, the population shift from the traditional to modern sector delays the growth of aggregate earnings before 2006 and then accelerates aggregate earnings growth afterward. As explained above, the initial "poverty" of the modern sector relative to traditional sector is due to the scarcity of the rich experienced workers in the modern sector at the early stages of transition. Thus, this force of modernization tends to *decrease* aggregate earnings at initial periods, but is counteracted by the exogenous productivity growth in the modern sector.

Despite rapid modernization, aggregate earnings are stagnant for the initial thirty years during 1976-2006 (Figure 9.4). Eventually, aggregate earnings take off and its growth rate keeps increases to a peak of 2.8% in 2051, and then decreases afterward, converging to the constant steady-state growth rate of 2.5%. Thus, aggregate earnings dynamics display the typical S-shaped transition. Recall that this growth enters as TFP in the typical aggregate production function, implying that TFP also evolves in an S-shape

[37] Detailed results are reported in Appendix A.5.

during transition.

Figure 9.5 displays the long-run simulation of sectoral earnings inequality. In Figure 9.6, the overall inequality is decomposed into within-sector inequality and between-sector inequality. They show that the long-run *trend* itself can be non-monotonic for inequality dynamics, declining and then inverted-U shaped. Note that the inverted-U shape of the long-run inequality emerges after 2006, when the modern sector becomes richer than the traditional sector. That is, the model predicts the inverted-U shape when population shifts from a poorer traditional sector to a richer modern sector, as Kuznets (1955) postulated. The decomposition of the Theil-L index suggests this long wave of inverted-U dynamics of overall inequality is driven by *between-sector inequality*, again as Kuznets postulated, while we find *within-sector inequality* declines monotonically. After 2096, when the entire population enters into the modern sector, the labor-experience ratio stays constant and the modern sector inequality and aggregate inequality become constant.

7 Conclusion

Lucas (2004) states that "a useful theory of economic development will necessarily be a theory of transition." In Thailand, transition occurs gradually out of a traditional sector with no labor productivity growth to a modern sector with positive labor productivity growth. Within each sector, there is a correlation between the experience premium and labor-experience ratio. These facts suggest that sector-specific complementarity between labor and experience combined with exogenous modern productivity growth are key forces driving transition dynamics.

We measured the model using micro data from Thailand, identifying the sectoral partition, and aligning the model to the parameter space that conforms to the data. At the parameter values estimated from a cross-sectional earnings equation, the model simulates well the observed earnings growth and inequality, together with the gradual transition of the labor force between sectors.

We documented how cross-sectional and dynamic features of earnings differ between the modern and traditional sectors. Modern sector earnings profiles are hump-shaped, and the highest experience premium ranges between 3 and 4, observations which are typical for developed countries. Traditional sector earnings profiles increase monotonically, and the highest experience premium is greater than in the modern sector. Labor-experience complementarity is much stronger in the traditional sector, and changes in the earnings profile are also much more pronounced in that sector.

Despite the higher productivity level and growth of the modern sector, average modern sector earnings can be lower than traditional earnings for a sustained period. This occurs when experienced workers are relatively scarce in the modern sector. As the workforce shifts toward the modern sector, this effect diminishes and is dominated by the higher modern productivity growth, such that modern sector earnings eventually become higher.

We highlight two implications for future work. First, given their quantitative importance, incorporating sectoral labor-experience ratios into micro earnings equations and human capital measurement is important in understanding earnings dynamics for economies in transition. Second, the process of economic development in terms of earnings growth and inequality can be nonlinear particularly during transition, and its specific curvature depends on the size of complementarities and the initial distribution of sector-specific experience. Identifying and measuring the microeconomic sources of these complementarities would advance our understanding of the diverse patterns of economic development.

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A Appendix

A.1 Proofs

Proof of Lemma 1. Proof by contradiction. Suppose the Lemma is not true, then we have $M_{t-1} = 1$ and $M_t < 1$. From (7) this implies, for period t,

$$\begin{aligned} & G(1,0) + \beta\lambda\left[g'\left(1+\frac{1-M_{t+1}}{\lambda(1-M_t)}\right) + \phi\left(1+\frac{1-M_{t+1}}{\lambda(1-M_t)}\right)\right] \\ = \; & \gamma^t X\left\{f'\left(1+\frac{M_t}{\lambda}\right) + \beta\lambda\gamma\left[f'\left(1+\frac{M_{t+1}}{\lambda M_t}\right) + \pi\left(1+\frac{M_{t+1}}{\lambda M_t}\right)\right]\right\}. \end{aligned}$$

This condition combined with (5) implies $M_{t+1} < M_t$. Iterating forwards using the same argument we eventually must have a period s such that $M_s = 0$. The participation constraint for this period is,

$$\begin{aligned} & g'\left(1+\frac{1}{\lambda(1-M_{s-1})}\right) + \beta\lambda\left[g'\left(1+\frac{1}{\lambda}\right) + \phi\left(1+\frac{1}{\lambda}\right)\right] \\ \geq \; & \gamma^j X\left\{f'(1) + \beta\lambda\gamma\left[f'(1) + \pi(1)\right]\right\} \end{aligned}$$

This constraint contradicts pivotal condition (5) when noting that,

$$\begin{aligned} & f'\left(1+\frac{1}{\lambda}\right) + \beta\lambda\gamma\left[f'\left(1+\frac{1}{\lambda}\right) + \pi\left(1+\frac{1}{\lambda}\right)\right] \\ < \; & f'(1) + \beta\lambda\gamma\left[f'(1) + \pi(1)\right] \end{aligned}$$

Since $f'(x) + \beta\lambda\gamma\left[f'(x) + \pi(x)\right]$ is falling in x for values of $x < 1 + \frac{1}{\lambda}$. ■

Proof of Proposition 1. The algorithm for constructing the equilibrium transition path is as follows:

Step 0: Given $M_{-1} < 0$, guess that $M_t = 1$ for $\forall t \geq 0$ (which by Lemma 1 is implied by $M_0 = 1$). Verify if $M_0 = 1$ by checking (9) for $\widehat{T} = 0$. If the inequality holds $\widehat{T} = 0$. If the inequality doesn't hold, $\widehat{T} > 0$ go to step 1.

Step 1: Given M_{-1}, determine $M_0 < 1$ guessing $M_t = 1$ for $\forall t \geq 1$. The participation constraint for M_0 is,

$$\begin{aligned} & g'\left(1+\frac{1-M_0}{\lambda(1-M_{-1})}\right) + \beta\lambda\left[g'(1) + \phi(1)\right] \\ = \; & X\left\{f'\left(1+\frac{M_0}{\lambda M_{-1}}\right) + \beta\lambda\gamma\left[f'\left(1+\frac{1}{\lambda M_0}\right) + \pi\left(1+\frac{1}{\lambda M_0}\right)\right]\right\} \end{aligned}$$

Since by construction $\frac{1}{M_0} > 1$, combining this constraint with (5) implies that $\frac{M_0}{M_{-1}} > 1 \Rightarrow \frac{1-M_0}{1-M_{-1}} < 1$. The left hand side of this constraint is rising in M_0, and the right hand side is falling in M_0. Thus, there exists a unique $M_0 \in (0,1)$ which solves this constraint. Verify if $M_1 = 1$ by checking (9) for $\widehat{T} = 1$. If the inequality holds, $\widehat{T} = 1$. If the inequality doesn't hold $\widehat{T} > 1$ go to step 2.

Step 2: Given M_{-1}, determine $M_0 < 0, M_1 < 0$ guessing $M_t = 1$ for $\forall t \geq 2$. The participation constraints for M_0, M_1 are,

$$\begin{aligned} & g'\left(1+\frac{1-M_0}{\lambda(1-M_{-1})}\right)+\beta\lambda\left[g'\left(1+\frac{1-M_1}{\lambda(1-M_0)}\right)+\phi\left(1+\frac{1-M_1}{\lambda(1-M_0)}\right)\right] \\ = \; & X\left\{f'\left(1+\frac{M_0}{\lambda M_{-1}}\right)+\beta\lambda\gamma\left[f'\left(1+\frac{M_1}{\lambda M_0}\right)+\pi\left(1+\frac{M_1}{\lambda M_0}\right)\right]\right\} \\ & g'\left(1+\frac{1-M_1}{\lambda(1-M_0)}\right)+\beta\lambda\left[g'(1)+\phi(1)\right] \\ = \; & X\gamma\left\{f'\left(1+\frac{M_1}{\lambda M_0}\right)+\beta\lambda\gamma\left[f'\left(1+\frac{1}{\lambda M_1}\right)+\pi\left(1+\frac{1}{\lambda M_1}\right)\right]\right\} \end{aligned}$$

Since $\frac{1}{M_1} > 1$, combining the second constraint with (5) implies that $\frac{M_1}{M_0} > 1 \Rightarrow \frac{M_0}{M_{-1}} > 1$ using (5) combined with the first constraint. In the first constraint, given $M_1 \in (0,1)$, there exists a unique $M_0 \in (0,1)$ which solves the equality. In the second equation, given $M_0 \in (0,1)$, there exists a unique $M_1 \in (0,1)$ solving the equation. Verify if $M_2 = 1$ by checking (9) for $\widehat{T} = 2$. If the inequality holds $\widehat{T} = 2$, if the inequality doesn't hold $\widehat{T} > 2$ go to step 3, and so on.

This algorithm identifies an equilibrium with the lowest $\widehat{T}$. Next we show, by contradiction, that given such an equilibrium there cannot exist another equilibrium with higher $T' > \widehat{T}$. Suppose not so, given an equilibrium $\left\{M_0, ..., M_{\hat{T}-1}, \widehat{T}\right\}$ there exists another equilibrium $\left\{M_0', ..., M_{T'-1}', T'\right\}$ where $T' > \widehat{T}$. From the participation constraints for the second equilibrium, using $\frac{1}{M'_{T'-1}} > 1 \Rightarrow \frac{M'_{T'-1}}{M'_{T'-2}} > 1$ in turn implies $\frac{M'_{t-1}}{M'_{t-2}} > 1$. The period $\hat{T}$ participation constraints in the two equilibria are,

$$\begin{aligned} & g'(1)+\beta\lambda\left[g'(1)+\phi(1)\right] \\ \leq \; & X\gamma\left\{f'\left(1+\frac{1}{\lambda M_{\widehat{T}-1}}\right)+\beta\lambda\gamma\left[f'\left(1+\frac{1}{\lambda}\right)+\pi\left(1+\frac{1}{\lambda}\right)\right]\right\}, \\ & g'\left(1+\frac{1-M'_{\widehat{T}}}{\lambda\left(1-M'_{\widehat{T}-1}\right)}\right)+\beta\lambda\left[g'\left(1+\frac{1-M'_{\widehat{T}+1}}{\lambda\left(1-M'_{\widehat{T}}\right)}\right)+\phi(1+\frac{1-M'_{\widehat{T}+1}}{\lambda\left(1-M'_{\widehat{T}}\right)})\right] \\ = \; & X\gamma\left\{f'\left(1+\frac{M'_{\widehat{T}}}{\lambda M'_{\widehat{T}-1}}\right)+\beta\lambda\gamma\left[f'\left(1+\frac{M'_{\widehat{T}+1}}{\lambda M'_{\widehat{T}}}\right)+\pi\left(1+\frac{M'_{\widehat{T}+1}}{\lambda M'_{\widehat{T}}}\right)\right]\right\} \end{aligned}$$

Since $\frac{M'_{\widehat{T}+1}}{M'_{\widehat{T}}} > 1$, a comparison of these constraints implies $\frac{M'_{\widehat{T}}}{M'_{\widehat{T}-1}} > \frac{1}{M_{\widehat{T}-1}}$. Since $M'_{\widehat{T}} < 1$, the last inequality implies $M'_{\widehat{T}-1} < M_{\widehat{T}-1}$. Using $\frac{M'_{\widehat{T}}}{M'_{\widehat{T}-1}} > \frac{1}{M_{\widehat{T}-1}}$ and comparing the period $\hat{T}-1$ participation constraints in the two equilibria implies $\frac{M'_{\widehat{T}-1}}{M'_{\widehat{T}-2}} > \frac{M_{\widehat{T}-1}}{M_{\widehat{T}-2}}$. Using the participation constraints repeatedly in this way implies, $\frac{M'_0}{M_{-1}} > \frac{M_0}{M_{-1}}$, so $M'_0 > M_0$. Combining the three implications that $M'_{\widehat{T}-1} < M_{\widehat{T}-1}$, that $M'_0 > M_0$ and that $\frac{M'_t}{M'_{t-1}} > \frac{M_t}{M_{t-1}}$ $\forall t \geq 1$ leads to a contradiction.

To complete the proof for uniqueness an equilibrium $\{M_0, ..., M_{\widehat{T}-1}\}$ must be unique given $\widehat{T}$. Suppose not, so that there exists a $M'_t \neq M_t$ for some $t \in \{0, ..., \widehat{T}-1\}$. Then participation constraints (8) imply that $M'_{\widehat{T}-1} \neq M_{\widehat{T}-1}$, so we just need to show that $M'_{\widehat{T}-1} \neq M_{\widehat{T}-1}$ leads to contradiction. Suppose $M'_{\widehat{T}-1} > M_{\widehat{T}-1}$, then to ensure the participation constraints (8) hold, $\frac{M'_t}{M'_{t-1}} < \frac{M_t}{M_{t-1}}$. Specifically, $\frac{M'_0}{M_{-1}} < \frac{M_0}{M_{-1}}$ implies $M'_0 < M_0$ given M_{-1}. Combining the three implications that $M'_{\widehat{T}-1} > M_{\widehat{T}-1}$, that $M'_0 < M_0$ and that $\frac{M'_t}{M'_{t-1}} < \frac{M_t}{M_{t-1}}$ $\forall t \geq 1$ leads to a contradiction.

Now suppose the opposite, $M'_{\widehat{T}-1} < M_{\widehat{T}-1}$. Now to ensure the participation constraints hold, $\frac{M'_t}{M'_{t-1}} > \frac{M_t}{M_{t-1}} \Rightarrow M'_0 > M_0$ given M_{-1}.Combining the three implications that $M'_{\widehat{T}-1} < M_{\widehat{T}-1}$, that $M'_0 > M_0$ and that $\frac{M'_t}{M'_{t-1}} > \frac{M_t}{M_{t-1}}$ $\forall t \geq 1$ leads to a contradiction.

Parts (iii) and (iv) are follow from participation constraints (8) and condition (9) for $\widehat{T}$. ■

Proof of Proposition 2. (i) Traditional sector lifetime income increasing over time is given by

$$\begin{aligned} & g'\left(1+\frac{1-M_1}{\lambda(1-M_0)}\right)+\beta\lambda\left[g'\left(1+\frac{1-M_1}{\lambda(1-M_0)}\right)+\phi\left(1+\frac{1-M_2}{\lambda(1-M_1)}\right)\right] \\ < \quad & ... < g'\left(1+\frac{1-M_{\widehat{T}-2}}{\lambda\left(1-M_{\widehat{T}-3}\right)}\right)+\beta\lambda\left[g'\left(1+\frac{1-M_{\widehat{T}-1}}{\lambda\left(1-M_{\widehat{T}-2}\right)}\right)+\phi\left(1+\frac{1-M_{\widehat{T}-1}}{\lambda\left(1-M_{\widehat{T}-2}\right)}\right)\right] \\ < \quad & g'\left(1+\frac{1-M_{\widehat{T}-1}}{\lambda\left(1-M_{\widehat{T}-2}\right)}\right)+\beta\lambda\left[g'(1)+\phi(1)\right]. \end{aligned}$$

$\frac{1-M_{\widehat{T}-1}}{1-M_{\widehat{T}-2}} > 0 \Rightarrow \frac{1-M_{\widehat{T}-2}}{1-M_{\widehat{T}-3}} > \frac{1-M_{\widehat{T}-1}}{1-M_{\widehat{T}-2}}$ since $g'(\cdot)$ is decreasing and $\phi(\cdot)$ is increasing. Then by induction, we get the result.

(ii) Define $\tilde{t}$ such that, for $t < \tilde{t}$, modern sector lifetime income is growing slower than γ,

$$\begin{aligned} & f'\left(1+\frac{M_{t-1}}{\lambda M_{t-2}}\right)+\beta\lambda\gamma\left[f'\left(1+\frac{M_t}{\lambda M_{t-1}}\right)+\pi\left(1+\frac{M_t}{\lambda M_{t-1}}\right)\right] \\ > \quad & f'\left(1+\frac{M_t}{\lambda M_{t-1}}\right)+\beta\lambda\gamma\left[f'\left(1+\frac{M_{t+1}}{\lambda M_t}\right)+\pi\left(1+\frac{M_{t+1}}{\lambda M_t}\right)\right], \end{aligned}$$

and for $t \geq \tilde{t}$, modern sector lifetime income is growing faster than γ,

$$\begin{aligned} & f'\left(1+\frac{M_{t-1}}{\lambda M_{t-2}}\right)+\beta\lambda\gamma\left[f'\left(1+\frac{M_t}{\lambda M_{t-1}}\right)+\pi\left(1+\frac{M_t}{\lambda M_{t-1}}\right)\right] \\ \leq\ & f'\left(1+\frac{M_t}{\lambda M_{t-1}}\right)+\beta\lambda\gamma\left[f'\left(1+\frac{M_{t+1}}{\lambda M_t}\right)+\pi\left(1+\frac{M_{t+1}}{\lambda M_t}\right)\right]. \end{aligned}$$

For $t \geq \tilde{t}$, $\frac{M_{t+1}}{M_t} < \frac{M_t}{M_{t-1}}$ by an argument resembling that used in part (i). Thus, modern sector population growth peaks before lifetime income increases faster than γ, that is $S < \tilde{t}$.

The proof for $t < \tilde{t}$ is in two parts. First, by construction we have $\frac{M_S}{M_{S-1}} \geq \frac{M_{S+1}}{M_S}$. During transition, for $t < \tilde{t}$,

$$\begin{aligned} & f'\left(1+\frac{M_S}{\lambda M_{S-1}}\right)+\beta\lambda\gamma\left[f'\left(1+\frac{M_{S+1}}{\lambda M_S}\right)+\pi\left(1+\frac{M_{S+1}}{\lambda M_S}\right)\right] \\ >\ & f'\left(1+\frac{M_{S+1}}{\lambda M_S}\right)+\beta\lambda\gamma\left[f'\left(1+\frac{M_{S+2}}{\lambda M_{S+1}}\right)+\pi\left(1+\frac{M_{S+2}}{\lambda M_{S+1}}\right)\right], \end{aligned}$$

which then implies falling population growth $\frac{M_{S+1}}{M_S} > \frac{M_{S+2}}{M_{S+1}}$. By induction population growth is falling in $t \geq S$.

Second, by construction we have $\frac{M_{S-1}}{M_{S-2}} < \frac{M_S}{M_{S-1}}$. During transition, for $t < \tilde{t}$,

$$\begin{aligned} & f'\left(1+\frac{M_{S-2}}{\lambda M_{S-3}}\right)+\beta\lambda\gamma\pi\left(1+\frac{M_{S-1}}{\lambda M_{S-2}}\right) \\ >\ & f'\left(1+\frac{M_{S-1}}{\lambda M_{S-2}}\right)+\beta\lambda\gamma\pi\left(1+\frac{M_S}{\lambda M_{S-1}}\right), \end{aligned}$$

which then implies rising population growth $\frac{M_{S-2}}{M_{S-3}} < \frac{M_{S-1}}{M_{S-2}}$. By induction population growth is rising in $t < S$.

In period $\widehat{T}$, lifetime income is $X\gamma^{\widehat{T}}\left[f'\left(1+\frac{1}{\lambda M_{T-1}}\right)+\beta\lambda\gamma\left[f'\left(1+\frac{1}{\lambda}\right)+\pi\left(1+\frac{1}{\lambda}\right)\right]\right]$. In period $\widehat{T}+1$, lifetime income is $X\gamma^{\widehat{T}+1}\left[f'\left(1+\frac{1}{\lambda}\right)+\beta\lambda\gamma\left[f'\left(1+\frac{1}{\lambda}\right)+\pi\left(1+\frac{1}{\lambda}\right)\right]\right]$. So between period $\widehat{T}$ and $\widehat{T}+1$, lifetime income is growing faster than γ, and after period $\widehat{T}+1$, it grows at rate γ. Thus, $S \leq \tilde{t} \leq \widehat{T}$.

There are three possibilities for the path of $\frac{M_{t+1}}{M_t}$: (i) it is rising until $t = \widehat{T}-1$ and $S = \widehat{T}-1$, (ii) it is falling and $S = 1$, and (iii) it is rising and then falling. Thus, the population growth of the modern sector is single peaked. ■

A.2 Aggregate Output versus Aggregate Earnings

As before, $G(L_{T,t}, E_{T,t})$, $\gamma^t XF(L_{M,t}, E_{M,t})$ denote efficiency units of labor, and let $K_{T,t}, K_{M,t}$ denote physical capital in the traditional and modern sectors respectively. In each sector, output is produced subject to constant returns to scale in all inputs. Aggregate output in period t is given by

$$\begin{aligned}\tilde{Y}_t &= \tilde{Y}_T\left[G\left(L_{T,t},E_{T,t}\right),K_{T,t}\right]+\tilde{Y}_M\left[\gamma^t\tilde{X}F\left(L_{M,t},E_{M,t}\right),K_{M,t}\right] \\ &\equiv \tilde{y}_T\left(\frac{K_{T,t}}{G\left(L_{T,t},E_{T,t}\right)}\right)G\left(L_{T,t},E_{T,t}\right)+\tilde{y}_M\left(\frac{K_{M,t}}{\gamma^t\tilde{X}F\left(L_{M,t},E_{M,t}\right)}\right)\gamma^t\tilde{X}F\left(L_{M,t},E_{M,t}\right) \\ &\equiv \tilde{y}_T\left(k_{T,t}\right)G\left(L_{T,t},E_{T,t}\right)+\tilde{y}_M\left(k_{M,t}\right)\gamma^t\tilde{X}F\left(L_{M,t},E_{M,t}\right).\end{aligned}$$

When the marginal product of capital is constant at $R=\frac{1}{\beta}$, the ratio of capital to efficiency units of labor is constant, and is implicitly given by

$$R=\tilde{y}_T'\left(k_T^*\right)=\tilde{y}_M'\left(k_M^*\right)$$

This in turn implies the labor share of output in each sector is a constant

$$\begin{aligned}s_T\left(k_T^*\right) &\equiv \frac{\tilde{y}_T\left(k_T^*\right)-\tilde{y}_T'\left(k_T^*\right)k_T^*}{\tilde{y}_T\left(k_T^*\right)} \\ s_M\left(k_M^*\right) &\equiv \frac{\tilde{y}_M\left(k_M^*\right)-\tilde{y}_M'\left(k_M^*\right)k_M^*}{\tilde{y}_M\left(k_M^*\right)}\end{aligned}$$

Then, we can express aggregate labor earnings as

$$\widetilde{LY}_t=s_T\left(k_T^*\right)\tilde{y}_T\left(k_T^*\right)G\left(L_{T,t},E_{T,t}\right)+s_M\left(k_M^*\right)\tilde{y}_M\left(k_M^*\right)\gamma^t\tilde{X}F\left(L_{M,t},E_{M,t}\right).$$

Re-normalizing the units of output by $s_T\left(k_T^*\right)\tilde{y}_T\left(k_T^*\right)$ and defining $X\equiv\frac{s_M\left(k_M^*\right)\tilde{y}_M\left(k_M^*\right)}{s_T\left(k_T^*\right)\tilde{y}_T\left(k_T^*\right)}\tilde{X}$, we get the formula for aggregate labor earnings LY_t, which used in our analysis.

Consider the aggregate labor share of output, which can be written as

$$\frac{\widetilde{LY}_t}{\tilde{Y}_t}=s_T\left(k_T^*\right)\frac{G\left(L_{T,t},E_{T,t}\right)+\frac{s_M\left(k_M^*\right)}{s_T\left(k_T^*\right)}\frac{\tilde{y}_M\left(k_M^*\right)}{\tilde{y}_T\left(k_T^*\right)}\gamma^t\tilde{X}F\left(L_{M,t},E_{M,t}\right)}{G\left(L_{T,t},E_{T,t}\right)+\frac{\tilde{y}_M\left(k_M^*\right)}{\tilde{y}_T\left(k_T^*\right)}\gamma^t\tilde{X}F\left(L_{M,t},E_{M,t}\right)}.$$

When everyone is producing in the traditional sector this share is $s_T\left(k_T^*\right)$, and when everyone is producing in the modern sector this share is $s_M\left(k_M^*\right)$. Depending on whether $s_T\left(k_T^*\right)\lesseqgtr s_M\left(k_M^*\right)$, output grows faster or slower than earnings. In particular, if the capital share is higher in the modern sector, aggregate output grows faster than aggregate earnings during transition.

A.3 Equilibrium for J-period Model

A *competitive equilibrium* consists of a sequence of sectoral cohort shares $\{(N_t,M_t)\}_{t=0}^{\infty}$ and interest factor R such that

1. every agent earns his marginal product;

2. young agents decide on a sector to work in and how much to consume to maximize their lifetime utility (12) subject to the budget constraint (13), and lifetime earnings given by

$$\text{(28)} \qquad \max \left\{ \begin{array}{c} \sum_{j=0}^{J-1} \beta^j \lambda_T(j) \left[g'\left(\frac{L_{T,t+j}}{E_{T,t+j}}\right) + \phi\left(\frac{L_{T,t+j}}{E_{T,t+j}}\right) j \right], \\ \gamma^t X \sum_{j=0}^{J-1} \beta^j \lambda_M(j) \gamma_M^j \left[f'\left(\frac{L_{M,t+j}}{E_{M,t+j}}\right) + \pi\left(\frac{L_{M,t+j}}{E_{M,t+j}}\right) j \right] \end{array} \right\}$$

3. the resource constraints (14)-(18) are satisfied, and

4. the credit market clears in every period.

Using the resource constraints and the definitions of labor and experience from (16)-(18),

$$\text{(29)} \quad \sum_{j=0}^{J-1} \beta^j \lambda_T(j) \left[g'\left(\frac{\sum_{i=0}^{J-1} \lambda_T(i)(1-M_{t+j-i})}{\sum_{i=0}^{J-1} i\lambda_T(i)(1-M_{t+j-i})}\right) + \phi\left(\frac{\sum_{i=0}^{J-1} \lambda_T(i)(1-M_{t+j-i})}{\sum_{i=0}^{J-1} i\lambda_T(i)(1-M_{t+j-i})}\right) j \right]$$
$$= \gamma^t X \sum_{j=0}^{J-1} \beta^j \lambda_M(j) \gamma^j \left[f'\left(\frac{\sum_{i=0}^{J-1} \lambda_M(i) M_{t+j-i}}{\sum_{i=0}^{J-1} i\lambda_M(i) M_{t+j-i}}\right) + \pi\left(\frac{\sum_{i=0}^{J-1} \lambda_M(i) M_{t+j-i}}{\sum_{i=0}^{J-1} i\lambda_M(i) M_{t+j-i}}\right) j \right]$$

If young agents enter the modern sector only in period t, $M_t = 1$,

$$\text{(30)} \quad \sum_{j=0}^{J-1} \beta^j \lambda_T(j) \left[g'\left(\frac{\sum_{i=0}^{J-1} \lambda_T(i)(1-M_{t+j-i})}{\sum_{i=0}^{J-1} i\lambda_T(i)(1-M_{t+j-i})}\right) + \phi\left(\frac{\sum_{i=0}^{J-1} \lambda_T(i)(1-M_{t+j-i})}{\sum_{i=0}^{J-1} i\lambda_T(i)(1-M_{t+j-i})}\right) j \right]$$
$$\leq \gamma^t X \sum_{j=0}^{J-1} \beta^j \lambda_M(j) \gamma^j \left[f'\left(\frac{\sum_{i=0}^{J-1} \lambda_M(i) M_{t+j-i}}{\sum_{i=0}^{J-1} i\lambda_M(i) M_{t+j-i}}\right) + \pi\left(\frac{\sum_{i=0}^{J-1} \lambda_M(i) M_{t+j-i}}{\sum_{i=0}^{J-1} i\lambda_M(i) M_{t+j-i}}\right) j \right]$$

In the $J = 2$ model there was a single terminal period condition. In the general model, there are $(J-1)$ terminal period conditions. (29) and (30) characterize a simultaneous difference equation system of M_t of order $2(J-1)$.

Equilibrium construction for J-period overlapping generations model

Since $\gamma > 1$, and the lifetime product of agents working in the traditional sector is always finite, there exists a finite terminal period $T^* < \infty$ for which transition is complete. That is, there exists a $T^* < \infty$ for which the inequality (30) holds for $M_{T^*-(J-1)} = 1$ through to $M_{T^*-1} = 1$.

In our simulations, the algorithm for constructing the equilibrium transition path is as follows:

Guess that once $M_{\hat{T}} = 1, M_t = 1\ \forall t \geq \hat{T}$, such that $T^* = \hat{T} + (J-1)$, and follow the steps below.

Step 0: If $M_{-1} < 1$, $T^* \geq J-1$. $T^* = J-1$ occurs if $M_t = 1\ \forall t \geq 0$. Given $\{M_{-i}\}_{i=1}^{J-1}$, guess that $M_t = 1\ \forall t \geq 0$.

Verify this by checking whether inequality (30) holds for $M_0 = 1$ through to $M_{J-2} = 1$. If these inequalities hold $T^* = J-1$. If they do not all hold, $T^* > J-1$ go to step 1.

Step 1: Given $\{M_{-i}\}_{i=1}^{J-1}$, guess that $M_t = 1\ \forall t \geq 1$. Then determine $M_0 \in (0,1)$ using participation constraint (29). The left hand side of this participation constraint is rising in M_0, and the right hand side is falling in M_0. Given $T^* > J-1$, there exists a unique $M_0 \in (0,1)$ which solves this equality.

Verify if $M_t = 1\ \forall t \geq 1$ by checking whether inequality (30) holds for $M_1 = 1$ through to $M_{J-1} = 1$. If these inequalities hold $T^* = J$. If they do not all hold, $T^* > J$ go to step 2.

Step 2: Given $\{M_{-i}\}_{i=1}^{J-1}$, guess that $M_t = 1\ \forall t \geq 2$. Then determine $M_1 \in (0,1)$ using participation constraint (29), and M_0 using participation constraints (29) and (30).

Verify if $M_t = 1\ \forall t \geq 2$ by checking whether inequality (30) holds for $M_2 = 1$ through to $M_J = 1$. If these inequalities hold $T^* = J+1$. If they do not all hold, $T^* > J+1$ go to step 3, and so on.

A.4 Data Appendix

Table A.1. NLSE Allowing Interaction Between Schooling and Experience

Sector	Traditional	Modern
g_k	-0.005 (0.0005)	0.025 (0.0009)
α_k	4.16e-13 (2.46e-13)	0.015 (0.010)
ρ_k	-12.70 (0.225)	-1.75 (0.401)
λ_{1k}	-0.0957 (0.0299)	-0.1193 (0.0493)
λ_{2k}	0.0359 (0.0072)	0.0202 (0.0117)
λ_{3k}	-0.0038 (0.0009)	-0.0013 (0.0013)
λ_{4k}	0.00015 (0.00005)	9.93e-06 (0.00007)
λ_{5k}	-2.18e-06 (1.11e-06)	7.86e-07 (1.48e-06)
Schooling*Experience	-0.0080 (0.0003)	-0.0034 (0.0003)
Schooling	0.206 (0.002)	0.148 (0.002)
Male	0.657 (0.006)	0.417 (0.010)
Urban	0.705 (0.011)	0.321 (0.012)
North	0.183 (0.008)	0.023 (0.017)
Central	0.573 (0.008)	0.326 (0.016)
South	0.535 (0.011)	0.237 (0.016)
Bangkok	0.927 (0.013)	0.608 (0.017)
Constant	3.49 (0.061)	4.65 (0.101)

Note: Number of observations = 178,428, $RMSE$ = 1.043856.

Table A.2. Labor Force Participation Rates across Experience Groups (%)

Experience	Average	1976	1981	1986	1988	1990	1992	1994	1996
0	5.69	3.04	4.23	6.69	7.90	7.27	5.95	4.85	4.22
1	6.22	5.80	7.11	5.79	6.46	7.20	6.55	5.90	5.06
2	6.48	6.61	7.15	6.17	6.08	6.39	6.54	6.77	6.28
3	6.57	6.17	6.37	6.68	6.24	5.81	6.47	7.00	7.43
4	6.79	6.69	7.54	6.80	6.84	6.71	6.05	6.65	7.22
5	6.75	6.49	7.83	7.15	6.75	6.34	7.02	6.52	6.20
6	7.40	6.43	7.59	8.18	7.92	6.77	7.36	7.57	7.08
7	7.19	6.39	6.23	7.56	7.30	7.93	7.02	6.80	7.65
8	7.12	7.15	5.71	6.77	7.40	7.25	7.66	7.66	6.92
9	6.36	6.55	5.50	5.62	5.87	6.38	6.73	6.73	7.11
10	5.77	6.91	5.83	5.32	4.78	5.42	5.96	6.15	6.21
11	5.24	6.60	5.54	4.79	4.63	4.65	4.98	5.38	5.98
12	4.82	5.81	5.45	4.92	4.80	4.36	4.46	4.70	4.81
13	3.93	4.23	4.22	4.16	3.70	4.15	3.76	3.70	3.83
14	3.75	3.74	3.74	4.01	3.91	3.62	3.66	3.76	3.64
15	3.20	3.09	3.13	3.44	3.25	3.39	3.09	3.04	3.13
16	2.55	2.87	2.22	2.22	2.5	2.69	2.69	2.64	2.62
17	2.00	2.39	1.90	1.66	1.84	1.72	2.18	2.07	2.33
18	1.29	1.61	1.60	1.13	1.01	1.25	1.08	1.37	1.49
19	0.87	1.42	1.11	0.95	0.83	0.71	0.80	0.75	0.80

A.5 Sensitivity Analysis

We perform a sensitivity analysis by varying the technology parameters $\{\rho_T,\ \rho_M,\ \alpha_T,\ \alpha_M,\ \gamma_M\}$ by plus and minus one standard error (from the estimation), and check the robustness of the simulation results by focusing on the simulated modern cohort share from 1976 onwards. Both the trend and level of the cohort shares are typically robust to these changes, but the simulated cohort share for the initial year 1976 only, M_0, can deviate substantially. For instance, increasing α_M by one standard deviation increases M_0 by 10 per cent relative to the benchmark simulation, but subsequent cohort shares are only about 4 per cent higher. We also varied the parameters β and X, by plus and minus 10 per cent of their calibrated values and find a similar robustness of the modern cohort share.

In terms of direction of change, higher ρ_T and lower ρ_M tend to speed up transition, as do lower α_T and higher α_M. As expected, higher γ_M and higher X speeds up transition, and we find higher β tends to speeds up transition also.

While $\{\rho_T,\ \rho_M\}$ affect labor-experience complementarity, and $\{\alpha_T,\ \alpha_M\}$ affects the importance of raw labor in output, they also affect the level of productivity of each technology. One way to isolate the effects of complementarity and labor share from affects on productivity levels is to perform sensitivity analysis while also varying X. Specifically, we re-conduct sensitivity checks for these variables allowing simulated X to vary in such a way that simulated M_0 always coincides with the data M_0. For several parameters this reversed the effect of parameter change on the speed of transition. Now lower ρ_T and higher ρ_M tend to speed up transition, as do lower α_T and lower α_M. These outcomes are consistent with the comparative statics exercises in the text where we also allow X to vary.

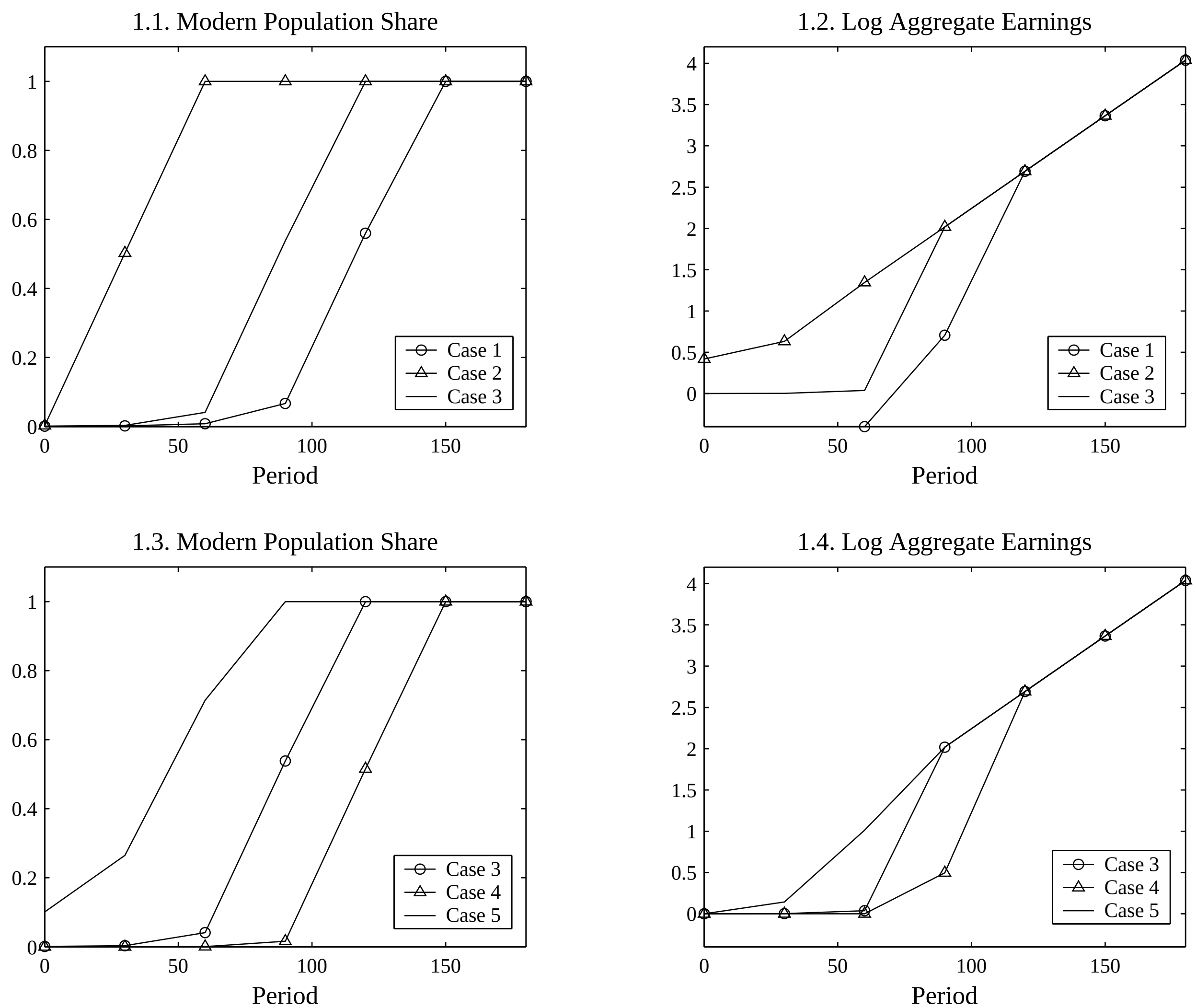

Figure 1. Comparative Statics

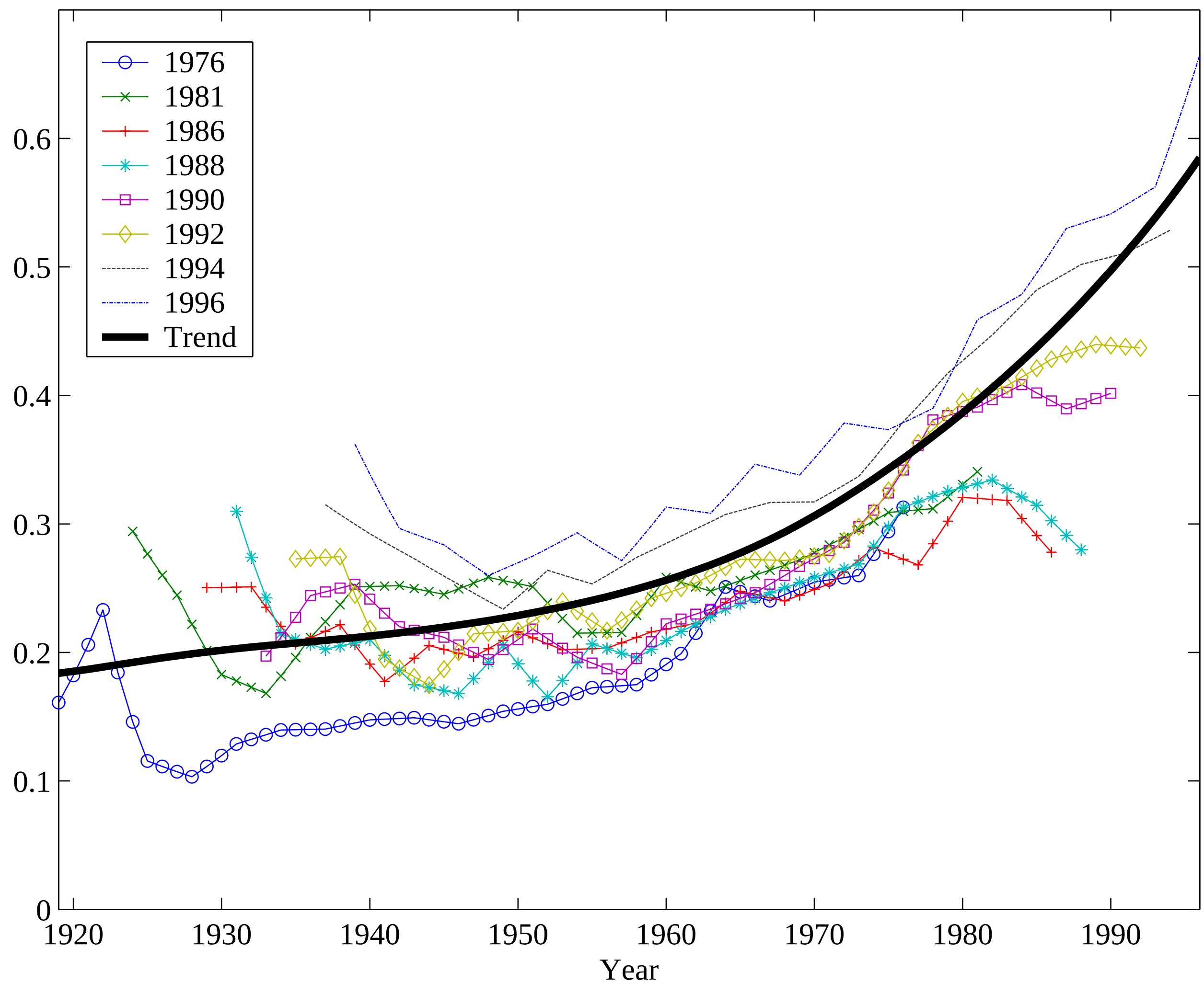

Figure 2. Thai Cohort Share of Modern Sector

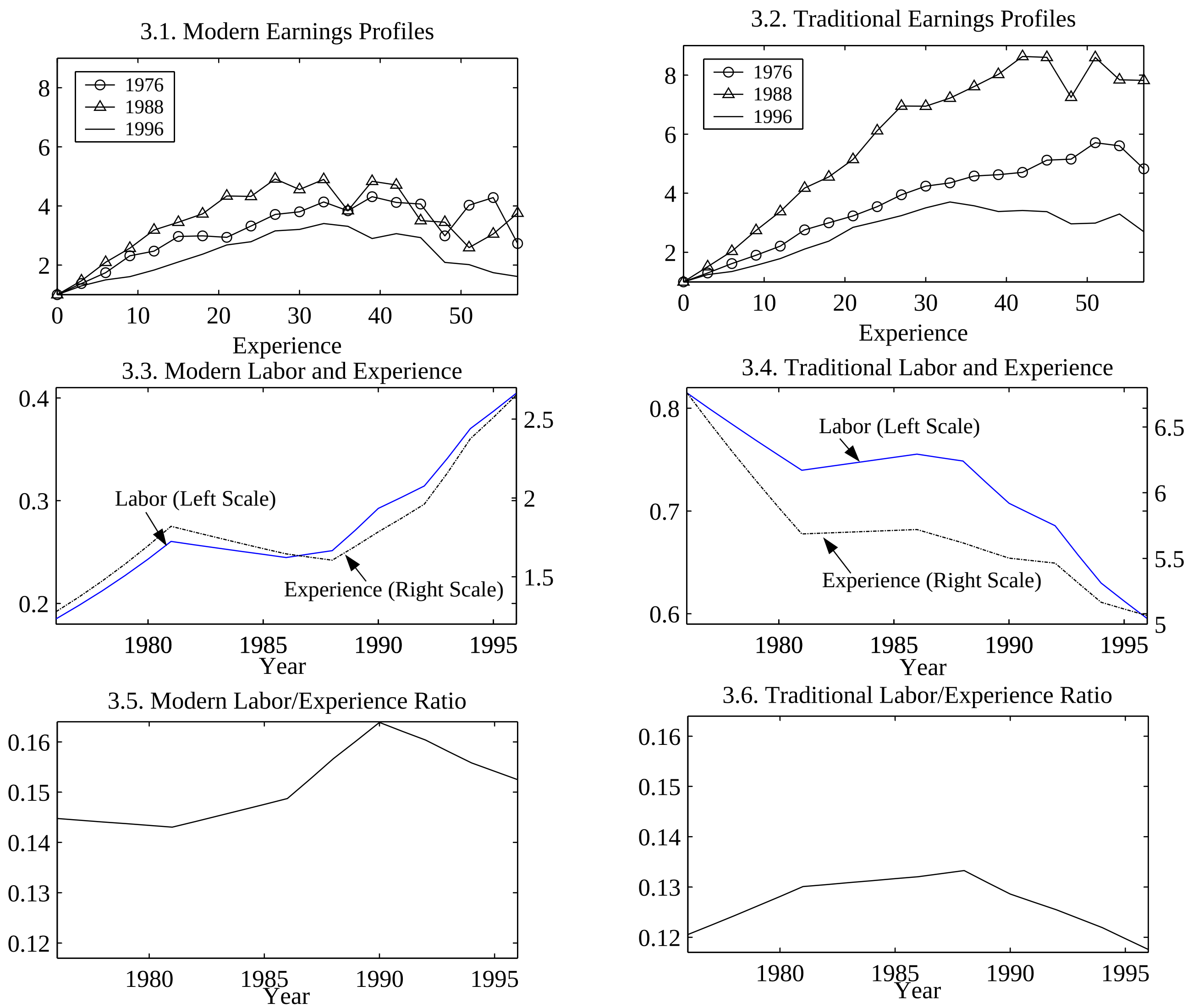

Figure 3. Movements of Sectoral Earnings Profiles

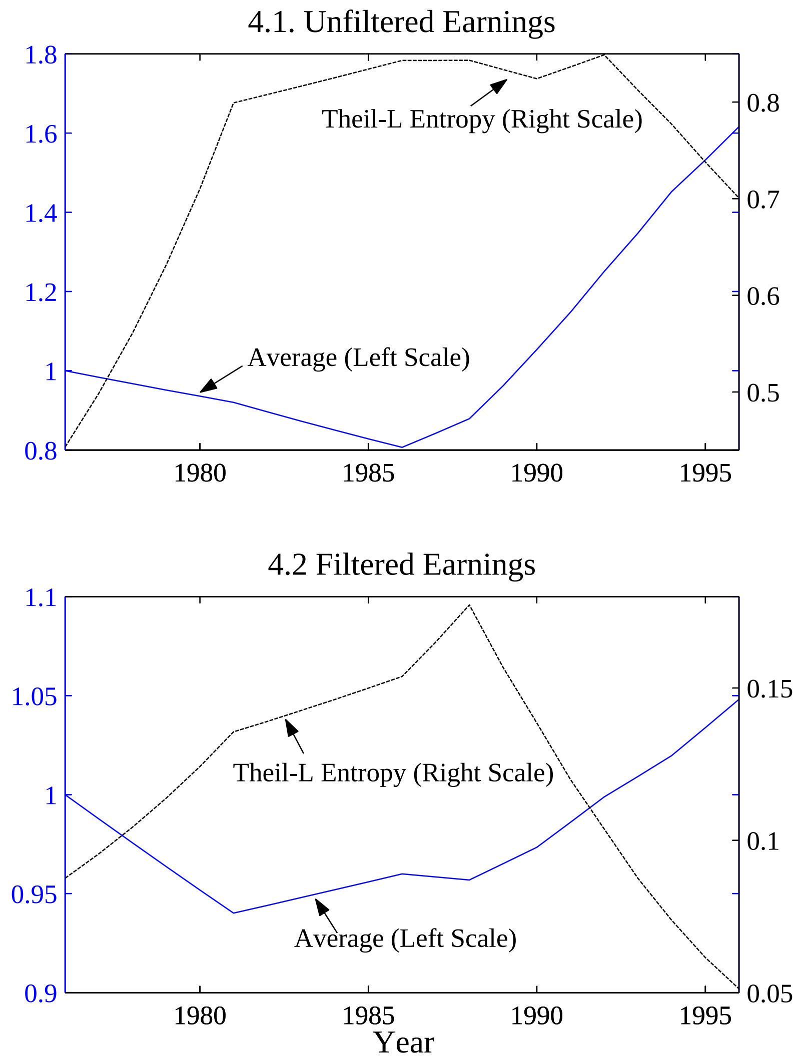

Figure 4. Growth and Inequality of Earnings

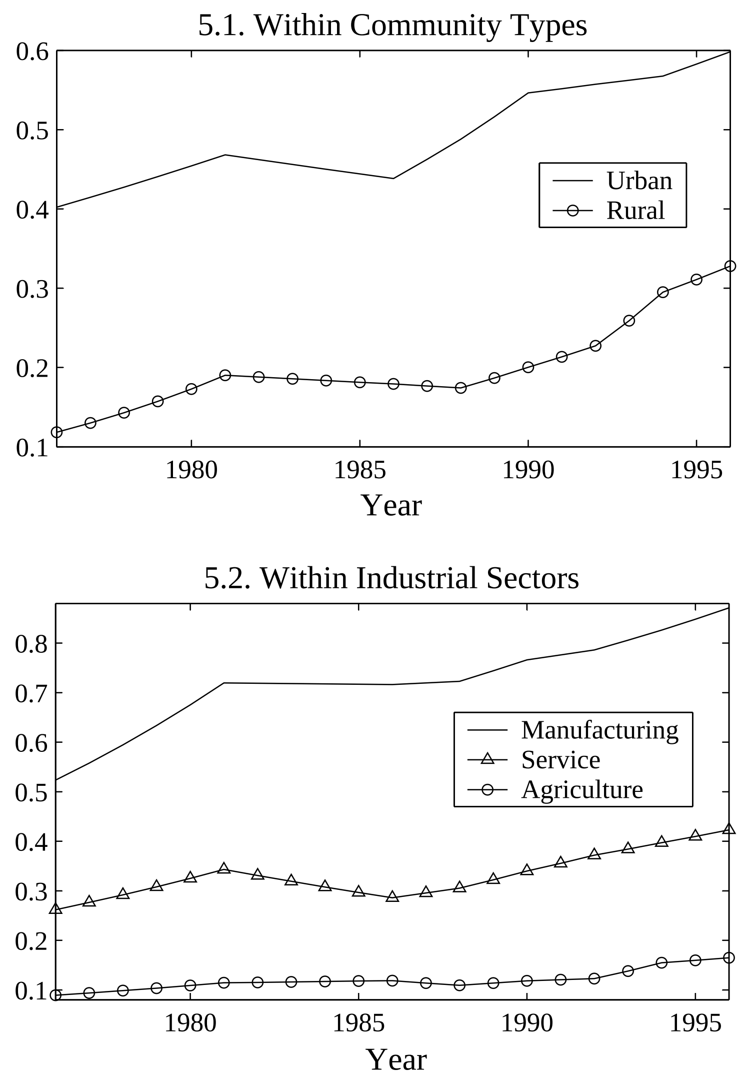

Figure 5. Transition to Modern Sector within Subgroups

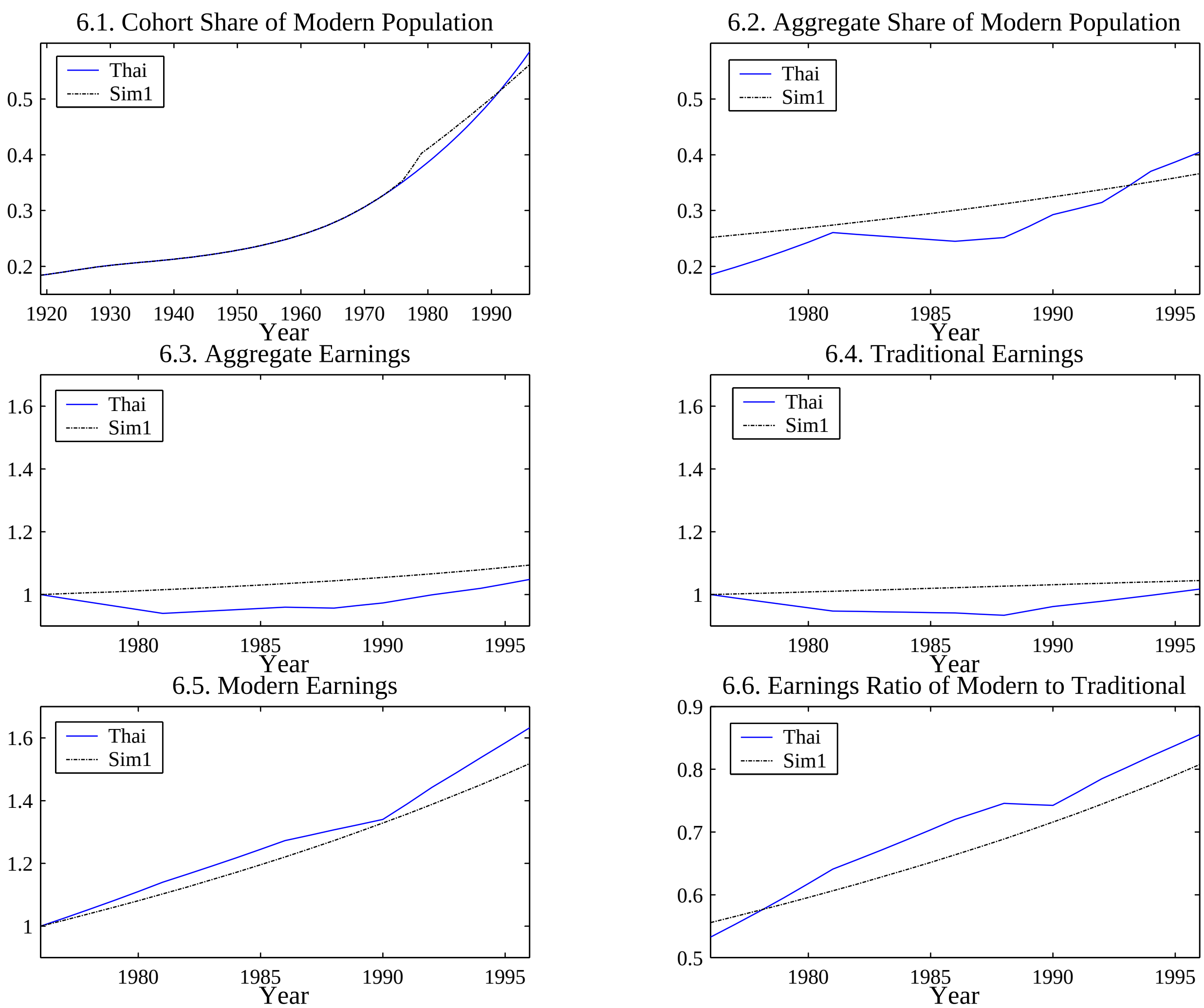

Figure 6. Aggregate Transition Dyanmics

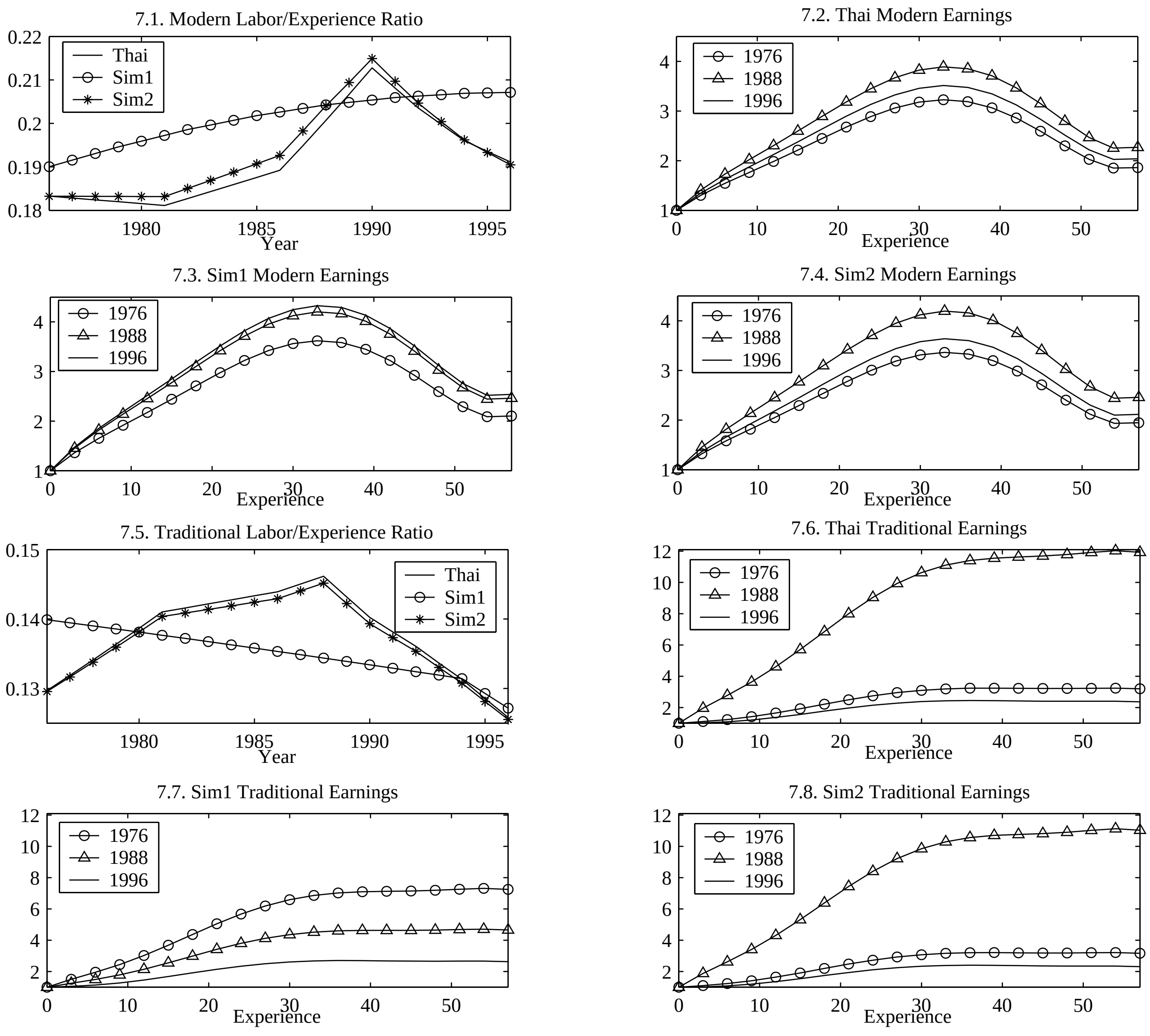

Figure 7. Experience-Earnings Profile Dynamics

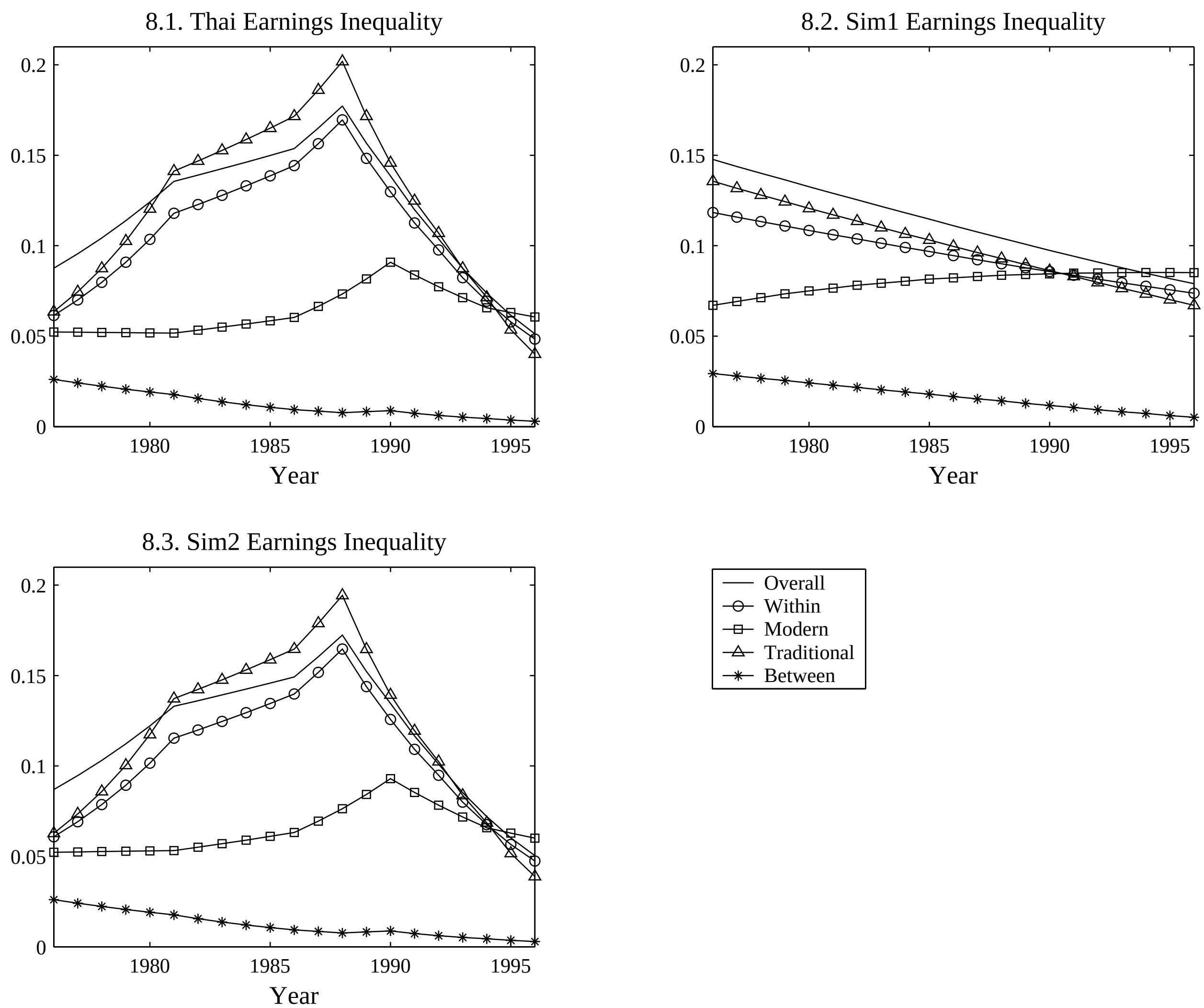

Figure 8. Earnings Inequality Decomposition

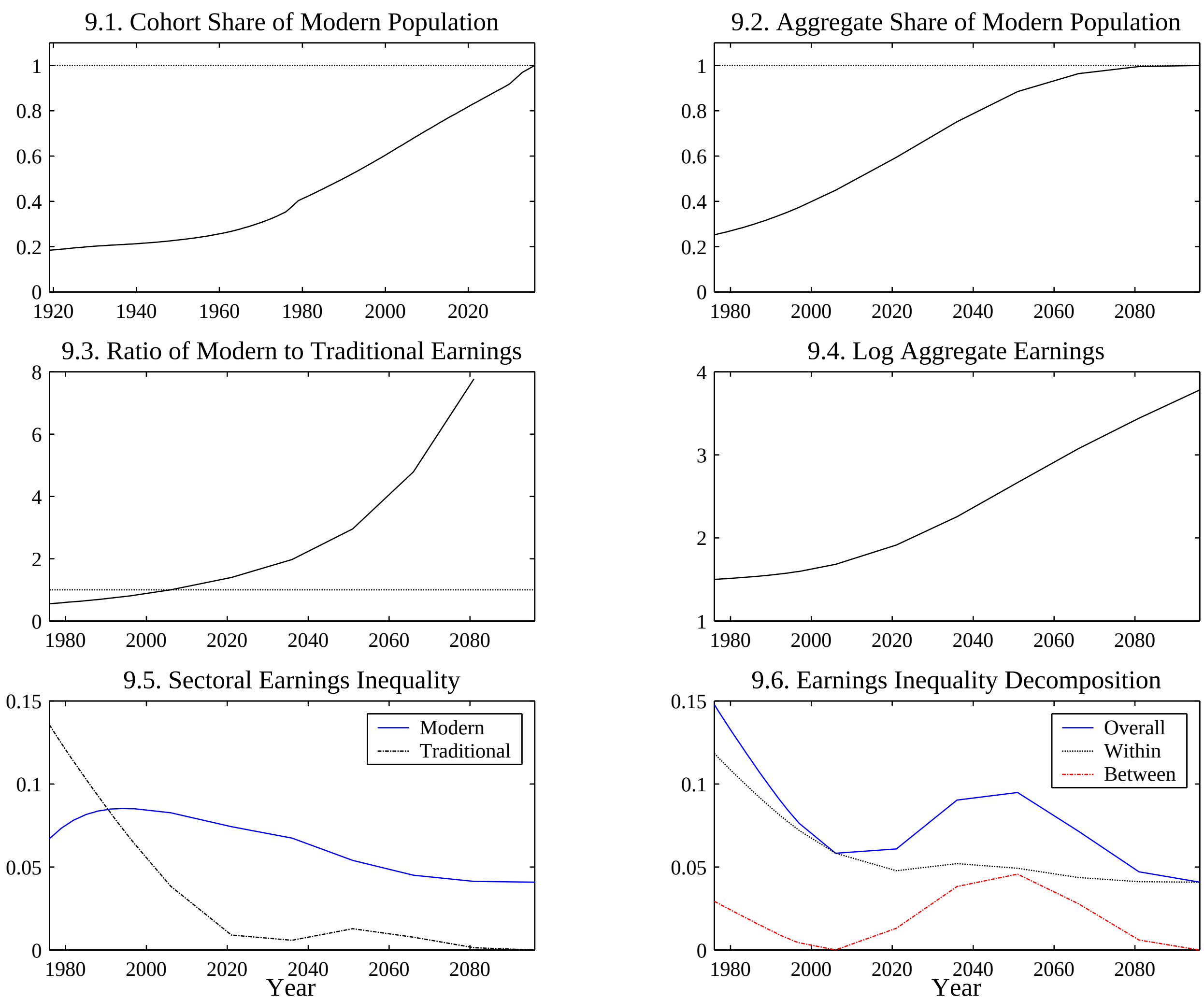

Figure 9. Long-run Forecast