Technical Progress and Allocative Efficiency*

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VERY PRELIMINARY AND INCOMPLETE

Abstract

I develop a growth model with heterogenous firms to study the relationship between technical progress and allocative efficiency. The model economy learns new technology from the world frontier, and reallocates resources to fit the new technology. When firms start to catch up the frontier, they face the uncertainty of future productivity, and delay the adjustment of production factors as a response. Technological achievement narrows the gap to the frontier, reduces the future uncertainty of productivity, and then, improve the efficiency of resource reallocation. As a byproduct of technical progress, the allocative efficiency raises up along with the catch-up process.

JEL *classification*: O41; L11.

Keywords. productivity, allocative efficiency, distance to frontier, international technology diffusion, uncertainty.

*This version is very preliminary and incomplete, for discussion only.

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1. Introduction

Productivity plays an essential role in economic growth and cross-country income difference (Parente and Prescott 2000, Hall and Jones 1999, Solow 1956, Swan 1956). Aggregate productivity can be decomposed into two components: technology used by individual firms and the efficiency of allocating nontechnological inputs across firms. This paper posts a new hypothesis linking the two. In developing countries, firms improve their productivity by learning from the world technology frontier. New technology opens a gate to uncertainty. As a response, firms do not immediately adjust their initial production factors to fit the current technology. When they are closer to the frontier, the further improvement will be more difficult, hence the uncertainty of productivity gradually decreases. Then, they can adjust the production factors to a more efficient level. As a result, allocative efficiency raises up along with technical progress.

The hypothesis is motivated by three stylized facts. First, technology gap is huge across countries (Fagerberg 1994). Poor countries narrow the gap by learning from the rich (Acemoglu, Aghion and Zilibotti 2006, Keller 2004). Second, poor countries experience higher level uncertainty than the riches do (Ramey and Ramey 1995, Koren and Tenreyro 2007). Third, poor countries do not efficiently allocate resources across firms (Haltiwanger and Scarpetta 2013, Hsieh and Klenow 2009). Empirical studies emphasize both technology and efficiency in explaining the cross-country productivity and output diffusion (Fagerberg 1994, Hsieh and Klenow 2009).

To test my hypothesis, I build a model that technical progress is the only source of economic growth, and then, check the change of allocative efficiency along with the change of technology. The model economy is composed by heterogenous firms as set by Hopenhayn and Rogerson (1993). Labour is the only production factor with a fixed supply. The economy grows up by learning new technology from the world frontier. How much a firm can learn is a random variable. Firms adjust labour to fit the new technology, but the adjustment is costly. Because of the uncertainty of productivity and the distortion of adjustment, labour allocation cannot reach the optimal level. Catch-up process releases the potential of technical progress, reduces future uncertainty, and then, raises up the allocative efficiency.

I estimate the value of parameters targeting on Chinese manufacturing firms. The estimations of parameters are separate by three groups in the concern of robustness and computational complexity. The parameters of adjustment costs are estimated by a simulated method of moment, since the model does not have analytical form solutions. The firm-level productivity is estimated by the Olley and Pakes (1996) approach. Other parameters are directly calibrated from real data.

I simulate firm dynamics for one hundred years after the baseline year. The aggregate output and productivity keep growing up in my simulation with average rate 3.32%. The growth is driven by efficiency improvement at the beginning, and then, mainly by technical progress. Along with the growth, there is a clear positive relationship between technology level and allocative efficiency. Since technological change is the only source of growth in the model, the relationship suggests a casuality that efficiency improvement can be a byproduct of technical progress. The pattern is robust in the numerical experiments on different initial distributions.

Literature on innovation and technology diffusion mainly focuses on the direct impact on individual productivity (Comin and Hobija 2010, Keller 2004). This study highlights an indirect impact on the allocation of production factors, which also influences the aggregate productivity.

The study is also a part of the discussion on the efficiency of resource allocation (see a review written by Hopenhayn 2014a). It indicates that resource misallocation is not only a cause of the low productivity in poor countries, but also can be a consequence of their long distance to frontier. The study focuses the transitional dynamics, following the effort by Buera and Shin (2013), Moll (2014). Along with the catch up process, allocative efficiency raises up even without correcting distortions. It suggests that the cross-country difference on allocative efficiency also can be a result of the different stages of development.

At last, the study contributes to the literature on the macroeconomic impact of uncertainty. Asker, Collard-Wexler, and De Loecker (2014) already emphasized the importance of volatility of idiosyncratic productivity in explaining allocative efficiency. My study goes one step further, endogenously generates the change of volatility in an emerging country.

The rest of the paper is organized as follows. In section 2, I build a theoretical model for the later analysis. In section 3, I describe the estimation of the parameters. In section 4, I simulate the model economy, and show the relationship between technical progress and allocative efficiency. Finally, section 5 concludes.

2. Model

Based on the discussion before, I build a model of heterogenous firms with international technology diffusion and adjustment frictions. The model is extended from Hopenhayn (1992), Hopenhayn and Rogerson (1993).

Households.– A measure one of households live in the economy. Every household provides a measure L of labour. These households are consumers, labour providers, and owners of establishments in the economy. Since the study focuses on firm behaviour, I simplify the household behaviour by the following three assumptions. First, the economy only produces a nondurable good, so the households have to consume all the products at the end of each period. In other words, no intertemporal transfer exists in the economy. Second, leisure does not generate utility, thus, the labour supply is perfectly inelastic. Third, the households own the establishments in the economy and equally distribute their profit or deficit, so the welfare maximization problem is equivalent to the output maximization problem.

Firms– The economy is composed by number N_t firms at time t. Every firm using the only input labour $l_{i,t}$ produces final good, and using the output pays wage $w_t l_{i,t}$, and adjustment costs $c_{ad}(l_{i,t}, l_{i,t-1})$. When a firm with productivity $z_{i,t}$ employs $l_{i,t}$ labour at time t, its one-period profit is

$$\pi(z_{i,t}, l_{i,t}, l_{i,t-1}; w_t) = f(z_{i,t}, l_{i,t}) - w_t l_{i,t} - c_{ad}(l_{i,t}, l_{i,t-1}). \tag{1}$$

Firms' production functions are in Cobb-Douglas form with the same labour supply elasticity α,

$$f(z_{i,t}, l_{i,t}) = z_{i,t} l_{i,t}^{\alpha}, \quad \alpha \in (0, 1). \tag{2}$$

I neglect other production factors, so the analysis can focus on resource allocation on one factor. In addition, I assume that the output is decreasing return to scale in the input. Theoretically, the assumption keeps the existence of heterogeneity. Empirically, the assumption is consistent with real data in the later quantitative analysis.

The productivity process follows a random coefficient autoregressive model,

$$\ln z_{i,t} = \delta \ln z_{i,t-1} + \epsilon_{i,t}(\ln z_{f,t} - \delta \ln z_{i,t-1}),$$

where

$$\ln z_{f,t} = g \ln z_{f,t-1}, \quad \epsilon_{i,t} \sim_{i.i.d.} \beta(a, b). \tag{3}$$

Technology will be out of date with a constant rate $\delta \in [0, 1]$. The assumption matches the productivity reduction in many firms in real data. On the other hand, firms improve productivity by learning from the world frontier $z_{f,t}$. The frontier grows up constantly from the initial level $z_{f,0}$ with the rate $g \geq 1$. How much they can narrow the gap to frontier, $z_{f,t} - z_{i,t-1}$, is a random variable $\epsilon_{i,t} \in (0, 1)$. Let

$$\tilde{z}_{i,t} \equiv g^{-t} \ln z_{i,t-1}.$$

Then, $\tilde{z}_{i,t}$ follows a stationary process,

$$\tilde{z}_{i,t} = \gamma \tilde{z}_{i,t-1} + \epsilon_{i,t}(\tilde{z}_{f,0} - \gamma \tilde{z}_{i,t-1}). \tag{4}$$

where

$$\gamma \equiv g^{-1}\delta \in [0, 1].$$

Labour adjustment is costly. When firms want to adjust labour as a response of the productivity shock, they have to pay adjustment costs. The study focuses on the consequence rather than cause of frictions, so I use a broadly adjustment costs which include hiring cost (Oi 1962), firing cost (Hopenhayn and Rogerson 1993), search friction (Cooper, Haltiwanger and Willis 2007). The labour adjustment behaviour is diverse in Chinese firm-level data. Cooper, Gong, and Yan (2015) find many firms adjust their labour smoothly and continuously. However, a large amount of firms do not adjust labour. To fit the pattern, I use a rich setup of adjustment costs following Cooper and Haltiwanger (2006), Bloom (2009). Three parts of adjustment costs exist in the economy. The first component is the disposable fixed cost $c_f \mathbf{1}_{l_{i,t} \neq l_{i,t-1}}$. Firms have to pay the cost when they hire/fire employees regardless the quantity of adjustment. When fixed cost are high, the majority of firms do not adjust labour, and a small fraction of firms make a huge labour adjustment at one period. The second component $c_p|\Delta l_{i,t}|$ is proportional to the gross firing/hiring. For example, training costs are proportional to the number of new employees, and unemployment compensations are proportional to the number of unemployed workers. The proportional cost also can generate an inaction region like the fixed cost. The third component are the quadratic cost $c_q \frac{(\Delta l_{i,t})^2}{l_{i,t}+l_{i,t-1}}$, which makes the sharp labour adjustment more costly. If the quadratic costs are high, most firm will smoothly change their labour. The total adjustment cost is the summation of the three costs,

$$c_{ad}(l_{i,t}, l_{i,t-1}) = c_q \frac{(\Delta l_{i,t})^2}{l_{i,t} + l_{i,t-1}} + c_p|\Delta l_{i,t}| + c_f \mathbf{1}_{l_{i,t} \neq l_{i,t-1}}. \tag{5}$$

I assume that the firing and hiring costs are symmetric in the concern of computational complexity in the later estimation.

Firms exit the market when keeping operation is not profitable. They consider the following Bellman equation of labour adjustment,

$$V(z_{i,t}, l_{i,t-1}; \bar{w}^t) = \max_{l_{i,t} \geq 0} \{\pi(z_{i,t}, l_{i,t}, l_{i,t-1}; w_t) + \beta \mathbb{E} V(z_{i,t+1}, l_{i,t}; \bar{w}^{t+1}), \tag{6}$$

where $\bar{w}^t$ is the wage from period t to infinity.

Equilibrium.– The study discusses both the steady state and the transitional path to the steady state, so I define two kinds of equilibra. Definition 1 is used to calculate the steady state.

Definition 1 *A stationary equilibrium of the model is a wage system in steady state, which satisfies the following conditions: (i) household optimization; (ii) firm optimization; (iii) labour market clear; (iv) invariant distribution over time.*

Definition 2 describes the relative recursive competitive equilibrium used in the computation of the transitional dynamics.

Definition 2 *A recursive competitive equilibrium of the model is a wage system, which satisfies the following conditions: (i) household optimization; (ii) firm optimization; (iii) labour market clear; (iv) law of motion* $\mu_t = M_t \mu_{t-1}$.

where M_t is the transition matrix across incumbent firms, which is determined by solving the Bellman equation (6).

3. Estimation

This section explains the estimation of the parameters. The estimation targets on Chinese manufacturing firms. I separately estimate three parts of model for the purpose of robustness and computational complexity. I estimate the labour productivity by Olley and Pakes approach, estimate the adjustment costs by simulated method of moments (SMM), and calibrate other parameters directly from data.

3.1. Data

The estimation is based on Chinese Industrial Enterprises Database, an annual survey of Chinese industrial firms. The data preprocessing mainly follows Brandt, Van Biesebroeck, and Zhang (2012). I pick up all the manufacturing firms in the concern of consistency. The data are frequently used in the analysis of productivity and resource allocation (e.g.

Table 1: Data descriptives

	Labour		Output (million RMB)		
Year	Mean	Std. dev.	Mean	Std. dev.	Observations
2000	241.65	295.80	7.12	12.11	125894
2001	211.56	266.51	7.03	12.14	140125
2002	204.73	257.73	7.54	13.00	148694
2003	198.76	249.85	8.70	15.18	167238
2004	171.19	232.02	NA	NA	245765
2005	173.50	215.06	11.70	20.58	230898
2006	164.59	204.28	13.91	24.51	257143
2007	158.21	196.33	16.65	28.86	290160

Hsieh & Klenow 2009, Song et al. 2011). The imbalanced panel data include all state-owned enterprises and most non-state firms with annual sales larger than five million RMB. I exclude observations with missing values and outliers in key variables. Since my model cannot handle aggregate shocks, I choose the period from 2000 to 2007 to avoid the influences from the Asian Financial Crisis and Global Financial Crisis. The data in 1999 is the baseline for estimation.

Table 1 describes the data grouped by years. First, the number of firms keeps increasing in the whole period. Second, the average size of the firms keeps decreasing. Third, the average output goes up although average input (labour) goes down, that indicates massive productivity growth in the economy. The simulations in the next section will try to fit these patterns.

3.2. Baseline parameters

I calibrate several baseline parameters before other estimations, the results are shown in the top panel of table 2. The discounting factor β is calculated from the average annual interest rate. The initial distribution is from the real data in 2007, the latest year before the Global Financial Crisis. In order to rule out the impact of demographic change, I assume the labour supply L is fixed as the total labour of all firms in 2007.

3.3. Productivity

I estimate the firm-level productivity $z_{i,t}$ by Olley and Pakes (1996) approach, and then, run a regression on the firm-level panel data to get the parameters of the technology progress process. The results are shown in the middle panel of table 2.

I use a semiparametric method to estimate the production function parameters for consistency. Literature highlights the endogeneity problem of productivity estimation, that input level is correlated with unobserved productivity shocks. Olley and Pakes (1996) introduce investment as a proxy of unobserved shocks, and then, develop a consistent estimator. This study uses the labour version of the Olley and Pakes (1996) approach. Labour is no longer a freely variable input when adjustment costs exist, so I can treat labour as the same as capital. Based on the same argument by Olley and Pakes (1996), I use employment as the proxy of unobserved productivity shocks. I also control for other production factors. Then, theoretically I can get a consistent estimator of the output elasticity of labour $\hat{\alpha}$. As shown in table 2, the estimate is near the labour income share and near most estimates in literature. The estimator of productivity is

$$\hat{A}_{i,t} = (y_{i,t} \cdot L_{i,t}^{-\hat{\alpha}})^{\frac{1}{1-\hat{\alpha}}}.$$

I use the highest grid point in the baseline year as the world technology frontier, and assume it grows up with the same rate as the United States GDP. No depreciation of technology in the benchmark economy. The β distribution is arbitrarily chosen. Under these values, the distribution of learning skill is hump shaped.

Table 2: Value assignment of parameters

Parameter	Explanation	Value	Target
		Baseline parameters	
β	Discounting factor	0.96	Annual interest rate
L	Labour supply (million)	45.91	Total labour supply in 2007
μ_0	Initial distribution	NaN	real distribution in 2007
		Idiosyncratic productivity	
α	Output elasticity of labor	0.64	Chinese firm-level panel data
δ	depreciation rate of technology	0.96	benchmark value
$\tilde{z}_{f,0}$	technology frontier	8.41	highest grid point in 2007
g	growth rate of frontier	1.017	prod. growth rate in the U. S.
a	parameter 1 of β distribution	1	benchmark value
b	parameter 2 of β distribution	2	benchmark value
	Adjustment frictions (proportion of baseline annual wage)		
c_p	Proportional adjustment cost	0.29	moments of labour adjustment
c_f	Fixed adjustment costs	0.21	(see table 3)
c_q	Quadratic adjustment costs	1.81	

3.4. Adjustment frictions: simulated method of moments

I estimate adjustment costs, entry cost, and exit cost by simulated method of moments, henceforth SMM, since the analytical form solution does not exist in the model. The main idea of SMM is selecting parameters to minimize the weighted distance between the moments of simulated data and real data (McFadden 1989, Pakes & Pollard 1989). The estimator is solved from the following minimization problem,

$$\hat{\theta} = \arg\min_{\theta \in \Theta} [M_{real} - M_{sim}(\theta)]' W [M_{real} - M_{sim}(\theta)].$$

I use the optimal weight matrix which Lee and Ingram (1991) provide. Under the estimating null, the real data and simulated data are independent and from the same data generation process. Based on this condition, Lee and Ingram (1991) prove that the efficient weight matrix is a function of the inverse of the variance-covariance matrix of $[M_{real} - M_{sim}(\theta)]$. I estimate the variance-covariance matrix by the bootstrap method.

As shown in table 3, five target moments are chosen for the five parameters. If the estimation targets on the relationship between labour and output, I might target on the productivity directly. To avoid the possibility, I use five moments on labour market and exit / entry only. The first one is the proportion of firms which do not adjust the last year's labour. The number would be high if adjustment costs, in particular the fixed disposable component, as high. The second one is the first order autocorrelation of labour adjustment, since adjustment costs mainly influence firms' intertemporal labour decision. The third one is the same autocorrelation across the firms with labour adjustment. The forth one is the average ratio of labour adjustment to last year's labour. If the fixed adjustment cost is high, the third moment would be high. If the quadratic component is high, the forth moment would be low. The fifth one is the same ratio across the firms with labour adjustment.

The simulation process for SMM is as follows. I take the 2000 real data as the initial distribution of labour and productivity, and then, randomly generate idiosyncratic productivity shocks for each firm. The first thirty periods are warm-up. I use the same

Table 3: Simulated and data moments

Moments	Data	Simulated
$Pr(\Delta l_t = 0)$	0.28	0.28
$corr(\Delta l_t/l_{t-1}, \Delta l_{t-1}/l_{t-2})$	-0.00	0.03
$corr(\Delta l_t/l_{t-1}, \Delta l_{t-1}/l_{t-2})_{\Delta l_t, \Delta l_{t-1} \neq 0}$	-0.00	0.05
$mean(\lvert\Delta l_t\rvert/l_{t-1})$	0.26	0.13
$mean(\lvert\Delta l_t\rvert/l_{t-1})_{\Delta l_t \neq 0}$	0.37	0.18

periods as the real data to calculate the simulated moments.

Table 3 reports the data moments and simulated moments. The simulated moments and data moments match well.

The bottom panel of table 2 reports the estimates. I only estimate frictions by SMM because of robustness and computational complexity. The multiplier of quadratic adjustment cost is the largest among the three components, and its effects are even larger in the later quantitative analysis. Fixed adjustment costs are small which is related to the fact that only 27.88% firms fix their labour in the real data. For the purpose of consistency and for robustness, I ignore the small labour adjustments within the grids in the former numerical works. Entry and exit costs are higher because they are compared to the future value of the firms rather than only one period profit.

4. Simulations

In this section, I simulate the catch-up process based on the estimates in the last section, and check the relationship between technical progress and improvement of allocative efficiency. At the beginning of the simulation, both aggregate productivity and allocative efficiency shapely grow up. The significant increment also can be driven by the adjustment of the initial inefficiency (Buera and Shin 2013). This alternative hypothesis is more likely to be true in China's labour market (Meng 2012). To rule of the impact of this channel, I use the first ten periods as a warm-up, and then, simulate the following one hundred years. I also run experiments to identify the impact of the initial distribution.

Catch-up.– How many firms can catch up the technological frontier is influenced mainly by two factors: learning skills and the growth rate of frontier. Figure 1 shows the stationary distribution of productivity with different value of parameters. When firms' learning skills are higher, or in other words, the distribution of learning skills is more right skewed; the economy is more likely to reach the frontier. On the other hand, the catch-up process is more difficult when the frontier grows up faster.

Distorted labour adjustment.– Figure 2 plots the labour adjustment decision of firms in the benchmark economy. The pattern is clear, while it is not smooth enough according to the computational accuracy. First, higher productivity indicates higher labour adjustment in the same size firms, that matches the increasing trend. Second, the trend is not linear. Firms are more sensitive to smaller productivity shocks than larger shocks, since the quadratic adjustment costs punish large scale hiring/firing. Third, the middle segment is flat. Firms adjust labour only if the productivity shock exceeds a threshold.

Size dynamics.– Figure 3 shows more details of the dynamics of the size distribution. The market reallocates the resource from the largest firms to the relatively smaller ones. It indicates that the large firm occupied too many resources in the real data. The size distribution keeps concentrating until reach the stationary distribution. Along with the grow up of the small firms, the allocative efficiency also raises up. I will discuss the details of efficiency dynamics later.

Growth decomposition.– The aggregate productivity keeps growing up in the simulation. The average growth rate is 3.32%. The growth is driven by both technology progress and efficiency improvement. In the warmup period, allocative improvement contributes a large proportion because of the transition from the initial inefficiency. However, as shown in figure 4, the impact from the efficienty channel is not significant in the following years. Technical progress makes the main contribution in the later economic growth.

Technology progress and allocative efficiency.– The growth of allocative efficiency is highly correlated with technical progress. Figure 5 shows a clear positive relationship between the two channels during the catch-up periods. Since learning from the frontier is the only source of growth in the model, the relationship can be explained as a causality. When a developing economy catches up the frontier, efficiency improvement can be a byproduct of technical progress.

The role of initial distribution.– As discussed before, China's labour market is historically inefficient. The economy may correct the initial inefficiency during the catch-up process. It can be an alternative explanation of the relationship between technology and efficiency. To rule out the possibility, I simulate an economy from the theoretically optimal allocation. In the warm-up periods, the start of the catch-up process generates a dramatic efficiency reduction at the first three periods, since the economy cannot immediately move the resource to the firms with the new technology. Then, the allocative efficiency gradually raises up as shown in figure 6. Because of the efficient initial distribution, the efficiency improvement is much faster than the simulation in figure 5, but the pattern is similar. In a sum, it is a robust result that technical progress can drive efficiency improvement.

5. Conclusion

The study posts a new hypothesis on growth theory, that technical progress can cause the improvement of allocative efficiency in an emerging economy. When the economy is closer to the world technology frontier, it faces lower uncertainty, and then, reallocates resource more efficiently. In the numerical experiments, the efficiency of the economy does raise up in the catch-up process even without reducing distortions.

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Appendix A. Growth decomposition

Productivity is the only source of growth in the model, since the total production input is fixed. Two channels contribute to the productivity growth. The first channel is the technical progress of the incumbent firms. The second channel is the allocative efficiency. Reallocating more resources to high productivity firms raises the aggregate productivity. I this appendix, I decompose the two channels following Hopenhayn (2014b).

I assume an social planner who can reallocate resource without any costs. Given the productivity distribution, the distance between the real productivity and social optimal productivity measure the allocative efficiency of the economy. The social optimal productivity is achieved in the competitive equilibrium without any frictions. It also can be solved for as a social planner problem (Hopenhayn 2014b),

$$\max_{l_{i,t}} \sum_i z_{i,t}^{1-\alpha} l_{i,t}^{\alpha},$$

subject to

$$\sum_i l_{i,t} \leq L.$$

The social planner problem has an analytical solution, that the optimal output is

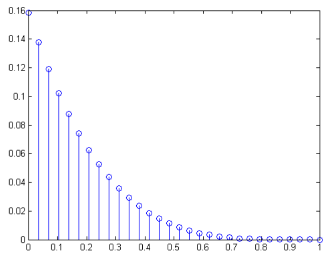
$$Y = \underbrace{(\mathbb{E} z_{i,t} \cdot N_t)^{1-\alpha}}_{A_{opt}} L^{\alpha}, \tag{7}$$

where N_t is the number of firms at period t. The allocative efficiency can be measured by the relative productivity,

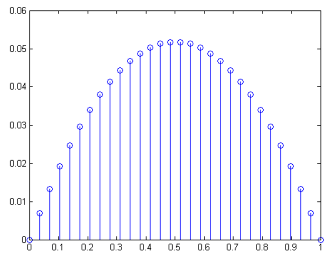
$$A_{rel,t} \equiv \frac{A_{sim,t}}{A_{opt,t}}. \tag{8}$$

The measure does not only include the reallocation within the surviving firms, but also the exit and entering firms. Now the growth of simulated productivity $\Delta \ln(A_{sim,t})$ can be decomposed by relative two components,

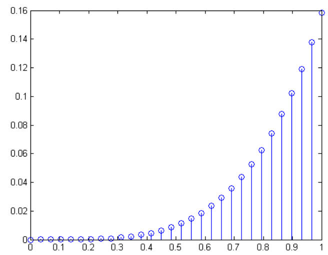
$$\Delta \ln(A_{sim,t}) = \Delta \ln(A_{rel,t}) + \Delta \ln(A_{opt,t}). \tag{9}$$



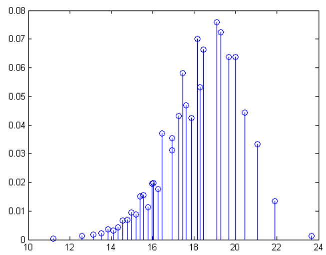
(a) the distribution of learning skills, $a = 1$, $b = 5$.



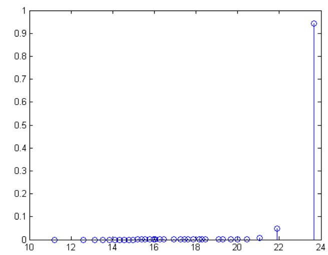
(b) the distribution of learning skills, $a = 2$, $b = 2$.



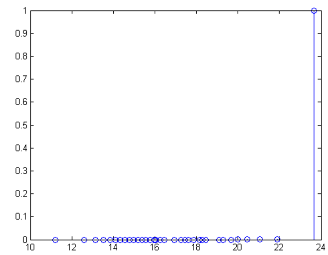
(c) the distribution of learning skills, $a = 5$, $b = 1$.



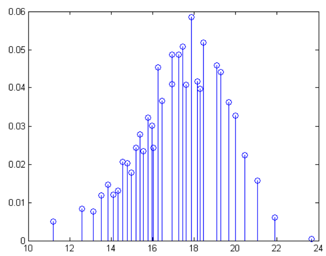
(d) the stat. dis. of log productivity, $a = 1$, $b = 5$, $g = 1.017$.



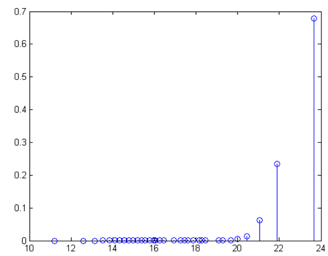
(e) the stat. dis. of log productivity, $a = 2$, $b = 2$, $g = 1.017$.



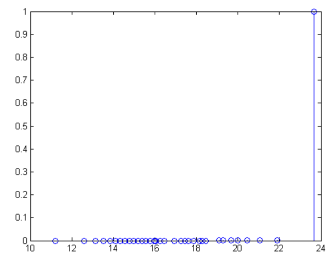
(f) the stat. dis. of log productivity, $a = 5$, $b = 1$, $g = 1.017$.



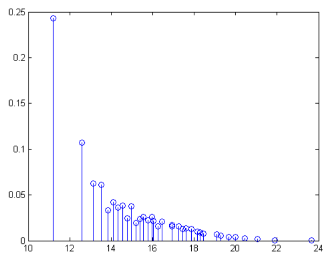
(g) the stat. dis. of log productivity, $a = 1$, $b = 5$, $g = 1.03$.



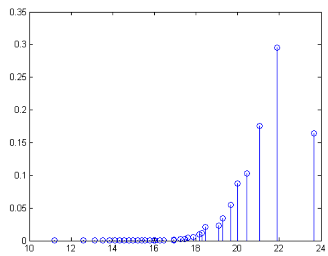
(h) the stat. dis. of log productivity, $a = 2$, $b = 2$, $g = 1.03$.



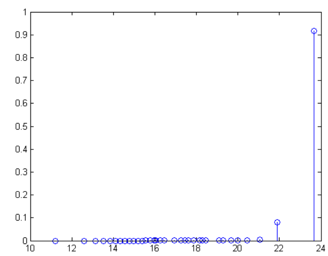
(i) the stat. dis. of log productivity, $a = 5$, $b = 1$, $g = 1.03$.



(j) the stat. dis. of log productivity, $a = 1$, $b = 5$, $g = 1.1$.



(k) the stat. dis. of log productivity, $a = 2$, $b = 2$, $g = 1.1$.



(l) the stat. dis. of log productivity, $a = 5$, $b = 1$, $g = 1.1$.

Figure 1: The stationary distribution (stat. dis.) of logarithmic productivity with different learning skills (a, b) and growth rate of frontier (g). The state space is decretized to 35 points.

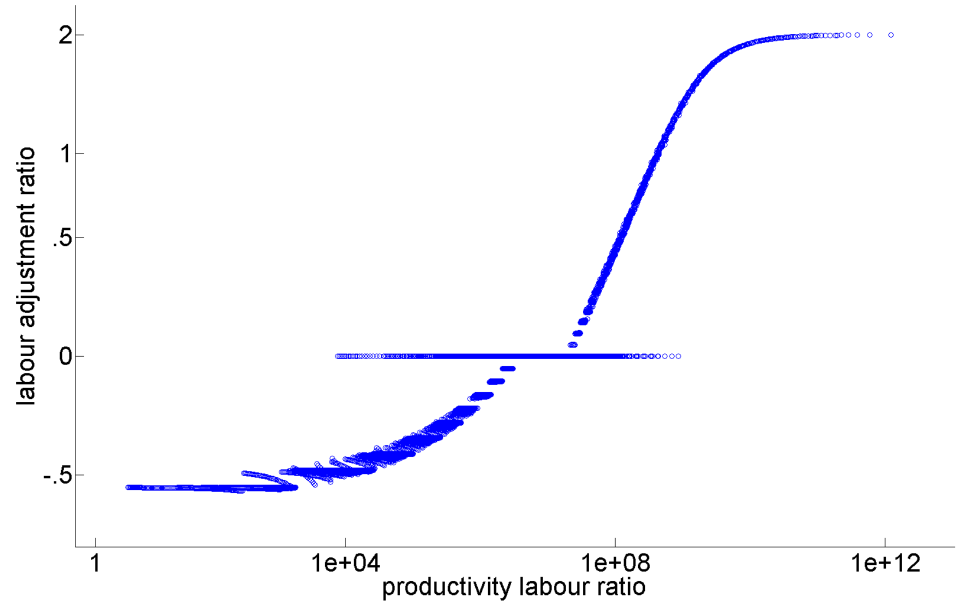


Figure 2: Policy function for labour adjustment

Notes. The horizontal axis is the productivity to labour ratio $z_{i,t}/l_{i,t-1}$. The vertical axis is the labour adjustment ratio $\frac{l_{i,t}-l_{i,t-1}}{l_{i,t}+l_{i,t-1}}$. Both the two ratios are rescaled by a concavification transformation $\tilde{x} = \ln(x+1)$.

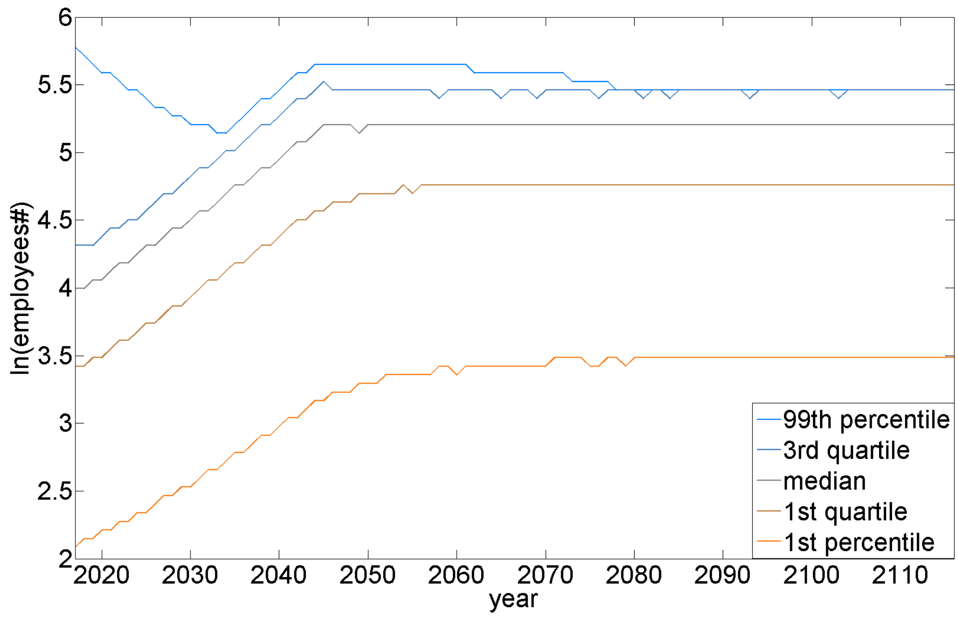


Figure 3: The dynamics of size distribution

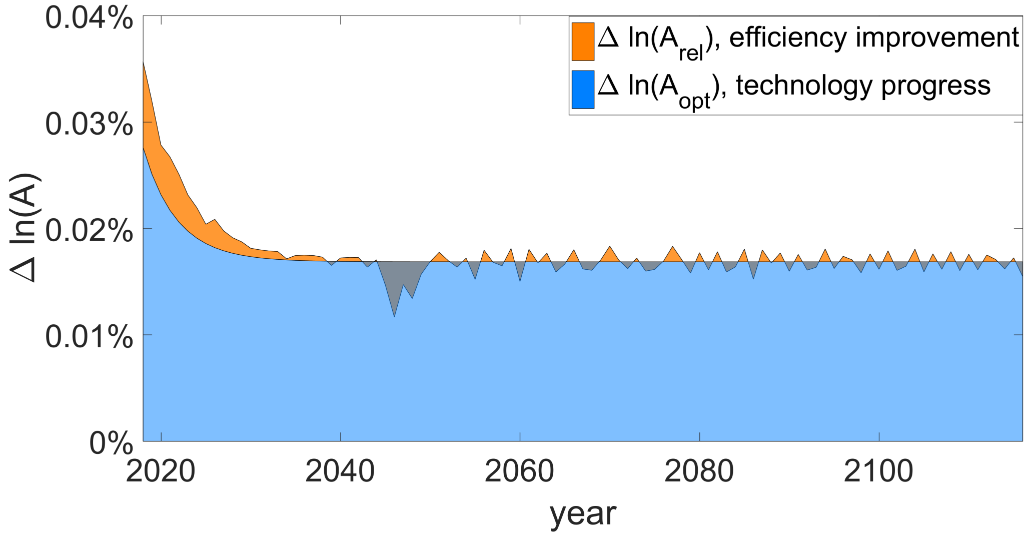


Figure 4: Growth decomposition

Notes. The decomposition follows equation 9 in the appendix A.

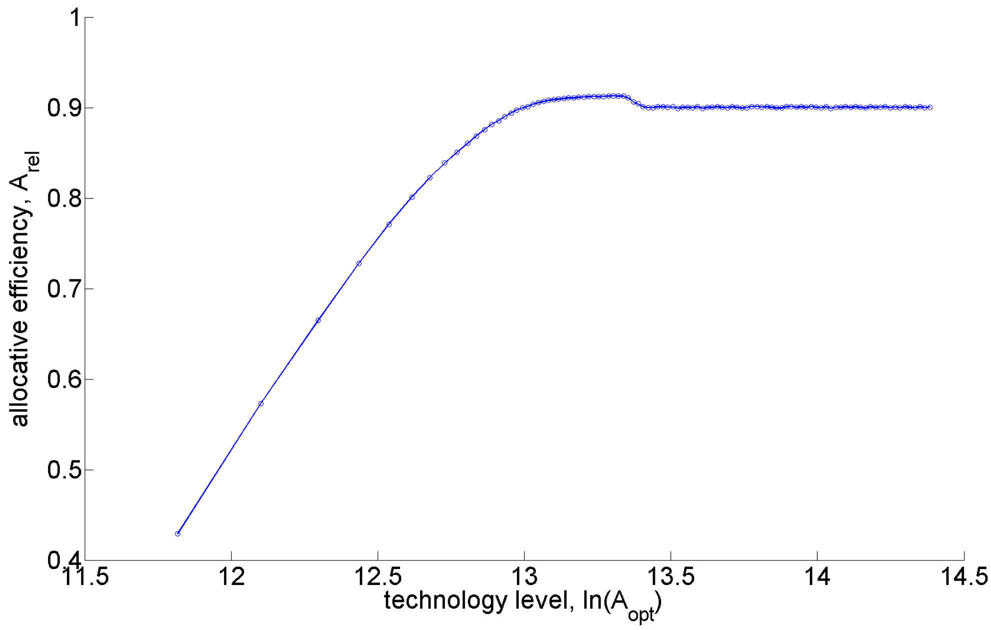


Figure 5: Technical progress and allocative efficiency

Notes. The horizontal axis measures technology level of the economy (see equation 7). The vertical axis measures allocative efficiency (see equation 8). Appendix A shows the derivation of the measures. The initial distribution is from the real data in 2007.

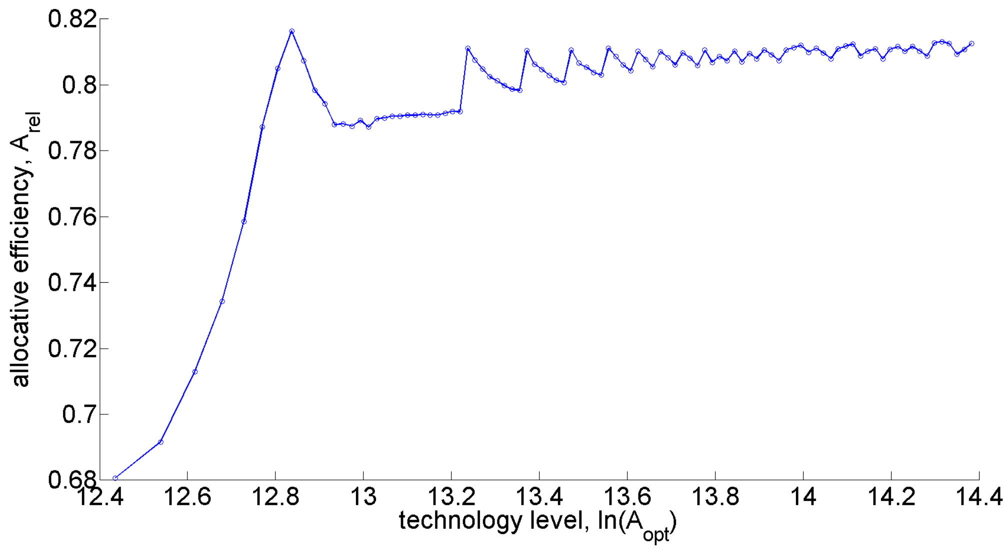


Figure 6: Technical progress and allocative efficiency

Notes. The initial allocation is theoretically optimal. The trend is slightly non-monotonic because of the numerical error from discretization.