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Assessing the Role of Technology Adoption in China's Growth Performance

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Abstract

China has experienced a period of tremendous economic growth in recent years. In an attempt to explain this development, several existing growth-accounting studies reveal that impressively high rates of productivity growth have been at the heart of China's performance. This study investigates to what extent these productivity increases can be explained by technology-adoption theory. In less developed countries, the key element behind technological progress is technology adoption, the process of copying technological knowledge invented throughout the world. To uncover a measure of China's technological advances, the paper constructs a hybrid of some prominent technology-adoption models and calibrates it to reasonable parameter values. The calibrated version of the model is then combined with Chinese economic data. For the period 1978-2005, the analysis finds that the Chinese performance can be explained to a surprisingly large extent by the suggested technology-adoption framework. It can account for roughly 80% of China's productivity gains.

Keywords: technological progress, technology adoption, TFP, China
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1 Introduction

The year 1978 marked the beginning of China's transformation from a rigid, centrally planned economy towards an increasingly open and market-oriented economy. Since then, the Chinese economy has seen a period of extraordinary growth. Over the past 25 years, China has achieved growth rates in income per capita of approximately 7% per year,[1] which is equivalent to doubling per-capita income every decade. This number already puts Chinese performance in its own class. Nevertheless, there are two particularly notable aspects of China's growth pattern. First, the phase of strong growth has lasted more than a quarter century. Although other economies, including those in East Asia, have displayed similar growth rates, none has maintained such pronounced growth for as long of a period as China. Second, the sources of China's economic growth differ markedly from the underlying forces of previous fast developers. Recent evidence suggests that a sizable portion of China's growth is attributable to increases in productivity (e.g., Borensztein and Ostry, 1996; Hu and Khan, 1997; IMF, 2006; Kuijs and Wang, 2006; Bosworth and Collins, 2008),[2] which contrasts with the East-Asian experience, for example. Namely, various studies have shown that the East-Asian catch-up to advanced economies was largely due to capital accumulation (e.g., Krugman, 1994; Young, 1995; IMF, 2006). Although the rate of Chinese investment into capital is one of the highest in the world, several studies document the fact that the capital-output ratio and the real return to capital have remained roughly constant over the last decades (e.g., Hu and Khan, 1997; Bai et al., 2006). Again, this indicates that productivity gains have been at the heart of China's catch-up to leading economies, making it an unprecedented growth experience.

An illustration of China's performance is provided in Figure 1. Subfigure 1(a) displays China's output trajectory, revealing that GDP per worker rose a five-fold from 1978 to 2005. In addition, a few numbers on total factor productivity (TFP) growth illustrate the extent to which China's performance exceeds prior norms. Bosworth and Collins (2008) perform a growth-accounting analysis, finding Chinese TFP growth rates of 3.6% during 1978-2004. By comparison, annual TFP growth around the world averaged 0.9%, annual TFP growth of industrial countries hovered around 1%, and annual TFP growth in East

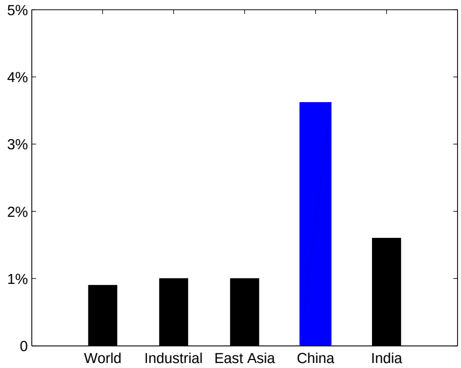
[1] Source: Total Economy Database (2008).

[2] Conversely, Young (2003) claims that China's productivity performance is respectable, but not outstanding. In his study, increases in participation rates, investment in education, and capital account for the major part of growth. However, a recent official revision in the Chinese national accounts raised the level and output growth in the services sector to correct for its previous underestimation. This adjustment, not included in Young (2003), is finally reflected in higher overall TFP growth: Bosworth and Collins (2008), using the same price deflator as Young to adjust the Chinese data, find strong TFP growth.

Asia averaged 1% during 1960-2000 (Bosworth and Collins, 2003).[3] India, presently one of the most prominent fast developers besides China, achieved average TFP growth rates of 1.6% during 1978-2004 (Bosworth and Collins, 2008). The TFP growth rates of different regions are summarized in Subfigure 1(b). As can be seen, China clearly outperforms other regions.

Figure 1: Illustration of the Chinese growth performance

(a) Evolution of real GDP per worker in China.
Source: Total Economy Database (2008).
Note: GDP in 1990 international PPP $s.



(b) Comparison of TFP growth rates
Source: as described in text.

China exemplifies a model of remarkable economic performance. It is natural to ask how we can account for such a growth miracle. In particular, how can we rationalize such impressively high productivity growth? Can it be explained by theory? The present paper aims to shed light on these questions. While neoclassical growth theory illuminates growth miracles with roots in factor accumulation, it remains silent about productivity increases. It would thus be a bad predictor of China's performance. Conversely, several authors have recently developed so-called technology-adoption models that aim to account for productivity advances in less developed countries. These models are centered around the concept of international technology diffusion, building on the idea that lagging economies can potentially copy and take advantage of technological knowledge invented abroad. Therefore, a new generation of growth models may be able to explain the Chinese performance. The present paper challenges this class of models: it investigates whether technology-adoption theory can explain the Chinese growth.

To my knowledge, no study has attempted to assess the importance of technology

[3]In Bosworth and Collins (2003), the 'World' group consists of 84 countries and the 'Industrial Economies' group of 22 countries. The region 'East Asia' encompasses Indonesia, Korea, Malaysia, Philippines, Singapore, Taiwan, and Thailand.

adoption in China's emergence. This paper aims to explore the evolution of productivity in China over the period 1952-2005 and through the lenses of technology-adoption theory. For this purpose, the paper constructs a hybrid growth model designed to capture the Chinese growth context. With this framework, along with Chinese economic data, the paper seeks to uncover an estimate of China's technology level. Since China can be categorized as technologically backward, technology-adoption theory is suitable in assessing China's performance. Technology-adoption models typically incorporate the potential for rapid growth arising from copying technologies invented in advanced economies. This study builds upon existing theoretical work along these lines.

Many of the early technology-adoption models, such as Nelson and Phelps (1966), Benhabib and Spiegel (1994), Parente and Prescott (1994), Barro and Sala-i Martin (1997), and Jones (2002), feature a so-called advantage of backwardness. That is, since technologically backward countries profit from discoveries made throughout the world, they should initially grow faster than leading economies and hence catch up. However, given the reported absence of improvement in Chinese TFP levels during the pre-reform years 1952-1978 (e.g., Chow, 1993; Borensztein and Ostry, 1996; Chow and Li, 2002; Wang and Yao, 2003),[4] advantage-of-backwardness models cannot be applied to China directly.

Therefore, the model applied in the context of China's performance should also be able to account for technological stagnation. Some of the more recent technology-adoption models augment the early models and are able to advance mechanisms that do not set off an automatic catch-up given a country's backwardness (e.g., Howitt, 2000; Papageorgiou, 2002; Benhabib and Spiegel, 2005; Aghion et al., 2005; Howitt and Mayer-Foulkes, 2005; Sadik, 2008). These models are in the spirit of Abramovitz' (1986) view that backward countries "have a potentiality for generating growth more rapid than that of more advanced countries, provided their social capabilities are sufficiently developed to permit successful exploitation of technologies already employed by the technological leaders" (p. 390). Abramovitz' idea points to the existence of thresholds, which are indeed inherent in the models mentioned above. Those theories propose that a certain human-capital, physical-capital, or financial-development level, for instance, may be critical for development. In a similar vein, the mechanism of the model offered in this paper requires a critical combination of human capital, physical capital, and technology-adoption capabilities in order to generate growth in technological knowledge. If the backward country, in this case China, surpasses the critical threshold combination, implementing new technologies becomes worthwhile. The country then exhibits growth

[4]This holds even after accounting for the various political upheavals that took place in the Mao era.

through technological progress. Within China's growth and institutional context, one can think of the regime switch in 1978 leading to improved social capabilities: loosened state control, and thereby greater profit incentives, should induce a positive effect. Firm owners, keen on increasing profits (and now able to retain more), devote more of their own revenue to increasing business performance (Hu and Khan, 1997). Thus, these incentives should induce innovation and technological progress (Chow, 1993).

This paper develops a hybrid of some prominent technology-adoption models that allows for technological stagnation as well as growth. Subsequently, it takes the model to Chinese economic data to obtain an estimate of how much of China's productivity gains come from improved productivity through technology adoption. More precisely, the paper calibrates the model to reasonable parameter values and runs a simulation to obtain a predicted path of the Chinese economy, which is then compared to the actual path. This study finds that the new generation of growth models, namely, technology-adoption theory, performs surprisingly well in explaining the Chinese growth. During 1952-1978, the actual data and the model display zero productivity growth. During 1978-2005, the calibration exercise suggests that a striking 80% of China's boost in total factor productivity can be explained by the technology-adoption framework.

Conceivably, the main candidate to explain the remainder of TFP growth is resource reallocation: relaxation of state control and moving toward a more market-oriented economy also induces efficiency gains through reallocation, ultimately resulting in a higher TFP measure. Some recent studies, such as Hsieh and Klenow (2007), have examined the contribution of improvements in allocative efficiency to China's TFP growth. Reassuringly, the findings of these studies square nicely with the results obtained in this paper. The estimated contribution of technology adoption therefore appears plausible. Consequently, technology-adoption theory can explain the Chinese growth miracle to a surprisingly large extent.

The paper proceeds as follows. Section 2 presents the model constructed to assess China's growth pattern and discusses its features. Section 3 describes how the model is applied to the Chinese economy and explains in detail the calibration approach. Section 4 presents the main results, and Section 5 provides a sensitivity analysis and a discussion. Section 6 offers some concluding remarks.

2 Theoretical Framework

This section outlines the hybrid model of technology adoption that aims to account for China's economic development over time, especially with respect to technology growth.

In the model, a following country ("the follower") has potential to take advantage of existing technologies invented in a leading economy. This section focuses on the follower economy. However, whenever necessary, it also introduces the characteristics of the country discovering new technology. Finally, this study allows the theoretical framework to confront actual performance, in an attempt to see how much of China's growth can be explained by technology adoption.

2.1 Setup

Think of two countries: one a technological leader and the other a follower. Throughout the paper, I consider the United States to be the leader, and China the follower. The leader engages in research and development, leading to discoveries and improvements in technological knowledge. In contrast, the trailing country imitates. Thus, it can only adopt technologies already invented in the advanced part of the world. The model's setup relies on the structure initiated by Romer (1990), Grossman and Helpman (1991), and Aghion and Howitt (1992). It involves a three-sector framework that also forms the base for several studies examining technology adoption, including Barro and Sala-i Martin (1997), Howitt (2000), and Papageorgiou (2002).[5] The market structure and the production function of both countries are identical, though inputs and factor shares can differ. There are three sectors in the economy: a perfectly competitive final-good sector that produces a homogenous output good; an intermediate-good sector that produces differentiated capital goods and supplies them to final-production firms; and an R&D or an imitation sector, respectively, that invents or adopts the blueprints for the intermediate goods. Implementing a new technology necessitates a fixed cost to be incurred by the adoption sector. Think of the R&D firm or the imitating firm as the research department of the intermediate-good firm. Technological progress takes the form of quality improvements of the differentiated capital goods. In other words, each innovation/imitation produces a new intermediate good that increases efficiency in the final-good sector. That is, input factors are transformed into output more efficiently in the new version, relative to the outdated version. To distinguish between the follower and the leader, variables and parameters associated with the leader are marked with a

[5]The model by Howitt (2000) is probably closest to the model and mechanism developed here. In contrast to many recent technology-adoption models, Howitt's model and the model presented in this paper feature a physical capital stock.

bar. The production function of the follower at any point in time is given by[6]

$$Y = (hL)^{1-\alpha} \int_0^1 A_j^{1-\alpha} x_j^\alpha \, dj, \tag{1}$$

where $0 < \alpha < 1$, and Y represents final output. x_j is the amount of the latest version of the intermediate good j used in final production. A_j measures state-of-the-art quality associated with intermediate good j produced in the follower country, and $[0, 1]$ corresponds to the range of industries that produce intermediate goods. L labels inelastic labor supply; h describes average human capital per worker. The leader's output $\overline{Y}$ reads analogously. Labor quality h takes the standard form,[7] namely

$$h = e^{\phi \cdot E}, \tag{2}$$

where ϕ represents the rate of return to schooling, and E measures average years of schooling in the economy. The same holds for the leader's labor quality $\overline{h}$, with $\overline{\phi}$ and $\overline{E}$ accordingly.

There is so-called raw capital K in the economy. Let us denote $K = \int_0^1 x_j \, dj$ (and $\overline{K} = \int_0^1 \overline{x}_j \, dj$ for the leader, respectively), indicating that the total amount of intermediate goods corresponds to overall capital or raw capital K in the economy. Time t is discrete. There is the accumulation of raw capital as the economy invests an exogenous fraction s_t of its income and depreciates at the constant rate δ

$$K_{t+1} = s_t Y_t + (1 - \delta) K_t. \tag{3}$$

The leader's capital $\overline{K}$ evolves analogously. The remainder of this section concentrates on the technologically lagging country.

Final-good firms. In each period, firms operating in the competitive final-good sector solve the following profit-maximization problem

$$\max_{L, x_j} (hL)^{1-\alpha} \int_0^1 A_j^{1-\alpha} x_j^\alpha \, dj - wL - \int_0^1 p_j x_j \, dj. \tag{4}$$

The price of the final good Y is set to unity. w is the wage rate paid to workers, and p_j is the rental price of the capital good j. From the viewpoint of the producer, w and p_j

[6] Whenever not misleading, time subscripts are suppressed.

[7] This functional form is found in Hall and Jones (1999) and Bosworth and Collins (2003, 2008).

are taken as given. The first-order conditions to the maximization problem lead to

$$w = (1-\alpha)\frac{Y}{L} \qquad \text{and} \tag{5}$$

$$p_j = \alpha(hL)^{1-\alpha} A_j^{1-\alpha} x_j^{\alpha-1} \qquad \text{for all } j. \tag{6}$$

The optimality conditions show that final-good producers choose input quantities such that the marginal products equal input prices. The final-good production function, along with the profit-maximizing behavior, implies that labor income in the economy totals $wL = (1-\alpha)Y$ and that the total compensation stream to intermediate-sector firms sums up to $\int_j p_j x_j \, dj = \alpha Y$. Note that equation (6) expresses the inverse demand function for capital good j, which intermediate-goods firms consider as given in their optimal-pricing behavior.

Intermediate-good firms. Each intermediate-good firm produces a particular type of capital good. Suppose that a firm incurs a fixed cost to adopt a certain quality from the leader country. The incumbent subsequently acts as a monopolist, realizing a profit in the first period. After the first period, profits shrink to zero as additional competitors enter the market for this version of good j. To develop an intuition, consider a patent that protects the incumbent only during a certain length of time, or the fact that it takes potential rivals some time to discover the same quality of a capital good. If there were no gains to be realized in the intermediate-good sector, start-up investment costs would prevent firms from entering. Hence, a stream of profits must accrue to these firms. Once the firm has incurred the fixed setup cost, each unit of a specific capital good can be exchanged for one unit of raw capital and vice versa.[8] In each period, monopolists decide on the profit-maximizing quantity

$$\max_{x_j} \pi_j = p_j(x_j)x_j - rx_j. \tag{7}$$

π_j labels per-period profit of firm j, and r represents the rental price of raw capital K. As mentioned above, the monopolist takes the demand function $p_j(x_j)$, stated in equation (6), as given. Solving yields $p_j'(x_j)x_j + p_j(x_j) = r$ and can be expressed as

$$p_j = \frac{1}{\alpha} r. \tag{8}$$

[8] Jones (1995), Howitt (2000), and Kumar (2003), for instance, take the same assumption.

This pricing rule implies that intermediate-good monopolists choose a price equal to a markup times the rental cost of capital. Equation (8) indicates that all monopolists sell their capital goods for the same price: $p = p_j$ for all j. Symmetry across sectors with respect to quality $A = A_j$ then implies $x = x_j$ for all j.[9] As the production function of the intermediate-good sector involves $K = \int_0^1 x_j \, dj = x$, rewriting the production function of the final good leads to the standard neoclassical production function

$$Y = K^{\alpha}(AhL)^{1-\alpha}. \tag{9}$$

Since total proceeds to the intermediate-good sector equal $\int_0^1 p_j x_j \, dj = \alpha K^{\alpha}(AhL)^{1-\alpha}$, the interest rate r is specified by

$$r = \alpha^2 \left(\frac{AhL}{K}\right)^{1-\alpha} = \alpha \frac{\partial Y}{\partial K}, \tag{10}$$

in the case of monopolistic competition. As firms are symmetric, I suppress sector subscripts j going forward. Using the monopolists' pricing rule (8) and the expression for their production costs (10), profits earned by each intermediate-good firm in a given period can be expressed as

$$\pi = \alpha(1-\alpha)Y = \alpha(1-\alpha)\left(\frac{K}{AhL}\right)^{\alpha} AhL, \tag{11}$$

where $\pi = \pi_j$ and $A = A_j$ hold for all j. Note that, if no new quality is introduced at a given point in time, perfect competition implies that prices equal marginal costs and profits are absent. The incumbent's profits from operating a specific technology then vanish after the first period in either event: its technology will become obsolete due either to a newer, better version of good j or to perfect competition if no new version is introduced. This property will influence the valuation of potential technology-adoption prospects.

Technology adoption. In the follower economy, the imitation of technology invented in the advanced country requires a non-recurring outlay $f(\cdot)$ per worker, which is undertaken by the adoption department of a firm. These expenses are required to adapt the technology to the present environment, including the training of workers. In other

[9]Following the literature, I assume that the technology level in the leading economy is the same across sectors at any point in time and that the follower's initial knowledge level is the same across sectors. This produces symmetry in the follower economy since all firms face the same adoption decision and there is no uncertainty in the technology-adoption process. Hence, firms are symmetric.

words, lump-sum costs are incurred by the intermediate-good entrepreneur to ensure that workers in the environment of the backward country manage to handle the new technology embodied in a capital-good version.

It is likely that a higher level of technology in the lagging country, relative to the world technology frontier $\bar{A}$, implies a higher cost of copying. As the follower country approaches the leader in technological knowledge, the imitation process becomes more difficult and more expensive. For this reason, this paper assumes that the cost of imitation is an increasing function of the ratio $\frac{A}{\bar{A}}$.[10] Specifically, the technology-adoption cost per worker at a given point in time, from the viewpoint of a firm in the follower country wishing to implement quality A, is of the form

$$f\left(\frac{A}{\bar{A}}, A\right) = \theta \left(\frac{A}{\bar{A}}\right)^{\sigma} A, \tag{12}$$

where $\sigma > 0$ and $\theta > 0$ index parameters of the cost function. The technology frontier $\bar{A}$ is exogenous to the follower country, growing at the constant rate $\bar{\varepsilon}$.[11] Comin and Hobijn (2006) adopt a similar cost function: the formulation (12) reflects the idea that it is more difficult to imitate more sophisticated technologies, both relative to the frontier, as explained above, and in absolute terms. The absolute term A in the cost function takes the force of increasing complexity into account, a notion found in Howitt (2000) and Aghion et al. (2005). That is, as technology advances, the outlays required for further improvements increase. Moreover, the presence of A is a standard assumption in growth models featuring quality improvements and guarantees a balanced growth path. The parameter θ reflects factors that affect the cost of adoption and can be interpreted as capabilities to adopt or, in the spirit of Parente and Prescott (1994), as barriers to adopt. Enhanced capabilities are associated with a lower value of θ. For example, international activity (such as trade and FDI), education, and good institutions have been suggested as facilitators of adoption.[12]

It is important to note that total outlays depend on the size of the workforce. The assumption that total outlays in an economy are proportional to the labor force results in the elimination of the counterfactual scale effect inherent in Barro and Sala-i Martin (1997), for instance. Furthermore, it seems natural to assume that overall adoption costs depend on the size of the workforce as introducing new varieties includes training

[10]The dependence of the adoption cost on the ratio $\frac{A}{\bar{A}}$ is widespread in the literature. For example, the ratio is also present in the cost functions imposed by Parente and Prescott (1994), Barro and Sala-i Martin (1997), and Comin and Hobijn (2006).

[11]The US, the leading country, has indeed displayed a rather constant rate of growth over the last century, as discussed below.

[12]For example, see Comin and Hobijn (2006) and Bloom et al. (2002) for empirical evidence.

workers.[13]

Suppose an intermediate-good firm acquires the blueprint for a certain technology. A specific firm pays $f(\cdot)L$. After firm j has incurred the setup cost, it knows how to convert a unit of raw capital into a specific capital good x_j and earns profits during the first period. Once the adoption department of the intermediate-good firm knows the design, the firm starts to operate immediately; it would forego earnings otherwise. I make the standard assumption of free entry into the intermediate-good market, which results in the present value elimination of profits. The start-up firm is willing to pay the up-front investment cost when it knows that it will generate enough future revenue to be compensated for the cost incurred at time t. The relevant interest rate for the valuation of a project is the real rate $r - \delta$. The value of a monopolistic firm, immediately after the introduction of a new quality, then amounts to

$$V_t = \frac{1}{1 + r_t - \delta} \pi_t.$$

The resulting technology adoption in the follower economy in a specific sector is analyzed in the following. At each point in time, a firm introduces a better quality good only if the following *technology-adoption condition* holds at the beginning of a period

$$\frac{\pi_{tb}}{1 + r_{tb} - \delta} \geq \theta \left(\frac{A_{tb}}{\bar{A}_t} \right)^{\sigma} A_{tb} L_t, \tag{13}$$

where the initial level of knowledge A_{tb} in a specific sector is given and corresponds to A_{t-1}. b denotes the beginning of a period before a potential adjustment. The technology-adoption condition (13) states that the present value of prospective profits must exceed up-front investment costs, such that firms are willing to adopt new technologies. Put differently, a rewarding business opportunity must exist.[14] The frontier technology $\bar{A}$ is taken as given. In the adoption process, the point at which the technology-adoption condition is satisfied or not in a given period is crucial. If it is satisfied, the economy's technology level improves and the country grows. If it is not, the follower country is stuck with stagnant technological growth.

However, this state of the economy need not last forever. As can be seen, equation (13) provides avenues for escaping from technological stagnation. On the one hand, as time passes, the leader advances the technology frontier $\bar{A}$. This steadily decreases the lump-sum cost of adoption until the cost of adoption may drop below the gains. In this

[13] This reasoning is found in Easterly et al. (1994) and Kumar (2003).

[14] In order to displace a current technology, a firm has to incur at least the amount stated on the right-hand side of equation (13).

event, implementing new technologies becomes worthwhile. On the other hand, policy changes that influence the cost parameter θ or that raise human capital h improve the absorptive capacity of a receiving country. These changes may cause technology adoption to become worthwhile. Additionally, a higher capital stock would be conducive to technology adoption.

In what follows, I illustrate the dynamics of a technologically lagging country that arises from the setup described above. It is useful to distinguish between the following two situations: a regime in which adoption is not worthwhile and one in which it is. The next subsection analyzes the economic behavior of a follower country in the no-adoption and adoption states and illustrates the transition. A description of the ways in which this framework can be applied to China follows in Section 2.3.

2.2 The Evolution of the Follower

No-technology-adoption state. Consider a sample economy. Suppose parameter and variable combinations are such that it is not worthwhile to copy new, so-far-unimplemented technologies. The intermediate-good sectors in the economy therefore prefer to stay with their initial technology level $A_{t=0}$ as the costs exceed potential profits. In this situation, the economy conforms to the neoclassical framework, summarized by the neoclassical production function and the capital-accumulation function stated in (9) and (3), respectively. The investment rate s, the capital depreciation rate δ, the level of labor quality h, and the labor force L are treated as exogenous.

Assume that the exogenous variables remain constant over time, or that employment grows at the stable rate n. Given that the technology-investment condition fails to hold, the country eventually settles into a state with zero technological progress, which is labeled the no-adoption steady state. Per-worker capital accumulation ceases when investment and depreciation offset one another exactly: $(\delta + n)k_t = sy_t$, using the notation $k \equiv \frac{K}{L}$ and $y \equiv \frac{Y}{L}$. Given $A_{t=0}$, no-adoption steady-state values read

$$k^*_{NA} = \frac{sy^*_{NA}}{\delta + n}, \tag{14}$$

$$y^*_{NA} = k^{*\alpha}_{NA}(A_{t=0}h)^{1-\alpha} \Leftrightarrow A_{t=0} = \left(\frac{y^*_{NA}}{k^{*\alpha}_{NA}h^{1-\alpha}}\right)^{\frac{1}{1-\alpha}}, \tag{15}$$

where variables marked with an asterisk and subscript NA denote the no-adoption steady state. The section specifying variables for the Chinese economy returns to these steady-state equations. Suppose the sample country finds itself in the no-adoption steady state at $t = 0$. With initial values at hand, the final-good production function (9) and the evolution of the capital stock (3)—taking employment, human capital, and the investment rate as given—fully identify the path of the economy. The potential sources of per-worker growth in a non-adopting economy would be increases in physical and human capital. The following paragraph shows how the follower country enters the technology-adoption state after a period of technological stagnation.

Technology-adoption state. Suppose the follower economy has been caught in the state of technological stagnation over the last years. At the beginning of period t, the economy is endowed with knowledge A_{tb}, corresponding to initial knowledge $A_{t=0}$ as there was no technological progress in the past. Furthermore, the economy is endowed with the predetermined capital stock K_t. Since variables can change during a given period, the paper distinguishes between values before (b) the adjustment and values after. Adjustments occur instantly, and A_t denotes the relevant value at time t, thus marking the value after the adjustment. Now, the developing country enters a period t, in which technology adoption is worthwhile for the first time: $\pi_{tb} > (1 + r_{tb} - \delta)\,\theta\left(\frac{A_{tb}}{\bar{A}_t}\right)^{\sigma} A_{tb}L_t$. This may arise from changes induced by the evolution of the frontier $\bar{A}$ or from a shift in θ, for instance. Potential profits induce intermediate-good firms to incur the setup cost to start their business. The research-arbitrage condition[15] implies that the quality level increases in each sector until the preset value of profits corresponds to the upfront costs: $\pi_t = (1 + r_t - \delta)\,\theta\left(\frac{A_t}{\bar{A}_t}\right)^{\sigma} A_tL_t$. This can be expressed as

$$\alpha(1-\alpha)\left(\frac{K_t}{A_th_tL_t}\right)^{\alpha} h_t = \left(1 + \alpha^2\left(\frac{A_th_tL_t}{K_t}\right)^{1-\alpha} - \delta\right)\theta\left(\frac{A_t}{\bar{A}_t}\right)^{\sigma} \quad \text{or} \tag{16}$$

$$\alpha(1-\alpha)\tilde{k}_t^{\alpha} h_t = \left(1 + \alpha^2\tilde{k}_t^{-(1-\alpha)} - \delta\right)\theta\left(\frac{A_t}{\bar{A}_t}\right)^{\sigma}, \tag{17}$$

where $\tilde{k} \equiv \frac{K}{AhL}$. To identify the technology-adoption path, turn to equation (16). In a certain period, capital K_t, world knowledge $\bar{A}_t$, labor L_t, and education h_t are given; the only unknown to equation (16) is A_t. The economy's path is therefore determined because equation (16) obtains a unique solution for A_t. If profits can be realized at the beginning of a period, firms start expanding the level of technological sophistication. Since the left-hand side of the adoption condition is strictly decreasing and the right-hand side is strictly increasing in A_t, technology increases until equality of (16) is obtained. The follower country improves its knowledge level from $A_{t-1} = A_{tb}$ to A_t. In a given

[15] The research-arbitrage condition states that investors must be indifferent between investing in raw capital and in a firm; it is equivalent to the free-entry condition.

period, total imitation outlays per worker in the economy amount to $\theta_F \left(\frac{A_t}{\bar{A}_t}\right)^\sigma A_t$.

To reiterate, the equations derived above allow me to compute the evolution of an economy through time as follows. Suppose the country enters a new period and adoption is worthwhile. The capital stock K_t is predetermined, and human capital h_t and employment L_t are exogenously given. The new technology level A_t results from equation (16). The solution cannot be written as a formula, but it is easily solved numerically. Plugging the new technology level into the production function $Y_t = K_t^\alpha (A_t h_t L_t)^{1-\alpha}$ yields the output of period t. The economy invests a fraction of the output s_t on raw capital accumulation. Capital formation obeys (3), which yields the capital stock of the next period K_{t+1}. Again, by means of the research-arbitrage equation (16), the new technology level is found and so forth. This allows me to compute the path of the trailing country through time. In what follows, I describe the properties of the long-run equilibrium.

The long-run steady state. In the context of a technology-adoption regime, the following considerations show where the economy is heading in the long run. The long-run equilibrium is labeled the technology-adoption steady state, marked with an asterisk and subscript TA. As derived above, the aggregate production function is Cobb-Douglas, and the capital accumulation is standard. The neoclassical growth literature demonstrates that, when a production function is of this form, per-worker output y, per-worker capital k, and technology A grow at the same constant rate in equilibrium. Put differently, $\tilde{k}$ and $\tilde{y}$ are constant in the long run, where $\tilde{k} \equiv \frac{K}{AhL}$ and $\tilde{y} \equiv \frac{Y}{AhL}$. This implies that interest rates and quality adjusted profits per worker remain stable: $r^*_{TA} = \alpha^2 \tilde{k}^{*\alpha-1}_{TA}$ and $\left(\frac{\pi}{AhL}\right)^*_{TA} = \alpha(1-\alpha)\tilde{k}^{*\alpha}_{TA}$. Therefore, the research-arbitrage constraint $\left(\frac{\pi}{AhL}\right)^*_{TA} = (1 + r^*_{TA} - \delta)\, \theta \left(\frac{A}{\bar{A}}\right)^{*\sigma}_{TA} h^{-1}$ calls for the ratio $\frac{A}{\bar{A}}$ to be constant. This holds true only if the follower's technology level grows at the leader's rate $\bar{\varepsilon}$. The long-run, steady-state growth rate in the follower country is thus pinned down by $\bar{\varepsilon}$.

Constant growth of per-worker income y, which grows at the same rate as A, is consistent with the evolution of the demand components. Namely, the different components of aggregate demand must grow at the same constant rate, too. It is easy to see that this holds for per-worker investment totalling sy. It also holds for the part spent on learning to master new technologies $\theta \left(\frac{A}{\bar{A}}\right)^\sigma A$. Given the fact that employment grows at a constant rate, that human capital and the investment rate are stable in the long run, the follower grows at the rate of the leader.

When the rate of technological progress in the lagging country, denoted ε, is constant and equals $\bar{\varepsilon}$, the capital-technology ratio evolves according to $\Delta\tilde{k} = s\tilde{y} - (\delta + n + \varepsilon)\tilde{k}$

and equals 0 in a steady state. Solving for $\tilde{k}$ yields $\tilde{k}^*_{TA} = \left(\frac{s}{\delta+n+\varepsilon}\right)^{1/(1-\alpha)}$, where $\varepsilon = \overline{\varepsilon}$. Hence, quality-adjusted profits per worker take the following value in the adoption steady state $\left(\frac{\pi}{AhL}\right)^*_{TA} = \alpha(1-\alpha)\left(\frac{s}{\delta+n+\varepsilon}\right)^{\alpha/(1-\alpha)}$.

The relative technology level in the long-run steady state can be computed as follows. Solving the research-arbitrage equation (17) for the ratio $\frac{A}{\bar{A}}$ and imposing the steady-state condition on $\tilde{k}$, I obtain the level of relative knowledge in the long run

$$\left(\frac{A}{\bar{A}}\right)^*_{TA} = \left(\frac{\alpha(1-\alpha)\left(\frac{s}{\delta+n+\varepsilon}\right)^{\alpha/(1-\alpha)} h}{(1+\alpha^2\left(\frac{\delta+n+\varepsilon}{s}\right)-\delta)\theta}\right)^{1/\sigma}. \tag{18}$$

Furthermore, the relative per-worker income ratio in the long run equals

$$\left(\frac{y}{\bar{y}}\right)^*_{TA} = \frac{h}{\bar{h}}\left(\frac{A}{\bar{A}}\right)^*_{TA}\left(\frac{s/(\delta+n+\overline{\varepsilon})}{\overline{s}/(\overline{\delta}+\overline{n}+\overline{\varepsilon})}\right)^{\alpha/(1-\alpha)}. \tag{19}$$

Using the formula for the relative knowledge level in the long run, the impacts on the steady-state technology ratio of the variables s, h, and θ are

$$\frac{\partial\left(A/\bar{A}\right)^*_{TA}}{\partial\theta} < 0, \qquad \frac{\partial\left(A/\bar{A}\right)^*_{TA}}{\partial s} > 0, \qquad \frac{\partial\left(A/\bar{A}\right)^*_{TA}}{\partial h} > 0,$$

and effects of the same sign hold for the relative income level. That is, changes in s, h and θ act on the relative position of a follower country in the long run. The derivatives suggest that technology adoption is nurtured by an abundance of capital, an educated workforce, and low barriers to adopting.[16] Enhancing s or h, or reducing θ improves the relative long-run position of the follower and thus induces a higher growth rate along the transition under the technology-adoption regime.

To summarize the model's features, consider a sample country that starts off in a state of technological stagnation, in which it does not pay to adopt new technologies. In this phase, due to the advances in the frontier-knowledge level or because the follower economy improves its adoption capabilities, imitation costs can eventually become low enough. For either reason, suppose adoption costs drop below the critical value. Consequently, the country escapes from the state of stagnation and begins to grow (technologically) at a rate that converges to the rate of the leader in the long run.

[16] This agrees with the finding in Bernanke and Gürkaynak (2001) suggesting that productivity growth is cross-sectionally related to investment and schooling rates.

Note that the investment rate and human capital are considered exogenous,[17] but they need not be constant. To illustrate this, consider the empirical trend that, as countries become richer, they tend to enhance rates of investment in education and physical capital. Increased availability of physical and human capital induce positive feedback effects on technological progress: more capital reduces the interest rate and increases profits while more human capital has a positive impact on profits, too. Increased education and capital accumulation are thus conducive to technology adoption. In turn, pronounced technology growth, and thus overall growth, may lead to enhanced investment in education and capital causing another boost in technology adoption. Therefore, complementarities prevail between those factors. The increase in those rates has been observed in China and among other fast developers: education and capital accumulation rose along the growth path. The formal analysis above has revealed that increases in s and h, and reductions in θ involve an improved relative technology level $\frac{A}{\bar{A}}$, and these changes entail that the growth rate accelerates along the transition.

The hybrid model suggested in this paper is able to produce stagnation and growth phases for developing countries. It provides a mechanism that allows for stagnation in the presence of potential international technology diffusion, stemming from the profit considerations of adoption firms, and it can generate growth in technology arising from technology adoption.

2.3 China and the Technology-Adoption Model

Before delving into the details of the calibration approach, it is useful to illustrate how the model and the actual Chinese experience fit together. This study follows the growth-accounting literature in dividing China's record during 1952-2005 into two subperiods: pre-reform period (1952-1978) and reform period (1978-2005). This distinction is made because the introduction of reforms in 1978 marks a regime shift and the two periods display disparate growth patterns. TFP growth was virtually nonexistent during 1952-1978 whereas high overall growth and sharp TFP increases were observed during 1978-2005. Consequently, the pre-reform years represent the no-adoption state, and the reform years represent the adoption state.

Several reasons substantiate the conjecture that China was in a no-technology-adoption state during 1952-1978. On the one side, the documented absence of TFP growth during 1952-1978 (e.g., Chow, 1993; Wang and Yao, 2003) suggests that technological progress, usually the main contributor to TFP growth, was nonexistent. On the other side, the

[17] As shown below, this study works with actual rates observed for China.

economic system in effect during that period discouraged the implementation of more sophisticated technologies. That is, a command structure characterized the economic system: agriculture was commune-based, business firms were state-owned, and prices were heavily controlled. Furthermore, pursuing a policy of autarkic self-reliance, the country was virtually isolated from the world economy (Gapinski, 2001; Maddison, 2007). Consequently, as Chow (1993) states, there are no reasons to believe that technological progress occurs under such a strict central planning regime that suppresses any incentives for private enterprise. Private initiatives are typically the main drivers of improvements in technological knowledge. The technology-adoption condition (13) could capture the Chinese pre-reform economic structure by accounting for the nature of institutions and for the effects of being cut-off from foreign trade and capital. These factors point to a large cost parameter θ. Furthermore, one can think of central planning involving a high implicit tax on firms' profits, which reduces the net gains that firms can collect. Overall, these features imply that the technology-adoption condition is unlikely to hold under strict state control.[18]

The second subperiod is characterized by an increasingly open and market-oriented economy, which paved the way for profit-seeking enterprises to advance technological knowledge. Indeed, the period 1978-2005 witnessed extraordinary productivity growth. I assume that the regime switch from strict state control toward a more decentralized and open economy led to a downward shift in the Chinese cost parameter θ. Therefore, the technology-adoption condition is satisfied in the Chinese economy for the first time in 1978. After 1978, the Chinese economy is governed by the technology-adoption regime. Detailed information on the calibration and the simulation procedure follows in the next section.

3 Calibration Approach

In order to shed light on China's astounding productivity growth, this study simulates a counterfactual path and confronts this path with China's actual experience. The simulation procedure allows for changes in only one contributor to TFP growth, namely, technological-knowledge enhancements. The simulation, in which technology improve-

[18]Conversely, one could argue that a central planner might advance technological knowledge. However, the contribution of China's pre-reform government to technological progress is believed to have been negligible. First, it is generally acknowledged that private enterprise is the key to technological progress. Second, in the case of China, the government was rather unsuccessful regarding its science activities. According to Greeven (2004), research, development, and engineering was guided by a state plan, but science and technology activities "missed every link to the economy" (p. 3). Moreover, the Cultural Revolution, which started in 1966, caused a complete halt in science and technology development (except for military) for over 10 years.

ments arise from the mechanism outlined above, proposes a growth performance, which I can compare to actual data. More precisely, I calculate the ratio of simulated productivity growth versus actual Chinese TFP growth obtained from standard growth-accounting. This yields an estimate on how much of China's growth can be attributed to technology adoption.

To obtain a simulated path, I assign parameter values and apply the calibrated model to Chinese economic data. The functional forms describe final-good production, human capital, capital accumulation, and technology-adoption cost, and each parameter requires specification. The parameters are as follows: α, $\overline{\alpha}$, δ, $\overline{\delta}$, ϕ, $\overline{\phi}$, θ, and σ. Furthermore, I must determine initial values of the capital stock, the follower's initial technology level A, and the leader's technology level $\bar{A}$, including its growth rate $\overline{\varepsilon}$. For the variables investment rate s_t, labor force L_t, and schooling E_t (contained in h_t), I use the observed time series for the Chinese and the US economies. The time period under investigation is 1952-2005. As the present analysis follows standard sources, detailed description of the data sources is contained in Appendix A.1.

Table 1 provides an overview of the baseline parameterization of the model. The subsequent paragraphs describe my preference for this parameterization.

Table 1: Parameters and initializing values of the baseline specification

parameter	interpretation	value
α	capital share	0.40
δ	depreciation rate	0.05
ϕ	return to schooling	0.07
σ	technology-adoption parameter: sensitivity to technology frontier	0.30
θ	technology-adoption parameter: absorptive capability	1.09
A_{52}	initial value of technological knowledge	858
k_{52}	initial value of capital stock	2089
$\overline{A}_{52}$	initial value of technology frontier	5507
$\overline{\varepsilon}$	growth rate of technology frontier	0.02

Capital share: α, $\overline{\alpha}$. This study follows the growth-accounting analysis by Bosworth and Collins (2008) in assuming that China's capital share α equals 0.4. It is worth noting that some studies (e.g., Chow and Li, 2002; Heytens and Zebregs, 2003; Kuijs and Wang, 2006) use a higher capital share of around 0.5. However, Bosworth and Collins (2008) argue that this is implausibly high and overstates the true value.[19] Furthermore,

[19] Bosworth and Collins (2008) conjecture that the frequent assumption of a rather high capital share hinges on regression studies, such as Chow (1993) and Chow and Li (2002), which obtain large coefficients on capital in estimates of an aggregate production function. According to Bosworth and Collins, a high estimate may be the

detailed analysis on Chinese capital by Holz (2006a) underpins the assumption of 0.4. As a robustness check, the study also simulates paths for different values of α. The capital share $\overline{\alpha}$ for the US takes the standard value of $\overline{\alpha} = 0.3$. For example, Bosworth and Collins (2003) include an overview of the US capital shares used in various studies. They report that the employed/estimated capital share in most studies is close to 0.3. The leader's capital share $\overline{\alpha}$ is used to obtain an estimate of the leader's technology level, which is relevant for the technology-adoption decision faced by the follower China.

Depreciation rate: δ, $\overline{\delta}$. This study assumes that the rate of capital depreciation $\delta = \overline{\delta} = 0.05$ applies to both countries. This value is widely used for various countries. Moreover, this assumption agrees with the rate reported in Holz (2006b), a study on Chinese capital.

Return to schooling: ϕ, $\overline{\phi}$. Although developing countries typically exhibit high returns to schooling, China's experience appears to contradict with this pattern. Several studies detect a rather low return to educational attainment in China (e.g., Young, 2003; Heckman and Li, 2004), justifying a modest ϕ. The present paper follows Bosworth and Collins (2008) in imposing $\phi = 7\%$. For the US, it assumes that $\overline{\phi} = 10\%$, which agrees with the findings in Psacharopoulos (1994) and Psacharopoulos and Patrinos (2004).

Technology frontier: $\bar{A}$, $\overline{\varepsilon}$. The evolution of the technology frontier is crucial to the follower's decision to imitate. Thus, I must specify the technological knowledge level of the leader country. It is an established fact that, over the last century, the United States has experienced a rather constant rate of per-capita growth, hovering around 2%. This suggests that the US economy has followed a steady-state growth path. In a steady state, per-person variables grow at the rate of technological progress. In the US, the average growth of per-capita GDP amounted to 2.0% during 1952-2005. Therefore, the rate of technological improvement $\overline{\varepsilon}$ is set to 2.0%.

To obtain a measure for the leader's technology level, the study first estimates the capital stock of the leader. Combining the production function with data on physical and human capital allows me to back out $\bar{A}$. Given that the US economy exhibits steady technological progress, capital expressed in labor-efficiency units evolves according to $\Delta\tilde{\overline{k}} = \overline{s}\tilde{\overline{y}} - (\overline{\delta}+\overline{n}+\overline{\varepsilon})\tilde{\overline{k}}$, which can be rewritten as $\overline{k}^* = \frac{\overline{sy}^*}{\delta+\overline{n}+\overline{\varepsilon}}$. By inserting actual values observed in 1952, I obtain an estimate of the initial capital stock $\overline{k}_{52}$. The inserted values read: $\overline{s} = 19\%$, $\overline{\delta} = 5\%$, $\overline{\varepsilon} = 2\%$, $\overline{n} = 1.5\%$, and $\overline{y}_{52} = 25393$. Then, $\overline{k}_{52} = 55520$ results.

result of endogeneity, overstating the true value.

$\overline{n}$ corresponds to US employment growth during 1952-2005. $\overline{s}$ measures the average investment share during the observation period and amounts to 19%. The inserted value for output $\overline{y}$ corresponds to real GDP per person employed in 1952 (1990 is the base year). To obtain a more precise measure of capital and, accordingly, for knowledge $\bar{A}$, I calculate the capital stock of subsequent periods according to the perpetual inventory method. This corresponds to using the capital-accumulation equation (3). I use the US investment share of real GDP and data on real output in each year.

As 1978 marks the break in China's regime and induces a shift in the adoption-cost function, it is important to have the measures pertaining to this year. This will become clear when determining the parameters of the adoption-cost function below. Therefore, the present analysis extracts the frontier-technology level that applies in 1978. Recall that the production function involves $\bar{A}_{78} = [\overline{y}_{78}/(\overline{k}_{78}^{\bar{\alpha}}\overline{h}_{78}^{1-\bar{\alpha}})]^{1/(1-\bar{\alpha})}$. $\overline{k}_{78}$ is the estimated capital stock equalling 85109 (obtained from the perpetual inventory method), and $\overline{y}_{78}$ stands for the actual real GDP per worker in 1978 amounting to 41590. Concerning human capital, $\overline{h}_{78} = e^{\overline{\phi}\cdot\overline{E}_{78}}$ holds, where $\overline{E}_{78}$ measures average years of schooling. The schooling value stems from Cohen and Soto (2007). Their study suggests that the number of schooling years in the United States remained largely stable around 12. I therefore use $\overline{E}_{78} = 12$. Inserting the relevant values yields $\bar{A}_{78} = 9216$. To abstract from short-run fluctuations, measures of the technology frontier for the remaining years are obtained by applying the growth rate $\overline{\varepsilon} = 2\%$.

The follower's technology level: A**.** The procedure to determine the follower's level of technological sophistication parallels the procedure to determine the technology frontier. Again, I estimate the capital stock and then extract the technology level A. As the follower's productivity level remained constant over the pre-reform period 1952-1978, the equation for the steady-state value of the capital stock (14) provides the estimate for the initial capital stock k_{52}: $k_{52} = \frac{sy_{52}}{\delta+n}$. I insert the following values: $\delta = 5\%$, $n = 2.3\%$, $s = 12\%$, and $y_{52} = 1273$. Growth in actual employment during the initial phase (1952-1962) identifies the value for n. s measures the investment share in 1952, and output y_{52} corresponds to real GDP per person employed in 1952 (measured in 1990 international PPP dollars). The estimate finds $k_{52} = 2089$. Recall that technological knowledge is modeled as follows: $A_{52} = [y_{52}/(k_{52}^{\alpha}h_{52}^{1-\alpha})]^{1/(1-\alpha)}$. Apart from measures for y_{52} and k_{52}, I consider average years of schooling E_{52}, which affect labor quality h_{52}. This information is taken from Wang and Yao (2003), who document $E_{52} = 0.92$. Inserting the respective measures yields $A_{52} = 858$. Using annual output data and annual investment rates observed in China, the perpetual inventory method produces capital-stock estimates for the whole observation period. Combining capital-stock estimates with information on observed real output per worker and schooling for each year yields an estimate of China's productivity for each year. The data implies that actual TFP growth amounts to 0.1% during 1952-1978. Hence, productivity is virtually stagnant, which is also reported in earlier studies, including Chow (1993) and Holz (2006a). Furthermore, I find that TFP growth during 1978-2005 amounted to 3.3%. Thus, the numbers from this growth-accounting exercise are closely in line with recent studies. For the simulation of China's hypothetical path, I use A_{52} and k_{52} as starting values and determine the follower's technology level in each year that results from the firms' decisions to predict the path through 1952-2005.

Adoption-cost parameters: σ, θ. Assigning values for the parameters of the adoption-cost function appears more difficult. First of all, it is important to note that σ is a measure of how a follower country reacts to changes in the frontier technology. σ ultimately influences the speed of convergence to a steady-state growth path. To specify the appropriate value of σ, I calculate the rate of convergence implied by the model. As shown in Appendix A.2, the convergence rate is a function of the parameter σ. The value of σ is chosen such that the model's speed of convergence matches the well-known cross-sectional evidence, finding a convergence rate of 2%. Appendix A.2 reports the determination of the speed of convergence and of the parameter σ in detail. It finds $\sigma = 0.30$.

Having the value for the reaction parameter σ allows me to identify the Chinese adoption-capability parameter θ. The discussion in Section 2.2 suggests that the argument stated in the technology-adoption condition (13) has to hold with equality in a country that advances its technology level according to the free-entry condition: after the adjustment, upfront investment costs coincide with prospective profits. The technology-adoption condition (13) and the free-entry condition (16), along with a given σ, restrict the value of the cost parameter θ. This is due to the fact that the parameter θ is the only unknown in these formulas (the discussion above specified the remaining parameter values, and the observed time series determine the economic variables).

The conjecture of no technology adoption was based on the type of economic regime in place prior to 1978. Thus, I assume that the technology-adoption condition (13) was violated during 1952-1978. Although all parameters and variables contained in (13) and (16) are known, the study cannot pinpoint the pre-1978 cost-function parameter θ because the technology-adoption condition does not hold with equality. Hence, I simply assume that the parameter and, accordingly, the cost of adoption was too high, meaning that technology adoption was not profitable.

The literature generally attributes the U-turn in the Chinese economic system to December 1978. The regime change in 1978 conceivably induced a shift in the barriers to adopt. The new, more market-oriented system in place provides incentives for private initiatives and therefore for technological progress. The actual Chinese experience, along with this fact, suggests that it has become worthwhile to implement new technologies. It suggests a decrease in θ such that the technology-adoption condition is satisfied. The study assumes that the technology-adoption (13) condition holds with equality in 1978, allowing me to extract the parameter θ. θ is obtained by solving the following free-entry condition (for $t = 1978$) for the technology-adoption parameter θ

$$\alpha(1-\alpha)\left(\frac{k_{78}}{A_{78}h_{78}}\right)^{\alpha} h_{78} = \left(1+\alpha^2\left(\frac{A_{78}h_{78}}{k_{78}}\right)^{1-\alpha} - \delta\right)\theta\left(\frac{A_{78}}{\bar{A}_{78}}\right)^{\sigma}.$$

The inserted values read: $\bar{A}_{78} = 9216$, $h_{78} = 1.29$ (as years of schooling total 3.64), $A_{78} = 858$, and $k_{78} = 4508$. This reveals that the cost parameter has to be $\theta = 1.09$. Regarding domestic technology, the identification of the parameter θ uses $A_{78} = A_{52} = 858$ as the model generates zero adoption from 1952 to 1978. The Chinese growth-accounting figures support this assumption. The capital stock k_{78} stems from the capital-accumulation equation (3), starting in 1952 with k_{52} and calculating capital stocks through time until a value for 1978 is obtained. The calculation holds the knowledge level constant at the initial value A_{52} while s_t, h_t, and L_t correspond to the observed Chinese time series.[20] For simplicity, the simulation assumes that the parameter $\theta = 1.09$ remains constant throughout the new regime in place after 1978. The fact that the adoption condition seems violated prior to 1978 suggests $\theta_{pre78} \geq 1.09$.

To summarize, the specification outlined above suggests that adopting is not worthwhile prior to 1978 whereas implementation costs and discounted profits are just equal in 1978. After 1978, the expanding technology frontier allows the technology-adoption condition to be satisfied at the beginning of the period (implying that adoption is worthwhile). Free-entry then leads to an adjustment in the domestic technology level during a given period, resulting in the equalized discounted profits and setup costs.

The paper now turns to the simulation. The derivation of the counterfactual path proceeds along the following lines. I assume that changes in technological knowledge

[20]Note that the values for k_{78} and A_{78} correspond to the values produced by the model. Using capital and technology measures from the growth accounts would yield a similar θ. This holds because the model and the growth accounts are closely in line with each other during the pre-reform period 1952-1978, which is shown in the results section.

are the only source of TFP growth. Imposing this assumption is useful since the study aims to shed light on TFP changes arising from changes in technological sophistication alone. The simulation then produces a counterfactual path, suggesting where the economy would have headed if other factors included in TFP (basically allocative efficiency) remained unaltered.

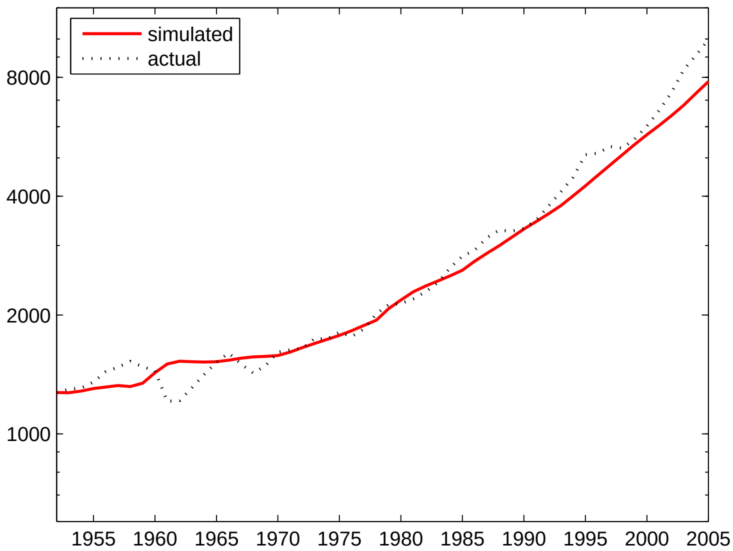
This section has outlined the parameterization and the initial values. Plugging those values into the theoretic formulas allows me to predict China's growth path. Further, the formulas require measures for employment L_t, investment s_t, and schooling E_t. These variables are considered exogenous in that they correspond to the actual measures observed in China in each year. The simulation starts in 1952, the first year in which official data on China is available (with initial values k_{52} and A_{52}). In any period, the capital stock K_t is predetermined. Observed employment and years of schooling determine L_t and h_t, respectively. For each year, the technology-adoption condition (13) evaluates whether technology adoption is worthwhile in China's hypothetical economy. If not, technology remains constant, $A_t = A_{t-1}$. Otherwise, the solution to the research-arbitrage condition (16) determines the new knowledge level. Note that the solution to (16) cannot be written out as a formula, but it can be solved numerically to obtain the new knowledge level, which is done in the simulation. Inserting the resulting technology level into the production function yields the hypothetical output of period t. The actual investment rate s_t, together with the hypothetical y_t, determines how much the counterfactual economy invests in raw capital accumulation. Capital evolves according to (3), which yields the counterfactual capital stock of the subsequent period K_{t+1}. For subsequent periods, the technology level is obtained along the same lines as explained above. In summary, I use the calibrated model and the observed time series for employment, schooling, and investment rates over the period 1952-2005 to predict China's performance.

4 Main Results

The results of the baseline simulation are shown in Figure 2, displaying the simulated and the actual path of China's per-worker output. It is apparent from the figure that the predicted path is remarkably close to the actual evolution during the entire observation period. Furthermore, the figure illustrates that both actual and simulated per-worker GDP show more pronounced growth after the introduction of the reforms in 1978.

In the first subperiod (1952-1978), the counterfactual path involves TFP stagnation since the simulation is constructed such that adopting new technologies is not worth-

Figure 2: China's growth path: output per worker



while. Technology stagnates, causing the level of TFP to stagnate. In this situation, the only sources of growth in per-worker GDP are increases in educational attainment and capital accumulation, which correspond to the forces of the neoclassical framework. It is well known that massive investments in education and capital were made in China. As the figure shows, the neoclassical framework appears to explain the actual pattern rather well. However, there are some differences between the actual and the simulated paths. They are mainly attributable to several severe political disruptions and natural disasters during the Mao era, namely, the Great Leap Forward (1958-1960), the Three Years of Natural Disasters (1958-1961), and the Cultural Revolution (1966-1969). The disruptions seem to have caused predicted and actual performances to drift apart. Considering averages, actual average TFP growth amounted to 0.1% in the pre-1978 period, compared with nonexistent TFP growth implied by the model. One may argue that the zero growth in real productivity result can be attributed to political upheavals in the Chinese economy. However, several studies, including Chow (1993) and Borensztein and Ostry (1996), report a zero growth rate even when the disruption periods are excluded. Inspecting the period unaffected by disturbances (1970-1978) reveals that the predicted and the actual paths are very close.

The second subperiod (1978-2005) is associated with technological progress resulting from technology adoption as the cost of adoption became low enough. This subperiod is characterized by further increases in actual physical and human capital, which induce direct and indirect (by fueling technology adoption) increases in output. It is interesting to learn from Figure 2 that the counterfactual path exhibits an astounding growth performance that is close to the actual Chinese experience. However, China's actual experience outperforms the counterfactual experience. Hardly surprisingly, the analysis suggests that actual growth in Chinese TFP is higher than the rate induced by a theory restricting changes in TFP to changes in technological sophistication only. The main candidate in explaining this discrepancy is a rise in efficiency due to improved resource allocation: relaxing state control and moving toward a more market-oriented economy induces efficiency gains through reallocation, ultimately resulting in a higher TFP measure. Table 2 presents the extent to which the simulation differs from the real path.

Table 2: China's growth performance

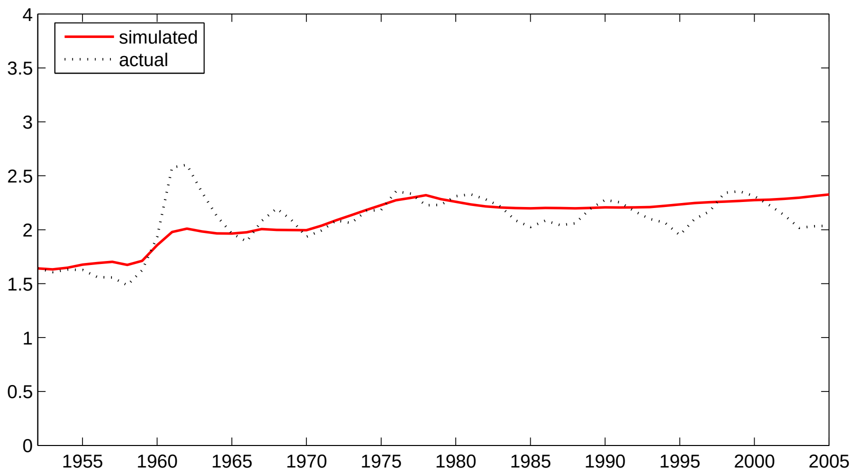
	GDP per worker		technology A		total factor productivity	
	simulated	actual	simulated	actual	simulated	actual
1952-1978	1.7%	1.8%	0.0%	0.2%	0.0%	0.1%
1978-2005	5.3%	6.1%	4.5%	5.6%	2.7%	3.3%
78-93	4.6%	4.9%	3.9%	4.3%	2.4%	2.6%
93-05	6.2%	7.7%	5.3%	7.2%	3.2%	4.3%

Table 2 compares the numbers of the Chinese record to the numbers obtained from the simulation, distinguishing between the pre-reform years (1952-1978) and the reform years (1978-2005). It reports the results for the annual rates of growth in real per-worker output, efficiency in terms of A, and total factor productivity. In the table, the measure for total factor productivity is simply a transformation according to $TFP = A^{1-\alpha} = A^{0.6}$, or $gr_{TFP} = 0.6 gr_A$ in terms of growth rates, where A stands for labor-enhancing efficiency present in the production function. The table documents both measures as both provide interesting insights.

On the one hand, the measure of actual efficiency in terms of A confirms the recent findings of a rather stable capital-output ratio during 1978-2005. This can be seen from the fact that the growth rate reported for A (5.6%) is almost as high as the rate for Chinese GDP per worker (6.1%) through 1978-2005. This leaves virtually no room for the role of changes in the capital-output ratio. That is, the growth of GDP per worker in the reform period can be mainly attributed to increases in labor-enhancing efficiency. This is due to the fact that there have been nearly no changes in the actual capital-output ratio. The simulation of the model economy is largely able to reproduce this feature. This is also evident from Figure 3, which displays the actual and simulated capital-output ratio. Indeed, the actual observation and the simulation both suggest that the capital-output ratio was rather stable during 1978-2005. However, the actual path of capital-to-output tends to be slightly downward sloping while the predicted path of capital-to-output does not display this decrease. This is in line with the slight undervaluation of productivity growth implied by the simulation.

On the other hand, Table 2 documents TFP growth rates, which allows me to compare the figures resulting from the present growth accounts to the ones documented in recent studies. I find TFP growth of 3.3% during 1978-2005, which is in accordance with recent growth-accounting analyses, mostly finding rates between 3% and 4%. Furthermore, actual TFP growth (0.1%) agrees with the rates found for 1952-1978 by Chow (1993) and Holz (2006a).

Figure 3: Capital-output ratio in China



It is instructive to compare actual and simulated measures. The results for 1952-1978 reported in Table 2 substantiate what the graph visualizes: the counterfactual and the actual paths are very close. Actual and simulated productivity growth is virtually absent. Furthermore, hypothetical and actual growth in GDP per worker is nearly identical. Therefore, the model in which technology adoption is not worthwhile and growth arises from factor accumulation alone does well in explaining the actual growth performance in the pre-reform era.

The numbers for 1978-2005 reveal that the model is able to generate impressive growth. Simulated per-worker output growth amounts to a remarkable 5.3% whereas the Chinese economy experienced 6.1%. In terms of the ratio of predicted versus actual growth in real output per worker, this means that 87% of China's performance can be explained by the suggested technology-adoption theory. For total factor productivity growth, I find that the ratio of the simulated advance (2.7%) to the actual advance (3.3%) sums up to a considerable 81% during the reform years. As recent investigations into China's growth accounts subdivide the reform period into 1978-1993 and 1993-2005, Table 2 depicts the numbers of the corresponding subperiods for comparison. As can be seen, actual output per worker and productivity both accelerated along the course, conforming to the findings of recent studies. Interestingly, the technology-adoption framework suggested here also predicts this acceleration over time. However, the ratio of simulated to observed growth slightly decreases over time.

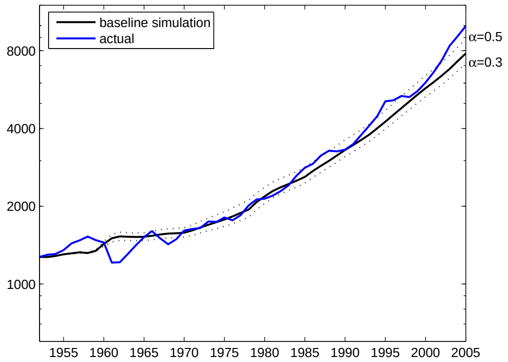
Nevertheless, it is hard to escape the conclusion that China has strongly profited from adopting foreign technology during the reform period. Seemingly, acceleration in investment, in part fueled by foreign direct investment, accompanied by sharp improvements in educational attainment, have put China in a favorable position to take advantage of existing technological knowledge and to generate fast growth. The analysis suggests that China has managed to catch up not only in terms of output per worker, but also in terms of technological knowledge. A mere 20% of TFP growth is unexplained by the technology-adoption framework during 1978-2005. The remainder can be mainly assigned to narrowed distortions in factor allocation.

5 Sensitivity Analysis and Discussion

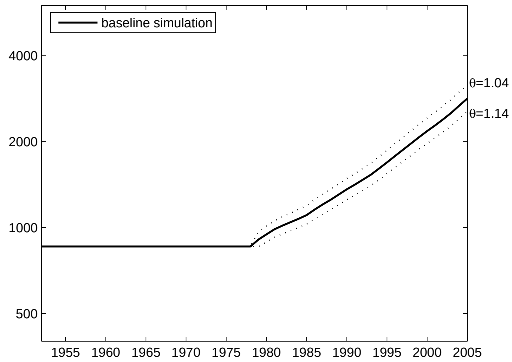
To give an impression of which parameters and calibration assumptions are important to the results, this section provides a sensitivity analysis and discusses related issues. Figure 4 and Table 3 show the results for alternative parameter choices: Figure 4 depicts the resulting trajectories obtained from a simulation using different parameter values, and Table 3 reports the growth rates implied by the same exercise. In what follows, I explain the sensitivity analysis in detail.

As the actual value of the Chinese capital share α is associated with some uncertainty, I run simulations for different α's. Besides the baseline specification, I test two alternative values: $\alpha = 0.5$ and $\alpha = 0.3$. As mentioned, a capital share of 0.5 is often found in growth-accounting studies examining China while 0.3 is the capital share typically used for the US economy. When imposing different values for α, one must consider the following. First, α not only influences the growth accounts of the model economy, but the growth accounts of the actual Chinese economy as well, and thus the reported

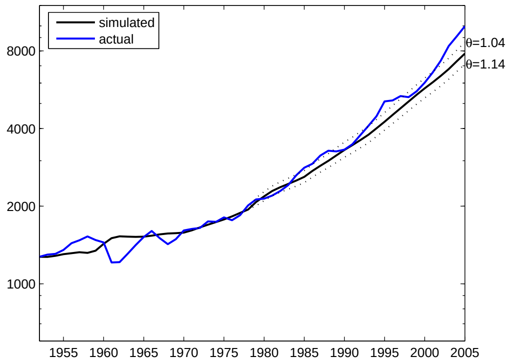
Figure 4: Sensitivity analysis: trajectories



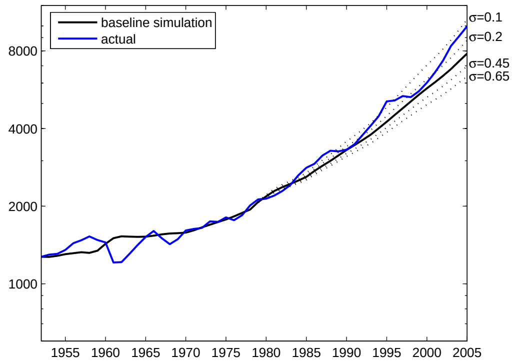
(a) Per-worker GDP path for various α



(b) Technology path for various θ



(c) Per-worker GDP path for various θ



(d) Per-worker GDP path for various σ

TFP growth rates. Second, a different α alters the capital accumulation of the hypothetical economy and hence requires another value of the technology-cost parameter θ to assure that the technology-adoption condition (16) holds in 1978. The procedure to back out the adoption-cost parameter θ remains the same as explained in the calibration section.[21] The growth rates implied by a simulation considering these adjustments can be found in Table 3(a). With a capital share of 0.5 (0.3), actual TFP growth amounted to -0.1% (0.3%) whereas the simulation again involves complete technological stagnation and corresponding stagnation in total factor productivity during 1952-1978. Simulated per-worker output growth equals 2.0% (1.4%), compared with the unchanged value of 1.8% for actual growth. For 1978-2005, the simulation produces an advance of 5.5% (5.2%) in per-worker GDP and 2.3% (3.1%) in TFP. By comparison, growth in actual

[21] Working with $\alpha = 0.5$ implies $\theta = 1.46$ whereas $\alpha = 0.3$ is associated with $\theta = 0.78$.

Table 3: Chinese growth performance: sensitivity analysis

(a) Growth rates for various values of α implied by simulation

	$\alpha = 0.3$		$\alpha = 0.4$		$\alpha = 0.5$	
	GDP	TFP	GDP	TFP	GDP	TFP
1952-1978	1.4%	0.0% (0.3%)	1.7%	0.0% (0.1%)	2.0%	0.0% (-0.1%)
1978-2005	5.2%	3.1% (3.8%)	5.3%	2.7% (3.3%)	5.5%	2.3% (2.8%)
78-93	4.6%	2.8% (2.9%)	4.6%	2.4% (2.6%)	4.6%	2.0% (2.2%)
93-05	6.0%	3.5% (5.0%)	6.2%	3.2% (4.3%)	6.5%	2.8% (3.6%)

Note: Values in brackets reflect the actual growth rates obtained from the growth accounts.

(b) Growth rates for various values of θ implied by simulation

	$\theta = 1.04$		$\theta = 1.09$		$\theta = 1.14$		actual	
	GDP	TFP	GDP	TFP	GDP	TFP	GDP	TFP
1979-2005	5.5%	2.8%	5.3%	2.7%	5.0%	2.6%	6.1%	3.4%
79-93	4.7%	2.4%	4.4%	2.3%	4.1%	2.1%	4.8%	2.6%
93-05	6.4%	3.3%	6.2%	3.2%	6.0%	3.1%	7.7%	4.3%

(c) Growth rates for various values of σ implied by simulation

	$\sigma = 0.1$		$\sigma = 0.2$		$\sigma = 0.3$		$\sigma = 0.45$		$\sigma = 0.65$	
	GDP	TFP	GDP	TFP	GDP	TFP	GDP	TFP	GDP	TFP
1978-2005	6.5%	3.6%	5.8%	3.1%	5.3%	2.7%	4.9%	2.4%	4.5%	2.1%
78-93	5.3%	2.9%	4.8%	2.6%	4.5%	2.4%	4.3%	2.1%	4.0%	1.9%
93-05	8.0%	4.5%	6.9%	3.7%	6.2%	3.2%	5.6%	2.7%	5.1%	2.3%

per-worker GDP amounted to 6.1% and growth in actual TFP to 2.8% (3.8%), respectively. These numbers illustrate the finding that the ratios of simulated to actual growth during the reform period (with $\alpha = 0.5$: 90% for per-worker GDP and 82% for TFP; and with $\alpha = 0.3$: 85% for per-worker GDP and 81% for TFP) remain largely unchanged when a different α is imposed. Adopting an alternative value for α appears to affect the simulated and the actual growth paths in a symmetric way. As shown in Figure 4(a), the only apparent difference is that the simulated output paths drift apart around 1961 (coinciding with the years of natural disasters), but display similar slopes and similar growth rates from then on. Thus, the choice of the capital share α does not appear to be critical for the results.

I now focus on what happens if the value of the technology-adoption capability parameter θ deviates from the main parameterization. Recall that θ is determined by the baseline specification where the technology-adoption condition is binding in 1978.

This assumption ties the model and the Chinese economy together and is keeping with the agreement in the literature that there was a regime switch in 1978. To investigate whether this assumption is critical, the Chinese trajectories are simulated for an alternative assumption: as above, I assume that technology adoption was not worthwhile before 1978, and θ takes an arbitrary value thereafter. Figure 4(b) and (c) and Table 3(b) document the corresponding outcomes for a cost function parameter that is lower ($\theta = 1.04$) and one that is higher ($\theta = 1.14$) than the main parameterization ($\theta = 1.09$). This alternative specification causes the paths to drift apart in 1979, the first year in which an alternate θ has an effect on the hypothetical economy. More precisely, it induces an adjustment in technology in 1979, as illustrated in Figure 4(b), which depicts the paths for technology A. After the adjustment in 1979, however, the different trajectories for technology (Figure 4(b)) and GDP per worker (Figure 4(c)) are similar. In other words, they display a similar slope. This means that the growth rates of GDP per worker and technology are largely unaffected after the adjustment period, which is confirmed by the numbers reported in Table 3(b).[22] Thus, in examining the growth rates generated by the technology-adoption framework, it can be seen that the exact specification of θ does not seem to matter much. Independent of θ, the model economy exhibits impressively high growth rates during the reform years.

While changing the assumptions with regard to the capital share α or the capability parameter θ hardly impacts on the results obtained from the theoretical framework, varying the technology-adoption parameter σ seems more critical for the implied growth rates. Figure 4(d) plots the simulated per-worker GDP trajectories for different values of σ, and Table 3(c) documents the respective growth rates.[23] As explained in the calibration section and Appendix A.2, σ is the sensitivity to the technology frontier and is associated with the speed of convergence to a steady state. The first best choice is to determine σ such that the convergence speed of the model corresponds to the cross-section observation of 2%, which requires $\sigma = 0.3$. The sensitivity analysis with respect to σ covers values between 0.1 and 0.65. Note that $\sigma = 0.1$ is associated with a convergence speed around 1%, $\sigma = 0.2$ with one around 1.5%, $\sigma = 0.45$ with one around 2.5%, and $\sigma = 0.65$ with one around 3%. The analysis thus covers a rather broad range of convergence rates. As illustrated in Figure 4(d), a low sensitivity parameter σ, corresponding to a low speed of convergence, would lead to more pronounced growth in

[22]Table 3(b) presents the growth rates from 1979 onwards, instead of 1978, such that the implied growth rates are not blurred by the adjustment that takes place in 1979.

[23]Note that imposing different values of σ implies different values for θ, such that the technology-adoption condition is binding in the year of the regime switch. Working with $\sigma = 0.1$ requires $\theta = 0.68$, $\sigma = 0.2$ involves $\theta = 0.86$, $\sigma = 0.45$ leads to $\theta = 1.55$, and $\sigma = 0.65$ necessitates $\theta = 2.49$.

the adoption regime 1978-2005 than the rate of advance found in the baseline simulation. Conversely, a high σ, corresponding to a high speed of convergence towards the steady state, would dampen the growth performance. This is due to the fact that a high value of σ reflects a strong reaction to the technology frontier, implying that the costs of adoption become more expensive within short order. The advantages of existing foreign knowledge therefore vanish faster, slowing simulated growth. In sum, since the parameter σ crucially influences the growth rates generated by the model, it is important to specify σ carefully. It seems reasonable to set σ such that the model's speed of convergence equals the observed speed in cross-section analyses.

I offer a few additional comments relating to the simulation analysis. In what follows, I discuss some of the assumptions and their effects on the simulation outcomes. The first matter relates to the valid objection that China's institutional change could have been seen as a gradual process instead of a clear regime switch, especially given the implementation of additional reforms after 1978. The assumption of a one-time regime switch has been made to pinpoint the parameter θ. Yet a gradual transformation points towards the notion that the cost-function parameter θ continually changes during the reform period (1978-2005). I do not take this into account as assigning reliable values for θ would not be possible. More precisely, as China's transition from central planning towards an increasingly market-based and open economy stands for an improvement in institutional quality, thereby strengthening technology adoption, θ should gradually decrease. However, this corroborates the finding that technological progress through technology adoption has been a crucial part of China's growth performance. That is, a steadily decreasing cost parameter would contribute to the profitability of adoption, leading to reinforced simulated gains from technology adoption. The ratio of simulated to actual productivity growth would accordingly be higher than the ratio implied by the baseline scenario presented above. Neglecting gradual changes in policies and institutions may be a caveat, but it hardly lends support to the argument that the counterfactual path derived in this study overstates technological progress.

Second, the counterfactual path involves the assumption that technological growth is the only source of TFP growth, implying that the level of other factors included in the TFP measure (such as the level of allocative efficiency) is implicitly held constant. This appears to be an appropriate assumption for generating a path to suggest where the economy would have headed regardless of other improvements in efficiency. As a matter of course, the analysis finds a discrepancy between productivity enhancements arising from technological progress and the ones actually observed, which amounts to roughly 20%. However, it is conceivable that technology adoption has been stimulated by increases in production efficiency related to factors other than technological progress, namely, ameliorated factor allocation. These efficiency increases would enhance profitability prospects, which could be observed by incorporating a variable capturing efficiency into the final-good production function. This variable would then play a role similar to that of education h in evaluating the profitability of a project. Profits accruing from a new technology would depend on the level of efficiency. Like enhanced h, increased efficiency would contribute to technology adoption. This leads to the conclusion that underlying technological progress may have been even greater in this case. This reinforces the finding of a strong role for technology adoption in observed productivity growth.

Lastly, the present assessment of technology adoption uses a rather simple framework. The setup does not highlight some of the distinct channels facilitating technology adoption and refrains from explicitly modeling the role of certain channels, such as trade, the presence of multinational firms, and the quality of financial institutions. Therefore, the true level of technology in China may deviate from the level uncovered by the model. However, it is unclear whether the counterfactual path resulting from the simulation would overstate or understate the role of technological progress. On the one hand, firms may not not fully exploit the adoption opportunities suggested by the model, implying that the path would overestimate the contribution of technology adoption to China's productivity advances. On the other hand, the following argument favors the notion that the simulation underestimates technology adoption. Aspects not explicitly modeled, including trade and multinational firms, ought to be captured by the adoption-cost parameter θ. This parameter captures residual effects as it is retrieved from the technology-adoption condition and ensures a close connection between actual data and the model. Note that trade and the presence of multinational firms in China have accelerated over the time period considered. In view of the empirical finding that those factors foster technology adoption (e.g., Keller, 2004; Comin and Hobijn, 2004, 2006), this speaks in favor of the importance of technological progress. These factors bring about a decrease in θ over time, encouraging technology adoption. Furthermore, it is important to note that this simple framework guarantees tractability. It has the property that the parameters present in the model have a rather straightforward interpretation, which facilitates the determination of parameters' values necessary for the simulation. In summary, it is especially interesting to discover that a simple setup, under plausible assumptions and reasonably calibrated parameter values, can rationalize such extraordinary progress in productivity and overall economic performance. Although the model and the simulation may have some caveats, one can imagine at least as many arguments in favor of an even stronger role of technology adoption than the simulation suggests.

Moreover, the results of this paper receive support from a recent study that investigates Chinese productivity increases from the opposite angle. The numbers found in the present paper square nicely with the results in the study on allocative efficiency by Hsieh and Klenow (2007). They find that China increased its manufacturing TFP by about 1% per year during 1998-2005 through factor reallocation. The estimated contribution of technology adoption thus appears plausible. Consequently, the suggested technology-adoption framework can explain the Chinese growth miracle to a surprisingly large extent. This study supports the view that technology adoption has been crucial to China's growth performance.

6 Concluding Remarks

A recent stream of papers document that China's explosive economic growth can be largely attributed to strong productivity increases. To the extent that productivity growth relies on technology adoption, rather than efficiency gains due to resource reallocation and improved material incentives, growth is more likely to prove sustainable into the future. The latter causes can be thought of as one-time adrenaline shots to the economy. The purpose of this paper is to assess the Chinese growth performance from the angle of technology-adoption theory.

Viewing Chinese economic data through the lenses of a technology-adoption framework, I uncover a measure of China's technology level to gauge the contribution of technology adoption to TFP growth. Using a simulation exercise, I show that the model captures the most salient features of the Chinese economy during the observation period 1952-2005. That is, the model captures the stagnation in productivity in the pre-reform period 1952-1978 and the impressive growth rate in the reform period 1978-2005. The analysis identifies technology adoption as a major driver for China's recent growth performance. Surprisingly, the simulation exercise suggests that the technology-adoption framework accounts for a striking 80% of China's productivity gains during 1978-2005. This is encouraging news regarding the economy's prospects. China has thus demonstrated a capacity for fast growth as a result of adopting foreign technologies during the reform years. As China is still far behind the technology frontier and has recently succeeded in raising the educational attainment of younger workers in particular (Bosworth and Collins, 2008), there is no good reason to infer that this capacity will evaporate in the near future.

A Appendix

A.1 Data

A.1.1 US Data

Information on the US economy is essential to obtain an estimate of its technology level and the corresponding growth rate. Data on *real output* (in 1990 US$) originates from the Total Economy Database (2008)[24]. More specifically, the study uses the series 'Total GDP (in 1990 US$)' and 'GDP per person employed (in 1990 US$)'. The Total Economy Database also provides information on the size of the *workforce*; namely, the study works with the series 'Employment'. It is convenient to work with this source as it covers a rather long time span for which economic data on China is available as well. The *rate of investment* along with actual output and depreciation is used to compute the capital stock; the series 'investment share of RGDPL' reported in the Penn World Table (2006)[25] serves as the source of the rate of investment. Details on *educational attainment* are obtained from Cohen and Soto (2007). More precisely, the measure is 'Years of schooling' in the population aged 15-64. It is worth mentioning that the years of schooling stay rather constant throughout the observation period.

Table A.1: Overview on data sources

variable	source	name of series
$\overline{Y}$: output, US	TED	total GDP (in 1990 US$)
$\overline{y}$: output per worker, US	TED	GDP per person employed (in 1990 US$)
$\overline{L}$: workforce, US	TED	employment
$\overline{s}$: investment rate, US	PWT	investment share of RGDPL
$\overline{E}$: educational attainment, US	CS	years of schooling in the population aged 15-64
Y: output, China	TED	total GDP (in 1990 US$, converted at Geary Khamis PPPs)
y: output per worker, China	TED	GDP per person employed (in 1990 US$, converted at Geary Khamis PPPs)
L: workforce, China	TED	employment
s: investment rate, China	PWT	investment share of RGDPL
E: educational attainment, China	WY	human capital (in average years of schooling)

Note: TED = Total Economy Database (2008). PWT = Penn World Table (2006).
CS = Cohen and Soto (2007). WY = Wang and Yao (2003)

[24]The Conference Board and Groningen Growth and Development Center, Total Economy Database, January 2008, available at http://www.conference-board.org/economics.

[25]Heston, A., R. Summers, and B. Aten, Penn World Table Version 6.2, Center for International Comparisons of Production, Income and Prices at the University of Pennsylvania, September 2006, available at http://pwt.econ.upenn.edu.

A.1.2 Chinese Data

Whenever available, the study relies on the same data source as for the United States to ensure consistency when comparing output and technology levels. Since the use of Chinese data might be more critical in the light of the well-known data quality issue, a few additional comments are advisable. Yet this study refrains from discussing the issue exhaustively as this has been done in detail in existing studies on Chinese growth[26] and approaches to mitigate the problem have been established. To circumvent the widely accepted claim that Chinese official statistics on growth contain serious upward biases, the study works with adjusted data.

China's transition from central planning towards a market-based economy gives rise to some concerns about its economic statistics. For example, China is still in the process of converting its previous statistical reporting system (Material Product System, MPS) to one more closely in line with the international standard (United Nations System of National Accounts, SNA). Although the recent official estimates represent a huge improvement over the previous system, there is still scope for further improvements (Maddison, 2007). The Chinese National Bureau of Statistics (NBS) publishes estimates on China's economic performance on a yearly basis back to 1952. This data is often claimed to exaggerate the rate of real output growth. Many authors put forward that the reported growth rate is too high because of an underestimation of price inflation and because the reported statistics tend to be skewed towards the government's economic targets, amongst others (e.g., Woo, 1998; Young, 2003; Dekle and Vandenbroucke, 2006; Maddison, 2007; Bosworth and Collins, 2008).

In view of the data quality problems, the paper abstains from working with the official statistics released by the NBS. It therefore employs data stemming from sources that already include adjustments. For data on Chinese output, the paper relies on the Total Economy Database (2008), which draws on a set of adjustments conducted by Maddison (2007). Maddison's reestimation of the Chinese figures follows the lines of the SNA, and the estimates aim to mitigate the above-mentioned problems. The details of these adjustments are reported in Maddison (2007, Appendix C). For illustration, Maddison's GDP estimates and, accordingly, the figures contained in the Total Economy Database result in lower growth than the NBS' estimates. The annual growth rate of real GDP in Maddison's analysis amounts to 4.4% against the official 4.7% during 1952-1978. For 1978-2005, the Maddison data produce an average growth rate of 8.0% versus the official 9.6%. In terms of real GDP per person employed, the Maddison data exhibit an annual

[26] For a discussion, see Wu (2002), Maddison (2007), and Bosworth and Collins (2008), for instance.

rate of 6.1%, compared to the rate of 7.2% of the NBS during 1978-2005. It is worth pointing out that the series from the Total Economy Database (corresponding to Maddison, 2007) include the recent revision of the official data. For data on *real output*, the present analysis uses the series 'Total GDP (in 1990 US$, converted at Geary Khamis PPPs)' and 'GDP per person employed (in 1990 US$, converted at Geary Khamis PPPs)' documented in the Total Economy Database. The same database provides information on the *workforce*, which is measured by the series 'Employment'. Information on accumulation of capital, namely, the *rate of investment*, draws on the series 'Investment share of RGDPL' (share of GDP at constant prices and converted into international dollars) documented in the Penn World Table. Note that the rate of investment is not only used to estimate the capital stock, but it also feeds into the counterfactual path. By drawing on the investment rate instead of domestic savings, the simulation includes investments undertaken by foreigners. The model thus implicitly takes foreign direct investment into account. With respect to labor quality, the study adopts the variable 'Human capital (in average years of schooling)' developed by Wang and Yao (2003). Wang and Yao's growth-accounts study includes an in-depth analysis of the evolution of educational attainment. Their study constructs flows of adult population that are added to the human capital stock of the previous year with simultaneous consideration of depreciation/mortality. Their method results in an estimate of average years of schooling in the population aged 15-64 for each year during 1952-1999. To my knowledge, this is the only study that provides annual estimates. Unfortunately, the reported series ends in 1999 while this investigation covers 1952-2005. Therefore, the study extends Wang and Yao's series through 2000-2005 by assuming that schooling during this period grew at the same rate as during the last ten years of their observation period. This appears to be a reasonable assumption since it agrees with the growth rate contained in the study on schooling by Cohen and Soto (2007) from 2000 to 2010 (measures are reported in 10-year-intervals).

A.2 σ and the Speed of Convergence

The cost-function parameter σ, which can be interpreted as a measure of how a follower reacts to changes in the technology frontier, is determined by setting the model's rate of convergence to the rate found in cross-sectional analyses. The model is first rewritten into accumulation equations, where each of them is stated in terms of a stationary variable. To derive the speed of convergence implied by the model, this section then linearizes the accumulation equations around the steady state. Thus, the determination of the convergence speed proceeds along similar lines as Howitt (2000).

Let a represent the relative technology level at any time t: $a \equiv \frac{A}{\bar{A}}$. a is stable in the long run as the follower's rate of technology growth corresponds to the leader's rate $\bar{\varepsilon}$. Further, $c \equiv \theta \left(\frac{A}{\bar{A}}\right)^{\sigma}$ defines the quality-adjusted cost that intermediate-goods firms incur to adopt a new technology. The research-arbitrage equation (17), $\alpha(1-\alpha)\tilde{k}_t^{\alpha} h_t = (1+\alpha^2 \tilde{k}_t^{-(1-\alpha)} - \delta)\theta \left(\frac{A_t}{\bar{A}_t}\right)^{\sigma}$, shows that the expense c is a function of effective capital $\tilde{k}_t$ and the capabilities to adopt Λ, summarized by $\Lambda \equiv (\theta, h)$. Thus, $\tilde{c}_t = \tilde{c}_t(\tilde{k}_t, \Lambda)$ applies, where $\tilde{c}_t$ solves equation (17). For future reference, note that $a_t = \left(\frac{\tilde{c}_t(\tilde{k}_t,\Lambda)}{\theta}\right)^{1/\sigma}$ and $A_t = \left(\frac{\tilde{c}_t(\tilde{k}_t,\Lambda)}{\theta}\right)^{1/\sigma} \bar{A}_t$. This allows to write the technological progress as

$$\frac{A_{t+1}}{A_t} - 1 = \frac{\left(\frac{\tilde{c}_{t+1}(\tilde{k}_{t+1},\Lambda)}{\theta}\right)^{1/\sigma} \bar{A}_{t+1}}{A_t} \frac{\bar{A}_t}{\bar{A}_t} - 1 = \left(\frac{\tilde{c}_{t+1}(\tilde{k}_{t+1},\Lambda)}{\theta}\right)^{1/\sigma} (1+\bar{\varepsilon}) a_t^{-1} - 1,$$

employing the fact that the frontier grows at $\bar{\varepsilon}$. The model's mechanism can be summarized by two accumulation equations, one for effective capital $\tilde{k}$ and one for relative technology a. They read

$$\begin{aligned} \Delta \tilde{k}_{t+1} =& s\tilde{k}_t^{\alpha} - (\delta + n + \frac{A_{t+1} - A_t}{A_t})\tilde{k}_t \\ =& s\tilde{k}_t^{\alpha} - (\delta + n + \left(\frac{\tilde{c}_{t+1}(\tilde{k}_{t+1},\Lambda)}{\theta}\right)^{1/\sigma} (1+\bar{\varepsilon}) a_t^{-1} - 1)\tilde{k}_t \end{aligned} \tag{A.1}$$

$$\Delta a_{t+1} = \left(\frac{\tilde{c}_{t+1}(\tilde{k}_{t+1},\Lambda)}{\theta}\right)^{1/\sigma} - a_t. \tag{A.2}$$

Before linearizing around the steady state, long-run steady-state values are pinpointed. The values for $\tilde{k}$, $\tilde{c}(\tilde{k},\Lambda)$, and a can be stated as

$$s\tilde{k}_{TA}^{*\alpha-1} = \delta + n + \bar{\varepsilon}, \tag{A.3}$$

$$\tilde{c}_{TA}^{*} = \frac{\alpha(1-\alpha)\tilde{k}_{TA}^{*\alpha} h}{1 + \alpha^2 \tilde{k}_{TA}^{*\alpha-1} - \delta}, \tag{A.4}$$

$$a_{TA}^{*} = \left(\frac{\tilde{c}_{TA}^{*}(\tilde{k}_{TA}^{*},\Lambda)}{\theta}\right)^{1/\sigma}. \tag{A.5}$$

Let hat-variables denote the deviation from the adoption steady state: $\hat{k}_t = \tilde{k}_t - \tilde{k}_{TA}^{*}$

and $\hat{a}_t = a_t - a^*_{TA}$. Linearizing (A.1) and (A.2) yields

$$\begin{aligned}
\Delta\tilde{k}_{t+1} =& \left(\alpha s \tilde{k}^{*\alpha-1}_{TA} - (\delta + n + \bar{\varepsilon})\right)\hat{k}_t - \frac{1}{\sigma \tilde{c}^*_{TA}}\left(\frac{\tilde{c}^*_{TA}}{\theta}\right)^{1/\sigma}\frac{\partial \tilde{c}^*_{TA}}{\partial \tilde{k}^*_{TA}}(1+\bar{\varepsilon})\frac{\tilde{k}^*_{TA}}{a^*_{TA}}\hat{k}_{t+1} \\
&+ \left(\frac{\tilde{c}^*_{TA}}{\theta}\right)^{1/\sigma}(1+\bar{\varepsilon})\frac{\tilde{k}^*_{TA}}{a^{*2}_{TA}}\hat{a}_t \qquad \text{(A.6)} \\
=& (\alpha-1)(\delta+n+\bar{\varepsilon})\hat{k}_t - \frac{\eta}{\sigma}(1+\bar{\varepsilon})\hat{k}_{t+1} + (1+\bar{\varepsilon})\frac{\tilde{k}^*_{TA}}{a^*_{TA}}\hat{a}_t \\
\Delta a_{t+1} =& \frac{1}{\sigma \tilde{c}^*_{TA}}\left(\frac{\tilde{c}^*_{TA}}{\theta}\right)^{1/\sigma}\frac{\partial \tilde{c}^*_{TA}}{\partial \tilde{k}^*_{TA}}\hat{k}_{t+1} - \hat{a}_t = \frac{\eta}{\sigma}\frac{a^*_{TA}}{\tilde{k}^*_{TA}}\hat{k}_{t+1} - \hat{a}_t \qquad \text{(A.7)}
\end{aligned}$$

where η labels the cost elasticity evaluated at the steady state: $\eta = (\partial \tilde{c}^*_{TA}/\partial \tilde{k}^*_{TA})(\tilde{k}^*_{TA}/\tilde{c}^*_{TA})$. Combining both accumulation equations results in the evolution of the model economy in terms of effective capital

$$\Delta\tilde{k}_{t+1} = \left((\alpha-1)(\delta+n+\bar{\varepsilon}) + \frac{\eta}{\sigma}(1+\bar{\varepsilon})\right)\hat{k}_t - \frac{\eta}{\sigma}(1+\bar{\varepsilon})\hat{k}_{t+1},$$

which can be rearranged into

$$\Delta\tilde{k}_{t+1} = -\underbrace{\frac{(1-\alpha)(\delta+n+\bar{\varepsilon})}{1+\frac{\eta}{\sigma}(1+\bar{\varepsilon})}}_{\beta}\hat{k}_t. \qquad \text{(A.8)}$$

This expression establishes the model's speed of convergence β. As a benchmark, the rate of convergence of the neoclassical model equals $(1-\alpha)(\delta+n+\bar{\varepsilon})$, which features in β, too. In an adopting economy, the adoption-cost elasticity is positive ($\eta > 0$). As can be seen from (A.8), the rate of convergence implied by the adoption model is lower than the rate of the neoclassical model. The intuitive reason is that, as the economy approaches its steady state from below, it runs into decreasing returns of capital. In contrast to the neoclassical setup, the decreasing marginal productivity of capital is partially offset by increases in the technology level as a rising capital stock spurs investment in technology adoption: a higher capital stock lowers the interest rate and increases profits from operating a specific technology. The finding that the model predicts a lower speed of convergence than the neoclassical model is reassuring since the speed implied by the neoclassical model is claimed to be too high.

As apparent from (A.8), a higher value of the sensitivity parameter σ is associated with faster convergence. To determine σ, this study imposes that the rate of convergence of the model equals the empirical evidence of a convergence rate around 2% (see Barro and Sala-i Martin (2003, chap. 11) for a discussion). This leads to

$$\sigma = \frac{\eta(1+\bar{\varepsilon})2\%}{(1-\alpha)(\delta+n+\bar{\varepsilon})-2\%}. \tag{A.9}$$

In an economy that adopts new technologies, the elasticity equals $\eta = \frac{\alpha(1-\delta)+\alpha^2\tilde{k}_{TA}^{*\alpha-1}}{1-\delta+\alpha^2\tilde{k}_{TA}^{*\alpha-1}}$, with $\tilde{k}_{TA}^* = \left(\frac{s}{\delta+n+\bar{\varepsilon}}\right)^{1/(1-\alpha)}$. The expression for η is derived from (A.4). As the variables contained in η ought to represent long-run values, the study uses values that have been observed for the OECD countries over that last decade. Namely, the values are: $n = 1.25\%$ and $s = 22.7\%$, where n corresponds to the average employment growth[27] during 1995-2005 and s corresponds to the average investment rate[28] during 1994-2004. The remaining parameters present in η take the values specified in the calibration section. With the corresponding values at hand, η turns out to be 0.43. Note that η is rather robust to alternative values of employment growth and investment; in either case, η takes a value very close to 0.43. The reaction parameter has to equal $\sigma = 0.3$ in order to reconcile the model's rate of convergence with the observed rate.

A final comment on how the study obtains a value for σ is in order. The analysis in this section focuses on the part of the model in which the country advances its technology level. Hence, the speed of convergence derived above corresponds to the rate that applies to an economy pursuing technology adoption. It is appropriate to look at that part of the model as the convergence rate of 2% is basically derived from countries or regions with growth in technology.

[27]Source: Total Economy Database (2008).
[28]Source: Penn World Table (2006).

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