Equipment Investment and Growth In Developing Countries

Lutz Hendricks
Arizona State University

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Abstract

Differences in equipment investment or equipment prices account for large variations in growth rates across countries. An important task is to understand the economic mechanism underlying the equipment-growth nexus and its policy implications. In order to study this issue, this paper develops a model in which growth is driven by the adoption of technologies that are embodied in equipment. I show that this model can quantitatively account for the observed cross-country relationships between equipment investment, equipment prices, and growth. I find that the competitive equilibrium is characterized by inefficiently low levels of learning and too slow growth and study which policies are able to remedy this inefficiency.

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Correspondence address: Arizona State University, Department of Economics, PO Box 873806, Tempe AZ 85287-3806. hendricks.lutz@asu.edu. http://www.public.asu.edu/~hendrick. (480) 965-1462. For helpful comments I am grateful to Lee Ohanian, Andrew Abel, Andrew Atkeson, Boyan Jovanovic, Matthias Kahl, Patrick Kehoe, Roberto Perli, and to two anonymous referees. Seminar participants at various institutions provided valuable suggestions. All errors are mine.

1. Introduction

A recent literature shows that equipment investment is strongly and robustly correlated with long-run growth rates in cross-country data (De Long and Summers 1991, 1992, 1993). The same is true for equipment prices (Jones 1994) and imports (Lee 1995). Moreover, variation in each of these variables accounts for large cross-country differences in growth rates in the order of 2 to 3 percentage points, pointing to the possibility that policies aimed at equipment investment may have large growth effects. Understanding the mechanism that links equipment investment and growth is thus of primary importance.

This paper develops a theory of growth through technology adoption that can quantitatively account for the observed relationships between equipment related variables and growth rates and studies its policy implications. The central element of the theory is the complementarity between technologies, which are embodied in capital goods, and skills which are embodied in workers. This focus is motivated by two observations. First, the notion that capital and skills are complements is supported by an extensive literature estimating aggregate production functions (Hamermesh 1993). Secondly, Greenwood, Hercowitz, and Krusell (1997) estimate that 60 percent of technical change in the U.S. is embodied in equipment.

The basic logic of the model is as follows. Investors choose the technology embodied in new capital goods. As shown by Jovanovic (1995), firms in developing countries tend to invest not in the most recent but in outdated technologies. A reason for this is suggested by plant data, which show that major technology upgrading is often followed by a drop in productivity and a period of rapid learning (Klenow 1998). In the model, this is captured by the assumption that productivity depends not only on the technology embodied in capital goods, but also on how well this technology matches the level of worker skills. Skills are accumulated through "learning-by-using," where using modern capital goods is essential for learning. Firms in developing countries invest in outdated technologies because available skills do not allow efficient use of more advanced technologies. Learning and technology adoption are thus complementary in the sense that the level of available experience limits the sophistication of capital goods a firm can use in production. Conversely, the capital vintages in use determine the rate of learning.

I interpret the large cross-country differences in the relative prices of capital goods as the result of distortionary policies and as the exogenous causes for growth rate and investment share differentials. Such distortions affect growth through (*i*) the rate at which old vintages of equipment are retired (obsolescence) and (*ii*) the choice of technologies embodied in new investment. Both in turn change the rate of learning and technology adoption.

The model is calibrated to U.S. data and its balanced growth path is computed numerically for a range of distortions that matches the range of relative equipment prices found in cross-country data. There are two main findings. First, the model can successfully account for the empirical relationships between growth rates, equipment investment shares and relative equipment prices. Secondly, however, the model's ability to generate growth rate differentials as large as those found in the data depends critically on two features of the technology governing the skill acquisition of workers: on the presence of learning spillovers and on the degree to which old and new technologies are substitutable in the process of skill accumulation. While there is compelling evidence in favor of spillovers in learning, no independent evidence exists about the second feature. However, the model makes additional quantitative predictions that could be examined empirically to more precisely identify the range of growth effects it is consistent with. In particular, the model predicts that large cross-country growth differentials are associated with sizable differences in equipment service lives, but with only minor variations in the rate and duration of productivity improvements following the adoption of new technologies. These predictions could be tested using plant level productivity data that have become available recently for a number of countries.

Since developing countries typically import most of their equipment from developed economies (Warner 1992), a natural interpretation is that differences in equipment prices reflect distortionary trade policies. Although the paper develops a closed economy model, it may be reinterpreted as a small open economy which imports capital goods. This does not affect the model structure or results and is consistent with Lee's (1995) findings that countries which import more equipment tend to grow faster.

A number of recent papers study how distortions to equipment prices may cause large cross-country variations in per capita output. Rodriguez-Clare (1996) develops a quality ladder model in which firms pay a fixed cost for adopting new technologies that are embodied in equipment. Higher equipment prices allow monopolists to charge higher markups. Technology upgrading is then less frequent and the technology gap between rich an poor countries is larger. Jovanovic and Rob (1997) show that differences in equipment prices can generate large dispersion in income levels in a vintage capital Solow model. Parente (1998) studies to what extent barriers to the adoption of embodied technologies can account for the observed cross-country differences in per capita output in a model that features a technology-skill complementarity similar to the one proposed in this paper. All of these studies focus on cross-country level differences and may be viewed as complementary to the one offered here.

The paper is organized as follows. Section 2 lays out the model in detail and characterizes its equilibrium. The choice of parameters is discussed in section 3. Section 4 studies to what extent the model can account for the observed relationships between equipment investment, equipment prices, and growth. The intuition behind the main numerical results is discussed in section 5. Section 6 examines the efficiency of the equilibrium allocation and discusses policy implications. The final section concludes.

2. Theory

The model is an extension of a standard closed economy, one-sector growth model. There are three types of agents: A continuum of firms, a single representative household, and a continuum of investors. Firms produce a single good using capital and labor services. Households consume the good and supply labor to firms and savings to investors. These purchase capital goods, which embody technologies of their choice, and rent them to the firms. As a by-product of working with modern technologies, workers acquire experience which enhances their labor productivity. A government imposes distortionary taxes (in the broad sense of Parente and Prescott 1994) on capital goods purchases. Only balanced growth equilibria are considered.

2.1 Technology

The production technology allows to produce a single good from the services of labor, structures and equipment. Equipment embodies technologies and labor embodies experience (*H*), whereas structures are homogeneous. The scalar $A_{v,t}$ indicates the sophistication of the technology adopted *v* periods before date *t*. Output produced using equipment vintage *v* and workers of skill *H* is given by

(1)
$$Y_{v,H} = S_{v,H}^{\alpha_S} \left(q(A_v, H)\, k_{v,H} \right)^{\alpha_E} L_{v,H}^{\alpha_L} ,$$

where $S_{v,H}$ denotes the amount of structures, $k_{v,H}$ represents the amount of equipment, and $L_{v,H}$ is the amount of labor time employed. There are constant returns to scale ($\alpha_S + \alpha_E + \alpha_L = 1$). Total output is given by the sum of the outputs produced with all available (A_v, *H*) combinations:

$$Y = \iint Y_{v,H}\, dv\, dH \ .$$

The new features central to the theory are the *efficiency function q* which determines how productivity depends on the match between technologies and worker skills and the *learning function* which governs the accumulation of skills. The key idea is that using sophisticated equipment efficiently requires highly skilled workers. Conversely, skill accumulation requires that workers use modern capital goods.[1]

2.1.1 The Efficiency Function

The grade of technology embodied in new equipment is chosen at the time of investment and cannot be altered subsequently. Let A denote the maximum amount of efficiency units of capital services that one unit of capital of grade A can provide. The fraction of A actually provided depends on worker skills. Denote this fraction by $0 \le f(H/A) \le 1$ and assume more sophisticated capital requires more skilled workers ($f' \ge 0$). The assumption that f depends on the ratio of H and A is necessary for the existence of a balanced growth path. The total amount of efficiency units provided by one physical unit of equipment is then given by the *efficiency function*

$$q(A,H) = A\,f(H/A)\,. \tag{2}$$

For each technology productivity is bounded so that sustained growth requires technology upgrading (Argote and Epple 1990). The fact that H grows over the lifetime of a capital good implies an intertemporal tradeoff for the investor. A higher A reduces payoffs early on because matching experience is not yet available, but it provides larger payoffs in the future when the match has improved due to further learning. Therefore, faster growth of H can be expected to induce investors to choose more sophisticated technologies.

Capital goods of any level of technology are available at all times. One may think of these as developed in the rest of the world at such a pace that the limits to technological sophistication never bind. What prevents investors from adopting more sophisticated technologies is the lack of skilled labor needed for the efficient use of sophisticated technologies. The key observation to be captured by this setup is that firms in developing countries invest in *outdated technologies*. In other words, diffusion lags for new technologies are long, especially across borders (Jovanovic 1995; Ray 1984).

Empirically, the reason for choosing outdated technologies is clearly not that newer capital goods are not available to firms.[2] Evenson and Westphal (1995, p. 2264) find that “relatively little of the technology required for rapid industrialization has been proprietary. … [P]urchases of imported capital goods play a vitally important role in the overall process. First has come learning how to use imported equipment.” Capital goods are traded extensively. In all but the wealthiest nations, the

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[1] Bahk and Gort (1993) provide evidence for the importance of vintage effects and learning-by-doing for productivity growth.

[2] Models of the "lab equipment" type (Rivera-Batiz and Romer, 1991) use such an assumption to explain differences in growth rates across countries.

fraction of imported equipment is typically quite high (Warner 1992). For example, in Mexico the share is 70 percent; in Colombia it is as high as 80 percent. Moreover, there is evidence that even capital goods are traded which are advanced by the standards of developed countries. For example, Baily and Gersbach (1995) find that proprietary technologies play only a minor role in explaining productivity differences among industries in industrialized countries.[3] Instead, as in the model, firms differ in their ability to *use* a given technology efficiently. Both arguments should hold even more for developing countries attempting to acquire older, less sophisticated technologies. I therefore assume that investors can choose any positive A.

For some reason, using older technologies must be more profitable than using newer ones. My explanation is similar to that of Parente (1994) and Lucas (1993): Using an advanced technology efficiently requires disembodied experience of matching sophistication. In these papers, learning is specific to a particular technology. Switching to a new technology imposes a loss in productivity as firms lose part of their technology-specific experience (H drops). In the present model, learning is not technology-specific and the productivity loss is not due to switching technologies per se. Instead, the tradeoff between current and future productivity stems from putty-clay nature of capital. By choosing capital of a particular grade, an investor commits to the embodied technology for the lifetime of the capital good. Since currently inefficient capital (with high A/H) is expected to become more efficient later on, it is optimal to invest in a technology that generates low current cash flows. All models have in common that the rate of learning depends on the fraction of labor allocated to using advanced technologies.

2.1.2 The Learning Function

The learning function determines that rate at which workers accumulate skills. In what follows, I assume that learning is a pure externality, so that all households share a common level of H and take its evolution as given. The extension to the case of no learning spillovers is discussed in section 2.8. The key idea is that experience is acquired by using capital goods in production that embody technologies which are modern relative to the current level of H_t. Specifically, the rate of learning is determined by

$$g(H_t) = \left\{ \int_0^{T_{\max}} \left(h(A_{v,t} / H_t)\, L_{v,t} / L \right)^{\psi} dv \right\}^{1/\psi} \tag{3}$$

[3] "By the time a new product or service becomes a large part of the market, the technology to provide it using best-practice methods is available worldwide, either through imitation or licensing." (p. 334)

where T_{max} is the maximum lifetime of equipment and L is the total amount of labor supplied, which is normalized to one.[4]

Learning, in this model, represents what Rosenberg (1994, p. 196) calls *learning by using*: "There are many ways of improving the design and operation of new equipment that become apparent only by observing difficulties or opportunities that emerge during the actual operation of the new equipment." This motivates the assumption that learning depends on the time spent working with a given technology.

The learning function h determines how much each technology contributes to learning. I assume that using more advanced capital speeds up learning ($h' \geq 0$) and that the rate of learning is bounded ($0 \leq h \leq \bar{h} < \infty$). The learning rate is a CES aggregator of the contributions of all vintages with substitution elasticity $(1-\psi)^{-1}$. The allocation of labor across technologies is therefore of crucial importance for the rate of learning. Allocating more labor to modern capital speeds up learning because old vintages contribute less to learning than new ones.

2.2 Households

A single representative household consumes c_t and supplies one unit of labor inelastically. The household at date 0 maximizes the discounted flow of utility

$$\int_0^\infty e^{-\rho t} u(c_t)\, dt$$

subject to the budget constraint

$$\dot{a}_t = (1+r)\, a_t + \int_{-T_{max}}^{0} w_{v,t}\, L_{v,t}\, dv - c_t, \quad a_0 \text{ given,} \tag{4}$$

the transversality condition $\lim_{t\to\infty} e^{-rt}\, a_t = 0$ and the time constraint $\int L_{v,t}\, dv = L = 1$. Here, a_t represents the value of asset holdings, and r is the interest rate, which will be constant in steady state. The household allocates labor across technological vintages, which pay a wage rate of $w_{v,t}$ per unit of time. Since learning is a pure externality, the worker takes the evolution of H_t as given and is indifferent as to the technology he works with. With $u(c) = c^{1-\sigma}/(1-\sigma)$, the Euler equation is

$$g(c) = \frac{r-\rho}{\sigma}, \tag{5}$$

[4] Since learning is, for now, a pure externality, all H subscripts may be dropped without risk of ambiguity. I therefore write $L_{v,t}$ instead of $L_{v,H,t}$, etc.

where $g(c) = (dc/dt)/c$ denotes the growth rate of c.

2.3 Firms

There is a continuum of firms that produce a single good using the technology introduced before. Constant returns to scale allow me to study one representative firm for each technological vintage. Firms maximize period profits,

(6) $$\max\ Y_{v,t} - r^S_{v,t}\, S_{v,t} - \pi_{v,t}\, K_{v,t} - w_{v,t}\, L_{v,t},$$

where π is the rental price per efficiency unit of equipment and r^S is the rental price for structures. The first-order conditions are

(7) $$w_{v,t} = \alpha_L\, Y_{v,t} / L_{v,t}, \quad r^S_{v,t} = \alpha_S\, Y_{v,t} / S_{v,t}, \quad \pi_{v,t} = \alpha_E\, Y_{v,t} / K_{v,t}.$$

Since all households share the same level of experience, there is no need to consider how the firm's choices vary with H and I therefore continue to suppress all H subscripts. However, this issue must be raised in the case of no learning spillovers described below.

2.4 Government

The aggregate technology allows to convert one unit of consumption into one unit of either structures or equipment embodying any technology.[5] However, as in Parente and Prescott (1994), a government imposes distortionary taxes, broadly interpreted, on the purchases of new capital. The tax rates, τ^E and τ^S, are constant over time and the revenues are discarded. Alternatively, it could be assumed without changing any results that revenues finance government expenditures that enter the household utility function in an additive fashion. From the point of view of private agents the resource costs of capital goods are thus $\pi^E = 1 + \tau^E$ and $\pi^S = 1 + \tau^S$.

2.5 Investors

All capital is owned by a single representative investor who behaves competitively.[6] It borrows funds from households, taking the competitive rate of return (r) as given, to purchase equipment or

[5] The essential aspect of this assumption is that relative prices of equipment grades do not differ across countries. As long as more sophisticated capital is more cost effective (in the sense of having a higher A / π^E), choosing units of equipment so as to normalize $\pi^E = 1$ preserves monotonicity of the efficiency function and the learning function. However, this is not merely a choice of units (see the Technical Appendix).

[6] This decentralization is chosen for simplicity only. Equivalently, it could be assumed that households own the capital and make the investment decisions.

structures which it rents out to firms. The investor's objective is to maximize the present value of profits. Structures depreciate at the constant rate δ_S. The rate of return of structures is therefore r^S / $\pi^S - \delta^S$.

The investor takes the market value of equipment embodying different technologies as given and chooses the technology that maximizes profits:

(8) $$A_{0,t} = \arg\max_{A} \, p_{0,t}(A) - \pi^E \,,$$

where $p_{0,t}(A)$ denotes the value of a new unit of equipment that embodies technology A (the dependence of p on A is suppressed in the notation below as it is implied, in equilibrium, by the age subscript v).

Equipment is retired as it ages and lasts for at most $T_{\max}$ years. Denote the fraction of the equipment installed at time t-v ($k_{0,t-v}$) that survives at time t by $\Delta_{v,t}$. Then the amount of equipment still in service at date t is given by

(9) $$k_{v,t} = k_{0,t-v}\, \Delta_{v,t}$$

and provides $K_{v,t} = k_{v,t}\, q(A_{v,t}, H_t)$ efficiency units of equipment services. This generates a revenue flow of $\pi_{v,t}\, K_{v,t} = \pi_{v,t}\, q\left(A_{v,t}, H_t\right) k_{v,t}$. The rental price per physical unit of equipment is thus $r^E_{v,t} = \pi_{v,t}\, q(A_{v,t}, H_t)$.

The rate at which equipment is retired is chosen optimally so as to maximize its value. The investor chooses a non-increasing age-survival profile $0 \leq \Delta_{v,t} \leq 1$, which is associated with a flow maintenance cost $m(\Delta_{v,t})$ with $m' > 0$. The surviving fraction of one unit of equipment embodying technology $A_{v,t}$ therefore generates a revenue flow net of maintenance costs of $\Delta_{v+s,t+s}\, \{r^E_{v+s,t+s} - m(\Delta_{v+s,t+s})\}$ at dates t through $t + T_{\max} - v$. The value of one unit of new equipment installed at date t must equal the discounted present value of the cash flows it generates over its lifetime. This is determined by the following optimization problem:

$$p_{0,t} = \max_{\Delta_{s,t+s}} \int_0^{T_{\max}} e^{-r\,s}\, \Delta_{s,t+s}\, \{r^E_{s,t+s} - m(\Delta_{s,t+s})\}\, ds$$

subject to $\Delta_{0,t} = 1$ and $\Delta_{s,t+s} \leq \Delta_{s',t+s'}$, if $s' > s$. The latter two constraints ensure that one unit of equipment is present at age 0 and that the survival profile is decreasing in age. Similarly, the value of the surviving fraction ($\Delta_{v,t}$) of one unit of equipment installed v periods earlier is given by

(10) $$\Delta_{v,t}\, p_{v,t} = \max_{\Delta_{v+s,t+s}} \int_0^{T_{\max}-v} e^{-r\,s}\, \Delta_{v+s,t+s}\, \{r^E_{v+s,t+s} - m(\Delta_{v+s,t+s})\}\, ds$$

subject to $\Delta_{v,t}$ given and $\Delta_{v+s,t+s} \le \Delta_{v+s',t+s'}$, if $s' > s$.

One interpretation of this structure, and the one implemented in the numerical procedure below, is that each unit of equipment consists of a continuum of individual "machines," each characterized by a time-invariant idiosyncratic maintenance cost. The investor then retires individual machines over time starting with those that cause the highest maintenance expenditures. The function $m(.)$ then represents the expected maintenance cost conditional on survival.

Free entry by investors will ensure zero profits in equilibrium. Because of constant returns to scale, the quantity of capital installed by each investor is then indeterminate.

2.6 Competitive Equilibrium

With external learning, the conditions characterizing a competitive equilibrium are as follows. Aggregate output is given by

(11) $$Y_t = \int_0^{T_{\max}} Y_{v,t}\, dv .$$

Goods market clearing requires

(12) $$Y_t = c_t + M_t + \pi^E k_{0,t} + \pi^S (\dot{S}_t + \delta^S S_t)$$

where $S_t = \int S_{v,t}\, dv$ is the aggregate stock of structures and $M_t = \int k_{v,t}\, m(\Delta_{v,t})\, dv$ denotes aggregate maintenance expenditures. The labor market clears if

(13) $$\int_0^{T_{\max}} L_{v,t}\, dv = 1 .$$

Free entry ensures zero profits for investors,

(14) $$p_{0,t} = \pi^E ,$$

and that the rate of return of structures equals the interest rate

(15) $$r_t = r_{v,t}^S / \pi^S - \delta^S .$$

The rental price of structures therefore cannot differ across vintages $(r_{v,t}^S = r_t^S)$. Similarly, the fact that households are indifferent as to the technology they are employed with guarantees that the wage rate is independent of v $(w_{v,t} = w_t)$. Finally, the firm's first-order condition (7) implies that all equipment vintages receive a common rental price per efficiency unit of capital services $(\pi_{v,t} = \pi_t)$.

The value of assets held by the household equals the value of capital.

$$a_t = \pi^S S_t + \int_0^{T_{\max}} p_{v,t}\, k_{v,t}\, dv \tag{16}$$

A *competitive equilibrium* is a collection of functions of time yielding prices $\{r_t^S, w_t, r_t\}$ and quantities $\{Y_t, c_t, a_t, H_t, A_t\}$. In addition, there is a set of functions that determine age profiles for all vintages: $\{Y_{v,t}, L_{v,t}, S_{v,t}, K_{v,t}, \Delta_{v,t}, \delta_{v,t}, r_{v,t}^E, p_{v,t}\}$. These functions satisfy the following equilibrium conditions:

1. the household Euler equation (5) and budget constraint (4);
2. the 3 first-order conditions of the firm as well as the technological restrictions (1) and (11);
3. the learning function (6);
4. the investor's conditions for optimal choice of A and of depreciation;
5. no arbitrage conditions for r^S (17) and for the prices of old equipment (10);
6. the zero profit condition (14);
7. the market clearing conditions for goods, labor, and assets together with the accounting relationship (9).

2.7 Balanced Growth

Since the observations that motivate the paper are commonly interpreted as characterizing long-run growth rates, the paper focuses on balanced growth paths along which the growth rates of all variables are constant over time. Define the relative sophistication of new investment as $\theta_t \equiv A_{0,t}/H_t$. It is easy to verify that relative growth rates obey the following conditions (Appendix 1):

$$g(Y) = g(S) = g(k) = g(c) = g(w) = (r-\rho)/\sigma$$

$$\gamma \equiv g(A_{0,t}) = g(H) = -g(\pi_t) = g(Y)\,\alpha_L/\alpha_E \tag{17}$$

The age profiles δ_v, Δ_v, r_v^E, and L_v are constant as are θ and $z = \pi_t\, A_{0,t}$. Define $\Theta_v = A_{v,t}/H_t = \theta e^{-\gamma v}$. A balanced growth path may then be defined by a triple of scalars (θ, z, r) and a function δ_v that satisfy the following conditions. From the learning equation (3):

$$\gamma = \left\{\int_0^{T_{\max}} [h(\Theta_v)\, L_v]^{\psi}\, dv\right\}^{1/\psi}. \tag{18}$$

To determine the labor allocation, note that equipment-labor ratios are equal for all technologies in terms of efficiency units: $L_{v,t} / L_{0,t} = K_{v,t} / K_{0,t}$. The capital allocation is determined by

$$\begin{aligned} K_{v,t} &= k_{v,t}\, A_{v,t}\, f(H_t / A_{v,t}) \\ &= k_{0,t-v}\, \Delta_v\, A_{v,t}\, f(1/\Theta_v) \end{aligned}$$

Therefore, relative labor inputs obey

$$\frac{L_v}{L_0} = \frac{K_{v,t}}{K_{0,t}} = e^{-g(Y)v}\, \Delta_v\, e^{-\gamma v}\, f(1/\Theta_v) / f\left(1/\theta\right). \tag{19}$$

The entire labor allocation is then determined by (19) together with labor market clearing (13). The choice of θ must obey (8) with

$$p_{v,t} = \int_0^{T_{\max}-v} e^{-r\tau} (\Delta_{v+\tau} / \Delta_v) \{ r^E_{v+\tau} - m(\Delta_{v+\tau}) \}\, d\tau$$

and

$$r^E_v = z\, e^{-\gamma v}\, f\left(e^{\gamma v} / \theta\right).$$

For the vintage installed at t this may be expressed in terms of time-invariant age profiles as

$$p_0 = \int_0^{T_{\max}} e^{-r\tau}\, \Delta_\tau \{ r^E_\tau - m(\Delta_\tau) \}\, d\tau = \pi^E .$$

Finally, the optimal depreciation function solves (10) and z satisfies the zero profit condition (8). This characterization suggests a computational algorithm which iterates over guesses of (θ, z, r) until (8), (10), and (18) are satisfied. A detailed description is provided in the Technical Appendix.

2.8 No Learning Spillovers

So far, learning has been treated as a pure externality. While there is evidence for learning spillovers (Grilliches 1992), this assumption is clearly too strong. This section therefore examines the polar opposite case of no learning spillovers where each worker's learning rate depends only on the allocation of his own labor across capital vintages. This modification does not alter the investor's problem. The changes to the firm's problem are trivial. It now has to contemplate the hiring of labor of various H levels, taking into account that wage rates vary with v and H. However, the household problem changes fundamentally.

In addition to the consumption allocation problem (which is unchanged) the household now maximizes the present value of earnings by choosing the labor allocation, taking into account that working with new vintages enhances learning and thus raises future earnings. Formally, the problem is

$$\max \int_0^{\infty} e^{-rt} \left[\int_0^{T_{\max}} L_{v,\tilde{H}_t,t}\, w_{v,\tilde{H}_t,t}\, dv \right] dt$$

s.t. $$d\tilde{H}_t / dt = \tilde{H}_t \int_0^{T_{\max}} L_{v,\tilde{H}_t,t}\, h\left(A_{v,t} / \tilde{H}_t\right) dv, \quad \tilde{H}_0 \text{ given}$$

$$\int_0^{T_{\max}} L_{v,\tilde{H}_t,t}\, dv = 1$$

I now distinguish between aggregate experience H and the worker's individual experience $\tilde{H}$, although in symmetric equilibrium these must be identical. To emphasize that the household now chooses $\tilde{H}_t$ and therefore has to consider how the wage rate varies with experience, I index labor inputs and wage rates by *H*. For simplicity, I present the case of $\psi = 1$. The current value Hamiltonian is

$$\mathrm{H} = \int_0^{T_{\max}} L_{v,\tilde{H}_t,t} \left\{ w_{v,\tilde{H}_t,t} + \upsilon_t\, \tilde{H}_t\, h\left(A_{v,t} / \tilde{H}_t\right) - \mu_t \right\} dv + \mu_t$$

The first order condition for labor determines the wage structure required to render the household indifferent between working with new or old vintages:

$$w_{v,\tilde{H}_t,t} + \upsilon_t\, \tilde{H}_t\, h\left(A_{v,t} / \tilde{H}_t\right) = \mu_t\,. \tag{20}$$

The co-state evolves according to

$$\dot{\upsilon}_t = r\,\upsilon_t - \int_0^{T_{\max}} L_{v,\tilde{H}_t,t} \left\{ \frac{\partial\, w_{v,\tilde{H}_t,t}}{\partial\, \tilde{H}_t} + \upsilon_t\, h\left(A_{v,t} / \tilde{H}_t\right) - \upsilon_t\, h'\left(A_{v,t} / \tilde{H}_t\right) A_{v,t} / \tilde{H}_t \right\} dv \tag{21}$$

with transversality conditions $\lim_{t\to\infty} e^{-rt}\, \upsilon_t\, \tilde{H}_t = 0$. The integrand represents the benefits derived from being more skilled: higher earnings, but slower learning. The main difference introduced by the absence of learning spillovers is that the wage rate is lower for vintages employed with newer capital [see (20)], reflecting a compensating differential for learning benefits. Otherwise, the changes to the equilibrium conditions are minimal because $\tilde{H} = H$ may be imposed. The household's first-order conditions are augmented by (20) and (21), where the derivative $\partial w / \partial H$ is obtained easily from the firm's first order conditions. A complete characterization of the balanced growth path without learning spillovers is provided in the Technical Appendix.

2.9 How Distortionary Policies Affect Growth

In order to provide intuition about the link between policies distorting the resource costs of equipment and growth, consider the analytically tractable special case where learning is external and the maintenance cost function is a step function. A unit of equipment remains operational as long as the investor pays a fixed flow cost *m*, but depreciates fully otherwise. I first study the partial analytic response of the investor to changing τ^E and then turn to general equilibrium effects.

The degenerate maintenance cost greatly simplifies the investor's problem, because all units of equipment of a given vintage are retired at the same date. That is, the investor may be thought of as choosing a scalar *T* instead of a depreciation profile Δ so as to maximize

$$\int_0^T e^{-rv}\left[\pi_{t+v}\, A_{0,t}\ f\left(H_{t+v}/A_{0,t}\right)-m\right]dv-\pi^E .$$

For simplicity, I assume that $T_{\max}$ is sufficiently large so that the constraint $T \le T_{\max}$ never binds. The necessary first-order conditions for *T* and *A* are

$$\pi_{t+T}\ q\left(A_{0,t}, H_{t+T}\right)=m \tag{22}$$

$$\int_0^T e^{-rv}\,\pi_{t+v}\,\frac{\partial q(A_{0,t}, H_{t+v})}{\partial A_{0,t}}\,dv=0 . \tag{23}$$

Second order conditions are satisfied, if $f''(H/A)$ is sufficiently negative (see the Technical Appendix). Equation (22) simplifies to $x=\theta\, e^{-\gamma T} f(e^{\gamma T}/\theta)$, where $x \equiv m/(\pi_t H_t)$ is constant over time. Assuming that capital eventually reaches full productivity,[7] we have

$$\theta = e^{\gamma T} x , \tag{24}$$

which is an upward-sloping schedule in (*T*, θ)-space, labeled *FOC-T* in Figure 1 (the investor takes *x* as given). The first-order condition for *A* can be written as

$$\int_0^T e^{-(r+\gamma)v}[f(1/\Theta_v)-f'(1/\Theta_v)/\Theta_v]\,dv=0 \tag{25}$$

This is labeled *FOC-A* in Figure 1 and also upward-sloping in (*T*, θ)-space. The condition for concavity of the objective function ensures that *FOC-A* is flat and has a unique intersection with *FOC-T*.

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[7] Bahk and Gort (1993) show that learning occurs only during the first few years of a new plant's life, and the model will be calibrated to replicate this observation.

[INSERT FIGURE 1 HERE]

Evidently, π^E does not directly affect the investor's problem. However, reducing π^E increases the profitability of equipment investment. Investors respond by installing additional equipment until the rental price π has dropped to the zero profit level. The *FOC-T* schedule shifts left and the investor's choice moves from *A* to *B*, which establishes the following result.

Proposition 1. The investor responds to a lower rental price of equipment by reducing service lives (T) and technology choice (θ).

Proof. Appendix 1

This somewhat surprising result suggests that firms facing lower equipment prices may install *inferior* technologies. The reason is that there is no direct effect of the (rental) price of equipment on the choice of technology. Since there is a common rental price per efficiency unit, changing π does not alter the *relative* profitability of different technologies. If T were fixed, the choice of technology would not change at all. There will simply be more, but not "better" capital.[8]

However, reducing π shifts the entire age-rental price profile down. Since equipment is retired when r^E falls below m, T declines. If new capital is cheap, there is no point keeping old capital operational for a long time. This has an indirect effect on technology choice. Shorter service lives shorten the period over which the learning investment pays off, so that investor switches to inferior technology.

Of course, this argument needs to be augmented to incorporate general equilibrium effects. In particular, the choices of service lives and technology are also affected by the growth rate. The chain of causality is summarized in Figure 2 (the Technical Appendix provides a formal analysis). As discussed above, lower equipment prices reduce the rental price for equipment and thus T which has the direct effect of reducing θ. However, shorter service lives also accelerate learning as more labor is allocated to new capital vintages (γ rises), which has two opposing effects on θ. Rapid growth means rapid learning which makes advanced technologies more attractive. On the other hand, future cash flows are discounted more heavily (the interest rate increases due to (5)) and the rental price falls more rapidly over time, making it more attractive to invest in technologies that yield payoffs early on (lower θ). The shift of the *FOC-A* curve is therefore ambiguous.

[INSERT FIGURE 2 HERE]

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[8] Moreover, it is easy to see that π^E would not affect growth, even if general equilibrium effects are taken into account. If T is exogenous, the system becomes block recursive. The growth rate is determined by the learning function and the first-order condition for A (25), which do not depend on π^E.

If the negative effect of higher discounting dominates, *FOC-A* shifts down as the investor prefers a lower θ for given T. If θ is lower, old vintages should be discarded earlier (T drops moving along the *FOC-T* curve). This is reinforced by the left-shift of *FOC-T* as γ rises, so that both θ and T decrease (point C). However, if the positive effect of faster learning dominates, *FOC-A* shifts up. It is then possible that both θ and T increase or that they move in opposite directions (θ rises and T falls). In sum, reducing the price of equipment may be expected to shorten service lives, but the change in technology choice is ambiguous. If the growth effects of reducing service lives are small, θ unambiguously falls (the direct effect of shorter T). If growth effects are large, θ may rise (the indirect effect of faster learning).

3. Calibration

An important benefit of the model is that it can be calibrated and solved numerically, which allows to compare its quantitative implications with the data. I choose the following functional forms.

Maintenance cost function. Capturing the choice of service lives is important because it determines the age structure of the capital stock. A simple and intuitively appealing specification achieves an accurate replication of observed retirement patterns for equipment, which should be thought of as individual machines in the data. Assume that each unit of equipment consists of a continuum of individual capital goods, each of which requires a constant flow maintenance cost in order to remain operational. This maintenance cost is distributed according to a normal distribution, truncated at zero (to ensure that maintenance costs are non-negative), with mean μ_m and standard deviation σ_m. The investor then determines the optimal retirement age for each equipment unit separately so that it maximizes the present value of revenue flows net of maintenance costs. This specification induces a maintenance cost function of the form $m(\Delta_v)$ as specified before.[9]

Efficiency function. A simple parametric specification satisfying the requirements imposed a priori on the efficiency function is

$$f(H/A) = 1 - \min\{\lambda(A/H - 1)^{\varphi}, 1\}.$$

Thus, $f = 1$ for $H/A > 1$ and falls smoothly to zero as H/A decreases. The exact specification of f is of course arbitrary, but sufficiently flexible to approximate more complicated functional forms, given the restrictions imposed.

[9] The technical appendix provides more detail and shows that $m(\Delta_v)$ is the expectated value of the random maintenance cost conditional on survival.

Learning function. The learning function h is restricted to be continuous, differentiable, and increasing in A/H. I explore two functional forms. The first assumes that learning varies directly with the amount that remains to be learned about a given vintage, $1 - f(H_t / A_{v,t})$:

$$(26) \qquad h(A/H) = \bar{h}[1 - f(H/A)],$$

If there are no learning spillovers, the learning function must put more weight on old vintages. Otherwise the age profiles of labor and capital inputs are biased too strongly towards new vintages which provide learning benefits. I therefore assume

$$(27) \qquad g(H) = \int_0^{T_{\max}} L_v \, \bar{h} \, (A_v / H)^{\Psi} \, dv$$

Model parameters, summarized in table 1, are chosen so as to replicate post-war U.S. data. The choice of σ = 2 is standard. Following Greenwood et al. (1997) I set α_L = 0.7, δ^S = 0.056, and choose α_E so as to replicate a gross investment share in GDP of 0.073. α_S is then implied by the requirement of constant returns to scale. The rate of time-preference matches the share of structures investment in GDP which is set to 0.07, a compromise between the values used in Greenwood et al. (1997) or 0.041 and the much larger value of DeLong and Summers (1993) of 0.145. I normalize $\pi^S = \pi^E = 1$.

[INSERT Table 1 HERE]

The remaining parameters are chosen to replicate the following steady state observations. The maintenance cost parameters μ_m and σ_m are chosen so as to replicate the observed ages at which Δ_v = 0.8 and 0.2, respectively. The empirical literature typically assumes that retirements follow a modified Winfrey S3 distribution with an average service life of12 years (Coen 1980). $T_{\max}$ is set to 40 years, sufficiently high to guarantee that almost all capital is retired at age $T_{\max}$. Since there is no retirement in the data up to age 5, it is assumed that no maintenance is required prior to this age. Figure 3 shows that the model replicates the empirical Winfrey S3 age-survival profile quite closely.

[INSERT FIGURE 3 HERE]

The slope parameter of the efficiency function λ is chosen to replicate observations concerning the duration of learning by new manufacturing plants $[T_L = \ln(\theta)/\gamma]$. A number of studies find that productivity of new plants is initially low, but grows faster than that of old plants. In the model, productivity differences are due to differences in $q(A, H)$ across plants of various ages. Productivity grows for young plants because f rises over time due to learning. For older plants, learning is exhausted and productivity declines with plant age. Baily et al. (1992) observe exactly this pattern in a panel of U.S. manufacturing plants. Estimates of the duration of learning are fairly diverse (see the

Technical Appendix for a summary). The baseline calibration follows Bahk and Gort (1993) and Gort et al. (1993) who estimate that learning continues for 6 years after plant startup, but alternative values are explored as well.

In principle, the curvature parameter φ could be chosen to match the amount of learning, defined as the total increase in productivity over the learning period. However, I find that the amount of learning predicted by the model $[\,f(1/\theta)^{-\alpha_E} - 1\,]$ is always close to 10% and almost entirely insensitive to the choice of φ (or most other parameters). Fortunately, the predicted amount of learning is roughly consistent with the data. Most estimates of learning rates are in the order of 1 to 2 percent per year, which implies a total amount of learning around 12 percent (Bahk and Gort 1993; Baily et al. 1992). The model's learning rate is somewhat higher than that implied by Hulten (1992) who estimates that embodied efficiency in best practice firms is about 23 percent above sample average. In the model, the difference between the maximum and average values of $q(A, H)$ in the cross section is 31 percent. As a baseline case, I assume that f is quadratic ($\varphi = 2$), but results are very robust to changing φ.

The slope parameter of the learning function, $\bar{h}$, is chosen to match the growth rate of per capita output. The curvature parameter ψ, however, cannot be identified from balanced growth observations. A set of possible values will be explored covering a broad range of substitution elasticities. Since the findings are most interesting for low values of ψ, the baseline value is a somewhat arbitrary $\psi = 1/6$.

The presence of a free parameter is of course reason for concern. However, in the present case such concerns are mitigated for two reasons. First, the model's predictions are evaluated not simply by its ability to replicate a scalar, such as the empirical coefficient in a regression of growth rates on equipment prices, but by its ability to generate artificial cross-country data about a set of variables that fall within the ranges found in empirical scatter plots. Secondly, the model generates additional predictions that allow to empirically identify whether ψ is high or low. These points are discussed in more detail below.

4. Numerical Results

This section investigates to what extent the model can account quantitatively for the relationships between equipment prices, equipment investment and growth rates found in the data. The experiment compares the balanced growth paths generated by exogenous variations in τ^E. Following Parente and Prescott (1994) I identify the distorted resource cost of equipment (π^E) with the relative price of equipment in the data. The main finding is that the model's predictions are largely consistent with the data. However, the model only generates large enough growth effects, if vintages are imperfect substitutes in learning ($\psi < 1$) and if learning spillovers are large.

The empirical relationship between equipment prices and growth is depicted in Figure 4. The horizontal axis shows the price of equipment relative to consumption, while the vertical axis shows the residual growth rate from a cross-country regression along the lines of Jones (1994). The relationship between growth rates and the real equipment investment share in GDP over the period 1960-85 is depicted in Figure 5. Since the underlying data and regressions are standard, their description is relegated to Appendix 2.

[INSERT Figure 4, Figure 5, Figure 6 HERE]

The growth effects obtained from cross-country regressions are large. A unit increase in equipment prices is associated with an drop in the growth rate of almost 1.2 percentage points (standard error: 0.3%) and a 10% increase in equipment investment is associated with 1.3% faster growth (standard error: 0.6%). Variations in either variable account for cross-country growth differentials of 3 percentage points.

The predictions of the model (with external learning) are shown in the figures by the solid lines. The predicted investment-growth relationship is close to linear with a slope coefficient that is somewhat larger than the empirical one: a 10% higher I_E/Y is associated with 2.2% faster growth. This is 1.5 standard errors above the empirical regression coefficient.[10] The predicted co-variation between equipment investment and equipment prices is very similar to the data (Figure 6).

The relationship between growth and equipment prices is more difficult to evaluate. For moderate changes in π^E the model matches the growth effect implied by the cross-country regression almost exactly. In particular, doubling π^E reduces the growth rate by 1.1% in the model compared with 1.2% in the data. However, for very large changes in π^E the growth effects predicted by the model increase less than linearly with π^E so that eventually (for $\pi^E = 3.5$) the model only accounts for half of the growth effect implied by a linear regression. On the other hand, inspection of Figure 4 raises doubts whether the empirical relationship is indeed linear.

Overall, the model's ability to simultaneously replicate the empirical relationships between equipment prices, equipment investment, and growth rates is satisfactory. It succeeds, in particular, in generating large growth effects in spite of the fact that the output elasticity of equipment is small.

[10] The fact that the model predicts a regression line that lies to the right of the empirical one in Figure 5 is not an anomaly. It simply reflects the position of the data point for the U.S. (which the model replicates) relative to other countries.

4.1 Sensitivity Analysis

Table 2 examines the sensitivity of the numerical results by comparing the effects of doubling π^E for alternative parameter values. Each row represents one comparative balanced growth experiment and deviates from the baseline case in exactly one parameter value or calibration target.[11] The columns show the resulting changes in per capital output growth (Δg_Y), the half-life of equipment ($\Delta T_{1/2}$), the technology step ($\Delta(\theta-1)$), and the predicted coefficient of a regression on the growth rate on equipment investment $(\Delta g_Y / \Delta I_E / Y)$. The main finding is that all figures are quite robust to changing the duration of learning (T_L), the curvature of the efficiency function (φ), and the half-life of equipment ($T_{1/2}$), but not to changing the elasticity of substitution of vintages in learning, $(1-\psi)^{-1}$. Replicating the large growth effects found in the data requires that this elasticity not be much larger than one.

As pointed out before, the amount of learning [$f(1/\theta)^{-1}$] is nearly unaffected by parameter changes. The technology step is almost constant in all cases. Perhaps surprisingly, in one case faster growth is associated with the adoption of *inferior* technologies (lower θ).

[INSERT TABLE 2 HERE]

Changes in equipment half-lives, in contrast, can be quite large (up to 20 years). This makes the relatively small magnitude of growth effects appear puzzling. Casual evidence supports the prediction that equipment is retired much later in developing countries; however, only limited formal evidence exists (see Heston and Mercer 1993). Jovanovic and Rob (1997) show that on average airplanes are older in poorer countries. However, since poor countries tend to purchase airplanes in the second hand market, this may not imply longer service lives. For the U.S. there is some evidence that service lives for equipment declined substantially since their initial estimation in 1942 (Young and Musgrave 1980).

Without learning spillovers (last row) results change dramatically. All changes are substantially smaller. In particular, doubling π^E reduces the growth rate by only 0.19%. Learning spillovers are thus required for the model to replicate the large growth effects found in the data.

These findings suggest an empirical strategy for overcoming the problem that ψ is not identified from steady state observations: In cases where the model is consistent with large growth effects of equipment distortions, it also predicts that equipment service lives should vary substantially with growth rates. Unfortunately, the quality of existing data on service lives may make it difficult to

[11] All calibrated parameters are, of course, adjusted as well so as to match the calibration targets described for the baseline case.

implement this approach at this time (see Heston and Mercer 1993). An additional prediction is potentially testable using plant level data sets that became available recently for a variety of countries. The fact that θ is almost unaffected by π^E implies that the amounts on durations of productivity improvements following the adoption of new technologies should vary little with equipment prices. Investigating these predictions is left for future research.

5. Discussion: External Learning

The main results obtained from the numerical experiments may be summarized as follows:

1. Equipment prices have almost no effect on the choice of new technologies (θ).
2. The changes in half-lives are large, yet the induced growth effects are modest, especially if vintages are perfect substitutes in learning.
3. Growth effects are much smaller without learning spillovers.

In order to provide intuition for these findings, I refer again to the special case where the maintenance cost distribution is degenerate ($\sigma_m = 0$). For simplicity, I also assume that vintages are perfect substitutes in learning ($\psi = 1$). These modifications leave the household's and firm's problems unchanged, but greatly simplify the investor's problem and the determination of the balanced growth rate.

5.1 Large Changes in Half-Lives

The first finding to be explained is that increasing equipment prices leads to large changes in half-lives. A simple, partial analytic argument provides the intuition. Higher equipment prices affect service lives by raising π so as to maintain zero profits. The optimal choice of service lives obeys $\pi A / m = e^{\gamma T}$. Thus

$$\frac{dT}{T} = \frac{d \ln(\pi A / m)}{\gamma T} - \frac{d\gamma}{\gamma}.$$

With $\gamma T \approx 0.08 \cdot 12 \approx 1$ doubling π increases T by a factor of roughly $\ln(2) \approx 2/3$ (recall that θ and thus A change little). The slowing of growth causes an additional increase in T, so that T is roughly proportional to π. Graphically, increasing π shifts the age-rental price profile (r_v^E) up, while slower growth flattens its slope. Since the investor retires capital when r^E falls below m, both changes induce the investor to maintain capital longer.

5.2 The Magnitude of Growth Effects

Given that equipment half-lives change by large amounts, it appears puzzling that the resulting growth effects are not larger, especially when vintages are perfect substitutes in learning (ψ = 1). If vintages are perfect substitutes in learning, the learning rate is approximately proportional to the fraction of labor employed with vintages that contribute to learning (L_L/L).[12] Figure 7 illustrates why this fraction is not sensitive to changes in T. The fraction of labor that contributes to learning is shown as the shaded area under the vintage-labor profile.

Now consider the effect of doubling T. Holding γ fixed, the ratio L_{T_L}/L_0 does not change and the are representing L_L is therefore unchanged as well. The only modification is to extend the tail of the L_v profile up to 2 T. Clearly, L_L/L falls by less than half, simply because the L_v profile is downward sloping. The elasticity of the learning rate with respect to T is therefore clearly less than one. Relaxing the assumption that vintages are perfect substitutes in learning breaks the rigid link between L_L/L and γ and is thus essential for replicating the sizeable growth effects found in the data.

This finding also explains why the change in θ is generally negative in table 2, but switches to positive for ψ = 1. As argued above, whether θ increases or decreases in response to higher equipment prices depends primarily on the strength of the link between T and γ (and thus r). With a high ψ, changes in T generate relative small growth effects and θ moves in the same direction as T (point C in Figure 1). If ψ is small (as in the baseline case), growth effects are larger and the lower channel in Figure 2 dominates so that θ and T move in opposite directions. In either case, the change in θ is small in absolute value because the opposing forces partly offset each other's effect on θ.

The prediction that γT is smaller in fast growing countries is consistent with Pack's (1988) findings that the dispersion of technologies is smaller in such countries. Since, with faster growth, both $A_{0,t}/A_{T,t} = e^{\gamma T}$ and $q_{0,t}/q_{T,t} = e^{\gamma T} f(1/\theta)$ are smaller, the oldest technologies are relatively more productive compared with the newest ones, so that the range of productivities is less dispersed.

6. Discussion: No Learning Spillovers

6.1 Distortions Induced by Learning Spillovers

If learning spillovers are absent, standard arguments establish that the competitive equilibrium is Pareto-optimal (Stokey, Lucas, and Prescott 1989, chapter 15). The comparison of balanced growth

[12] It can be shown that this proportionality is exact, if h is a step function and θ does not change, which is almost the case in the numerical experiments.

paths with and without learning spillovers then allows to identify the deviations from first best induced by the learning externality.

Figure 8 compares the labor allocations (L_v in panel (a)) and the age-survival profiles (Δ_v in panel (b)) with and without learning spillovers for otherwise identical parameter values.[13] As expected, without learning spillovers capital is retired earlier and more labor is allocated to vintages that contribute to learning. What is remarkable is the magnitude of these differences. Without learning spillovers almost no labor is allocated to vintages older than 6 years (the duration of learning). Correspondingly, 90 percent of capital is retired after 9 years, compared with a half-life of 12 years when learning is external. In addition, $(\theta-1)$ is about 10 percent higher.

Of course, assuming that learning is fully external overstates the deviations from the first best. Still, the fact that there is ample evidence for partial learning spillovers in innovation (e.g., Grilliches 1992) suggests that learning externalities may severely distort the allocation.

[INSERT Figure 8 HERE]

6.2 Smaller Growth Effects without Learning Spillovers

The observation that considerably more labor is allocated to new vintages when there are no learning spillovers is central for understanding the considerably smaller effects of equipment prices on half-lives and growth found in the numerical experiments. If more labor is initially employed with new vintages, then a given change in the rental price of equipment causes a smaller change in T. Moreover, a given change in T changes the growth rate by less.

To see this, consider first the change in T induced by a given increase in the rental price of capital. In particular, compare two economies that are calibrated to match the same T, γ, and θ, one with and the other without learning spillovers, and suppose that r_0^E/m doubles in both cases. Capital is retired when $r_T^E = m$. If r_0^E/m doubles, the age at which this occurs increases by the amount of time it takes r^E to fall by half. Thus, the change in the half-life caused by a given proportional increase in r_0^E/m is smaller the steeper the r^E profile. For example, $g(r^E)$ is constant, then T satisfies $r_T^E = r_0^E e^{-g(r^E)T} = m$ or $dT = d\ln(r_0^E/m)/g(r^E)$ so that the change in half-lives is inversely proportional to the slope of the r^E profile. Therefore, the change in T is smaller without learning spillovers.

Moreover, a given change in T causes a smaller change in the learning rate when more labor is allocated to new vintages. This may be seen directly from Figure 7. It is obvious from the graph that

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[13] For reasons of comparability, both cases use the same learning function (27).

a given increase in T leads to a smaller proportional drop in L_L / L if the vintage labor profile is steep as in the case without learning spillovers (L_L is shown by the shaded area). If h is a step function, this implies a smaller change in the growth rate as $\gamma = \bar{h}\, L_L / L$. If h is increasing in A/H, the argument is reinforced because this puts additional weight on new vintages.

6.3 Policy Implications

If learning spillovers are present, the competitive outcome allocates too much labor to old vintages and thus grows at a suboptimally slow rate. This observation might rationalize the observation that governments frequently subsidize the use of new technologies ("strategic industries"). It is important to note, however, that neither capital nor output subsidies allow to implement the first best. Instead, a labor subsidy is required that varies with the grade of technology (A relative to H).

To see this, note that with external learning, the household maximizes the current period value of earnings $\int_0^{T_{\max}} w_{v,t}\, L_{v,t}\, dv$ subject to the time constraint $\int_0^{T_{\max}} L_{v,t}\, dv = 1$. Clearly, the wage rate must be identical for all vintages with positive employment. Now suppose the government pays a wage subsidy to the worker, financed by lump-sum taxation, so that workers receive a wage rate of

$$\overline{w}_{v,t} = w_{v,t} + \upsilon_t\, H_t\, h\left(A_{v,t} / H_t\right).$$

The government lets υ evolve according to (21). Since the worker is indifferent between vintages, relative wages $w_{v,t}$ adjust so that worker's wages $\overline{w}_{v,t}$ are the same for all v. The problems of firms and investors as well as market clearing conditions are not altered by the presence of learning spillovers.[14] It is therefore immediate that the equilibrium conditions are the same as for the case without learning spillovers so that this policy implements the first best.

The reason why subsidies to capital or output cannot attain the Pareto optimum is that they fail to induce the appropriate variation capital-labor ratios across vintages. It can be shown that the efficient allocation has lower capital-labor ratios in efficiency units for more sophisticated capital, whereas subsidizing modern capital achieves the converse.

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[14] This is not to say that the equilibrium conditions of section 2 continue to hold. They make use of simplifications (such as $w_{v,t} = w_v$ for all v) that require learning spillovers *and* no wage subsidies.

7. Conclusion

This paper proposes a theory of technology adoption that can account quantitatively for the relationships between equipment prices, equipment investment and long-run growth rates observed in cross-country data. The theory highlights the importance of obsolescence in determining the rate of growth. Faster growth is achieved not through investment in more sophisticated technologies, but by upgrading technologies more frequently. The optimal policies implied by the theory differ from those of existing models of learning by doing, but resemble those commonly observed in attempts to promote strategic sectors. In particular, in the presence of learning spillovers, subsidizing labor employed with advanced technologies can achieve the first best.

The model's ability to replicate the large cross-country differences in growth rates found in the data depends critically on two features of the technology governing the acquisition of worker skills: on the size of learning spillovers and on the substitutability of new and old technologies in learning. Independent evidence supports the former, but is silent on the latter. A final evaluation of the theory thus requires additional empirical work which confronts additional predictions with the data. In particular, the theory implies: (*i*) Countries that grow faster have substantially shorter equipment service lives. (*ii*) The amount and duration of learning following the adoption of new technologies differs very little across fast and slow growing countries. (*iii*) In fast growing countries the average age and the dispersion of technologies in use is low (in a technological as well as chronological sense). (*iv*) Restrictions to capital goods imports are harmful for long-run growth.

Some existing evidence provides preliminary support for these hypotheses. Lee (1995) finds that growth rates are positively correlated with the fraction of capital goods imports. Coe, Helpman and Hoffmaister (1995) show that countries that grow rapidly tend to import more from countries with high cumulative R&D expenditures. Heston and Mercer (1993) discuss the limited evidence of cross-country variation in equipment service lives. A more detailed examination of these predictions is left for future research.

Finally, an important policy implication of the model deserves to be pointed out. Since most countries import the bulk of their equipment (Warner 1992), it is natural to interpret the model as that of a small open economy that imports equipment from the rest of the world (this does not affect the model structure in any way). The implication is then: Policies that raise the relative price of imported capital goods, such as tariffs or import quotas, have highly detrimental effects on economic growth.

This prediction stands in marked contrast to other models based on learning and technology upgrading. For example, the assumptions about learning made by Young (1991) are very similar to the ones made here: learning is general, a pure externality, and depends on the allocation of labor across activities of different technological sophistication. Yet in his model, free trade leads to slower growth in developing countries which appears inconsistent with the empirical evidence (see, for example, Edwards 1997). The key difference is that Young (as well as Lucas 1993) assumes that learning depends on which commodities are *produced* ("learning-by-doing"), not on the technologies *used* in their production ("learning-by-using"). Comparative advantage then pushes poor countries towards the production of simple goods that contribute little to learning. In the case of learning-by-using, the comparative advantage argument does not apply and the growth effects of openness (reducing p^E) are positive, even for poorer countries.

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