Rise of the Machines Redux — Skill Obsolescence, Technological Cycles and Long-run Growth*

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Abstract

How does our current era of "techno-pessimism" connect with the history of industrialization, and what can it teach us about future growth? To explore these questions we analyze the effects of different forms of technological change on human capital accumulation and economic growth. We develop a growth model with over-lapping generations that endogenizes skill acquisition and TWO forms of technical change, one that raises the *quality* of existing capital goods, and one that increases the number of types of *new* capital goods. The former kind of technological change obsoletes certain middle-range skills but can promote higher-range abstract skills. The model demonstrates the possibility of technological cycles, where the development of new capital goods slows down and gives way to disruptive quality improvements of existing capital goods. The approach here allows us gain new insights into theories of unified growth, historical patterns of de-skilling technologies, and current debates about automation and skill acquisition.

- *Keywords*: employment polarization, job polarization, endogenous growth, human capital, unified growth theory, skill obsolescence
- *JEL Codes*: J24, J31, O31, O33

*Preliminary version.

1 Introduction

Recent technological developments have caused a great deal of consternation, as new technologies appear to be replacing middle and even some quite high skill level jobs thought previously to be immune to the forces of codification and mechanization. These trends however, are neither a-historical nor unprecedented — they have deep roots in the early industrialization of western Europe and North America.

This work endeavors to develop a growth theory that carefully develops the evolution and interaction between technological change and education. Specifically, we develop a growth model with over-lapping generations that endogenizes skill acquisition and *two* forms of technical change, one that raises the quality of existing capital goods, and one that increases the number of types of new capital goods. The former kind of technological change obsoletes certain middle-range skills but can raise the value of higher-range abstract skills. These technological changes in turn affect education decisions by households.

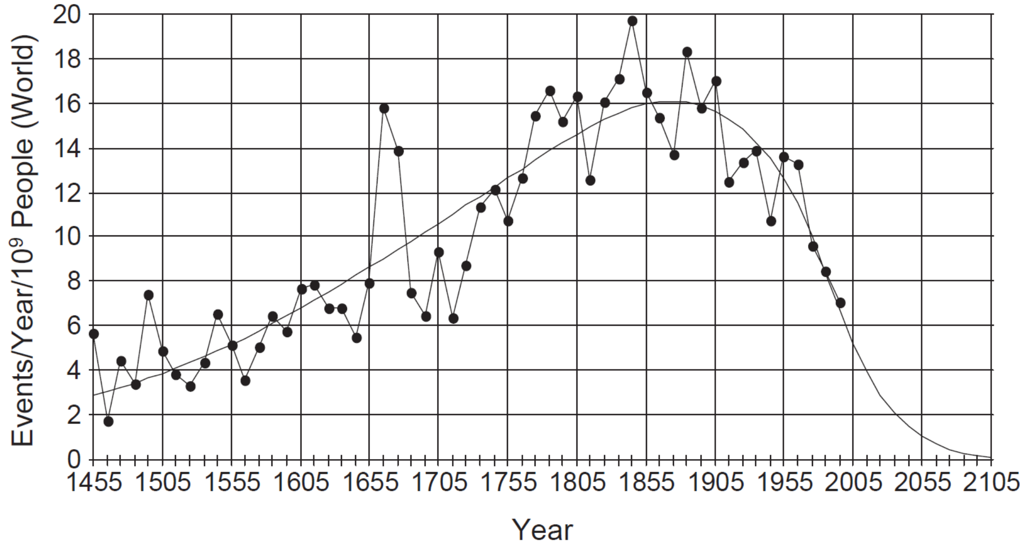
The framework allows us to consider the potential historical developments in technology and education over the last few centuries. It also provides the potential to unify our growth experiences in history and relate them to our own economic circumstances.[1] Indeed it is important to take such theory and extrapolate forward to understand long-run economic growth patterns that we might expect in the near future.

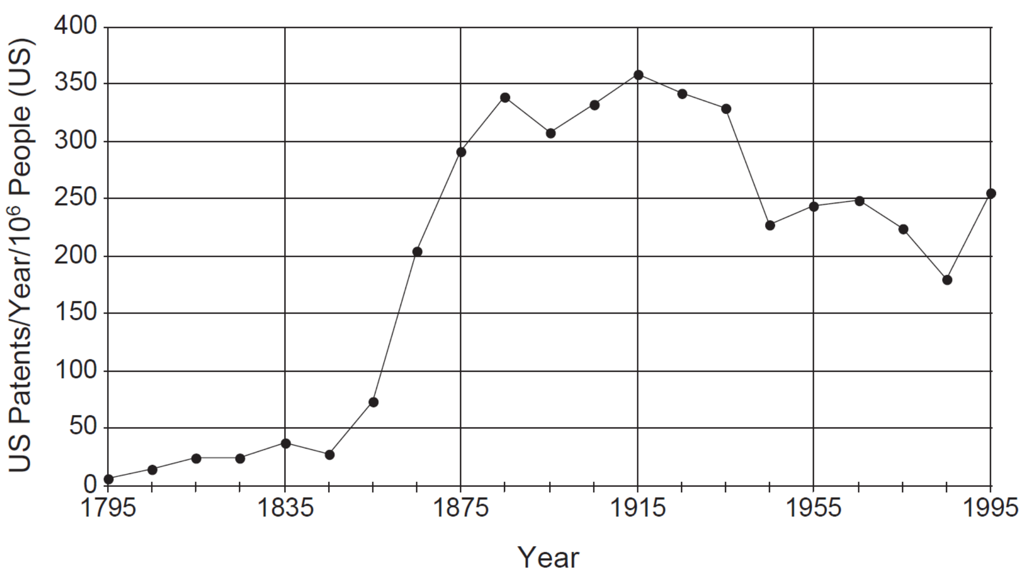
Different Forms of Technological Change

The approach taken here allows us to tackle some big questions. For example, why is there such pessimism over technological progress these days, even as we witness the rapid advancement of many new technologies? One strain of the argument that we are experiencing technological stasis (Cowen 2011 among others) hinges on the idea that the world has essentially run out of big ideas. Gordon (2000) suggests the big fundamental innovations have all been made in the

[1] This work is however not intended to be a proper unified growth theory, as framed by Galor (2011). For example we abstract away from fertility here and therefore cannot comment on the nature or timing of the Demographic Transition.

Figure 1: Historical Rates of Innovation





Source: Huebner (2005). Points are an average over 10 years with the last point covering the period from 1990 to 1999.

late 19th and early 20th centuries.[2] Field (2011) is even more precise, declaring the 1930s as the most productive decade in terms of technological breakthroughs.

The techno-pessimistic sentiment is nicely captured by the top diagram in Figure 1 (replicated from Huebner 2005). It charts rates of innovation per capita for the world beginning in the fifteenth century and projected into the twenty-second. Here we see a steady rise in innovative activity, followed by a burst consistent with the Industrial Revolution. Innovations appear to peak in the late 19th century, after which point innovations start declining. At its current trend the world will fall below innovation rates achieved during the Middle Ages at some point this century!

At the same time however, research activities appear to continue unabated. Taken from the same study, the bottom diagram in Figure 1 charts patents per capita for the United States over the past two centuries. While patent filings took a steep drop in the inter-war years, they have remained roughly consistent since the second World War. Jones (2002) in fact suggests patent filings rose during the second half of the twentieth century. And Zoulay and Jones (2006) suggests that although there are more people in research oriented positions than ever before, each is far less innovative than their predecessors.

To deepen the puzzle, lack of technological change would seem inconsistent with the recent notion of technological *unemployment* — the fear that machines and robots are starting to automate many of our jobs. Brynjolfsson and McAfee (2014) suggest machine intelligence has been on the rise for some time and will soon be everywhere, creating uncertainty over once stable middle-skill jobs.[3] By this line of reasoning, current technological change has been robust and transformative, even if a bi-product of this change is unwelcome.

This work attempts to reconcile these different views on the past and future paths of technology by distinguishing between two types of technological change. In our model innovators can either "tinker" with existing forms of technologies, or perform more basic research to develop new

[2]These include electrification, internal-combustible engines, indoor plumbing, petro-chemicals, and the telephone.

[3]An apt anecdote from their book is about the Dutch chess grandmaster Jan Hein Donner, who was asked how he would prepare for a chess match against a computer. Donner replied, much like a dour Luddite from centuries ago: "I would bring a hammer."

technologies. A key feature here is that successful tinkerers will improve the quality of existing technologies but in the process obsolete the skills associated with the old technology. Basic researchers on the other hand create brand new industries, producing future opportunities for mid-skilled workers but leaving current groups of mid-skilled unharmed.[4] Here we echo the idea that society can provide too little investment in basic research (Jones and Williams 2000), and provide a mechanism to help understand why.

This approach also has the benefit of connecting the past with the present. For example Khan (2015) suggests that early growth arose mainly from the efforts of tinkerers (resolving "perceived industrial problems"), but then this eventually gave way to the scientists, engineers and technicians performing more basic and breakthrough research. The model here may shed some light on how these two apparent growth regimes are related. Further, the model suggests our current economy may resemble in some ways early industrialization and the age of tinkerers. Contrary to Brynjolfsson and McAfee (2014), who suggest that what we face in the 21st century is somehow new, we allege that the technological hurricane we currently see is one that we have weathered before.

This paper argues that technological progress always takes two distinctive forms. If we consider the second Industrial Revolution of the late 19th century, for example, we see that railroads replaced stagecoaches, steamships replaced sailboats, and mechanized cranes replaced rudimentary pulley systems. These technological advances rendered groups of stagecoach drivers, sailors, and pulley operatives obsolete. Yet at the same time technological changes involved newer production methods requiring machinists, engineers, repairmen, managers and financiers newly-trained in the new methods. Similarly, today we see digital technologies replace certain production processes, and thereby replace certain mid-skilled workers, while other more novel digital methods require new engineers and designers. There is indeed a rise of machines, but in some ways it is a familiar one.

[4]This approach is similar in spirit to Aghion and Howitt (1994), which also looks at job destruction with technological growth. Their work looks however at unemployment, whereas we look at the effects to education. Young (1993) includes both invention and learning-by-doing in this model, without focusing on skill obsolescence.

Education and Technology

Another large question we wish to address is the potential effects of technological change on education, both historically and recently. For example, it has been argued that early industrialization could not have been consistent with larger demands for education because skill premia appear to be falling during this period (Clark 2004, Clark and Hamilton 2003). In our model we also can observe falling premia for high-end skills. But our model also demonstrates that early industrialization could have been both de-skilling (as routine labor is increasingly obsoleted by the efforts of tinkerers) and fostering growth in higher-end skills (as those on the higher end of the educational distribution shy away from risky mid-skills).

Further, the model demonstrates how gradual increases in high-level abstract human capital can occur during the "age of tinkerers." This gradual rise would then be able to reach a critical level where sustained long run micro-inventions (new machine blueprints) would be possible. The approach is also consistent with the idea of slow growth in living standards during early industrialization, with more rapid growth as the economy transitions to more robust inventive activities.

Yet at the same time, we will see that sustained innovation can be consistent with *falling* rates of education. To the extent that highly educated individuals are necessary for sustained inventive activity, this can threaten a growth slowdown and a renewed emphasis on "tinkering." We will argue later in the paper that new injections of highly educated people may be necessary through governmental or institutional channels (Goldin 2003) to sustain economic progress.

Related to the effects of technologies on education are their potential effects on income inequality. Does their exist a growth-inequality tradeoff? Galor and Tsiddon (1997) find that polarization in the early stages of development may be necessary for a future growth takeoff. We argue something similar here, although the mechanism is quite different.

We also acknowledge that there may be differences between skills and tasks (Acemoglu and Autor 2010). This distinction may be crucial when certain skills become obsolete. In these cases, one's acquired skill may not relate to one's current job, and this will naturally affect income inequality. This paper acknowledges that new technologies can sometimes be disruptive, or even outright destructive, and sometimes they can lead to great wealth and shared prosperity.

Related Literature and Findings

This work fits in with a number of growth literatures. The first are growth models which generate cycles of economic activity. These include models focused on adoption and implementation of general purpose technologies such as Helpman and Trajtenberg (1998) and Howitt (1998). Other works generate cycles by differentiating between technological breakthroughs and improvements, such as Cheng and Dinopoulos (1992), or creating a delay in implementation of new technologies as in Felli and Ortalo-Magne (1997). The technological cycles generated here will stem from a different source than those produced in these works.

Another strain of literature aims to unify different phases of economic growth in one consistent model. These so-called "unified growth" theories endeavor to model Malthusian growth dynamics and also allow for a transition to modern economic growth (Galor and Weil 2000. See Galor 2005, 2011 for detailed summaries of this literature). Our paper abstracts away from fertility, and so cannot comment on either Malthusian traps or the Demographic Transition. We do however attempt to understand long-run phases of technological progress and education in history with this approach.

Finally our model joins those that make a distinction between fundamental and secondary innovation. These include Young (1991,1993), Lucas (1993), Jovanovic and Nyarko (1996) and Redding (2002). In this final work fundamental knowledge destroys a portion of secondary knowledge, where in our model quality improvements destroy certain skills. More recently and perhaps more closely related to this paper is Acemoglu and Restrepo (2015); here periods when secondary innovation (which they call 'automation') runs ahead of more fundamental innovation will tend to self-correct. In their model automation lowers labor costs, inducing newer labor-intensive technological developments. Here we suggest two differences that fundamentally change this outcome — endogenous skill acquisition, and the inclusion of a (relatively) unskilled service sector. In a world where mid-level education or training must be associated with a specific and established production process, routinization will destroy not only jobs but *skills*. The relative scarcity of surviving mid-level skills can then *raise* routine labor costs, inducing more routinization. Further, new technologies eventually require new mid-level skills to operate them. But if displaced mid-skilled workers end up in unskilled service occupations, education can not rise to meet this demand. Thus rather than self-correct, we demonstrate the potential for routinization to be self-reinforcing.

Along with technological cycles, this work produces a number of other novel insights. Skill obsoleting technologies can increase rates of education. This is a startling claim but it makes sense, particularly in today's context where education is still perceived as the gateway to higher earnings even though technological changes appear to be destroying the relevance of many of these skills. Technological obsolescence in fact boosts education on both the low and high ends of the educational spectrum. As we will demonstrate later in the paper, the former acts like purchasing a lottery ticket (with a higher potential payout), while the latter acts like purchasing insurance.

On the other side of the coin, fundamental technological increases can dampen education. Lower human capital levels can slow down this kind of innovation in the future, particularly if high-level skills are necessary for consistent micro-inventive activity. Thus we suggest technological cycles can emerge unless governments can someone "inject" human capital into the economy, though educational subsidies or immigration policies.

The remainder of the paper proceeds as follows. Section 2 relays the key features of the model. Section 3 simulates the economy under various technological scenarios, and demonstrates how technological cycles can form endogenously. Section 4 provides some parting thoughts.

2 The Model

We begin with a utility and production structure with unbalanced technological change reminiscent of Baumol (1967), with extensions by Autor et al. (2003), Weiss (2008), and Autor and Dorn (2013). The economy consists of two sectors which produce goods or services. These products are imperfectly substitutable in utility. For any period t, the planner's problem is to maximize an aggregate consumption bundle given by:

$$C = \left(\gamma C_s^{\frac{\sigma-1}{\sigma}} + (1-\gamma) C_g^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \quad (1)$$

where C_s are services, C_g are manufactured products, and γ is the relative weight placed on services in utility. $\sigma \leq 1$ determines the elasticity of substitution between goods and services. We will assume throughout that $\sigma > 0$, so that goods and services grossly complement each other in utility (a standard assumption in the literature). For now we suppress time subscripts.

There are three basic forms of labor. Purely unskilled workers (L_u) use no human capital and can only work in the service industry (as manual laborers). Those who invest in human capital can invest either in mid-level routine skills, or high-level abstract skills. A key feature in this model is that mid-level routine skills will be specific to a particular manufacturing sector, and faces potential obsolescence. High-level abstract skills on the other hand is not tied to a specific task and faces no potential for obsolescence.

We will build an endogenous growth model that will have two potential types of technological changes — those that improve the quality of existing machines, and those that produce machines altogether new. There will thus be three (potential) types of capital goods. K^{old} is capital used in the production of already extant old machine types. K^* is capital used to make machines of newly improved quality. Finally K^{new} is capital devoted to constructing machines from brand new blueprints.

Production of service and manufacturing goods involve the following respective production functions:

$$C_s = Y_s = L_s \tag{2}$$

$$C_g = Y_g - p^{old}K^{old} - p^*K^* - p^{new}K^{new} \tag{3}$$

$$Y_g = L_a^{1-\beta}X^{\beta} \tag{4}$$

where Y_s is total production of services, Y_g is total production of manufactured goods, $[p^{old}, p^*, p^{new}]$ is a vector of capital prices, and X is a capital aggregator which we explain below.

2.1 Production

Factors are paid their marginal products. Unskilled service workers earn w_u, mid-skilled workers earn w_r times the mid-level human capital they accumulate, and abstract workers earn w_a times the high-level human capital they accumulate. We will see in section 2.3 that human capital amounts will differ across individuals.

Capital is used only in the manufacturing sector. A portion of the final consumption good must be allocated to the production of capital for the building of old-type machines, and may also be devoted for the building of improved-quality machines and/or new-type machines. Capital fully depreciates after each period. The full capital aggregator X is given by:

$$X = \int_0^{N^{old}} q^{old}(i) \left(x^{old}(i)\right)^{\alpha} L_r(i)^{1-\alpha} di + \int_0^{N^*} q^{new}(j) \left(x^*(j)\right)^{\alpha} dj + \int_0^{N^{new}} q^{new}(k) \left(x^{new}(k)\right)^{\alpha} dk \quad (5)$$

where q^{old} is the quality of old-type machines which are not being quality-upgraded, and q^{new} is the quality of old-type machines which have been tinkered with and are being quality-upgraded. The first term shows manufacturing production in old sectors. The second term shows production in sectors where the quality of machines (whose blueprints already exist) have been improved that time period. The final term shows production in sectors using newly invented machines. Thus at any given time t there exists $N^* \subset [0, \infty)$ of existing machine types that are being quality-upgraded, and $N^{new} \subset [0, \infty)$ of machine types newly invented. Also note that new-type machines are always produced at the highest current level of quality.[5]

Note that mid-level routine skills can only be employed in old manufacturing sectors, and that these skills are assigned to a specific sector. Each mid-level skill can only be used in its assigned sector. This assumption reflects the idea that mid-level skills are typically linked to a specific industry or production process. Historical examples include the major areas of growth during the Industrial Revolution such as textile production and steam engineering — education for workers in these industries typically took the form of training in industry-specific tasks.[6] Of course there

[5]This is merely a matter of convenience.

[6]Economic historians have suggested that even basic literacy was not an important skill during this period (Mitch 1982).

are many examples of industry-specific skills used today in production and craft occupations, operative and assembler occupations, and transportation, construction, mechanical, mining, and farm occupations, many which are threatened by technological obsolescence (Autor and Dorn 2013).

As is standard in the endogenous growth literature (Romer 1990, along with many others) we will assume that qualities and capital uses are symmetrical in each area of production. While this will not strictly be correct, since sectors will improve at different rates and have different levels of quality, we will be interested in *average* values, and so taking average measures will suffice. So for example, the total amount of capital used in old manufacturing sectors can be written as

$$Kold = N^{old} q^{old} \left(\overline{x^{old}}\right)^{\alpha} Lr^{1-\alpha} \tag{6}$$

where now L_r denotes the total stock of mid-skilled capital used in production across all sectors, q^{old} is the average quality of old machines, and $\overline{x^{old}}$ is the average amount of capital in each sector. Note that we can then write $\overline{x^{old}}$ as $\left(K^{old}/N^{old}q^{old}\right)^{1/\alpha}$. Using similar notation for quality-upgraded machines and new machines, we have:

$$X = \left(N^{old} q^{old}\right)^{1-\alpha} (K^{old})^{\alpha} L_r^{1-\alpha} + (N^* q^{new})^{1-\alpha} (K^*)^{\alpha} + (N^{new} q^{new})^{1-\alpha} (K^{new})^{\alpha} \tag{7}$$

Given this, perfectly competitive manufacturers demand different types of capital and labor, given technological levels (both in terms of number of machine blueprints and average qualities of machines), machine prices and wages. We thus have six potential first order conditions:

$$\frac{\partial Y_g}{\partial K^{old}} = \beta L_a^{1-\beta} X^{\beta-1} \left(\frac{\partial X}{\partial K^{old}}\right) = p^{old} \tag{8}$$

$$\frac{\partial Y_g}{\partial K^{*}} = \beta L_a^{1-\beta} X^{\beta-1} \left(\frac{\partial X}{\partial K^{*}}\right) = p^{*} \tag{9}$$

$$\frac{\partial Y_g}{\partial K^{new}} = \beta L_a^{1-\beta} X^{\beta-1} \left(\frac{\partial X}{\partial K^{new}}\right) = p^{new} \tag{10}$$

$$\frac{\partial Y_g}{\partial L_a} = (1-\beta) L_a^{-\beta} X^{\beta} = w_a \tag{11}$$

$$\frac{\partial Y_g}{\partial L_r} = (\beta) L_a^{1-\beta} X^{\beta-1} \left(\frac{\partial X}{\partial L_r}\right) = w_r \tag{12}$$

$$\left(\frac{\gamma}{1-\gamma}\right)\left(\frac{C_s}{C_g}\right)^{\frac{-1}{\sigma}} = w_u \tag{13}$$

Equations (8) – (10) are machine prices, which will be charged by machine producers. Equations (11) – (13) are *ex ante* spot wages for raw labor or human capital. We discuss each in tern.

2.2 Technological Change

We will assume an over-lapping generations framework where individuals live for two time periods. On the technology side, we assume that "young" innovators decide either to invest resources to invent new-type machines, or to spend their time tinkering with old-type machines, and that they can enjoy the fruits of their labors when they are "old" — that is, for one time period only.

We will assume that the marginal cost of producing a machine is equal to its average quality. Since old machines are competitively produced, we have $p^{old} = q^{old}$.

An innovator who newly improves the quality of an existing type of machine at time t (we will call this sort of individual a "tinkerer") has monopoly rights to that machine for one period. These machines were part of N^{old} in $t-1$ (and linked with specific mid-skilled workers) and become part of N^* during t. Manufactures however remain free to purchase an older, inferior quality machine at a cheaper price — these machines would be perfectly substitutable. Thus producers of newly improved machines would engage in limit pricing, and charge $p^* = q^{new}$.

An innovator who invents a new type of machine also has monopoly rights to it for one period. There are no substitutes for this machine. These machines become part of N^{new}. Given iso-elastic demand, this machine producer charges a constant mark-up over marginal cost of machine production. Thus $p^{new} = (1/\alpha)\, q^{new}$.

Note that since it is possible that at any given period there exists both machines that are newly of higher quality, and also machines that are from new blueprints, the average quality of old machines will adjust as these newer machines become old machines the following period. If we have N_t as the total number of machine blueprints at time t, we can say that the average quality of old machines is given by the following "law of motion" of machine quality:

$$q_t^{old} = \left(\frac{N_t^{old}}{N_t}\right) q_{t-1}^{old} \quad + \quad \left(\frac{N_{t-1}^{*} + N_{t-1}^{new}}{N_t}\right) q_{t-1}^{new} \tag{14}$$

The first term captures the quality of machines that have remained old, while the second term captures the quality of machines that are *newly* old.

Finally, note that if machines from a sector are upgraded by tinkerers, that sector can no longer employ routine labor, the idea being that that mid-level skill is no longer applicable, and that only when that sector goes back to being an "old" sector that mid-level skills be used again.[7] Thus a fraction of erstwhile routine laborers will be unable to use their human capital (more on this in next section). Let us define ϕ as the fraction of sectors that were old last period which are being upgraded in terms of quality this period. This is given by:

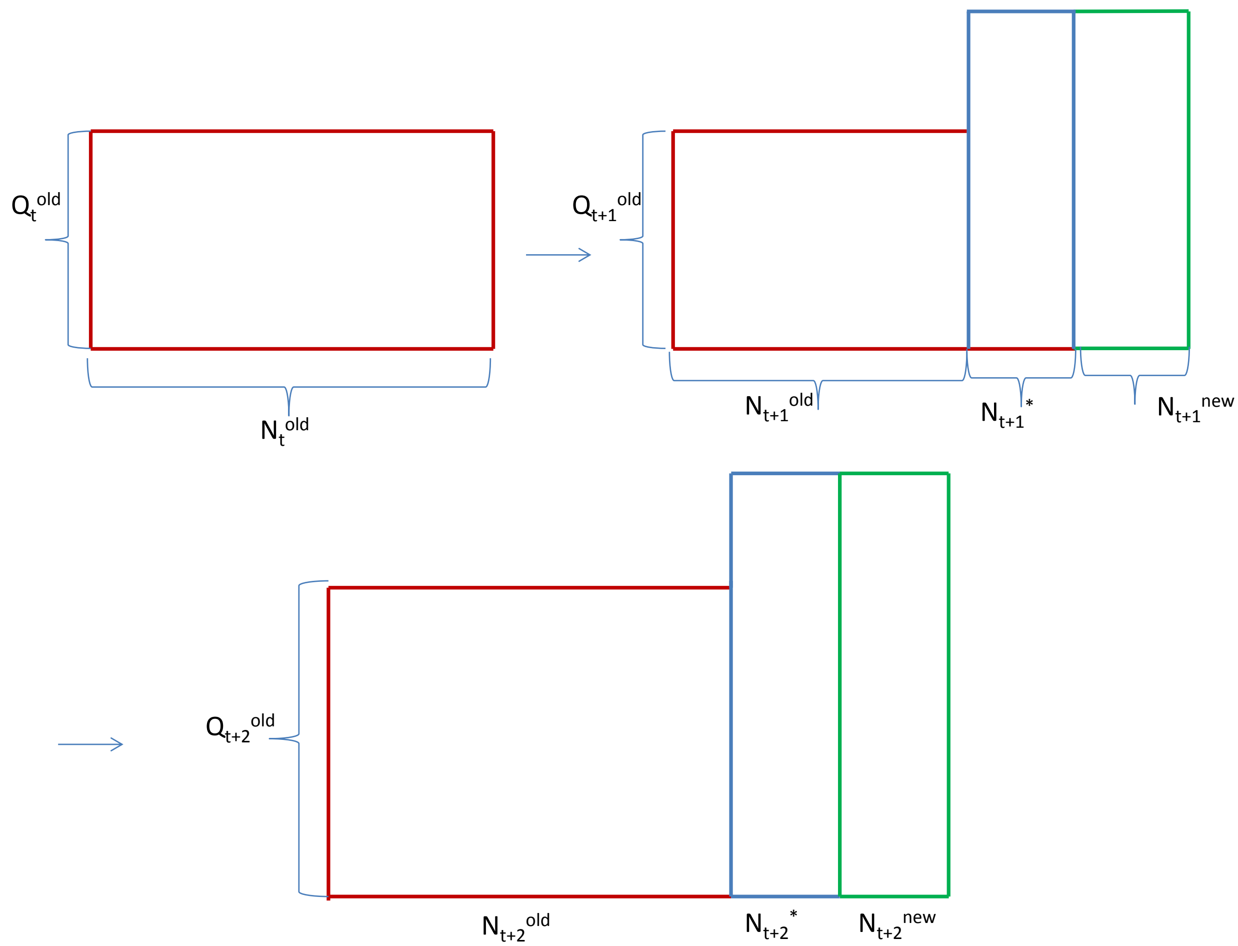
$$\phi \equiv \frac{N^*}{N^* + N^{old}} \tag{15}$$

Figure 2 shows an example of the quality and quantity of machines when *both* machine quality-upgrading and new machine inventions occur. Quality improvements raise a certain fraction of machines vertically — this vertical rise shows up within a sub-group of old machines the following period. Newly invented machines on the other hand push the machines out horizontally.

It is important to note that this form of technological change is skill-replacing, but not in a form that is unskill-biased (as in O'Rourke et al. 2013). In this world unskilled workers are in service sectors, which are technologically stagnant. Instead skills are obsoleted, and new-updated skills will be employed when the technology becomes more seasoned. One might also consider this a form of short-term automation. Contrary to Acemoglu and Restrepo (2015) however, the

[7] We do not allow for the possibility for manufacturers to simply hire the old machines and use existing routine workers trained in the old technology. Given limit pricing firms can be induced to marginally prefer adopting the newly upgraded machines without any routine workers.

Figure 2: Illustration of Growth in Both Quality of Machines and New Machines



Vertical growth implies quality-improvement, which comes from a portion of existing machines. Horizontal growth implies new innovation.

new technologies will be linked with new skills next period.

2.3 Endogenous Skill Choice

As individuals live for two time periods, we suggest that they maximize an expected utility function given by:

$$EU\left(C_{t-1}, C_t\right) = \left(C_{t-1}^{\omega} + E\left(C_t\right)^{\omega}\right)^{1/\omega} \tag{16}$$

where $\omega < 1$. Individuals are indexed over a number line of constant size $\overline{L}$. They are born with a pair of potential endowments that rise linearly with this index. That is, individual l is born with a pair of potential endowments $[a_l^r, a_l^a]$ — when young they can choose to invest in one type of skill, and receive the endowment in the next time period. At time $t-1$ the individual chooses what kind of worker they would like to be at time t. If the individual chooses not to get any education, she will work as an unskilled laborer for both time periods and earn $1 + w_u$ each period. If the individual chooses to become a mid-skilled worker she will invest her time at $t-1$ getting an education, thus earning no wages. Her education is devoted to a specific sector i (for analytical convenience this will be randomly chosen). At time t she acquires a_l^r units of mid-skilled human capital and earns $w_t^r a_l^r$, *provided* that i remains an old sector at time t. If machines from sector i have been tinkered with and improved in terms of quality, l's routine skills have become obsolete and she becomes an unskilled worker. Finally, if the individual chooses to become a high-skilled worker she will invest her time at $t-1$ getting a high-level education, also earning no wages. At time t she acquires a_l^a units of abstract human capital and earns $w_t^a a_l^r$ with certainty.

Given these payoffs, the individual who chooses to be unskilled receives a utility of:

$$U_u = \left((1 + w_u)^{\omega} + (1 + w_u)^{\omega}\right)^{1/\omega} \tag{17}$$

The individual who chooses to be semi-skilled worker faces an *ex ante* utility of:

$$U_r = \left(1 + (1 + E_l)^{\omega}\right)^{1/\omega} \tag{18}$$

where E_l is the *expected* wage that individual l can earn when investing in mid-skills. Finally, the individual who chooses to be a high-skilled abstract worker receives a utility of:

$$U_a = \left(1 + (1 + a_l^a w_a)^\omega\right)^{1/\omega} \tag{19}$$

Given these potential utilities, agent l decides whether to work two periods as an unskilled worker, to invest their time at $t-1$ to receive a_l^r units of mid-skill human capital to potentially use in period t, or to invest their time at $t-1$ to receive a_l^a units of high-skill human capital to use in period t.

Note that there is uncertainty over whether one's investment in mid-skilled human capital will actually pay off at t, since there is a possibility that those skills will become obsolete with technological upgrading. Here we treat one's expected wage for routine labor linearly:

$$E_{l,t-1} = (1-\phi)a_{l,t}^r w_{r,t} + \phi w_{u,t} \tag{20}$$

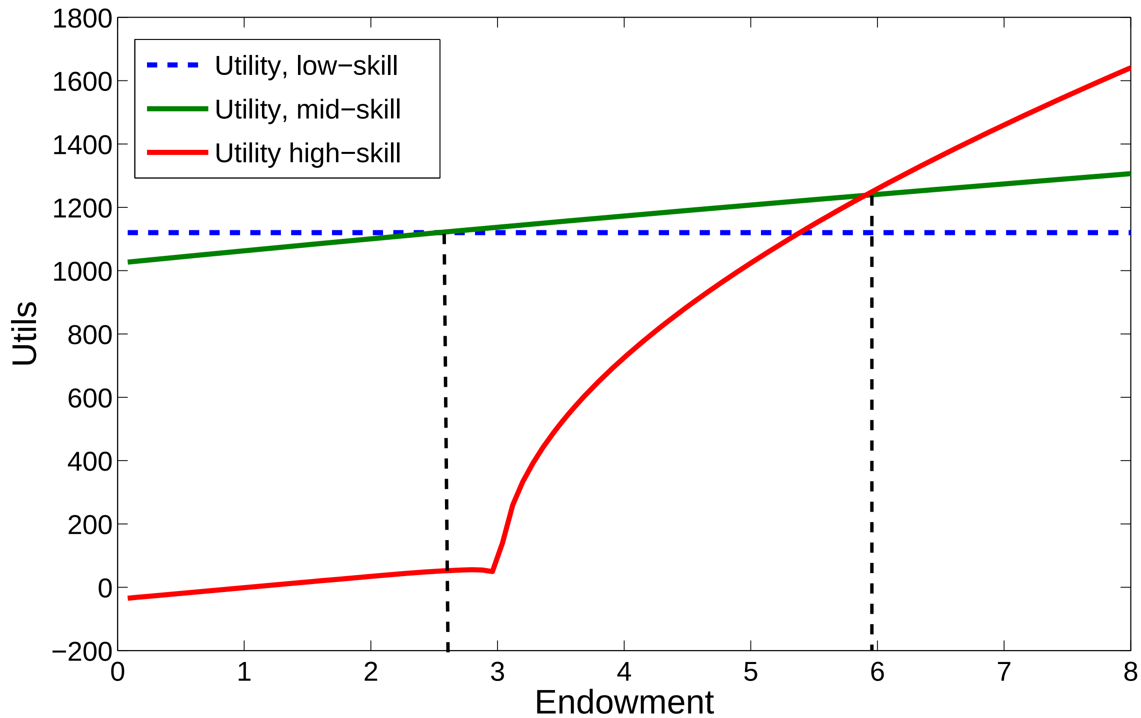
That is, with probably ϕ individual l finds that his mid-level human capital is obsolete, and he instead works as an unskilled worker.

Finally, assume that potential skill endowments rise at linear rate γ_1 along the labor index for mid-level routine skills, and at linear rate γ_2 along the index for high-level abstract skills. Further assume that for a range of $[0, \hat{L}]$, a_l^a is zero. That is, those under $\hat{L}$ can never become abstract workers. This suggests that individual l is endowed with $\gamma_1 l$ units of potential mid-level human capital and $\gamma_2(l - \hat{L})$ units of potential high-level human capital.

With this set-up, we can solve for equilibrium levels of each type of worker by calculating *threshold points* where individuals would be indifferent between two outcomes. We illustrate these two points in Figure 3. First, define L_1 as the worker who is indifferent between being an unskilled worker and investing in routine skills. This individual's expected return to routine skill investment is $E_{L_1} = (1-\phi)\gamma_1 L_1 w_r + \phi w_u$, and her utilities are such that $U_{u,L_1} = U_{r,L_1}$. Solving for L_1 we get

$$L_1 = \frac{\left((1 + w_{u,t-1})^\omega + (1 + w_{u,t})^\omega - 1\right)^{1/\omega} - 1 - \phi w_{u,t}}{\gamma_1 (1-\phi)\, w_{r,t}} \tag{21}$$

Figure 3: Utility from Different Endowments



Here $\overline{L} = 8$, wages are constant, and $w_u < w_r < w_a$. In this illustrative example, those below $L_1 = 2.6$ will be unskilled, while those above $L_2 = 5.95$ will be highly skilled. Those in the middle will opt to be routine-skilled. Note that wage changes would shift these utility curves, changing threshold levels L_1 and L_2.

Next we define L_2 as the worker who is indifferent between being a routine worker and being an abstract worker. This individual's expected return to routine skill investment is $E_{L_2} = (1-\phi)\gamma_1 L_2 w_r + \phi w_u$, and her utilities are such that $U_{r,L_2} = U_{a,L_2}$. Solving for L_2 we get

$$L_2 = \frac{\gamma_2 \hat{L} w_{a,t} + \phi w_{u,t}}{\gamma_2 w_{a,t} - (1-\phi)\,\gamma_1 w_{r,t}} \tag{22}$$

Given wages, we can use these thresholds to solve for equilibrium levels of each type of labor. Figure 4 shows how this looks.

The area under each linear line between the thresholds indicate the total mass of each type of human capital, at least *ex ante*. *Ex post* of course there will be less L_r, as fraction ϕ will be reallocated to unskilled jobs — this will be uniformly random across all endowment levels. *Ex ante* labor amounts are thus given by:

$$L_u = L_{1,t-1} + L_{1,t} + \phi\,(L_2 - L_1) \tag{23}$$

$$L_r = (1-\phi)\left((L_2 - L_1)\,\gamma_1 L_1 + \frac{1}{2}\,(L_2 - L_1)\,\gamma_1\,(L_2 - L_1)\right) \tag{24}$$

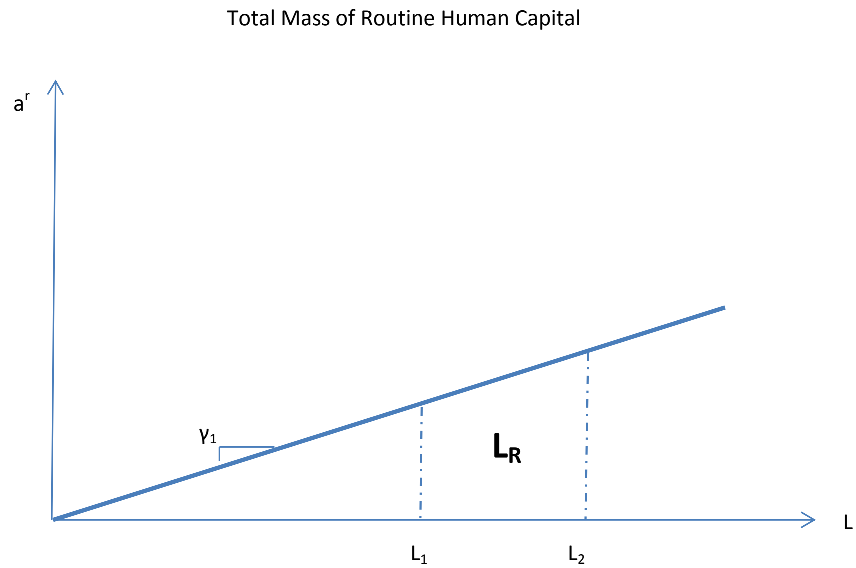
$$L_a = \left(\bar{L} - L_2\right)\gamma_2\left(L_2 - \hat{L}\right) + \frac{1}{2}\left(\bar{L} - L_2\right)\gamma_2\left(\bar{L} - L_2\right) \tag{25}$$

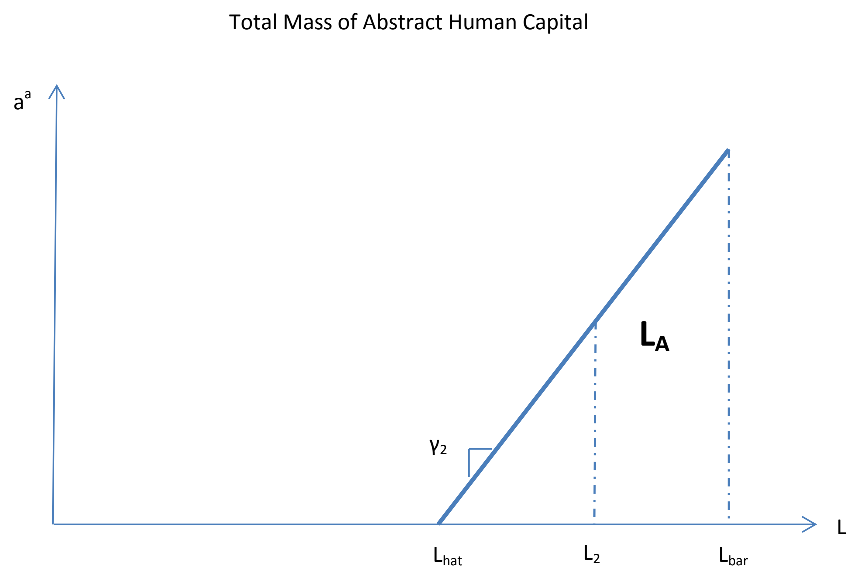
2.4 General Equilibrium

A static general equilibrium follows from the above discussion. Given an existing level of machine blueprints and average machine quality, equilibrium is given by solving (8), (11), (12), (13), (21), (22), (23), (24), and (25) for equilibrium values of capital, wages, threshold levels and labor amounts. Note that in this case ϕ is zero, as there are no machines being upgraded and so no uncertainly over whether or not certain mid-skilled workers will find their human capital obsoleted.

With technological changes will come changes to marginal products of factors and changes to the factors themselves through changes in education choice. We can anticipate some of the changes by observing our equilibrium conditions. First, observe the equilibrium threshold person

Figure 4: Equilibrium Amounts of Human Capital





The total amount of routine human capital, L_r, is given by the trapezoid in the top diagram. The total amount of abstract human capital, L_a, is given by the trapezoid in the bottom diagram.

indifferent to investing in mid-skill human capital or remaining an unskilled worker (equation 21). If w_u falls or w_r rises, it is clear that L_1 will unambiguously fall. That is, the threshold person falls down the spectrum of workers, fewer people choose to remain an unskilled worker, and more people choose to invest in mid-level skills.

With quality improvements, ϕ will rise, and the effects on education at this lower end of the skill spectrum is unclear. On the one hand rises in ϕ makes investing in routine skills a more risky proposition, and so more may wish to remain unskilled. On the other hand, this also can make w_r rise, so more individuals may choose to invest in mid-level skills.

Looking at potential changes in L_2 (equation 22) allows us to understand the marginal choice at the higher end of the educational spectrum. If no quality changes, w_u is not part of the calculation. We see that while the effects of higher abstract wages have an attenuated effect on higher-end human capital (w_a is in both numerator and denominator), higher routine wages unambiguously raises L_2 and so raises mid-skills and lowers high-skills. Here we see that stable higher-paying routine jobs pulls people into routine occupations from the higher educational spectrum.

With quality improvements on the other hand, the level of unskilled wages now matters for the calculation. We can suggest the following:

Proposition 1 *A sufficient condition for* $\frac{\partial L_2}{\partial \phi} < 0$ *is* $w_u < \gamma_1 \hat{L} w_r$.

Proof: Quotient rule.

That is, a greater share of sectors going through quality improvements will induce more people to invest in higher-level skills as long as the skill premium between mid-skilled and unskilled workers is sufficiently high. Intuitively, a higher ϕ means a higher probability of receiving a wage of w_u. This would be a big fall in earnings for those at the higher end of the endowment spectrum. Better then to be an abstract worker with a stable wage.

3 Simulating Technological Change

Here we simulate the economy described in the prior section to demonstrate how different forms of technological change influence our variables of interest. It will be convenient to first demonstrate each form of technological change separately and exogenously. We then combine both by developing an explicit technology sector made up of a separate group of innovators who endogenously decide to either "tinker" with existing technologies or develop altogether new technologies.[8]

3.1 Quality Improvements Only

We now demonstrate changes in the economy when the quality of machines are improved. Here we do this exogenously, by assuming that in each period a greater fraction of sectors are experiencing quality upgrade (ϕ rises each period). The total number of sectors here however is kept fixed — that is, there are no new machines being invented and so no new sectors being created (that is , $K^{new} = 0$).

We simulate this economy for ten periods. In each period, we exogenously have 10 percent more sectors being quality upgraded (we start with twenty percent of all sectors being upgraded). The number of existing machine blueprints on the other hand is held fixed.

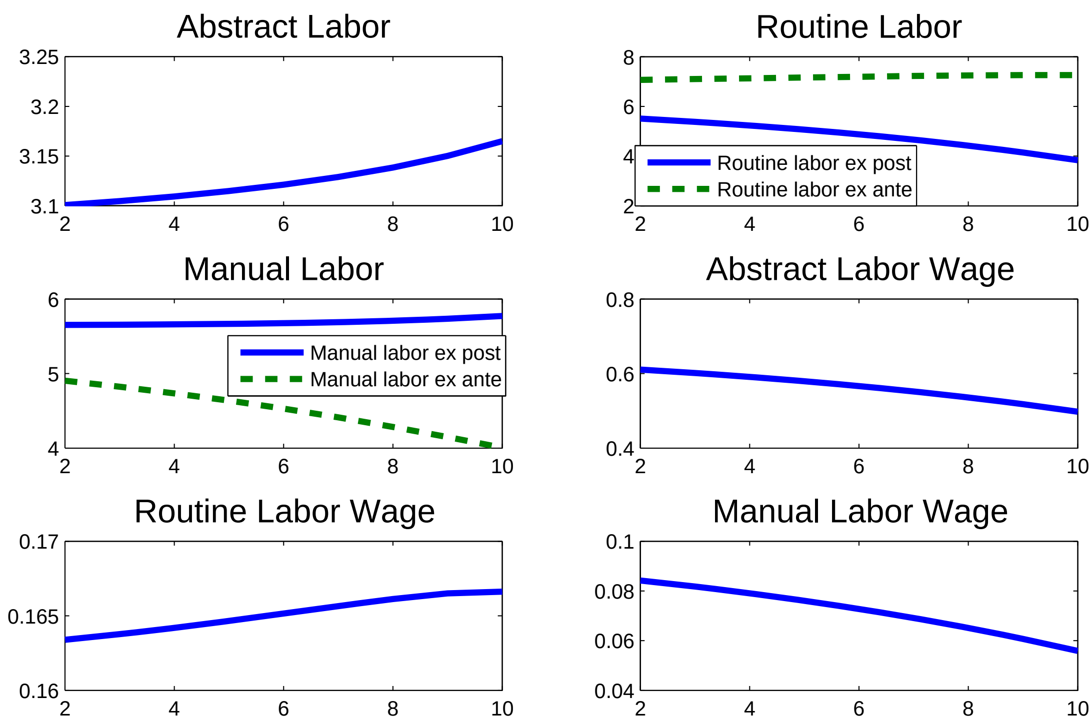
Figures 5 and 6 demonstrates the results from this simulation. A novel and somewhat surprising finding is that this form of technological change actually enhances rates of education. This is true for both ends of the educational spectrum.

First, consider the lower end. Even though routine-level jobs are becoming more and more risky, the "investment rate" for routine skills rises over time. We see this since L_1 falls over time. Why? As routine jobs become increasingly scarce, the value of having a still-existing routine job rises. At the same time, as more and more individuals get reallocated from mid-skill to unskilled jobs, wages for unskilled labor falls. Both together induce more investment in routine skills at the lower end of the endowment distribution. We can clearly see that while *ex ante* routine labor rises (as more and more individuals choose to invest in mid-level skills), *ex post* routine labor falls (and more and more of these investments become obsoleted).

Investing in routine skills in this world is like buying a lottery ticket with a higher and

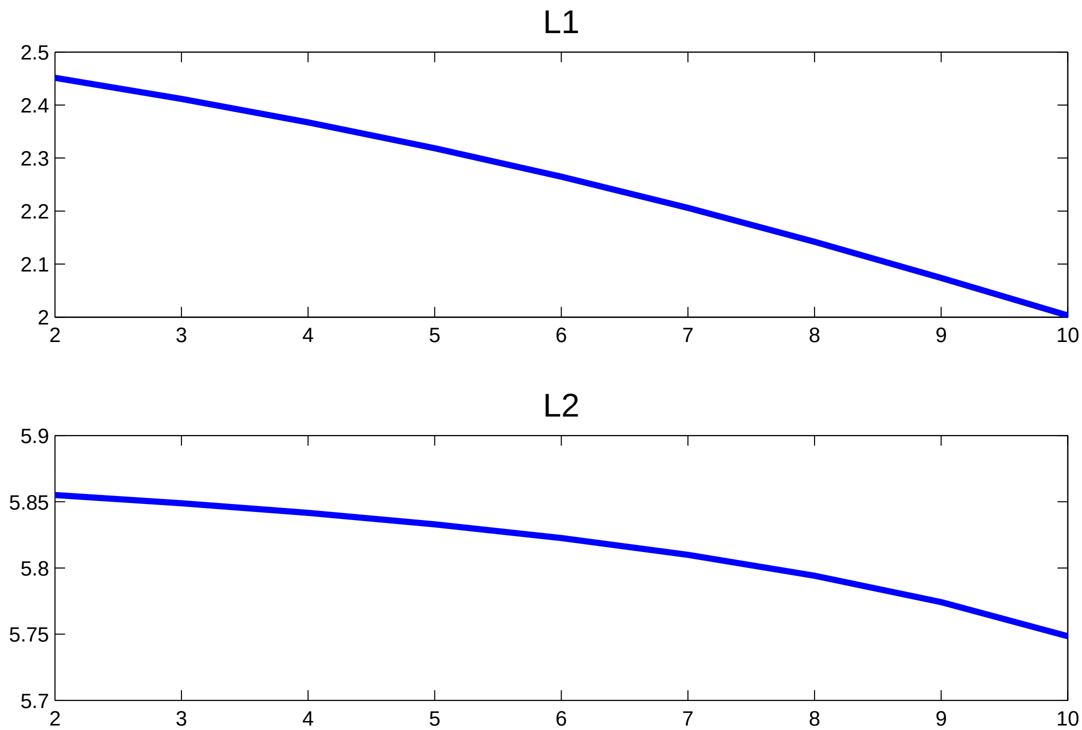
[8]For all simulations, parameter values are set as follows. $\gamma = 0.5$, $\sigma = 0.5$, $\alpha = 0.5$, $\beta = 0.5$, $\omega = 0.1$, $\gamma_1 = 0.5$, $\gamma_2 = 0.75$. Initial levels of technologies are $N^{old} = 5$ and $q^{old} = 1.5$. Quality improvements occur by a factor of 1.1. Qualitative directions of variable changes appear insensitive to specific parameterizations, provided $\sigma > 0$ (that is, provided goods and services are grossly substitutable).

Figure 5: Effects from Exogenous Quality-Improvements in Machines on Labor-Types and Wages



With machine quality improvements we see abstract labor rise but routine labor fall. The latter falls due to the ever-widening gulf between those who invest in mid-level skills and those who can ultimately use those skills in manufacturing. We also observe reverse wage polarization — mid-skill worker wages rise while abstract and manual labor wages fall.

Figure 6: Effects from Exogenous Quality-Improvements in Machines on Education Thresholds



With machine quality improvements we see rates of education rise. This is reflected by a lower threshold for the individual indifferent between being an unskilled worker or a routine worker (top diagram), and a lower threshold for the individual indifferent between being a routine worker or a high-skilled worker (bottom diagram).

higher potential payout, but a lower and lower probability of winning. This can also explain the burgeoning of an informal sector, where workers migrate to cities hoping to get a higher paying job (Harris and Todaro 1970). This would then be consistent with urbanization and the displacement of workers in early industrialization, as well as in developing regions today.

On the other end of the education spectrum, we see that abstract labor rises. Some of this has to do with the fact that more and more people producing services raises the value of manufactured goods. Notice however that abstract wages are also falling, so something else must be going on. More workers choose to invest in high-level skills because unskilled wages are falling. As mentioned in the previous section and as we learn from Proposition 1, the risk of getting a lower-paying unskilled job raises the relative value of getting a secure abstract job. So contrary to the lower end who are embracing risk because of a higher potential payoff, the higher end is willing to forgo some earnings for greater earnings security. For both reasons, the economy's rates of education are rising over time, even though routine human capital falls over time due to obsolescence.

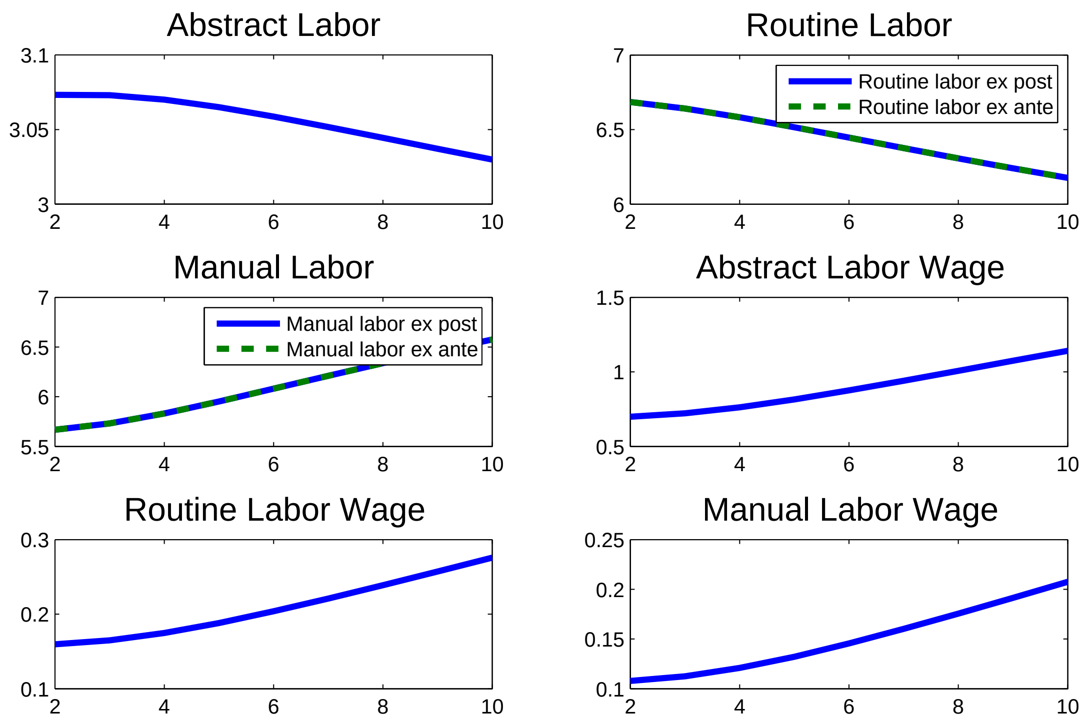
We should also note that this form of technological change is quite disruptive. It actually lowers incomes because it eliminates an erstwhile valuable amount of mid-level skills. This serves to put downward pressure on all wages. While this is admittedly an extreme scenario, what is important is looking at these wages *relative* to wages when fundamental innovations occur (illustrated in the next section).

An interesting aspect of the model is what it suggests about inequality. Here we see that with disruptive quality improvements wage inequality compresses on the high end (abstract wages rise relative to routine wages) but rises on the low end (routine wages rise relative to unskilled wages). This makes sense given the technological environment — part of the value of getting a high-level education is the insurance it provides against obsolescence. On the other hand, those on the lower end find mid-level education attractive, even if some get thrown into low-skilled service occupations. So in this world we observe the *opposite* of wage polarization — mid-skilled workers get the biggest boost.

3.2 New Machine Blueprints Only

Here we demonstrate the case where new machine types are exogenously "invented" each time period. Machine quality in this case remains constant at q^{old} for all machines, whatever their vintage, and K^* is always zero. Specifically, we simply raise the level of new machines by 0.5 each time period for 10 periods. The results of this exercise are demonstrated in Figures 7 and 8.

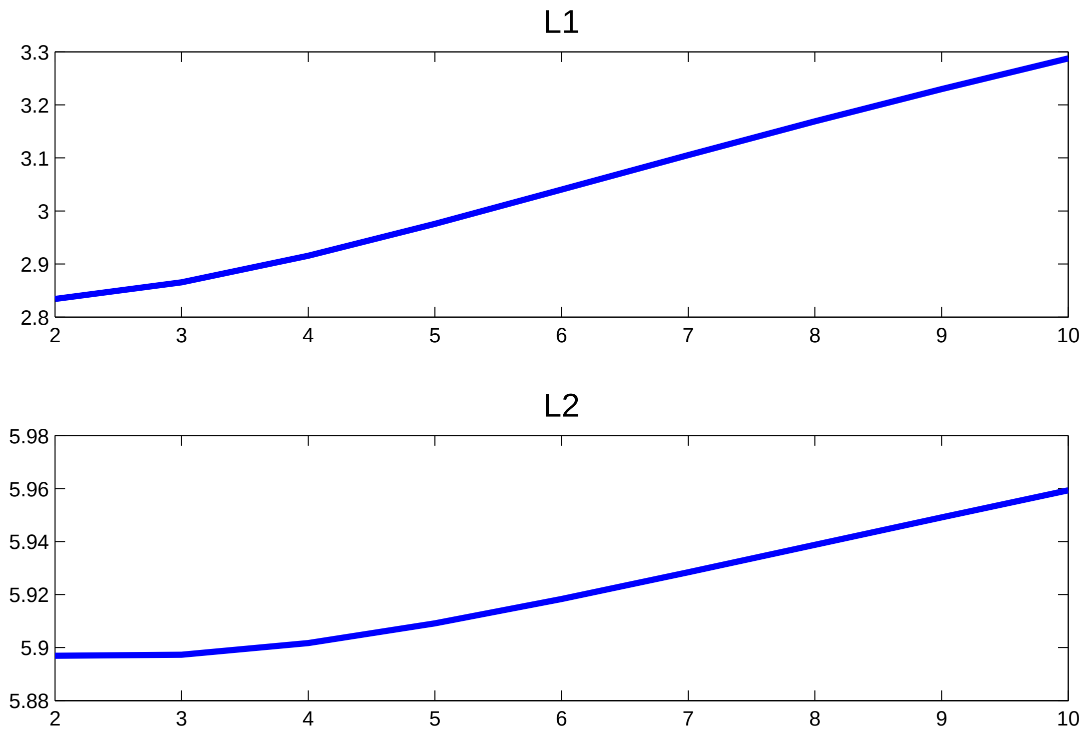
Figure 7: Effects from Exogenous Growth in Machine Blueprints on Labor-Types and Wages



With growth in new machine blueprints we see declines in skilled labor and rises in unskilled labor. Routine labor faces no obsolescence, which allows all wages to rise. We also observe wage polarization, especially at the lower end of the distribution.

First notice that because this form of technological progress does not destroy human capital, all wages rise, albeit at different rates. Technological progress raises the marginal product of high- and mid-skilled workers, raising their wages. It also raises the wages for unskilled service jobs because the relative value for services rises.

Figure 8: Effects from Exogenous Growth in Machine Blueprints on Education Thresholds



With growth in new machine blueprints we see rates of education fall on both ends of the distribution. This is reflected by a higher threshold for the individual indifferent between being an unskilled worker or a routine worker (top diagram), and a higher threshold for the individual indifferent between being a routine worker or a high-skilled worker (bottom diagram).

We also observe skill polarization. High-skill labor falls, and mid-skill routine labor falls by more. Looking at (21), we see that given $\phi = 0$, unskilled wages rising faster than mid-skilled wages will pull people away from mid-skills at the lower end of the endowment distribution. Looking at (22), on the other hand, we see that routine wage increases exert a powerful upward pull on L_2 That is, due to no insurance value for high-skilled education, technological progress lowers overall investment in high-level skills.

With respect to the discussion of Autor and Dorn (2013) we have a couple of new findings. One is that employment polarization can occur even if capital and routine skills are not grossly substitutable. The other finding is that this polarization from technological change occurs at the low end of the skill distribution, but is somewhat attenuated at the high end of the distribution. Here we observe de-skilling as a function of the existence of a non-productive unskilled-intensive service sector.

3.3 All Together Now — An Endogenous Technology Approach

The growth scenarios illustrated above highlight the effects of each type of technological change on education, employment and wages. Of course if technological changes arise from the micro-inventive activities of researchers and tinkerers, education and employment adjustments can in turn affect both the direction and extent of future technological developments. Past research has demonstrated how factors of production and technologies "directed" at different factors can interact in economically important ways (Acemoglu 1998, O'Rourke 2013, Rahman 2013). Here we attempt to endogenize technological changes to observe interactions in this framework.

To accomplish this we now develop a simple technology sector to explore the possibility of two technology types evolving endogenously. We assume a separate and fixed mass of "nerds," in the spirit of Legros et al. (2014). A nerd will either tinker or truly innovate.[9] A nerd who decides to innovate will increase the number of new machine blueprints by some fixed amount η. A nerd who decides to tinker on the other hand will raise the quality level of a certain quantity of old machines. These activities do not involve any uncertainty — while tinkering will involve

[9] We do not allow nerds to "vegetate," to use the verbiage in Legros et al. (2014.) — that is, nerds will always be active in some technological activity. We also assume a nerd can only innovate or tinker; she cannot do both.

quality upgrades to sectors which will be randomly assigned, nerds know exactly how much their efforts will translate into innovation or quality improvements.

While we treat nerds as a fixed group distinct from the general population, nerds are still motived by value and cost. In order to innovate, nerds must expend a resource cost c upfront. Similar to Rahman (2013), we assume this cost changes in technological factors. Specifically, we assume that research costs rise in the total number of existing blueprints N, but fall in the average quality of machines q. This captures the idea that tinkering with existing technologies can spillover into areas of new research. History abounds with these types of spillovers.[10] Finally, we also assume here that research costs also fall in L_a, the idea being that positive research spillovers are generated by higher amounts of high human capital (Lucas 1988).

The value of a new innovation for a nerd, V, is the ability to charge a mark-up to manufacturers for their machines for one time period (in the next period the blueprint becomes public knowledge, and the machine is competitively produced). Specifically, this value is given by:

$$V = \left(\frac{1}{\alpha} q^{new} - q^{new} \right) \bar{x}^{new} \tag{26}$$

Innovative activities among nerds continue as long as $V \geq c(N, q^{old}, L_a)$, where $\frac{\partial c}{\partial N} > 0$, $\frac{\partial c}{\partial q^{old}} < 0$, and $\frac{\partial c}{\partial L_a} < 0$.

As nerds innovate research costs rise, since innovation raises N. If after all the nerds innovate research costs remain smaller than the value of innovation, no tinkering in the economy takes place and no existing machine-types are quality upgraded. If on the other hand $V = c$ is reached and there remain nerds who have not innovated, the rest of the nerds tinker with existing technologies, thereby raising both N^* and q^{new}. Tinkering requires no resource cost, but also generates no profits since the greater quality of upgraded machines is exactly offset by their higher costs. Thus we suggest that in every period nerds first scramble to research and earn profits up to the point where $V = c$.

Results from this case are presented in Figures 9 and 10. In the beginning we see very limited growth in new machine blueprints. With low initial levels of both q and L_a, the costs of research

[10] Mokyr (2002) provides many historical cases where "prescriptive" knowledge can then lead to new insights which bolster "propositional" knowledge.

Figure 9: Effects from Both Types of Growth on Labor-Types and Wages

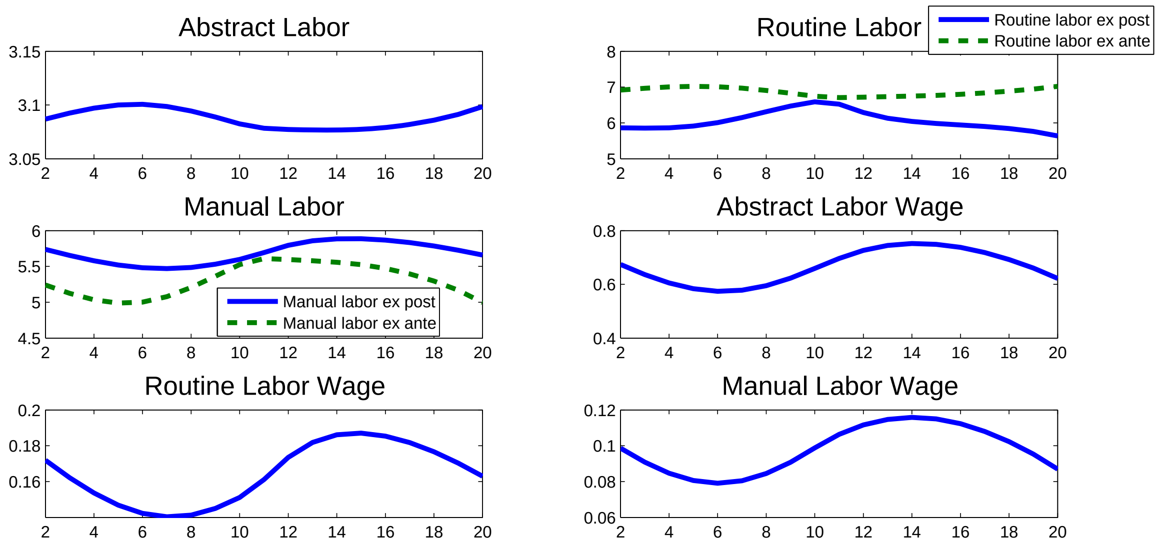
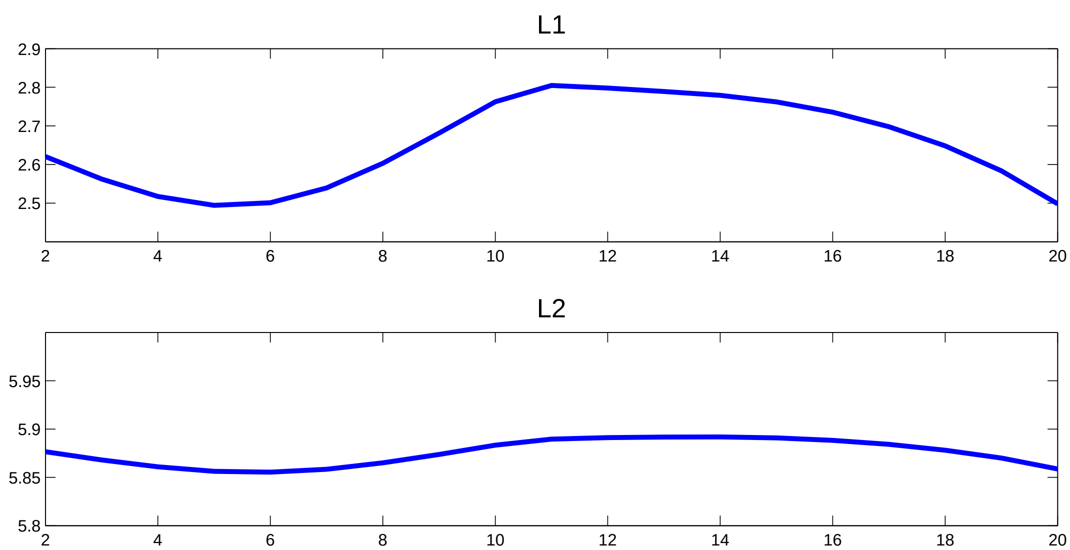


Figure 10: Effects from Both Types of Growth on Education Thresholds



are prohibitively high, and so most nerd activity is devoted to tinkering. The evolution of the early economy resembles the case displayed in figure 4, where wages tend to fall and rates of education tend to rise.

However, as both q and L_a rise, the costs of innovation begins falling. This induces an increasing share of nerds to produce new innovations instead of tinkering. Consequently N begins to rise. Further, as the economy grows the value of innovation itself (V) rises as the market scale for new innovations expand. This reinforces the growth in new machine blueprints.

Thus we have a framework for thinking on the transition from early industrialization to a modern growth regime. In this economy nerds transition from mostly tinkering to mostly innovating. This would seem basically consistent with the historical transition from early industrialization (with modest improvements in technologies and small rises in per capita GDP) to modern economic growth (with more breakthrough innovations and robust per capita growth) (Galor 2005, Khan 2015).

A feature that may be surprising however is that here modern growth is associated with falling rates of education. Yet this is wholly consistent with unbalanced technological progress where factors are compelled to work in less productive sectors of the economy (Baumol 1967) if those sectors are less skill-intensive. Here we provide a cautionary tale that when education is devoted to sectors with the potential for technological improvement, such improvement can in fact lower the incentives for education. Service occupations such as food service workers, hairdressers and beauticians, recreation occupations, security guards, janitors and gardeners, cleaners, home health aides and child care workers become more attractive positions and require little formal education. In order to understand how education advanced so rapidly in the United States during the early 20th century then, one must look to factors such as institutional or governmental support, as described extensively by Claudia Goldin and others (Goldin 03).

Finally, the implications for future growth are in one sense bleak. They suggest that as L_a continues to fall, the costs for subsequent innovation rise to the point where nerds inevitably go back to mostly tinkering. This simple framework also suggests that economies can face waves of tinkering and breakthrough innovation. The "techno-pessimism" of our current age may be in part a function of prohibitively high costs of true innovation. The goods news is that this can pave the way for later technological marvels. Governments can potentially help speed the transition by subsidizing the accumulation of abstract skills, or raising the scale of the market for breakthroughs (Acemoglu and Linn 2004). The structure developed here allows policy makers to consider certain factors to ensure that robust innovative activities continue to grow their economies.

4 Conclusion

This paper explores the interactions between different forms of technological changes and different types of skilled labor. We derive a number of new insights in order to better understand the evolution of technologies and human capital over the last few centuries.

Given the technological cycles generated by the model, one might wonder about the possible phase of economic growth we in the United States currently find ourselves. In truth we see aspects of both. On the one hand, techno-pessimistic grumblings about low productivity growth and job insecurity suggests the presence of a "tinkering" economy. Yet we also see evidence of skill and employment polarization, which in our model is consistent with more robust technological activity.

While what we present here is a closed macro model designed to represent the overall economy, countries might be better characterized as a series of economies spatially integrated (Autor and Dorn 2013). Such an extension may help us further explore which regions are better characterized as tinkering economies (marked by burgeoning informal sectors and job displacement) and which as fundamentally innovating ones (with robust *overall* wage growth).

Another aspect is to look at the economic evolutions of different economies to see if there is any evidence of such technological cycles over the long run. Evidence of technological slowdowns and re-emphasis on tinkering may motivate educational policies designed to help spur virtuous feedback between high-level human capital and innovative breakthroughs.

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