MIT 14.662 Graduate Labor Economics II Spring 2009 Lecture Note 3: Skill-Biased Technological Change and Wage Structure: Many Hypotheses and Some Evidence

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1 Lecture Note 3: Technical Change, Organizational Change and Wage Structure

We now address the evidence on the contribution of technical and organizational change to changes in the wage structure. From my perspective, there are at rough six classes of hypotheses that have appeared in the literature:

1. Capital-skill complementarity, or a more sophisticated variant such as Beaudry and Green 2003 in the *AER* (which I will cover after trade theory).
2. Correlations and timing: Computer technology and skill upgrading
3. Characteristics of technology and tasks: Changes in the organization of work
4. Nelson/Phelps 'disequilibrium' view
5. Changes in market structure
6. Endogenous acceleration view

We will have something (briefly) to say about each of them.

2 Capital-skill complementarity

In 1969, Zvi Griliches advanced the hypothesis that capital and skill are relative complements. [Be sure you are clear what it means for two goods to be complements, and that you can distinguish between p-complementarity and q-complementarity.] By this he meant that although capital is likely to be complementary to both skilled and unskilled labor, it tends to be more complementary to skilled labor.

If this hypothesis is correct, capital deepening—that is the process of capital accumulation—will tend to increase the relative demand for skilled labor. Under this hypothesis, explicit technical change per se is not needed to explain rising skill demands (though one might think that there is a deeper model of technical change underlying this). We simply need capital accumulation.

As stressed in the 1st lecture note, this hypothesis is clearly wrong if one takes it to apply to all times and places in even recent human history. The capital deepening the 19th century (i.e., the factory system) was probably quite complementary to unskilled labor. But it could potentially be a valid hypothesis for the post-WWII era.

2.1 The Declining Price of Equipment Capital: Krussell, Ohanian, Rios-Rull and Violante 2001 (*Econometrica*)

The paper that takes this idea most seriously is Krussell, Ohanian, Rios-Rull and Violante (2001 *Econometrica*). They build on an interesting fact observed by Gordon that the relative price of capital equipment has been falling steadily in the postwar period. Moreover, this rate of decline of equipment prices *may have* accelerated sometime during the mid to late 1970s. This observation, combined with the assumption of capital-skill complementarity, could potentially give rise to an increase in the relative demand for skilled labor.

KORV consider the following aggregate production function

$$Y = K_s^{\alpha}\left[b_1 L^{\mu} + (1-b_1)\left(b_2 K_e^{\lambda} + (1-b_2)\, H^{\lambda}\right)^{\mu/\lambda}\right]^{(1-\alpha)/\mu}$$

where K_s is structures capital (such as buildings), and K_e is equipment capital (such as machines), and $b_1, b_2 \in [0,1]$.

- Notice that structures capital K_s enters this production function Cobb-Douglas style—so there is no capital-skill complementarity between structures and skilled labor.

- The parameter $\sigma_{es} = 1/(1-\lambda)$ is the elasticity of substitution between equipment and skilled workers

- The parameter $\sigma_{us} = 1/(1-\mu)$ is the elasticity of substitution between unskilled workers and the equipment-skilled worker aggregate.

- [Note that a similar theoretical model is used by Autor, Acemoglu and Lyle 2004. You could consult that paper for an alternative exposition if you don't find KORV clear.]

- If $\sigma_{es} < \sigma_{us}$ (i.e., $\mu > \lambda$), equipment capital is more complementary (less substitutable) to skilled workers than unskilled workers, and as a result, an increase in K_e will increase the wages of skilled workers more than the wages of unskilled workers.

The skill premium in this model is

$$\omega = \frac{w_H}{w_L} = \frac{(1-b_2)(1-b_1)\, H^{\lambda-1}\left(b_2 K_e^{\lambda} + (1-b_2)\, H^{\lambda}\right)^{(\mu-\lambda)/\lambda}}{b_1 L^{\mu-1}}$$

Differentiation shows that as long as $\mu > \lambda$, $\partial\omega/\partial K_e > 0$. So provided that equipment capital is more complementary to skilled workers than unskilled workers, an increase in the quantity of equipment capital will increase the demand for skills. Since the post-war period has been characterized by a decline in the relative price of equipment goods, there will be an associated increase in the of equipment capital, K_e, increasing the demand for skills steadily.

KORV estimate this model and find that declining price of equipment capital can explain a large share of the rise in relative demand for skilled workers in the United States.

But there are a number of problems with this explanation that limit its plausibility:

1. First, it is hard to develop much confidence in measures of the real or even relative price of capital. Due to issues of simple measurement, quality change and inflation, one needs to be quite skeptical about making too much of a potential change in the rate of change (i.e., the second derivative) of a price series. While no economist would dispute that the price of capital equipment declined dramatically in recent decades (computers being the best example), whether that rate has increased or decreased in a given period is much harder to prove. (This same point applies to the debate about acceleration/steady demand in the labor market, and is one reason that this debate is unlikely to be satisfactorily resolved.)

2. One would generally expect a decline in the price of capital to yield faster productivity growth and higher living standards, etc.

    - As we discussed in the first lecture, incomes stagnated in exactly the period when relative equipment prices were ostensibly declining. It is hard to reconcile vast technological improvements with declining or stagnating living standards (although you can be sure that many authors have tried). Moreover, it is hard to see how this hypothesis can explain falling *real* (in addition to relative) wages of less-skilled workers. Since the equipment-high-skill CES aggregate is a q-complement of low-skilled workers, capital deepening should also *raise* real wages of low-skilled workers, even if it raises wages of high-skilled workers by more.

    - [Note this point above should be distinguished from the idea that technical change is skill-biased. A skill-biased technological shift does not have to raise living standards by a great deal to substantially affect relative earnings (a point made by Krugman in his 2000 *Journal of International Economics* article). But a rapid decline in the real price of capital should directly raise real living standards.]

3. Probably the most damaging evidence against the simple capital-skill complementarity explanation is empirical.

   - Katz-Autor [1999] write, "Their [KORV] measure of the capital-skill complementarity effect on relative wages evolves similarly to a linear time trend. Thus the aggregate time series model of Krusell et al. (1997) attributes variations in changes in the skill premium around trend (such as a sharp decline in the skill premium in the 1970s and sharp rise in the 1980s) to variations in the rate of growth of the relative skill supplies and to unobserved demand shocks (the residual)."
   - Translation: the KORV time series on capital equipment prices is not the variable providing the explanatory power in their model; it is primarily the supply measure that is affecting the skill premium as in the Katz-Murphy model.
   - Acemoglu (2002) makes this point more forcefully. He estimates the Katz-Murphy regression augmented with the KORV series for relative capital prices and a simple linear time trend. As Table 2 of Acemoglu shows, the KORV measure performs less well than a linear time trend. In fact, it is never significant when a time trend is included.
   - Hence, the KORV analysis is elegant but not especially persuasive. Moreover, it is widely misunderstood in that most readers of KORV appear to believe that it is the equipment-price variable that is doing the work in their model. Actually, it appears that KORV primarily rediscovered the Katz-Murphy results: relative supplies plus a linear time trend do a very good job of explaining relative wages of skilled versus unskilled in the U.S. for the last 40 years.

2.2 Competing Organizational Forms and Skill Supply: Acemoglu 1999 *AER*

The 1999 *AER* paper by Acemoglu considers a model that is conceptually related to B&G but does not make use of the crucial capital-efficiency assumption. Acemoglu considers a search model in which firms can use two types of technology: one that uses only high skill workers and the second that uses both high and low skill. The former technology has higher TFP conditional on having a high skill workforce. But if high skill workers are relatively rate, they will have a low arrival rate in the search model. This makes it costly to open vacancies using the strongly skill-dependent technology. Hence, firms will primarily use the mixed technology. However, an exogenous increase in skill supply may induce firms to open skill-dependent jobs. This will raise wages of high skill workers (since they are more productive in the skill-dependent sector) but lower wages of low-skill workers (under the assumption that high and low skill workers are q-complements under the mixed technology).

This model is analytically complex, which may be a virtue if you are a search theorist, otherwise probably not. Acemoglu's 2002 *JEL* paper offers a much simpler alternative that has the same flavor. There is a scarce supply of some factor K, which could be capital or entrepreneurial talent, for example. Skilled workers work with the production function

$$Y_h = A_h^{\alpha} K_h^{1-\alpha} H^{\alpha},$$

and unskilled workers work with the production function

$$Y_l = A_l^{\alpha} K_l^{1-\alpha} L^{\alpha},$$

where Y_h and Y_l are perfect substitutes and $K_l + K_h = K$. Observe: if both production functions are in use, the return to capital K must be equated across H and L sectors.

Now consider a factor-augmenting technological change, specifically an increase in α_h. This raises productivity in the H sector, which increases the return to K in the H sector (since K and H are q-complements). To equilibrate the return to capital across sectors, K must flow from the L sector to the H sector. Given the q-complementarity between K and L, wages of L workers must fall.

Hence, this model also generates a falling wage of low-skilled workers. This model also implies a rise in the return to K. So, if K is elastically supplied—that is, the stock of K rises until returns fall back to the prior level—the real wages of low-skill workers do not fall.

The key difference between this simple version of the Acemoglu model and the B&G model above is that in the B&G model, the rising supply of skilled workers causes work to reallocate from the low-skill to high-skill sector, ultimately leading to capital starvation in the low-skill sector. In the short Acemoglu model, by contrast, traditional, factor-biased technical change leads to rising demand for high skilled workers. But again, it is the inelastic supply of capital that allows low skilled wages to fall.

2.3 Correlations and timing: Computer technology and skill upgrading

The analysis by Autor, Katz, Krueger discussed earlier suggests that there was some acceleration in the skill-bias of technical change in the 1970s or 1980s. Many economists believe that the advent of computerization is in part responsible. Should you believe this?

1. The first piece of evidence often put forth in support of an acceleration relates to the role of computers in the labor market.

    - Krueger (1993) has argued that computers have changed the structure of wages, and showed that workers using computers are paid more, and this computer wage premium has increased over time.
    - Although this pattern is striking, it is not particularly informative about the presence or acceleration of skill-biased technical change. It is hard to know whether the computer wage premium is for computer skills, or whether it is even related to the widespread use of computers in the labor market. For example, DiNardo and Pischke (1997), and Enhorf and Kramarz (1998) show that the computer wage premium is likely to be a premium for unobserved skills. Equally, however, it would be wrong to interpret the findings of DiNardo and Pischke (1997) and Enhorf and Kramarz (1998) as evidence against an acceleration in skill-biased technical change, since, as argued below, such technical change would increase the market prices for a variety of skills, including unobserved skills.

2. The second set of evidence comes from the cross-industry studies of, among others, Berman, Bound and Griliches (1994), Autor, Katz and Krueger (1998), and Machin and Van Reenan (1998).

    - These papers document that almost all industries began employing more educated workers during the 1970s and the 1980s. (See Machin and Van Reenan, Figure I or Autor, Katz, Krueger Table III).

- The fact that skill upgrading occurred primarily within industries during the 1980s *despite* the rising price of skill is a critical piece of evidence. For given technology, standard production theory predicts that industries should substitute towards unskilled workers in response to a skill price increase. (Note: this implies that sectoral shifts will accommodate changes in quantities of skilled workers available.)

- The fact that within-industry substitution against skilled workers did *not* occur—in fact, just the opposite—is a critical observation that we will return to when we discuss the evidence on the competing roles of trade and technology. We'll discuss this evidence in more detail when we examine the debate over trade and skill demands.

3. A third piece of evidence consistent with SBTC is the striking correlations between computerization and other high-tech capital investments and cross-industry patterns of skill upgrading.

    - AKK show that more computerized industries have experienced more rapid *skill upgrading*, i.e., they have increased their demand for college-educated workers more rapidly. (See AKK, Figure I). For example, AKK run regressions of changes in the college wage-bill share in three digit industries on computer use between 1984 and 1993. They find, for example, that

$$
\begin{array}{rll}
\Delta Sc_{80-90} = & \underset{(.108)}{.287} & + \; \underset{(.046)}{.147}\Delta cu_{84-93} \\
\Delta Sc_{90-96} = & \underset{(.196)}{-.171} & + \; \underset{(.081)}{.289}\Delta cu_{84-93}
\end{array}
$$

    where ΔSc denotes the annual change in the wage bill share of college graduates in that industry (between the indicated dates), and Δcu_{84-93} is the increase in the fraction of workers using computers in that industry between 1984 and 1993.

    - These regressions are informative since the college wage bill share is related to the demand for skills. The results indicate that in an industry where computer use increases by 10 percent, the college wage bill share grows by about 0.015 percent faster every year between 1980 and 1990, and 0.03 percent faster in every year between 1990 and 1996.

- Although this evidence is suggestive, it does not establish that there has been a change in the trend growth of skill-biased technology. As pointed out above, the only way to make sense of post-war trends is to incorporate skill-biased technical change over the whole period. Therefore, the question is whether computers and the associated information technology advances have increased the demand for skills *more* than other technologies did during the 1950s and 1960s, or even earlier. This question *cannot be answered* by documenting that computerized industries demand more skilled workers.

- Cross-industry studies also may not reveal the true impact of computers on the demand for skills, since industries that are highly computerized may demand more skilled workers for other reasons as well. In fact, when Autor Katz and Krueger (1998) run the above regressions for 1960-1970 college wage bill shares, they obtain

$$\Delta Sc_{60-70} = \underset{(.058)}{.085} + \underset{(.025)}{.071}\Delta cu_{84-93}$$

  Therefore, industries investing more in computers during the 1980s were already experiencing more skill upgrading during the 1960s, before the arrival of computers (though perhaps slower, since the coefficient here is about half of that between 1980 and 1990).

- This suggests that at least part of the increase in the demand for skills coming from highly computerized industries may not be the direct effect of computers, but reflect an ongoing long-run shift towards more skilled workers. In this light, faster skill upgrading by highly computerized industries is not inconsistent with the steady-demand hypothesis. It is however noteworthy that the regression coefficient becomes larger in each decade (hence, a difference in difference model would show acceleration).

- While many economists date the 'computer era' to the advent of the PC (cf. Card and DiNardo, 2002), most data indicate that the period of rapid acceleration in computer investment began in the 1970s during the period of rapid introduction of mainframes, minicomputers, and workstations (cf. AKK, 1998, Appendix Table 2; Bresnahan, 1999 in the *Economic Journal).* This fact is potentially consistent with an acceleration in skill bias beginning in the 1970s.

4. As we discussed in an earlier lecture, one piece of macro evidence favoring an acceleration is skill demands is that the supply of skills grew faster between 1970 and 1995 than between 1940 and 1970—by 3.06 percent a year during the latter period compared to 2.36 percent a year during the earlier 30 years. In contrast, returns to college increased between 1970 and 1995 by about 0.39 percent a year, while they fell by about 0.11 percent a year during the earlier period. If demand for skills had increased at a steady pace, the skill premium should have also fallen since 1970.

   However, it is useful to bear in mind that the unusual increase in the demand for skills might be non-technological. It might reflect effect of increased international trade with skill-scarce countries, or it may reflect the collapse of some labor market institutions. Hence, this evidence should be kept in mind as consistent with SBTC but far from definitive proof.

3 Characteristics of technology and tasks: Microfoundations

The models discussed so far operate at a very high level. They posit a dramatic change in the organization of work but do not tell a detailed story about how specifically work organization has changed nor why this change has been especially demanding of skilled labor. It would be helpful to have a substantive theory of the nature of recent technological or organizational change that didn't ultimately boil down to the assumed sign on a derivative or the magnitude of some (ultimately unmeasurable) elasticity.

There is now a variety of theoretical and empirical work that offers explicit hypotheses on the link between computerization and changes in the content of work and organization of production. This work attempts to add microfoundations to the 'reduced form' approach. Some recent careful case studies are in my view among the richest material in this literature (which may suggest that economic theory would benefit if economic theorists would leave their desks more often). Ann Bartel, Casey Ichniowski, and Kathryn Shaw have performed detailed case studies of changing production technology in three industries: steel, medical devices, and valves. The 2007 QJE paper on your syllabus is specifically about the valve industry.

My interpretation of their main findings is as follows:

1. Information technology has removed much of the mechanized, repetitive, rote components of production. Many repetitive tasks are now performed by machines that coordinate and

monitor production. In the BIS valve study, computer-guided industrial lasers inspect completed valves for specification compliance with precision measured in microns. Previously, this time-consuming inspection step was done by hand. Similarly, the process of machine setup for new runs and the coordination of production as products move between machining phases have also been extensively computerized. This automation is feasible because computerized machining tools are far more flexible than older forms of capital. Much of the cumbersome reconfiguration of the assembly line needed for different products and batches is now handled directly by the machinery. All of these production changes are *process improvements*.

2. One consequence of the increased flexibility of the *process* is a change in the set of *products* produced. The valve firms studied by BIS, which are those that have continued producing in the U.S., have increasingly moved out of commodity production and into 'mass customization.' They exploit the flexibility of the new capital to do shorter runs of more complex products. This in turn requires greater flexibility on the part of the workforce. But notice that commodity valve manufacturing, which is increasingly performed overseas, may not be undergoing similar changes in skill demand. [A 2005 paper by Chong Xiang of Purdue in the *ReStat* ("New Goods and Rising Skill Premium: An Empirical Investigation") presents detailed evidence that *new goods* are increasingly skill intensive. This is valuable, representative evidence on the importance of product (rather than process) innovations for changing skill demands. I neglected to put this paper on the syllabus.]

3. Workers are increasingly required to use abstract reasoning to manage production. Whereas workers used to spend much of their time in contact with physical materials, much of the 'work' is now performed from the 'control pulpit' of highly automated factories where the key task is to monitor multiple assembly lines via large displays. The challenge is to be alert to problems as they arise and make subtle adjustments that improve efficiency, reduce error, enhance quality. In this setting, a good decision can have enormous value added and a bad decision can destroy large amounts of output.

4. Production work is frequently reorganized into teams where workers have responsibility for quality control and are required to solve problems and develop better ways to organize

production. As observed by BIS, and Bresnahan, Bryjolffson and Hitt (2002), and Caroli and van Reenan (2001) problem solving teams and other 'lean production techniques' are often paired with information technologies, suggesting that these Human newer Resource Practices (HRM) and IT are complements. (More on why this might be below...)

These observations are drawn from the manufacturing sector, which provides a declining share of employment in almost all advanced countries. How relevant are they to the service sector? Similar case studies for the service sector are not in abundance. One by Autor, Levy, Murnane (2002, ILRR) on the computerization of the back office check-processing function of a bank provides descriptive evidence that is consistent with the observations in Bartel, Ichniowski and Shaw (though the examples are not nearly as dramatic as those in manufacturing). In the bank studied by ALM, the introduction of Optical Character Recognition and electronic imaging of paper checks reduced the rote component of check processing for the 'exceptions processors,' reducing time spent on routine 'paper chase' activities and increasing time spent on problem solving and account management. Notably, for the 'check preparers' who perform the physical handling of the checks, there was little net change in skill demands—but there was a dramatic reduction in employment.

BIS specifically investigate four hypotheses:

1. New IT-enhanced machines improve production process efficiency. Setup time, run time, and inspection time fall after new IT-enhanced equipment in these stages is adopted.

2. New IT promotes product customization and innovation. New 3D-CAD technologies should directly affect the plant's capabilities of designing more customized valves, while other technologies that reduce setup time would also promote customization.

3. IT adoption may increase (or decrease) skill demand.

4. IT adoption may require new HRM practices.

The theoretical foundation for these hypotheses is BIS' observation that IT reduces setup time, which is otherwise particularly costly for customized, small batch jobs. This cost reduction differentially reduces the price of producing customized relative to commodity products. What happens when IT prices fall:

1. Firms purchase more IT
2. production efficiency rises, setup time, run time and inspectime time fall.
3. Firms make a strategic move towards producing more customized products. This is due to fall in setup times.
4. Optimal skill demand changes, but the direction is ambiguous. If setup is the most skill-intensive task (as seems likely), when setup time falls, skill demand falls. But the move to more setup-intensive products exerts a countervailing force. Third, IT-based machinery increasingly displaces routine tasks, thereby raising skill content of labor input. This goes in the direction of increasing skill requirements.
5. Finally, new HRM practices may complement use of higher skill levels or new machinery, though a microfoundation for this idea is not given.

3.1 Microfoundations for Technologies and Tasks (and a Test of Sorts): A Framework (ALM **2003** *QJE*)

- There have been a variety of efforts to formalize the observations from these closely observed studies. One is given by Autor, Levy and Murnane (2003). They take a 'task-based' approach to understanding the 'skill-content' of technical change: modeling the human tasks that computers complement and those for which they substitute.
- ALM argue that the 'skill bias' of recent technological change is non-monote, in contrast to what the simplest capital-skill complementarity stories would suggest. Their argument, focusing on the role of computerization, has three papers:
    1. Computer technology has two intrinsic characteristics. One, it can process symbols, meaning that it can execute *any* well specified information processing task. Two, its capability is circumscribed by what programmers, engineers and scientists know how to describe using computer code. This is more limiting than it might seem. Many tasks involving vision, locomotion, problem solving, pattern recognition, language interpretation and communication cannot current be described with computer code—that is, we do not know 'the rules'—even though we accomplish these tasks almost effortlessly.

2. Because of these properties, computers are primarily used to substitute for 'routine' tasks—those that are readily formalized and 'routinized' in computer code—while complementing 'non-routine' cognitive tasks such as problem solving.
3. Although computer technology's core attributes are static (that is, it hasn't fundamentally changed in 200 years), the price of computer capital has fallen considerably. Nordhaus 2001 ("The Progress of Computing") writes, "There has been a phenomenal increase in computer power over the twentieth century. Performance in constant dollars or in terms of labor units has improved since 1900 by a factor in the order of 1 trillion to 5 trillion, which represent compound growth rates of over 30 percent per year for a century." It is this (assumed) exogenous price decline that is the driving force in the ALM model.

- The conceptual building blocks of the ALM framework are given in Table 1 of their paper.
- The ALM model makes three assumptions that appear reasonably well motivated by the qualitative evidence above.

1. Computer capital is more substitutable for humans in carrying out routine tasks than non-routine tasks (this is similar to Krussell et al. in *Econometrica*).
2. Routine and non-routine tasks are themselves imperfect substitutes.
3. Third, at least for cognitive tasks, greater intensity of routine inputs increases the marginal productivity of non-routine inputs (Q-complements).

- The ALM model is derived below. I probably will not spend much time on this in class. You are not responsible for the specifics of this model. You may or may not find the derivation interesting.

3.1.1 Production

- ALM embed these three assumptions in a framework that nests a Roy (1951) model—whereby workers self-select the sector where they hold comparative advantage—inside a simple Cobb-Douglas production framework. (See also the 2006 Autor-Katz-Kearney NBER Paper #11986 which presents a slightly richer—and probably simpler—version of this model.)

- Specifically, the ALM model is built on production function with 'two tasks:'

$$Q = (L_r + C)^{1-\beta} L_n^{\beta} \tag{1}$$

where N, R are efficiency units of Routine and Non-Routine labor inputs and C is computer capital. (note, they are combined Cobb-Douglas, meaning that $\sigma_{rn} = 1$).

- Computer capital is supplied perfectly elastically at market price ρ per efficiency unit ALM assume that computer capital is a perfect substitute for routine tasks (this assumption can be weakened of course), where ρ is falling exogenously with time due to technical advances. *The declining price of computer capital is the causal force in the model.*

- Three observations on this prod'n function:

  1. C and L_r are perfect substitutes
  2. Routine and nonroutine labor inputs are Q-complements: doing more of one raises the marginal productivity of the other
  3. The elasticity of substitution σ between L_r and L_n is 1 due to the Cobb-Douglas production structure. This means that computer capital is more substitutable for routine than nonroutine labor. By implication, computer capital and nonroutine labor are *relative complements.*

3.1.2 Labor supply

- Assume a large number of income-maximizing workers, each of whom inelastically supplies one unit of labor.

- Workers have heterogeneous productivity endowments in both routine and non routine tasks, with $E_i = [r_i, n_i]$ and $1 > r_i, n_i > 0 \; \forall \; i$. A given worker can choose to supply r_i efficiency units of routine task input, n_i efficiency units of nonroutine task input, or any convex combination of the two. Hence, $L_i = [\lambda_i r_i, (1 - \lambda_i) n_i]$ where $0 \leq \lambda \leq 1$. [In equilibrium, each worker will choose to specialize in one task or the other. Choices will differ among workers.]

- These assumptions imply that workers will choose tasks according to comparative advantage as in Roy [1951]. Hence, relative task supply will respond elastically to relative wage levels. [If instead workers were bound to given tasks, the implications of the model for task productivity would be unchanged, but technical progress, reflected by a decline in ρ, would not generate re-sorting of workers across jobs.]

3.1.3 Equilibrium conditions

Two conditions govern equilibrium in this model:

1. Given the perfect substitutability of routine tasks and computer capital, the wage per efficiency unit of routine task input is pinned down by the price of computer capital:

$$w_r = \rho. \tag{2}$$

   Computer capital in this model is a directly skill-replacing technology and advances in computer technology lower the wages of workers for whom computers are a substitute.

2. Worker self-selection among tasks—routine versus nonroutine—must clear the labor market.

- Define the relative efficiency of individual at nonroutine versus routine tasks as

$$\eta_i = n_i / r_i. \tag{3}$$

  Our assumptions above imply that $\eta_i \in (0, \infty)$.

- At the labor market equilibrium, the marginal worker with relative efficiency units η^* is indifferent between performing routine and nonroutine tasks when

$$\eta^* = \frac{w_r}{w_n}. \tag{4}$$

- Individual i supplies routine labor ($\lambda_i = 1$) iff $\eta_i < \eta^*$, and supplies nonroutine labor otherwise ($\lambda_i = 0$). (Note that λ equals either zero or one—a result of the model not an assumption.) So, if $\frac{w_r}{w_n}$ falls (the relative wage of nonroutine tasks rises), labor supply to nonroutine tasks rises.

- To quantify labor supply, write the functions $g(\eta)$, $h(\eta)$, which sum population endowments in efficiency units of routine and nonroutine tasks respectively at each value of η.

So, $g(\eta) = \sum_i r_i \cdot 1\{\eta_i < \eta\}$ and $h(\eta) = \sum_i r_i \cdot 1\{\eta_i \geq \eta\}$ where $1\{\cdot\}$ is the indicator function. We further assume that η has non-zero support at all $\eta \in (0, \infty)$, so that $g(\eta)$ is continuously upward sloping in η, and $h(\eta)$ is continuously downward sloping.

- Assuming that the economy operates on the demand curve, productive efficiency requires:

$$w_r = \frac{\partial Q}{\partial L_r} = (1-\beta)\,\theta^{-\beta} \text{ and } w_n = \frac{\partial Q}{\partial L_n} = \beta\theta^{1-\beta}, \tag{5}$$

where $\theta = (C + g(\eta^*))/h(\eta^*)$, is the ratio of routine to nonroutine task input in production.

- It is now an easy step to solve for the model's 5 endogenous variables: $(w_r, w_n, \theta, C, \eta)$.

3.1.4 Solution

- We know that a decline in the price of C must reduce w_r one-for-one: $\partial \ln w_r / \partial \ln \rho = 1$. Using equation (5), this implies that

$$\frac{\partial \ln \theta}{\partial \ln \rho} = -\frac{1}{\beta}.$$

(b/c $\ln w_r = \ln(1-\beta) - \beta \ln \theta$, hence $\partial \ln w_r / \partial \ln \theta = -\beta\,(\partial \ln \theta / \partial \ln \rho)$. So, if $\partial \ln w_r / \partial \ln \rho = 1$, this implies $\partial \ln \theta / \partial \ln \rho = -1/\beta$.)

- By implication—and not surprisingly—the economy becomes more 'routine-task-intensive' when the price of computer capital falls.

- From the perspective of producers, the rise in routine task demand could be met by either an increase in C or an increase in L_r (or both). Only the first of these will occur. Because routine and nonroutine tasks are q-complements, the relative wage paid to nonroutine tasks rises as ρ declines:

$$\frac{\partial \ln (w_n/w_r)}{\partial \ln \rho} = -\frac{1}{\beta} \text{ and } \frac{\partial \ln \eta}{\partial \ln \rho} = \frac{1}{\beta}.$$

Consequently, marginal workers reallocate labor input from routine to nonroutine tasks. This means that increased demand for routine tasks is met by an influx of computer capital not labor.

- So, an exogenous decline in the price of computer capital raises the marginal productivity of nonroutine tasks, causing workers to reallocate labor supply from routine to nonroutine task input. Although routine labor input declines, an inflow of computer capital more than compensates, yielding a net increase in the intensity of routine task input in production..

3.1.5 Industry level implications

- Does this model have testable microeconomic implications? So far, no. Because the causal force in the model is the price of computer capital, we have only a single macroeconomic time series available.

- ALM argue that additional leverage may be gained by considering equation (1) as representing the production function of a single industry, with distinct industries j producing outputs q_j that demand different mixes of routine and nonroutine tasks.

- Write the production function for industry j as,

$$q_j = r_j^{1-\beta_j} n_j^{\beta_j},$$

where β_j is the industry-specific factor share of nonroutine tasks, and r_j, n_j denote the industry's task inputs. All industries use Cobb-Douglas technology, but industries with β_j smaller are more routine task intensive.

- Assume that consumer preferences in this economy can be represented with a Dixit-Stiglitz (*AER*, 1977), utility function,

$$U(q_1, q_2, ..., q_J) = \left(\sum_j q_j^{1-\nu} \right)^{\frac{1}{1-\nu}},$$

where $0 < \nu < 1$. The elasticity of demand for each good is $-1/\nu$, with the market clearing price inversely proportional to the quantity produced: $p_j(q_j) \propto q_j^{-\nu}$. The key feature of this utility function is that all goods are gross-substitutes and demand for each is elastic. With many goods, one approaches constant elasticity of demand for each good. (This follows because the expenditure share for any one good is negligible so one can effectively ignore the cross-price effects.)

- Industry profit maximization yields the following first order conditions for wages:

$$\begin{aligned} w_r &= n_j^{\beta_j} r_j^{-\beta_j} \left(1-\beta_j\right)(1-\nu)\left(n_j^{\beta_j} r_j^{-\beta_j}\right)^{-\nu}, \\ w_n &= n^{\beta_j - 1} r^{1-\beta_j} \beta_j (1-\nu)\left(n_j^{\beta_j} r_j^{-\beta_j}\right)^{-\nu}. \end{aligned}$$

- Rearranging to obtain factor demands gives

$$\begin{aligned} n_j &= w_n \left(\beta_j (1-\nu)\right)^{1/\nu} \left(\frac{w_n}{\rho} \cdot \frac{\left(1-\beta_j\right)}{\beta_j}\right)^{\frac{\left(1-\beta_j\right)(1-\nu)}{\nu}}, \\ r_j &= w_r \left(\left(1-\beta_j\right)(1-\nu)\right)^{1/\nu} \left(\frac{w_n}{\rho} \cdot \frac{\left(1-\beta_j\right)}{\beta_j}\right)^{\frac{\beta_j (1-\nu)}{\nu}}, \end{aligned}$$

  which are kind of messy.

- Two or three propositions follow from these equations:

  1. Although all industries face the same price of computer capital, the degree to which industries adopt computer capital as its price declines depends upon β_j. For a given price decline, the proportionate increase in demand for routine task input is larger in routine task intensive (β_j small) industries, as may be seen by taking the cross-partial derivative of routine task demand with respect to ρ and β_j:

  $$\frac{\partial \ln r_j}{\partial \rho} = \frac{\beta_j (1-\nu) - 1}{\nu \rho} < 0 \text{ and } \frac{\partial^2 \ln r_j}{\partial \rho \partial \beta_j} = \frac{1-\nu}{\nu \rho} > 0.$$

     Although we cannot observe β_j, a logical proxy for it is the observed industry level of routine task input in the pre-computerization era. We can therefore test whether industries that were historically (i.e., pre-computer era) intensive in routine tasks adopted computer capital to a greater extent than industries that were not.

  2. Due to the complementarity between routine and nonroutine inputs, a decline in the price of computer capital also raises demand for nonroutine task input. This demand increase is proportionately larger in routine task intensive industries:

  $$\frac{\partial \ln n_j}{\partial \rho} = \frac{\left(\beta_j - 1\right)(1-\nu)}{\nu \rho} < 0 \text{ and } \frac{\partial^2 \ln n_j}{\partial \rho \partial \beta_j} = \frac{1-\nu}{\nu \rho} > 0.$$

Recall, however, that labor supply to routine tasks declines with ρ. Rising routine task demand must therefore be satisfied with computer capital. Hence, sectors that invest relatively more in computer capital will show a larger rise in nonroutine labor input and a larger decline in routine labor input.

3. Analogously (by an informal argument), ALM suggest that occupations that make relatively larger investments in computer capital will, for the same reasons, show larger increases in labor input of nonroutine tasks and larger decreases in labor input of routine tasks.

3.1.6 ALM and related empirical evidence

Using the *Dictionary of Occupational Titles*, which provides observational measures of job content in representative occupations in the U.S. over several decades, ALM provide a number of pieces of evidence indicating this 'task based' story has empirical traction:

1. The skill content measures move as predicted over 1960 - 1998 (Figure I).
2. ALM find task movement in the predicted direction along 3 margins:
   (a) Within industries: Industries that computerize change task input as predicted, and this relationship grows much more pronounced with time. (Table III)
   (b) Within education groups within industries: Industries that computerize relative more change task input even among workers with identical education. So, industry-level computerization is not simply mechanically reflecting educational upgrading but is correlated with changes in the structure of task changes among workers at all education levels. (Table V)
   (c) Within occupations: Using data from successive editions of the DOT, ALM find that occupations that intensively computerized also experienced large declines in routine cognitive tasks and increases in cognitive analytic content. (Table VI)
3. The ALM framework also predicts where computers should have been adopted: Industries with high levels of routine task content should have become computer intensive as the

price of computing fell. They find this

$$\text{Computer adoption}_{j,1960-1997} = \underset{(19.18)}{-24.56} \underset{(0.48)}{+1.85} \times \text{Routine Task Share}_{j,1960}$$

$$R^2 = 0.10,\ n = 140$$

The paper by Alexandra Spitz on your syllabus uses much better data German to explore a similar set of task changes over 1979 - 1999. Surprisingly, her evidence is quite consistent with ALM. Her paper also potentially opens a new chapter in the debate over why wage structure changes occurred in the U.S. but not continental Europe. As noted in class, one of the huge puzzles of the SBTC literature is that almost all of the evidence linking technical change to wage structure changes comes from the U.S. and the U.K. By contrast, continental Europe—which presumably has access to the same technology—has not had the same surge of inequality. And the two biggest 'slackers' are France and Germany. This puzzle is discussed by Piketty and Saez in the QJE, by Krueger and Pischke in their widely cited book chapter on "Observations and Conjectures on the U.S. Employment Miracle," by Card, Kramarz and Lemieux (1999), etc. This pattern has caused Piketty and Saez to advance "Social norms" rather than demand shifts as an explanation for rising inequality in the Anglo countries relative to continental Europe.

Spitz's paper offers a new angle of attack on this question. Rather than focusing on wage structure changes—which are a long run outcome of changes in skill demand, possibly strongly mediated by labor market institutions—Spitz instead analyzes the link between changing technology and changing job tasks—a primitive in any skill-bias story. Here, Spitz demonstrates that in Germany, as in the United States: 1) job skill requirements have been strongly rising along the lines predicted by ALM; 2) these changing skill requirements are all strikingly concentrated in computer-using occupations.

So, the Spitz paper possibly moves the debate forward by reframing the puzzle of the U.S. versus continental Europe (at least for Germany): rather than asking why SBTC has changed skill requirements in the US/UK but not continental Europe, it may be fruitful to ask why similar changes in skill requirements in Anglo countries and continental Europe have not lead to similar changes in wage structures.

An interesting paper by Goos and Manning (2003) takes another line of attack on the question of changing skill requirements. G&M note that the ALM task framework implies a 'polarization' of the distribution of jobs, with growth of very low and very high skill positions (non-routine manual and non-routine cognitive) and a culling of the ranks of 'medium skill' jobs such as accountants, clerical workers, insurance adjusters, etc. G&M take this idea to the data and find evidence for "Lousy and Lovely Jobs: The Rising Polarization of Work in Britain." (See the paper for details.)

3.1.7 Other evidence on organizational change

Caroli and Van Reenan study—in a reduced form manner—the impact of work reorganization on skill demands. They provide evidence from British and French establishments that measures of organizational change—such as decentralization of authority—have a strong predictive power for the demand for skills at the establishment level, even after controlling for other determinants of the demand for skills, such as computers.

Bresnahan, Brynjolfsson and Hitt (2000) provide U.S. based evidence in a similar vein. Neither of these studies get a great deal further than documenting correlations between reorganization and skill input, but the correlations are striking.

In sum, this evidence brings the debate beyond the 'black-box' level towards an understanding of *why* computerization is so strongly associated (at the cross-country, national, industry, and plant level) with increased use of non-production and better-educated workers in production. As above, one does not have to subscribe to the 'accelerationist' view of SBTC to believe that computer technology has intrinsic characteristics that distinguish it from previous technologies and that these characteristics are shaping workplace (re-)organization.

Note, however, that none of the evidence in these papers rises to the experimental or quasi-experimental standard that many applied microeconomists strongly favor. In Professor Acemoglu's words, "you could drive a truck through the holes in the identification strategies of all of these papers." The world awaits better evidence on the validity (or lack thereof) of these hypotheses linking computerization to changes in skill demands. Perhaps you will produce this evidence. (Also see the paper by Ethan Lewis on choice of technique that we will discuss later in the term.)

4 Understanding the Polarization of Employment *and* Wage Growth (Autor and Dorn, 2008)

5 Theoretical framework

Building on work in ALM (2003) and Weiss (2008), this section offers a simple theoretical model to explore the effects of ongoing, routine task-replacing technological change on three general equilibrium outcomes: the allocation of labor among competing low-skilled activities (in particular, routine versus manual tasks); the scale of service employment; and the inequality of wages between high and low-skill workers.

5.0.8 Environment

We consider an economy with two consumption items, goods and services, $j = g, s$ and four factors of production. Three of these factors are labor (task) inputs: Manual, Routine and Abstract $(L = m, r, a)$. These labor inputs are supplied by two types of workers, $i = H, U$. The fourth factor of production is computer capital. In each sector, a continuum of mass one of firms produce consumption goods.

Production of Goods combines Routine labor, Abstract labor, and computer capital (K), measured in efficiency units, using the following technology:

$$Y_g = L_a^{1-\beta} \left[(1-\lambda) (\alpha_r L_r)^{\mu} + \lambda (\alpha_k K)^{\mu} \right]^{\beta/\mu}, \tag{6}$$

with $\beta, \mu \in (0, 1)$. In this production function, the elasticity of substitution between Abstract labor and the Routine task input is 1 while the elasticity of substitution between Routine labor and computer capital is $\sigma_r = 1/(1-\mu)$ and, by assumption, is greater than 1. By implication, K is a *relative complement* to Abstract labor and a *relative substitute* for Routine labor.[1]

The second sector, which produces Services, uses only Manual labor, measured in efficiency units as L_m:

$$Y_s = \alpha_s L_m, \tag{7}$$

where $\alpha_s > 0$ is an efficiency parameter. We will normalize α_s to 1 in the rest of the paper, and so α_r may be thought of as a relative efficiency term.

There is a continuum of mass one of high-skilled workers, H, who are fully specialized in Abstract labor. Each H worker supplies Abstract labor inelastically to the good sector.

[1] In the Theory Appendix, we also consider the case where $\mu < 0$ and so L_r and K are gross complements.

There is a continuum of mass one of low-skilled workers, U, each of whom supplies either Manual or Routine labor. Low-skill workers have homogeneous skill at performing manual tasks. If all U workers were to perform manual tasks, they would supply a unit mass of Manual labor.

Low-skilled workers have heterogeneous skills in performing Routine tasks. Let η equal a worker's skill in routine tasks, measured in efficiency units, with density and distribution functions $f(\eta)$ and $F(\eta)$. There is a mass of one of potential Routine labor input: $\int \eta f(\eta)\, d\eta = 1$. Each worker of type U supplies labor inelastically to the task offering the highest income level given her endowment, η.

It is convenient to choose a functional form for $f(\eta)$ to permit analytic solutions of the model. The choice of functional form is innocuous, however, since the long run equilibrium of the model (i.e., as $t \to \infty$) depends on technology and preferences, not on labor supply per se. Let η be distributed exponentially on the interval $[0, \infty]$ with $f(\eta) = e^{-\eta}$.

Computer capital, K, is produced and competitively supplied using the following technology:

$$K = Y_k(t)\, e^{\delta t}/\theta. \tag{8}$$

where $Y_k(t)$ is the amount of the final consumption good allocated to production of K, $\delta > 0$ is a positive constant, and $\theta = e^{\delta}$ is an efficiency parameter. Productivity is rising at δ, reflecting technological progress. At time 1, one unit of the consumption good Y can be used to produce one efficiency unit of computer capital:

$$1 = e^{\delta}/\theta. \tag{9}$$

Competition will guarantee that the real price of computer capital (measured in efficiency units) is equal to marginal (and average) cost. So, at time $t = 1$, $p_k = 1$. As time advances, this price falls, with

$$p_k = \frac{Y_k}{K} = \theta e^{-\delta t}. \tag{10}$$

All workers/consumers have identical CES utility functions defined over consumption of Goods and Services:

$$u_i = \left(c_{si}^{\rho} + c_{gi}^{\rho}\right)^{1/\rho}, \tag{11}$$

$$\text{where } \rho < 1. \tag{12}$$

The elasticity of substitution in consumption between goods and services is $\sigma_c = 1/(1-\rho)$. Consumers hold equal shares of all firms.

Consumers take prices and wages as given and maximize utility subject to the budget constraint that wages equal consumption. Firms maximize profits taking the price of consumption goods and wages as given. The CRS technology insures that equilibrium profits will be zero.

Of interest in this model is the long-run (as $t \to \infty$) allocation of low-skilled labor to goods and services, and the evolution of inequality, measured by the Manual to Abstract and Manual to Routine wage ratios.

5.1 Equilibrium

We normalize the price of good g to 1, i.e. $p_g(t) = 1$ for all t, without loss of generality. We can define the equilibrium as follows.

Definition 1 *An equilibrium in this economy is a tuple of aggregate allocations and prices* $(Y_s(t), Y_g(t), C_s(t), C_g(t), K(t), L_a(t), L_m(t), L_r(t), p_s(t), w_a(t), w_m(t), w_k(t))$ *and a cut-off skill for unskilled workers* $\eta^*(t)$ *such that*

1. *The representative consumer maximizes* (11) *subject to the budget constraint*

$$C_g(t) + C_s(t)\,p_s(t) \leq L_a(t)\,w_a(t) + L_m(t)\,w_m(t) + L_r(t)\,w_r(t)\,.$$

2. *The firms that produce services and goods maximize profits, that is*

$$w_m(t) = \alpha_s p_s(t) \tag{13}$$

$$w_a(t) = \frac{d\left(L_a(t)^{1-\beta}\left[(1-\lambda)(\alpha_r L_r(t))^{\mu} + \lambda(\alpha_k K(t))^{\mu}\right]^{\beta/\mu}\right)}{dL_a(t)} \tag{14}$$

$$w_r(t) = \frac{d\left(L_a(t)^{1-\beta}\left[(1-\lambda)(\alpha_r L_r(t))^{\mu} + \lambda(\alpha_k K(t))^{\mu}\right]^{\beta/\mu}\right)}{dL_r(t)} \tag{15}$$

$$w_k(t) = \frac{d\left(L_a(t)^{1-\beta}\left[(1-\lambda)(\alpha_r L_r(t))^{\mu} + \lambda(\alpha_k K(t))^{\mu}\right]^{\beta/\mu}\right)}{dK(t)} \tag{16}$$

The firms that can convert output goods to capital goods (within the period) maximize profits, that is

$$w_k(t) \leq \theta e^{-\delta t} \text{ (with equality if } K(t) > 0\text{)} \tag{17}$$

The unskilled workers allocate their labor between routine and manual tasks optimally, that is

$$w_m(t)\begin{cases} \geq \eta^*(t)\, w_r(t) & \textit{if } L_m(t) = 1 \\ = \eta^*(t)\, w_r(t) & \textit{if } L_m(t) \in (0,1) \\ \leq \eta^*(t)\, w_r(t) & \textit{if } L_m(t) = 0. \end{cases} \tag{18}$$

3. Labor and goods markets clear, that is

$$L_a(t) = 1,$$

$$L_m(t) = \int_0^{\eta^*} e^{-\eta} d\eta = 1 - e^{-\eta^*} \tag{19}$$

$$L_r(t) = \int_{\eta^*}^{1} \eta e^{-\eta} d\eta = (\eta^* + 1)\, e^{-\eta^*} \tag{20}$$

$$C_s(t) = Y_s(t) = \alpha_s L_m(t)$$

$$C_g(t) + K(t)\,\theta e^{-\delta t} = Y_g(t)\,. \tag{21}$$

5.2 Capital demand

First note that there are no dynamic linkages, hence the equilibrium at each t can be separately characterized given the level of productivity $\theta e^{-\delta t}$.

We claim that the choice of capital in this economy solves

$$\max_{K(t)\in\mathbb{R}_+} L_a(t)^{1-\beta}\left[(1-\lambda)\left(\alpha_r L_r(t)\right)^{\mu} + \lambda\left(\alpha_k K(t)\right)^{\mu}\right]^{\beta/\mu} - \theta e^{-\delta t} K(t)\,. \tag{22}$$

This can be seen by combining Eqs. (16) and (17) and noting that the choice of capital satisfies the first order condition for the above concave maximization problem. Note that, by the market clearing condition (21), the objective function for Problem (22) is equal to C_g. Therefore, the choice of capital in equilibrium maximizes net output in the economy (which is consumed by the representative agent). We denote the optimal value of Problem (22) $F(L_a(t), L_r(t), t)$. We have that $F(L_a(t), L_r(t), t)$ is strictly increasing and differentiable in $L_a(t)$ and $L_r(t)$ with derivatives

$$w_r = \frac{dF(L_a(t), L_r(t), t)}{dL_r(t)} \tag{23}$$

$$w_a = \frac{dF(L_a(t), L_r(t), t)}{dL_a(t)} \tag{24}$$

where the equivalence with wages w_r and w_a comes from the equilibrium conditions (15) and (14) along with the envelope theorem for Problem (22). We will not explicitly solve for F

since the exact algebraic expression is messy. Instead we will derive its asymptotic properties (sufficient for our analysis) for each of the cases we analyze below.

5.3 Demand for manual labor

We next derive a demand and a supply curve for $L_m(t)$ given price p_s, which will characterize the static equilibrium. The consumer optimization implies

$$p_s = \left(\frac{L_m(t)}{F(1, L_r(t), t)}\right)^{-1/\sigma_c}. \tag{25}$$

Note that, given the cutoff $\eta^*(t)$, we have that $L_m(t)$ and $L_r(t)$ are given by Eqs. (19) and (20), hence they are related with

$$\begin{aligned} L_r(t) &= (1 - \log(1 - L_m(t)))(1 - L_m(t)) \\ &\equiv g(L_m(t)), \end{aligned} \tag{26}$$

where $g : [0,1] \to [0,1]$ is a strictly decreasing function with $g(0) = 1$ and $g(1) = 0$. Plugging this in Eq.(25) gives

$$p_s = \left(\frac{F(1, g(L_m(t)), t)}{L_m(t)}\right)^{1/\sigma_c}, \tag{27}$$

which gives a demand equation for $L_m(t)$. Note that F is strictly increasing in the second variable and g is strictly decreasing, so the demand curve is strictly decreasing. Note that the demand curve starts from $p_s(L_m = 0) = \infty$ and goes down to $p_s(L_m = 1) = (F(1,0,t))^{1/\sigma_c}$ (which is 0 when $\mu < 0$, but may be positive when $\mu > 0$).

5.4 Supply of manual labor

To derive a supply equation for $L_m(t)$, we use Eqs. (13) and (23) in the equation

$$w_m(t) = \eta^*(t)\, w_r(t).$$

to get

$$p_s(t) = \eta^*(t)\frac{dF(1, L_r(t), t)}{dL_r(t)}.$$

Plugging in $L_r(t) = g(L_m(t))$ and also

$$\eta^*(t) = \eta(L_m) \equiv -\log(1 - L_m(t)),$$

we have

$$p_s(t) = -\log(1 - L_m(t)) \frac{dF(1, g(L_m(t)), t)}{dL_r(t)}. \tag{28}$$

The supply equation will typically be increasing, but it may not be increasing everywhere. It starts from $p_s(L_m = 0) = 0$ and limits to $p_s(L_m = 1) = \infty$ hence the supply and demand curves always intersect.

Putting the demand and supply equations together, we have

$$F(1, g(L_m(t)), t)^{1/\sigma_c} = -L_m(t)^{1/\sigma_c} \log(1 - L_m(t)) \frac{dF(1, g(L_m(t)), t)}{dL_r(t)}. \tag{29}$$

which characterizes the equilibrium value of $L_m(t)$. The following proposition shows that an equilibrium always exists.

Proposition 1 *An equilibrium exists. The equilibrium level of $L_m(t)$ is characterized as the solution to Eq.* (29)*. Once $L_m(t)$ is determined, the remaining variables are determined from the equilibrium conditions in Definition 1.*

Typically, there will be a unique intersection for supply and demand curves and we will be able to analyze the dynamics (as technology progresses) by looking at how the intersection point moves. We will study the dynamics in a simulation. Next, we will analyze the limiting behavior of this economy as $t \to \infty$.

5.5 Asymptotic Equilibrium

Assume (it is easy to verify this assumption) that $L_m(t)$ asymptotes to a constant in the limit, $\lim_{t\to\infty} L_m(t) = L_m^*$. Note that the Theorem of the Maximum applied to Problem (22) implies that the optimum level of $K(t)$ is increasing in t. Moreover, at $t = \infty$, cost of capital would be zero and $K = \infty$ would be optimal, hence optimal $K(t)$ will be arbitrarily large for sufficiently large t, i.e., we have $\lim_{t\to\infty} K(t) = \infty$. To make progress for solving Eq. (29) in the limit, we need to evaluate the limit values for $F(1, g(L_m(t)), t)$ and $\frac{dF(1,g(L_m(t)),t)}{dL_r(t)}$.

5.5.1 Capital input

Rewrite Problem (22) as

$$\max_{K(t)\in\mathbb{R}_+} \lambda^{\beta/\mu} (\alpha_k K(t))^\beta \frac{[(1-\lambda)(\alpha_r L_r(t))^\mu + \lambda(\alpha_k K(t))^\mu]^{\beta/\mu}}{\lambda^{\beta/\mu}(\alpha_k K(t))^\beta} - \theta e^{-\delta t} K(t). \tag{30}$$

Note that the term $\frac{[(1-\lambda)(\alpha_r L_r(t))^\mu+\lambda(\alpha_k K(t))^\mu]^{\beta/\mu}}{\lambda^{\mu/\beta}(\alpha_k K(t))^\beta} \downarrow 1$ as $K(t) \to \infty$. This suggests that we introduce another maximization problem

$$G(1,t) = \max_{K(t)} \lambda^{\beta/\mu} (\alpha_k K(t))^\beta - \theta e^{-\delta t} K(t), \tag{31}$$

and denote its solution by $\tilde{K}(t)$. We claim that, in the limit, the value and the optimal solution to this maximization problem behaves like those of the optimization problem in (30). More specifically, we claim

$$\lim_{t\to\infty} \frac{F(1, g(L_m(t)), t)}{G(1,t)} = 1 \text{ and } \lim_{t\to\infty} \frac{K(t)}{\tilde{K}(t)} = 1. \tag{32}$$

To prove this statement formally, consider the first order condition for Problem (30)

$$\beta\lambda\alpha_k^\mu K(t)^{\mu-1} [(1-\lambda)(\alpha_r L_r(t))^\mu + \lambda(\alpha_k K(t))^\mu]^{(\beta-\mu)/\mu} = \theta e^{-\delta t}.$$

Similarly, consider the first order condition for Problem (31)

$$\beta\lambda^{\beta/\mu}\alpha_k^\beta \tilde{K}(t)^{\beta-1} = \theta e^{-\delta t}.$$

Dividing the last two displayed equations, taking the limit and noting that $K(t) \to \infty$ proves our claim in Eq. (32). Note that by straightforward algebra, $G(1,t)$ and $\tilde{K}(t)$ can be calculated as

$$\tilde{K}(t) = \left(\lambda^{\mu/\beta} (\alpha_k)^\beta \frac{e^{\delta t}}{\theta}\right)^{1/(1-\beta)} \text{ and } G(1,t) = (1-\beta)\lambda^{\mu/\beta}\alpha_k^\beta \tilde{K}(t)^\beta.$$

Combining the last equation and Eq. (32), we have

$$\lim_{t\to\infty} \frac{F(1, g(L_m(t)), t)}{c_1 K(t)^\beta} = 1, \tag{33}$$

where $c_1 \equiv (1-\beta)\lambda^{\mu/\beta}\alpha_k^\beta$ is some constant. Eq. (33) characterizes the behavior of F in the limit. In words, in the limit, routine labor become less and less important in production (since $\mu > 0$) and F behaves as a production function that does not use routine labor at all.

Next, we consider $\frac{dF(1,g(L_m(t)),t)}{dL_r(t)}$. Since $K(t) \to \infty$, we have

$$\begin{aligned}
&\lim_{t\to\infty} \frac{\frac{dF(1,g(L_m(t)),t)}{dL_r(t)}}{\beta(1-\lambda)\alpha_r^\mu\lambda^{(\beta-\mu)/\mu} L_r(t)^{\mu-1} (\alpha_k K(t))^{(\beta-\mu)}} \\
= &\lim_{t\to\infty} \frac{\beta(1-\lambda)\alpha_r^\mu L_r(t)^{\mu-1} [(1-\lambda)(\alpha_r L_r(t))^\mu + \lambda(\alpha_k K(t))^\mu]^{(\beta-\mu)/\mu}}{\beta(1-\lambda)\alpha_r^\mu\lambda^{(\beta-\mu)/\mu} L_r(t)^{\mu-1} (\alpha_k K(t))^{(\beta-\mu)}} \\
= &1,
\end{aligned}$$

where the first line uses the expression in (44) and the last line uses the fact that $\lim_{t\to\infty} K(t) = \infty$. Hence we have

$$\lim_{t\to\infty} \frac{\frac{dF(1,g(L_m(t)),t)}{dL_r(t)}}{c_2 g(L_m(t))^{\mu-1} K(t)^{\beta-\mu}} = 1, \tag{34}$$

where $c_2 \equiv \beta(1-\lambda)\alpha_r^{\mu}\lambda^{(\beta-\mu)/\mu}\alpha_k^{\beta-\mu}$ is some constant and we have used $L_r(t) = g(L_m(t))$. This characterizes the limiting behavior for $\frac{dF(1,g(L_m(t)),t)}{dL_r(t)}$.

5.5.2 Labor supply asymptotics

We now use Eqs. (33) and (34) in Eq. (29) to solve for the asymptotic equilibrium level of $L_m(t)$. We can rewrite Eq. (29) as

$$\begin{aligned} & \left[\frac{F(1,g(L_m(t)),t)}{c_1 K(t)^{\beta/(1-\beta)}}\right]^{1/\sigma_c} c_1^{1/\sigma_c} K(t)^{\beta/\sigma_c} \\ = \; & -L_m(t)^{1/\sigma_c}\log(1-L_m(t))\, c_2 K(t)^{\beta-\mu} g(L_m(t))^{\mu-1}\left[\frac{\frac{dF(1,g(L_m(t)),t)}{dL_r(t)}}{c_2 g(L_m(t))^{\mu-1} K(t)^{\beta-\mu}}\right] \end{aligned}$$

which, with some algebra and using Eq. (26), can be simplified to

$$\begin{aligned} & \frac{c_1^{1/\sigma_c}}{c_2} \frac{\left[\frac{F(1,g(L_m(t)),t)}{c_1 K(t)^{\beta/(1-\beta)}}\right]^{1/\sigma_c}}{\left[\frac{\frac{dF(1,g(L_m(t)),t)}{dL_r(t)}}{c_2 g(L_m(t))^{\mu-1} K(t)^{\beta-\mu}}\right]} K(t)^{\beta/\sigma_c-(\beta-\mu)} \\ = \; & -\log(1-L_m(t))\, L_m(t)^{1/\sigma_c}(1-\log(1-L_m(t)))^{\mu-1}(1-L_m(t))^{\mu-1}. \end{aligned}$$

When we take the limit as $t\to\infty$, the terms in brackets go to 1, hence

$$\begin{aligned} & \frac{c_1^{1/\sigma_c}}{c_2} \lim_{t\to\infty} K(t)^{\beta/\sigma_c-(\beta-\mu)} \\ = \; & \lim_{t\to\infty} -\log(1-L_m(t))\, L_m(t)^{1/\sigma_c}(1-\log(1-L_m(t)))^{\mu-1}(1-L_m(t))^{\mu-1}. \end{aligned} \tag{35}$$

Since $K(t)\to\infty$, the left hand side either goes to 0 or ∞ depending on the sign of $\beta/\sigma_c - (\beta-\mu)$. The right hand side goes to 0 if $L_m(t)\to 0$, and to ∞ if $L_m(t)\to 1$.[2] Hence, the fact

[2] Proving that the RHS limits to ∞ as $L_m(t)\to 1$ requires some careful algebra. First, note that, as $L_m(t)\to 1$ $\lim_{t\to\infty}\frac{(1-\log(1-L_m(t)))^{\mu-1}}{-\log(1-L_m(t))^{\mu-1}} = 1$. Then, in this case the RHS limit can be rewritten as

$$(-\log(1-L_m(t)))^{\mu} L_m(t)^{1/\sigma_c}(1-L_m(t))^{\mu-1}.$$

that the equality above holds in the limit implies

$$\lim_{t\to\infty} L_m(t) = \begin{cases} 0 \text{ if } \frac{1}{\sigma_c} < \frac{\beta-\mu}{\beta} \\ 1 \text{ if } \frac{1}{\sigma_c} > \frac{\beta-\mu}{\beta}. \end{cases} \quad (36)$$

In words, if share of machines in goods production is sufficiently small ($\beta < \mu$) or if goods and services are sufficiently complementary $\left(\frac{1}{\sigma_c} > \frac{\beta-\mu}{\beta}\right)$, then then in the limit all unskilled labor is drawn to manual tasks. Else if $\beta > \mu$ and $\frac{1}{\sigma_c} < \frac{\beta-\mu}{\beta}$, that is, the share of machine in goods production is large and goods and services are sufficiently substitutable, then routine tasks continue to be important in the limit and all labor is drawn to routine tasks.

5.5.3 Wage inequality asymptotics

We calculate the limiting behavior for abstract, manual and routine wages. For manual wages, we have

$$w_m(t) = p_s(t) = \left(\frac{F(1, g(L_m(t)), t)}{L_m(t)}\right)^{1/\sigma_c},$$

where we have used the demand equation. Hence, using Eq. (33), we have

$$\lim_{t\to\infty} \frac{w_m(t)}{c_1^{1/\sigma_c}\left(K(t)^{\beta}/L_m(t)\right)^{1/\sigma_c}} = 1, \quad (37)$$

For abstract wages, we have

$$w_a(t) = \frac{dF(1, g(L_m(t)), t)}{dL_a(t)} = (1-\beta) F(1, g(L_m(t)), t),$$

hence using Eq. (33), we have

$$\lim_{t\to\infty} \frac{w_a(t)}{(1-\beta) c_1 K(t)^{\beta}} = 1. \quad (38)$$

Now using the fact that

$$w_m(t) = w_r(t)\, \eta(L_m)$$

in equilibrium, we also derive the limiting behavior for routine wages as

$$\lim_{t\to\infty} \frac{w_r(t)}{c_1^{1/\sigma_c} K(t)^{\beta/\sigma_c} / \left[L_m(t)^{1/\sigma_c} \times -\log(1-L_m)\right]} = 1. \quad (39)$$

Recall that we are analyzing the case $\mu > 0$. Hence the first term in this expression goes to ∞ at exponential rate. If $\mu < 1$, then the last term goes to ∞ as well and the limit is ∞ as claimed. Else if $\mu > 1$, the last term goes to 0, but it goes to zero at a polynomial rate. Since the first term goes to ∞ at an exponential rate and the last term goes to zero at polynomial rate, the product goes to ∞ as claimed. This step can more rigorously be proven using the L'Hospital Rule.

We are also interested in relative wages. From $w_m(t) = w_r(t)\,\eta(L_m)$, we clearly have

$$\frac{w_m(t)}{w_r(t)} = \eta(L_m) = \begin{cases} 0 \text{ if } \frac{1}{\sigma_c} < \frac{\beta-\mu}{\beta} \\ \infty \text{ if } \frac{1}{\sigma_c} > \frac{\beta-\mu}{\beta}. \end{cases}$$

Also, from Eqs.(37) and (38), we have

$$\lim_{t\to\infty} \frac{w_a(t)}{w_m(t)} = \lim_{t\to\infty} \frac{(1-\beta)\,c_1 K(t)^{\beta}}{c_1^{1/\sigma_c}\left(K(t)^{\beta}/L_m(t)\right)^{1/\sigma_c}} = \begin{cases} \infty \text{ if } \sigma_c > 1 \\ (1-\beta) \text{ if } \sigma_c = 1 \\ 0 \text{ if } \sigma_c < 1. \end{cases}$$

Hence, we summarize our findings for wages and relative wages in this case ($\mu > 0$) as follows. We have that wages for manual and abstract labor always go to infinity. The relative wage of manual labor to routine labor $w_m(t)/w_r(t)$ go to infinity if $\frac{1}{\sigma_c} > \frac{\beta-\mu}{\beta}$ and to zero otherwise (which is, not surprisingly, the same condition which determines the limiting value of $L_m(t)$). Finally, relative wages for abstract to manual labor depend on σ_c: If $\sigma_c < 1$, then $w_a(t)/w_m(t)$ is 0; if $\sigma_c = 1$, then $w_a(t)/w_m(t)$ is $(1-\beta)$, and if $\sigma_c < 1$, then $w_a(t)/w_m(t)$ is 0. We summarize our findings in the following proposition.

Proposition 2 *When $\mu > 0$, we have $L_m(t) \to 1$ if $\frac{1}{\sigma_c} > \frac{\beta-\mu}{\beta}$ and $L_m(t) \to 0$ if $\frac{1}{\sigma_c} < \frac{\beta-\mu}{\beta}$. For the limit wages, we have*

$$\begin{aligned} \lim_{t\to\infty} \frac{w_m(t)}{w_r(t)} &= \begin{cases} \infty \textit{ if } \frac{1}{\sigma_c} > \frac{\beta-\mu}{\beta} \\ 0 \textit{ if } \frac{1}{\sigma_c} < \frac{\beta-\mu}{\beta}. \end{cases} \\ \lim_{t\to\infty} \frac{w_a(t)}{w_r(t)} &= \infty \\ \lim_{t\to\infty} \frac{w_a(t)}{w_m(t)} &= \begin{cases} 0 \textit{ if } \sigma_c < 1, \\ \infty \textit{ otherwise.} \end{cases} \end{aligned}$$

5.6 Summary and empirical implications

In summary, the ongoing substitution of computer capital for routine labor input in our model (driven by the falling price of computer power) spurs low-skilled workers to reallocate labor input from routine tasks in goods production to manual tasks in the production of services. Employment and wages in middle-skill clerical and routine production jobs declines. Employment in low-skill service occupations rises. Wage inequality rises between high and middle-skill workers due to the combination of rising productivity of abstract tasks and and a falling price of routine tasks. Inequality between high and low-skill workers may ultimately converge to a state or may expand indefinitely. Specifically:

1. When the share of routine tasks in goods production is sufficiently small ($\beta < \mu$) or the elasticity of substitution between goods and services is sufficiently small ($1/\sigma_c > [(\beta - \mu)/\beta]$), then all unskilled labor gets allocated to manual tasks, and the wages of routine labor relative to manual labor go to 0.

2. When the share of routine tasks in goods production is sufficiently large ($\beta > \mu$) and the elasticity of substitution between goods and services is sufficiently large ($1/\sigma_c < [(\beta - \mu)/\beta]$), then all unskilled labor is allocated to routine tasks in the limit. The manual wage to routine wage ratio limits to 0. The abstract wage to routine wage ratio in this case always limits to infinity (since we necessarily have $\sigma_c > 1$). Hence, in the limit, the abstract wage is greater than the routine wage which is in turn greater than the manual wage.

3. The relative wage of abstract to manual labor limits to infinity if $\sigma_c > 1$, to zero if $\sigma_c < 1$, and to $1 - \beta$ if $\sigma_c = 1$.

One element intentionally left absent from the model is the opportunity for workers to invest in human capital.[3] While in reality, rising earnings inequality spur further skills investment, we omit this possibility from the model to emphasize that even with human capital stocks held constant, ongoing skilled–labor augmenting technical change need not imply ongoing growth of inequality.

Can this aggregate model be applied to the analysis of employment and wages in detailed geographic areas, such as cities or commuting zones? The answer depends on whether these areas can plausibly be treated as approximating separate markets. If yes, the model predicts that markets with higher initial concentration in routine tasks—corresponding to higher values of β in local goods production—will see greater growth of service employment and greater polarization of wages as computerization progresses.[4] If no, we must consider to what extent the model applies in local labor markets that interact in a full spatial equilibrium.

[3] Indeed, in our data, the non-college share of worked hours falls from 58 to 38 percent between 1980 and 2005.

[4] Formally, we could rewrite equation (6) at the city (or commuting zone) level with a city-specific routine task intensity: $y_{jg} = \alpha_g R^{b_j} A^{1-b_j}$ where j denotes cities and a higher value of b_j indicates greater initial routine task intensity. If all other preference and labor supply parameters are comparable across cities (that is, uncorrelated with b_j), a uniform decline in the routine task price that is common across cities will induce greater growth in wage inequality and service employment in high b cities.

There is one key factor that aids the identification of the model in the more general, spatial equilibrium case: the output of service occupations is non-traded, and hence inter-region trade is not expected to enforce a uniform service wage across geographic areas. In the short run, local demand shocks should affect local service occupation wage levels. And the rate at which these regional wage differences are arbitraged depends upon the responsiveness of labor movements to cross-region wage variation. Much evidence suggests that mobility responses to labor demand shocks across US cities and states are typically slow and incomplete (Topel, 1986; Blanchard and Katz, 1992; Glaeser and Gyourko, 2005). Mobility is particularly low for the less-educated, who comprise the majority of service occupation workers (Bound and Holzer, 2000). It is therefore plausible that local demand shocks may affect service wages even over the medium term.

The non-tradeability of service outputs has a second useful implication: because demanders and suppliers of service occupations must collocate, the geographic analysis can potentially identify the local determinants of the demand for service jobs, even in the case when service wage levels are not set locally. Consequently, we expect the 'quantity' implications of the theoretical framework to hold at the local labor market level, even in full spatial equilibrium. The wage side of the analysis must be treated as more speculative.

6 Theory appendix

Here we derive the solution to the model for a case where L_r and K are complements ($\mu < 1$). Note that we have $K(t) \rightarrow \infty$, so

$$\lim_{t\rightarrow\infty} \left[(1-\lambda) \left(\alpha_r L_r(t)\right)^{\mu} + \lambda \left(\alpha_k K(t)\right)^{\mu} \right]^{\beta/\mu} = (1-\lambda)^{\beta/\mu} \left(\alpha_r L_r^*\right)^{\beta}. \quad (40)$$

Consequently,

$$\begin{aligned} \lim_{t\rightarrow\infty} F\left(1, g\left(L_m(t)\right), t\right) &= \lim_{t\rightarrow\infty} \left[(1-\lambda) \left(\alpha_r L_r(t)\right)^{\mu} + \lambda \left(\alpha_k K(t)\right)^{\mu} \right]^{\beta/\mu} - \theta e^{-\delta t} K(t) \quad (41) \\ &\leq \lim_{t\rightarrow\infty} \left[(1-\lambda) \left(\alpha_r L_r(t)\right)^{\mu} + \lambda \left(\alpha_k K(t)\right)^{\mu} \right]^{\beta/\mu} \\ &= (1-\lambda)^{\beta/\mu} \left(\alpha_r g\left(L_m^*\right)\right)^{\beta} \end{aligned}$$

Moreover, since $K(t)$ solves Eq. (22), it does better than an arbitrary choice for the capital function. In particular, it does better than $\tilde{K}(t) = t$. Then, we have

$$\begin{aligned}
\lim_{t\to\infty} F(1, g(L_m(t)), t) &\geq \lim_{t\to\infty} \left[(1-\lambda)(\alpha_r L_r(t))^\mu + \lambda\left(\alpha_k \tilde{K}(t)\right)^\mu\right]^{\beta/\mu} - \theta e^{-\delta t}\tilde{K}(t) \quad (42)\\
&= \lim_{t\to\infty} \left[(1-\lambda)(\alpha_r L_r(t))^\mu + \lambda\left(\alpha_k \tilde{K}(t)\right)^\mu\right]^{\beta/\mu}\\
&= (1-\lambda)^{\beta/\mu}(\alpha_r g(L_m^*))^\beta .
\end{aligned}$$

Combining Eqs. (41) and (42), we have

$$\lim_{t\to\infty} F(1, g(L_m(t)), t) = (1-\lambda)^{\beta/\mu}(\alpha_r g(L_m^*))^\beta . \quad (43)$$

In words, since L_r and K are gross complements and K grows, in the limit $L_r(t) = g(L_m(t))$ becomes the bottleneck and determines the production.

Next consider

$$\frac{dF(1, g(L_m(t)), t)}{dL_r(t)} = \beta(1-\lambda)\alpha_r^\mu L_r(t)^{\mu-1}\left[(1-\lambda)(\alpha_r L_r(t))^\mu + \lambda(\alpha_k K(t))^\mu\right]^{(\beta-\mu)/\mu} \quad (44)$$

Since $K(t) \to \infty$, taking the limit of this expression yields

$$\lim_{t\to\infty} \frac{dF(1, g(L_m(t)), t)}{dL_r(t)} = \beta(1-\lambda)^{\beta/\mu}\alpha_r^\beta g(L_m^*)^{\beta-1} . \quad (45)$$

Taking the limit of Eq. (29) and plugging in Eqs. (43) and (45), we have

$$\left[(1-\lambda)^{\beta/\mu}(\alpha_r g(L_m^*))^\beta\right]^{1/\sigma_c} = -L_m^{*\,1/\sigma_c}\log(1-L_m^*)\,\beta(1-\lambda)^{\beta/\mu}\alpha_r^\beta g(L_m^*)^{\beta-1} . \quad (46)$$

The equilibrium level of L_m^* in the limit is the solution to the previous equation, which will be in the interval $(0, 1)$.

Moreover, in this case we have

$$p_s \to p_s^*,\ w_m \to w_m^*,\ w_r \to w_r^*,\ w_a \to w_a^*,\ \eta \to \eta^*,$$

i.e. all variables converge to a finite constant. Intuitively, in this case machines and routine labor are gross complements so technological progress is not sufficient to increase output beyond a finite limit (since routine labor becomes the bottleneck). Consequently, the price of services and hence the wage for the manual labor also remain constant. The wage for routine labor remains constant since the routine labor is the bottleneck so there is still value to routine tasks. The abstract wage is also constant since the abstract workers receive a constant share of output, which is constant.

In this case, $w_a(t)/w_m(t)$ ratio also goes to a constant w_a^*/w_m^* regardless of σ_c, in contrast with the conjecture. We summarize our results in the following proposition.

Proposition 3 *When* $\mu < 0$, $\lim_{t\to\infty} L_m(t) = L_m^*$ *where* $L_m^* \in (0,1)$ *is a solution to Eq.* (46). *In the limit, unskilled labor works in both manual and routine tasks and the wages limit to finite levels*

$$w_m \to w_m^*,\ w_r \to w_r^*,\ w_a \to w_a^*.$$

6.1 Schultz/Nelson-Phelps/Welch (1970) 'disequilibrium' view

The frameworks discussed above suggest that changes in technology raise the demand for human capital effectively *permanently* (i.e., by raising A_{ht}/A_{lt} in the CES framework). An alternative view is the Schultz/Nelson-Phelps hypothesis, which posits that human capital is most valuable—i.e., in highest demand—when workers are adapting to a changing environment, what Schultz would call "disequilibria." A closely related hypothesis was advanced by Finis Welch (1970) in a famous article titled "Education in Production," in which Welch proposed that educated workers have a comparative advantage in 'allocative efficiency,' the ability to combine inputs productively. Development economists have demonstrated that educated farmers are the first to adopt improved agricultural technologies (even technologies that are commonly available from other countries). This is important evidence favoring the Schultz/Nelson-Phelps view: In the long run, all farmers—including the less educated—may adapt the best technologies. But when technologies are new, farmers with greater human capital appear to hold a comparative advantage in adapting rapidly.

In the Schultz/Nelson-Phelps view, we might expect a technological revolution to increase the demand for skills. This view has been advanced by a number of authors, including Greenwood and Yorukoglu (1997), Caselli (1999), Galor and Moav (2000). For example, Greenwood and Yorukoglu (1997, p. 87) argue:

> "Setting up, and operating, new technologies often involves acquiring and processing information. Skill facilitates this adoption process. Therefore, times of rapid technological advancement should be associated with a rise in the return to skill."

Here is a brief formalization of this approach built on Galor and Moav (2000)—and borrowed from Acemoglu (2002)—adapted to the above framework. Suppose that in terms of the CES framework developed above

$$A_l = \phi_l(g)a \text{ and } A_h = \phi_h a \tag{47}$$

where a is a measure of aggregate technology, and g is the growth rate of a, i.e., $g \equiv \dot{a}/a$. The presumption that skilled workers are better equipped to deal with technological progress can be captured by assuming that $\phi_l' < 0$. Galor and Moav (2000) refer to this assumption as the "erosion effect," since it implies that technical change erodes some of the established expertise of unskilled workers, and causes them to benefit less from technological advances than skilled workers do. Substituting into our familiar CES relative wage equation, the skill premium is

$$\omega = \frac{w_H}{w_L} = \left(\frac{A_h}{A_l}\right)^{(\sigma-1)/\sigma}\left(\frac{H}{L}\right)^{-1/\sigma} = \left(\frac{\phi_h}{\phi_l(g)}\right)^{(\sigma-1)/\sigma}\left(\frac{H}{L}\right)^{-1/\sigma}. \tag{48}$$

Therefore, as long as $\phi_l' < 0$, more rapid technological progress, as captured by a higher level of g, will increase the skill premium.

This approach therefore presumes that the recent past has been characterized by faster than usual technological progress, and explains the acceleration in skill bias by the direct effect of more rapid technical change on the demand for skills.

There are two empirical papers that explore this hypothesis. One is an early and interesting paper by Bartel and Lichtenberg (1987, *ReStat*), "The Comparative Advantage of Educated Workers in Implementing New Technology." Bartel and Lichtenberg find in a panel of U.S. industries that controlling for the level of capital per worker, industries with a 'younger' capital stock appear to have greater demand for more educated workers. This result is potentially consistent with either of two hypotheses: 1) when capital is new, skilled workers are needed to adopt it and routinize its use; or 2) newer capital is simply inherently more skill demanding (this latter possibility would be called a 'vintage' effect).

In a closely related recent contribution, Hyunbae Chun (*ReStat*, 2003) makes an effort to separately distinguish the effects of 'use' of computers (that is, increase in the computer stock) and 'adoption of computers,' that is, the age of the computer stock. His analysis indicates that at least two-thirds of the estimated impact of computerization on industry level demand for skilled labor arises through the 'use' rather than 'adoption' effects. (Neither paper is esp. well identified by contemporary standards.)

If this conclusion is correct, it suggests that the impacts of computerization skill demand—if any—will not abate any time soon. Because measurement of the age of the capital stock is probably even less reliable than measurement of its level, however, the fact that Chun finds any effect *at all* of the age of the computer stock on skill demand should perhaps be taken as surprisingly strong evidence in favor of the Nelson-Phelps hypothesis. Although Chun's analysis suffers from the same ambiguity of interpretation as the Bartel and Lichtenberg results—i.e., the difficulty of distinguishing vintage versus true 'Nelson/Phelps' effects—vintage effects may be less of a concern when studying only one specific form of capital than when studying the entire capital stock.

It is possible to interpret the evidence in the case studies cited above—particularly the Bartel, Ichniowski and Shaw study—as supporting the Nelson/Phelps view of skill demands. The increased demand for problem-solving skills observed by these authors may be a 'disequilibrium' phenomenon that will abate as the technology becomes routinized. The view suggested by the ALM framework, by contrast, is that as tasks are 'routinized,' they will be delegated to machinery and hence the human component will continue to remain 'non-routine.'

6.2 Changes in market structure

An innovative hypothesis linking reorganization to skill demands is suggested by Thesmar and Thoenig (1999, QJE). Their claim is that firms have been gradually changing from mechanistic organizations, which are highly productive at a given task but inflexible, towards 'adaptive' organizations, which may be less efficient at a given task, but can quickly adjust to changes. They link this switch in organizational form to globalization—which is likely to be in part technologically induced—and to the increased availability of skilled workers (as in the above story). Because 'adaptive' organizations require relatively more skilled workers than 'mechanistic' organizations, this change in organizational form increases the demand for skills. The 2003 *AER* paper by Thoenig and Verdier posits of endogenous innovation (and concomitant increase in skill demand) as a response to globalization. A related idea (but dissimilar model) was earlier pursued by Acemoglu (2003) in the *ReStud*, "Patterns of Skill Bias."

6.3 Endogenous acceleration of skill bias

This hypothesis, due to Daron Acemoglu, takes the acceleration of skill bias as *given* and asks what economic incentives might have caused this acceleration to occur. Acemoglu explicitly links the type of technologies that are developed and adopted to (profit) incentives.

The key idea is that the development of skill-biased technologies will be more profitable when these technologies have a larger market size—i.e., when there are more skilled workers. Therefore, the equilibrium degree of skill bias, which will be determined endogenously, could be an increasing function of the relative supply of skilled workers. An increase in the supply of skills will then lead to skill-biased technical change. Furthermore, in the extreme, an acceleration in the supply of skills can lead to an acceleration in the demand for skills.

6.3.1 Acemoglu framework: A basic model

Imagine that the CES production functions used earlier are modified to:

$$Y_L = \frac{1}{1-\beta}\left(\int_0^{N_L} x_L(j)^{1-\beta}\, dj\right) L^{\beta}, \tag{49}$$

and

$$Y_H = \frac{1}{1-\beta}\left(\int_0^{N_H} x_H(j)^{1-\beta}\, dj\right) H^{\beta}, \tag{50}$$

where $x_L(j)$ and $x_H(j)$ denote machines used in the production of the labor-intensive and skill-intensive goods. This formulation with the use of these machines replaces the exogenous technology terms A_l and A_h above.

N_L and N_H denote the range of machines that can be used in these two sectors. As is standard in Dixit-Stiglitz-type models (for example endogenous technical change models), these ranges of machines will be measures of productivity in the two sectors. Therefore, change in N_H/N_L will change the skill bias of technology.

Assume that machines to both sectors are supplied by "technology monopolists".

Each monopolist sets a rental price $\chi_L(j)$ or $\chi_H(j)$ for the machine it supplies to the market.

The marginal cost of production is the same for all machines and equal to $\psi \equiv 1-\beta$ in terms of the final good.

Price taking by the producers of the labor-intensive goods implies

$$\max_{L,\{x_L(j)\}} p_L Y_L - w_L L - \int_0^{N_L} \chi_L(j)\, x_L(j)\, dj, \tag{51}$$

This gives machine demands as

$$x_L(j) = \left[\frac{p_L}{\chi_L(j)}\right]^{1/\beta} L. \tag{52}$$

Similarly

$$x_H(j) = \left[\frac{p_H}{\chi_H(j)}\right]^{1/\beta} H, \tag{53}$$

Since the demand curve for machines facing the monopolist, (52), is iso-elastic, the profit-maximizing price will be a constant markup over marginal cost. In particular, all machine prices will be given by

$$\chi_L(j) = \chi_H(j) = 1 \tag{54}$$

Profits of technology monopolists are obtained as

$$\pi_L = \beta p_L^{1/\beta} L \text{ and } \pi_H = \beta p_H^{1/\beta} H. \tag{55}$$

Let V_H and V_L be the net present discounted values of new innovations. Then in steady state:

$$V_L = \frac{\beta p_L^{1/\beta} L}{r} \text{ and } V_H = \frac{\beta p_H^{1/\beta} H}{r}. \tag{56}$$

The greater is V_H relative to V_L, the greater are the incentives to develop H-complementary machines, N_H, rather than N_L.

This highlights the two effects on the direction of technical change that I mentioned above:

1. The price effect: a greater incentive to invent technologies producing more expensive goods.

2. The market size effect: a larger market for the technology leads to more innovation. The market size effect encourages innovation for the more abundant factor.

Substituting for relative prices, relative profitability is

$$\frac{V_H}{V_L} = \left(\frac{1-\gamma}{\gamma}\right)^{\frac{\varepsilon}{\sigma}} \left(\frac{N_H}{N_L}\right)^{-\frac{1}{\sigma}} \left(\frac{H}{L}\right)^{\frac{\sigma-1}{\sigma}}. \tag{57}$$

where

$$\sigma \equiv \varepsilon - (\varepsilon - 1)(1-\beta).$$

is the (derived) elasticity of substitution between the two factors. When V_H/V_L there will be more research towards inventing new skill-complementary varieties, and N_H/N_L will increase. This is the essence of the model of endogenous skill bias. Greater profitability of skill-complementary technologies leads to more innovations that are skill complementary.

As discussed above, in the case of substitution between skilled and unskilled workers, a high elasticity is reasonable. So here I presume that $\sigma > 1$. Then equation (57) immediately implies that the higher relative supply of skills, H/L, increases V_H/V_L, and via this channel, it induces an increase in N_H/N_L, creating skill-biased technical change.

Also note that relative factor prices are

$$\frac{w_H}{w_L} = p^{1/\beta}\frac{N_H}{N_L} = \left(\frac{1-\gamma}{\gamma}\right)^{\frac{\varepsilon}{\sigma}} \left(\frac{N_H}{N_L}\right)^{-\frac{\sigma-1}{\sigma}} \left(\frac{H}{L}\right)^{-\frac{1}{\sigma}}. \tag{58}$$

First, the relative factor reward, w_H/w_L, is decreasing in the relative factor supply, H/L, this is simply the usual substitution effect, making the short-run (exogenous-technology) relative demand for skills downward sloping.

Second, greater H/L leads to a greater N_H/N_L, which is biased toward skilled workers, and therefore increases w_H/w_L. In other words, an increase in the relative supply of skills causes skill-biased technical change.

Next, the question is whether this induced skill bias effect could be strong enough to outweigh the substitution effect, and lead to an upward sloping relative demand curve.

To answer this question, we need to specify the production function for the creation of new varieties of machines. Suppose that new varieties are created as follows:

$$\dot{N}_L = \eta_L X_L \text{ and } \dot{N}_H = \eta_H X_H, \tag{59}$$

where X denotes R&D expenditure.

This gives the following "technology market clearing" condition:

$$\eta_L \pi_L = \eta_H \pi_{H.} \tag{60}$$

Then, relative physical productivities can be solved for

$$\frac{N_H}{N_L} = \eta^{\sigma} \left(\frac{1-\gamma}{\gamma}\right)^{\varepsilon} \left(\frac{H}{L}\right)^{\sigma-1}. \tag{61}$$

Substituting for (61) into (58), endogenous-technology factor rewards are obtained as

$$\frac{w_H}{w_L} = \eta^{\sigma-1} \left(\frac{1-\gamma}{\gamma}\right)^{\varepsilon} \left(\frac{H}{L}\right)^{\sigma-2}. \tag{62}$$

Comparing this equation to the relative demand for a given technology, we see that the response of relative factor rewards to changes in relative supply is always more elastic in (62) than in (58).

This is simply an application of the LeChatelier principle, which states that demand curves become more elastic when other factors adjust—that is, the relative demand curves become flatter when "technology" adjusts.

The more important and surprising result here is that if σ is sufficiently large, in particular if $\sigma > 2$, the relationship between relative factor supplies and relative factor rewards can be upward sloping.

6.3.2 Acemoglu Framework: Implications

If $\sigma > 2$, then the long-run relationship between the relative supply of skills and the skill premium is positive.

Why is this interesting? Three important facts about demand for skills are:

1. Secular skill-biased technical change increasing the demand for skills throughout 20th century.

2. Possible acceleration in skill-biased technical change over the past 30 years.

3. Many skill-replacing technologies during the 19th century (e.g., the 'factory system.').

With an upward sloping relative demand curve, or simply with the degree of skilled bias endogenized, we have a potential explanation for all of these patterns.

1. The increase in the number of skilled workers that has taken place throughout 20th century is predicted to cause steady skill-biased technical change.

2. Acceleration in the increase in the number of skilled workers over the past 30 years is predicted to induce an acceleration in skill-biased technical change.

3. Large increase in the number of unskilled workers available to be employed in the factories during the 19th century could be expected to induce skill-replacing/labor-biased technical change.

In addition, this framework with endogenous technology also gives a nice interpretation for the dynamics of the college premium during the 1970s and 1980s. It is reasonable to presume that the equilibrium skill bias of technologies, N_h/N_l, is a sluggish variable determined by the slow buildup and development of new technologies. In this case, a rapid increase in the supply of skills would first reduce the skill premium as the economy would be moving along a constant technology (constant N_h/N_l) curve in the figure. After a while the technology would start adjusting, and the economy would move back to the upward sloping relative demand curve, with a very sharp increase in the college premium. This approach can therefore explain both the decline in the college premium during the 1970s and the subsequent large surge, and relates both to the large increase in the supply of skilled workers.

If on the other hand we have $\sigma < 2$, the long-run relative demand curve will be downward sloping, though again it will be shallower than the short-run relative demand curve. Then following the increase in the relative supply of skills there will be an initial decline in the skill premium (college premium), and as technology starts adjusting the skill premium will increase. But it will end up below its initial level. To explain the larger increase in the 1980s, in this case we need some exogenous skill-biased technical change.

The Acemoglu hypothesis is an elegant interpretation of a large number of facts. It does not make any new testable predictions for the SBTC hypothesis and hence at this point is primarily interpretive. The Acemoglu hypothesis can (and will) be tested in other contexts, however, where the facts are not already known and hence the test is 'blind'. One promising testing ground may be pharmaceutical research and development expenditures.

6.4 SBTC: Summary of evidence

The major pieces of evidence suggesting that SBTC has shaped skill demand in recent decades are:

1. Evidence of demand acceleration in the most recent three decades relative to prior three. The supply of skills grew faster between 1970 and 1995 than between 1940 and 1970—by 3.06 percent a year during the latter period compared to 2.36 percent a year during the earlier 30 years. Returns to college increased between 1970 and 1995 by about 0.39 percent a year, while they fell by about 0.11 percent a year during the earlier period.

2. Evidence from U.S. and OECD that almost all skill upgrading occurred within (rather than between) detailed industrial sectors, even as the relative price of skill was rising. [As we will see in the lecture on trade, this within/between distinction turns out to be crucial in distinguishing trade versus technology explanations of inequality.]

3. A uniform finding of strong correlations between measures of computer investment and skill upgrading within industries and plants in essentially all industrialized countries in the U.S., Canada, OECD, and to some extent the developing world.

4. Developing evidence linking changes in job content and organization in manufacturing and service sectors to implementation of new technology. This evidence is available from case studies and is finding its way to representative empirical work.

Three summary points.

- Economists have limited ability to answer the 'acceleration question' often posed in the SBTC debate. It is almost impossible to develop a meaningful counterfactual for the rate of technical change that *would have prevailed* in a given decade were it not for a specific technological advance. And it is equally difficult empirically to compare rates of technical change across time periods. Although the question of acceleration may be well posed from a production function framework, the issues of measurement makes almost all answers inconclusive. We can say with confidence that the rate skill-biased change was more rapid in the 1970s - 1990s than in the Middle Ages. Finer comparisons are less certain.

- The massive influx of computers over three decades has *at a minimum* continued a process of rising skill demand that has been ongoing in advanced countries since the Industrial Revolution.

- Much case study and a growing trove of representative evidence indicates that recent technological change has distinct characteristics from previous innovations (such as the factory system, continuous and batch processes, Taylorism, etc.). These characteristics—generally favoring problem solving and adaptive skills—are altering workplace organization, working conditions and skill demands. We'll have more to say about these organizational changes in the next lecture.

Not all economists find this evidence equally compelling—and some distinguished labor economists (e.g., David Card) view the SBTC hypothesis as vacuous or worse. The definitive evidence for or against this hypothesis has yet to be produced—and perhaps it never will be. You should draw your own conclusions.