Skill-Biased Technical Change[1]

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Abstract

Skill-Biased Technical Change is a shift in the production technology that favors skilled over unskilled labor by increasing its relative productivity and, therefore, its relative demand. Traditionally, technical change is viewed as factor-neutral. However, the observed rapid rise in the relative wage of skilled workers in conjunction with an upward trend in their relative supply means that recent technological change has been skill-biased. Theories and data suggest that new information technologies are complementary with skilled labor, at least in their adoption phase. The direction of technical change–i.e., whether new capital complements skilled or unskilled labor– may be determined endogenously by innovators' economic incentives shaped by relative prices, the size of the market, and institutions. The "factor-bias" attribute puts technological change at the centerstage of the income distribution debate.

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Skill-Biased Technical Change (SBTC thereafter) is a shift in the production technology that favors skilled (e.g., more educated, more able, more experienced) labor over unskilled labor by increasing its relative productivity and, therefore, its relative demand. Ceteris paribus, SBTC induces a rise in the skill premium—the ratio of skilled to unskilled wages.

From factor-neutral to factor-biased technical change

Economic theory views the production technology as a function describing how a collection of factor inputs can be transformed into output, and it defines technical change as a shift in the production function, i.e., a change in output for given inputs. The traditional measure of economy-wide technological change, introduced by Solow (1957), is aggregate total factor productivity (TFP, thereafter). Solow defines a TFP advancement as an increase in output that leaves marginal rates of transformations untouched for given inputs; thus, a change in TFP is a form of *factor-neutral* technical change.

For illustrative purposes, suppose that the aggregate production function is constant returns to scale and Cobb-Douglas in aggregate capital (K) and aggregate labor (L) services, i.e. $Y = ZK^{\alpha}L^{1-\alpha}$, where Y is aggregate output, α is the elasticity of output to capital, and Z denotes precisely TFP. If output and input markets are competitive, then the share of income going to capital equals α. Solow's (1957) fundamental insight is that, armed with this estimate of α and measures of (Y, K, L) from national accounts, neutral technical change can be quantified "residually". This clever and parsimonious approach to growth accounting has dominated the literature for decades, creating an overwhelming consensus that neutral technological improvements are the primary source of growth in income per capita.

However, a key fact recently emerged from the data highlights the limits of this conceptualization of technical change. In the last three decades, the rental price of skilled labor has soared dramatically relatively to that of unskilled labor despite a major uprise in the relative supply of skills: for example, the college wage premium–defined as the ratio between the wage of college graduates and the wage of high-school graduates– jumped from 1.45 in 1965 to 1.7 in 1995, while the relative supply of college skills tripled over the same period. Given the observed movements in the relative quantities, these price changes could not be generated by movements "along the production function". Neutral technical change is, by definition, silent on changes in relative prices. Therefore, to make sense of these recent developments, one must introduce the concept of *factor-biased* technical change.

For this purpose, I now generalize the aggregate production function above by letting labor input, L, be a constant elasticity of substitution (CES) function of skilled and unskilled labor, L_s and L_u, with factor-specific productivities A_s and A_u:

$$L = \left[(A_s L_s)^\sigma + (A_u L_u)^\sigma \right]^{1/\sigma}, \ \sigma \leq 1. \tag{1}$$

At this point, it is not necessary to specify what makes a worker more skilled than another: it could be education, innate ability or experience. The (log of the) marginal rate of transformation (MRT) between the two labor inputs is

$$\ln \left(MRT_{s,u} \right) = \sigma \ln \left(\frac{A_s}{A_u} \right) + (1 - \sigma) \ln \left(\frac{L_u}{L_s} \right). \tag{2}$$

Note that the TFP term Z does not enter the above equation. A change in the ratio A_s/A_u is a form of factor-biased technical change since it modifies the marginal rates of transformation, at a given input ratio. In particular, under the empirically plausible parametric assumption $\sigma > 0$, technical change is *skill-biased* if A_s/A_u increases. With competitive input markets, the (log of the) skill premium can be read off the right-hand side of (2) as well. Therefore, skill-biased technical change induces an increase in the relative productivity of skilled labor that raises its relative demand and, ceteris paribus, the skill premium.

Taking this logic one step further, given an estimate of the elasticity of substitution between types of labor $1/(1-\sigma)$, and time-series on relative wages and relative factor supplies, one can measure skill-biased technical change residually from (2). For example, with an elasticity of substitution of 1.4 (or $\sigma = 0.29$) between college graduates and the rest of the labor force, the dynamics of the U.S. college premium and of the relative supply of college skills imply a growth of skill-biased technical change (i.e., of the ratio A_s/A_u) in excess of 10 percent per year from 1963-1987 (Katz and Murphy, 1992).

The skill-bias of information technologies

Recent shifts in technology have been skill-biased. But SBTC appears all but an unexplained residual very much like Solow TFP, a "black box" that needs to be filled with economic content. What really accounts for this shift in the production process over the past three decades? The timing of the rise in the skill premium has coincided with the rapid diffusion of information and communication technologies in the work place. Thus, a natural candidate for this wave of SBTC is the "information technology revolution".

Expenditures in information processing equipment and software, as a share of U.S. private nonresidential fixed investment, rose from 6% in 1960 to 40% in 2000. At the heart of these dynamics there is a staggering improvement in the quality and productivity of all those equipment goods relying heavily on semiconductors, like computers, software, and switching equipment underlying much of communication technology.

Ample micro-econometric research and several case-studies document a statistical correlation between the use of new technologies, like computers, and either the employment share of skilled workers (Bartel and Lichtenberg, 1987) or their wage share (Autor, Katz and Krueger, 1998) across industries. These studies firmly establish that the new technologies are deployed with better qualified and better paid labor, but they fail to explain *why.* This deeper question requires a quantitative theory built around an explicit economic mechanism.

Technology-skill complementarity

A large number of economic models in the literature provides a foundation for SBTC (for surveys, see Acemoglu, 2002; Aghion, 2002; Hornstein et al., 2005). The central tenet of all these theories is technology-skill complementarity and takes three alternative formulations.

The first formulation is built on a defining feature of the postwar U.S. economy: the sharp decline of the constant-quality relative price of equipment investment (Gordon, 1990; Greenwood et al. 1997), especially evident for information technologies whose prices fell at 10% per year. Krusell et al. (2000) argue that the substantial cheapening of equipment capital is the force behind SBTC. This decline in price led to an increased use of equipment capital in production. At least since Griliches (1969), various empirical papers support the idea that skilled labor is relatively more complementary to equipment capital than is unskilled labor. As a result of capital-skill complementarity in production, the faster growth of the equipment stock pushed up the relative demand for skilled labor and, in turn, the skill premium.

More explicitly, these authors generalize the aggregate production function to:

$$Y = K_s^{\alpha} \left[\lambda \left[\mu \left(K_e \right)^{\rho} + (1-\mu) \left(L_s \right)^{\rho} \right]^{\frac{\sigma}{\rho}} + (1-\lambda) \left(L_u \right)^{\sigma} \right]^{\frac{1-\alpha}{\sigma}}, \tag{3}$$

where K_s denotes structures capital, and K_e equipment capital. Profit-maximizing behavior of price-taking firms implies that the skill premium (and the MRT between labor inputs) can be approximately written as

$$\ln\left(\frac{w_s}{w_u}\right) \simeq \lambda \frac{\sigma - \rho}{\rho} \ln\left(\frac{K_e}{L_s}\right)^{\rho} + (1-\sigma) \ln\left(\frac{L_u}{L_s}\right). \tag{4}$$

If $\sigma > \rho$, as estimated by Krusell et al., the relative demand for skills increases with the stock of equipment capital. Note the difference between equations (2) and (4): capital-skill complementarity gives economic content to the notion of SBTC by replacing an unobserved residual trend (A_s/A_u) with the actual upward trend in equipment-skilled labor ratio. This model replicates well the dynamics of the U.S. skill premium over the past 40 years. Moreover, historical evidence suggests that complementarity between skilled labor and capital has characterized technological developments throughout the entire 20th century (Goldin and Katz, 1998).

The second formulation is inspired by the Nelson-Phelps view of human capital. In the words on Nelson and Phelps (1966), *"educated people make good innovators, so that education speeds the process of technological diffusion"* (page 70). In particular, they contend that more educated, able or experienced labor deals better with technological change. Skilled workers are less adversely affected by the turmoil created by major technological transformations since it is less costly for them to learn the additional knowledge needed to adopt a new technology. Therefore, rapid technological transitions—such as that witnessed in the past three decades—are skill-biased, as more able workers adapt better to change (Greenwood and Yorukoglu, 1997; Caselli, 1999; Galor and Moav, 2000).

Incidentally, this version of the technology-skill complementarity hypothesis, by emphasizing the importance of learning during episodes of drastic technical change, is consistent with the TFP slowdown experienced by most developed economies in the 1980s: upon the arrival of the new information technologies, aggregate productivity can fall temporarily as workers and firms learn how to deploy the new production methods at their best (Hornstein and Krusell, 1996; Aghion, 2002).

The Nelson-Phelps conjecture implies that the rise in the skill premium is transitory: it is only in the early adoption phase of a new technology that those who adapt more quickly can reap some benefits. As time goes by, there will be enough workers learning how to work with the new technology to offset the wage differential. Note the difference with the hypothesis set forth by Krusell et al., where the effect of capital deepening on the skill premium is permanent.

The third formalization of this hypothesis is based on Milgrom and Roberts (1990). These authors argue that information technologies reduce costs of data storage, communication, monitoring and supervision activities within the firm which trigger a shift towards a new organizational design. In particular, the layers in the hierarchical structure can be reduced, so that the organization of the firm becomes "flatter." Workers no longer perform routinized, specialized tasks, but they are now responsible for a wide range of tasks within teams. Therefore, adaptable workers who have general skills and who are more versed at multi-tasking activities benefits from this transformation. In other words, the change in technology induces an organizational shift which is skill-biased. An elegant formalization of this hypothesis is contained in Garicano and Rossi (2004).

Microeconomic evidence consistent with all these formulations of the technology-skill complementarity hypothesis is offered by Autor, Levy and Murnane (2003). Based on data on the skill content and tasks of various occupations, they split job requirements into "routine" and "non-routine" tasks and document that, starting from the 1970s, the labor input of non-routine analytic and interactive tasks increased sharply relative to routine cognitive and manual tasks. This shift was concentrated in rapidly computerizing industries and it was pervasive at all educational levels. They interpret these findings as evidence that information technologies substituted unskilled labor employed on simple and more repetitive tasks–more amenable to computerization–and complemented workers endowed with generalized problem-solving, complex communication, and analytical skills.

Endogenous direction of technical change

In the same vein as the endogenous growth literature developed in the 1990s, one could contend that not only the speed—as traditionally argued—but also the *direction* of technical change is endogenous. Profit incentives of innovators determine the amount of R&D activity directed towards different factors of production (Acemoglu, 1998). The main determinants of profit incentives are market size, relative prices and institutions. These forces can shed light on numerous episodes in the history of technology.

Under the assumption that the R&D cost is fixed, the market size of the innovation determines its revenues. The expansion of educated labor over the postwar period made it profitable to develop machines complementary to skilled workers. The vast migration wave towards English cities during the late eighteenth century opened the way to the development of the factory system and, later, to the Tayloristic assembly line which quickly replaced skilled artisans' craft shops. Incidentally, this is a notable example of *unskill-bias* which proves that, historically, the direction of technical progress has varied.

Profit maximization dictates that, ceteris paribus, innovation be directed towards those factors that are more intensely used in the production of highly priced goods. The recent burst of North-South trade increased the relative price of skilled-intensive goods in the North representing yet another force which pushed towards skill-biased innovations in the postwar period.

Labor institutions that keep wages high despite reductions in productivity induce firms to direct efforts towards labor-saving technologies. Such a fall in labor demand may explain the rise in European unemployment, after the upward wage push obtained by the "labor movement" in the 1970s. The hump-shaped dynamics of the European labor share between 1970 and 1990 validates this conjecture.

The theory of endogenous factor-bias in technology is, potentially, far reaching. The main limit, at this early stage of development, is the lack of quantitative analysis of the proposed mechanisms. For example, is the acceleration in the growth of college skills of the 1970s large enough to generate the observed rise in the productivity of skilled labor and in the skill premium, under a plausible model calibration? Such questions remain unanswered to date.

To conclude: traditionally, in the growth literature, technological progress is associated to productivity improvements that benefits all workers and it is viewed as the chief long-run determinant of *average income* levels. The notion of "skill-bias"—and the literature that has recently blossomed around it—has introduced the theoretical possibility that technological progress benefits only a sub-group of workers, placing technical change also at the centerstage of the *income distribution* debate.

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See also: biased and unbiased technical change; capital measurement; diffusion of technology; economic growth in the very long run; endogenous growth; general purpose technologies; Griliches, Zvi; growth and human capital; growth, models of; Habakkuk, John Hrothgar (v1915); human capital; Industrial Revolution: mechanisms; inequality and growth; inequality: explanations; information technology and economic growth; labor's share of income; measurement of economic growth; production functions; productivity: measurement problems; Solow, Robert; substitutes and complements; technical change; technology; Technology and wage inequality; total factor productivity; vintage capital.

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