Wage Inequality and Innovative Intelligence-Biased Technological Change

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Abstract

In this paper, "innovative intelligence–biased technological change" (IIBTC) is examined as an alternative to the traditional concept of skill-biased technological change (SBTC) as a source of increases in wage inequality. The innovative intelligence of ordinary or average workers is an important element in productivity and can be heterogeneous across workers. Because technologies are heterogeneous in that they have different characteristics and are used in different situations, some technologies are "innovative intelligence-biased" and are advantageous for workers with relatively high innovative intelligence. If IIBTC prevails over a certain period of time, these workers become additionally advantaged and thereby wage inequality will increase during the period.

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Keywords: Wage inequality; Innovative intelligence; Technological change; Total factor productivity; Approximate effective production function

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1 INTRODUCTION

Until the early 2000s, the view that skill-biased technological change (SBTC) is the main cause of the recent increase in wage inequality was widely accepted (Katz and Murphy, 1992; Autor et al., 1998, 2003). Explanations based on SBTC were often combined with the Stolper–Samuelson theorem (Stolper and Samuelson, 1941). However, neither the original explanations nor those combined with the Stolper–Samuelson theorem have been sufficiently supported empirically (Leamer, 1998; Card and DiNardo, 2002; Goldberg and Pavcnik, 2007).

It still seems likely that a change in the characteristics of technological change affects wages and wage inequality, although the mechanism behind the effect is most likely not SBTC. In many studies on wage inequality, there seems to be an implicit assumption that workers are differentiated only by skills that can be acquired by any worker at the same cost. That is, workers are heterogeneous only in whether they intentionally acquire skills or not. However, this view seems to be too simple and seems to neglect some important elements in worker heterogeneity. Under the assumption that the source of heterogeneity of workers is only acquirable skills, the number of skilled workers will be determined at equilibrium where the "net" income (income minus cost of acquiring skills) is equalized across workers. At equilibrium, the net incomes of skilled and unskilled workers become identical. Hence, the difference in wages between them must always be equal to the cost of acquiring skills, but this seems unrealistic. Therefore, it seems highly likely that workers are heterogeneous before they acquire skills; this scenario seems more realistic, because each individual worker is in fact different from all other workers. In this paper, I focus on a different source of worker heterogeneity to examine wage inequality based on the model of total factor productivity (TFP) shown by Harashima (2009, 2016).

Harashima's model is constructed on the basis of ordinary or average workers' innovative intelligences, by which innovations for solving unexpected minor problems are created. The workers' innovative intelligences are an important element in TFP because the knowledge and technologies that humans currently possess are far from perfect; therefore, workers encounter many unexpected day-to-day and even minute-to-minute problems at production sites. Most of these unexpected problems will be minor, but they still have to be solved by creating innovations. TFP will vary depending on how many unexpected problems workers at production sites can solve. If workers' innovative intelligences are higher, they can solve more unexpected problems. That is, TFP depends on workers' innovative intelligences. An important point is that workers' innovative intelligences are naturally heterogeneous. In addition, workers' wages will differ depending on their innovative intelligences, because innovative intelligences are directly related to productivities. In other words, heterogeneity in innovative intelligences will generate wage inequality across workers.

Some technologies will be advantageous for workers with relatively high innovative intelligences and disadvantageous for workers with relatively low innovative intelligences. Therefore, the effectiveness of the innovative intelligences of workers will vary, and thereby their wages will vary depending on the types of technology used. If technologies that are advantageous for workers with higher innovative intelligence are introduced more frequently in a certain period of time, the wage inequality between workers with higher and lower innovative intelligence will increase during this period.

2 A MECHANISM OF WAGE INEQUALITY

2.1 Approximate effective production function

In the TFP model of Harashima (2009, 2016), an essential element is the "approximate effective production function" (AEPF). This concept is based on ordinary or average workers' innovative intelligences—that is, the intelligences used to create innovations to solve unexpected problems. Innovative intelligence is essential for efficient production, as will be shown in Section 3.1.1.

The simplest form of AEPF is

$$Y = \bar{\sigma}\omega A^{\alpha} K^{1-\alpha} L^{\alpha} \quad , \tag{1}$$

where Y, A, K, and L are production, technology, capital inputs, and labor inputs, respectively; ω (> 0) is a parameter that indicates the productivity resulting from a worker's innovative intelligence and also represents the worker's ability to solve unexpected problems; $\bar{\sigma}(> 0)$ is a parameter that indicates a worker's accessibility limit to capital with regard to location; and α (> 0) is a parameter that represents the experience curve effect. Because equation (1) has the same form as a Cobb-Douglas production function with regard to α, the parameter α can be interpreted as the labor share. In equation (1), let $T = \bar{\sigma}\omega A^{\alpha}$, which indicates TFP.

Suppose that there are two types of workers (HI and LI) who are identical except for their values of ω. Let ω_{HI} and ω_{LI} be the ω of HI and LI workers, respectively. HI workers have a higher innovative intelligence than LI workers and thereby $\omega_{HI} > \omega_{LI}$. HI and LI workers are not interchangeable with each other, and the numbers of them are exogenously given. Note that the reasons why workers have different values of ω and are not interchangeable are beyond the scope of economics and are the subject of studies in other fields. In this paper, I examine only what happens to wages when a technological change occurs to these exogenously given HI and LI workers.

Let L_{HI} and L_{LI} be the numbers of HI and LI workers, respectively, in an economy. Let L_S be a unit of the "size" of the economy, and initially $L_S = L_{HI} + L_{LI}$. In addition, let $S_{HI} = \frac{L_{HI}}{L_S}$ and $S_{LI} = \frac{L_{LI}}{L_S}$; thus, initially $S_{HI} = \frac{L_{HI}}{L_{HI} + L_{LI}}$ and $S_{LI} = \frac{L_{LI}}{L_{HI} + L_{LI}}$. S_{HI} and S_{LI} can be interpreted as the sizes of the economies composed of HI and LI workers, respectively. Capital inputs move perfectly elastically. By modifying the simplest form of the AEPF (equation [1]), the production function of the economy can be described as

$$Y = \bar{\sigma} A K^{1-\alpha}\left(\omega_{HI} L_{HI}^{\alpha} S_{HI}^{1-\alpha} + \omega_{LI} L_{LI}^{\alpha} S_{LI}^{1-\alpha}\right) \tag{2}$$

(see Harashima, 2017). Equation (2) can be interpreted such that the economy is a combination of the economies composed of HI and LI workers. Let $\bar{L}_S$ be a unit of the size of the economy when the population density is optimal (thereby $\bar{L}_s$ is constant). In the long run, the population density is optimal (see Harashima, 2017); therefore, by equation (2), the production function in the long run is

$$Y = \bar{\sigma} A K^{1-\alpha} \bar{L}_S^{\alpha-1}\left(\omega_{HI} L_{HI} + \omega_{LI} L_{LI}\right) \ . \tag{3}$$

The population density is assumed to be optimal initially; thereby, $\bar{L}_S = \bar{L}_{HI} + \bar{L}_{LI}$, where $\bar{L}_{HI}$ and $\bar{L}_{LI}$ are the initial values of L_{HI} and L_{LI}.

2.2 Inequality in wages

Let w_{HI} and w_{LI} be the wages for HI and LI workers, respectively. Because $L_S = \bar{L}_S = \bar{L}_{HI} + \bar{L}_{LI}$ holds in the long run, w_{HI} and w_{LI} in the long run are, by equation (3),

$$w_{HI} = \frac{\partial Y}{\partial L_{HI}} = \bar{\sigma}\omega_{HI} A K^{1-\alpha} \bar{L}_S^{\alpha-1}$$

and

$$w_{LI} = \frac{\partial Y}{\partial L_{LI}} = \bar{\sigma}\omega_{LI} A K^{1-\alpha} \bar{L}_S^{\alpha-1} \quad .$$

Hence, the following equation and inequalities are always true:

$$w_{HI} > 0 \quad ,$$

$$w_{LI} > 0 \quad ,$$

and

$$\frac{w_{HI}}{w_{LI}} = \frac{\omega_{HI}}{\omega_{LI}} > 1 \quad . \tag{4}$$

That is, in the long run, the ratio of w_{HI} to w_{LI} is constant and always equal to the ratio of ω_{HI} to ω_{LI}, and thereby

$$w_{HI} > w_{LI} > 0 \quad .$$

3 INOVATIVE INTELLIGENCE-BIASED TECHNOLOGICAL CHANGE

3.1 A model of innovative intelligence

3.1.1 Essential role of workers' innovative intelligences

The current state of knowledge and technologies is far from perfect and always will be. As a result, a large number of unexpected problems occur daily at every production site, although most of them are minor. These numerous unexpected minor problems must be solved by creating innovations, and it is the ordinary or average workers at production sites who do so. Therefore, ordinary workers' innovative intelligences are a significantly important element in TFP.

Workers also encounter, and have to fix, many unexpected minor problems, because it is impossible to provide workers with perfect manuals or to teach them everything about the technologies they use. Even if a manual for a technology is written in great detail, some parts of it will remain unwritten because it is too costly to make a perfect manual. The extent to which a manual is complete (or incomplete) depends on the balance between the cost of making the manual more complete and the increase in efficiency in production by making it more complete. The costs of producing a "thicker" manual include not only printing and other production costs, but also the cost of investigating the natures of an extremely large number of possible variations of rarely occurring minor incidents by experimenting with the problems the incidents generate. The cost of creating innovations to fix these problems individually will increase as the manual is made more complete. Therefore, a manual will be complete to the point where the marginal cost to enlarge it is equal to the consequent marginal increase in productivity. As a result, a large part of the complete instructions to use any particular piece of technology will usually be left unwritten.

Because not only the technologies themselves but also their corresponding instruction manuals are imperfect, many unexpected minor problems are going to occur day by day and minute by minute at production sites, and ordinary or average workers at the sites must solve them. Workers' innovative intelligences (ω) therefore are essential for productivity.

3.1.2 The model

Workers' innovative intelligences can be modeled on the basis of item response theory, which is widely used in psychometric studies (e.g., Lord and Novick, 1968; van der Linden and Hambleton, 1997). In particular, the item response function is used to describe the relationship between abilities and item responses (e.g., test scores or performances). A typical item response function is

$$\tilde{p}\left(\tilde{\theta}\right)=\tilde{c}+\frac{1-\tilde{c}}{1+\exp\left[-\tilde{a}\left(\tilde{\theta}-\tilde{b}\right)\right]} \quad ,$$

where $\tilde{p}$ is the probability of a correct response (e.g., answer) to an item (e.g., test or question), $\tilde{\theta}$ ($\infty > \tilde{\theta} > -\infty$) is a parameter that indicates an individual's ability, $\tilde{a}$ (> 0) is a parameter that characterizes the slope of the function, $\tilde{b}$ ($\infty \geq \tilde{b} \geq -\infty$) is a parameter that represents the difficulty of an item, and $\tilde{c}$ ($1 \geq \tilde{c} \geq 0$) is a parameter that indicates the probability that an item can be answered correctly by chance.

As Harashima (2012) showed, on the basis of item response theory, the probability of a worker solving unexpected problems in a unit of time, $p(\theta)$, can be modeled as

$$p(\theta)=c+\frac{1-c}{1+\exp\left[-a(\theta-b)\right]} \quad , \tag{5}$$

where θ ($\infty > \theta > -\infty$) indicates a worker's innovative intelligence, a (> 0) is a parameter that characterizes the slope of the function, b is a parameter that indicates the average difficulty of unexpected problems that workers have to solve, and c ($1 \geq c \geq 0$) is the probability that unexpected problems are solved by chance. As is evident from this function, the higher the worker's innovative intelligence (i.e., the higher the value of θ), the higher the probability of solving unexpected problems in a unit of time.

Because ω in equation (1) indicates the worker's ability to solve unexpected problems by utilizing innovative intelligence, ω will be positively and monotonically correlated with $p(\theta)$; therefore, ω can be described as a function of θ. By equation (5), therefore, TFP in equation (1) (i.e., $T=\bar{\sigma}\omega A^{\alpha}$) can be described as

$$T=\bar{\sigma}\omega A^{\alpha}=\left\{c+\frac{1-c}{1+\exp\left[-a(\theta-b)\right]}\right\}\bar{\varpi}\bar{\sigma}A^{\alpha}$$

and thereby

$$\omega=\left\{c+\frac{1-c}{1+\exp\left[-a(\theta-b)\right]}\right\}\bar{\varpi} \quad , \tag{6}$$

where $\bar{\varpi}$ is the unit of measurement and constant.

The innovative intelligence θ of each worker is assumed to be exogenously given and constant. Let θ_{HI} and θ_{LI} be θ of HI and LI workers, respectively, and $\theta_{HI} > \theta_{LI}$. Therefore,

$$\omega_{HI}=\left\{c+\frac{1-c}{1+\exp\left[-a(\theta_{HI}-b)\right]}\right\}\bar{\varpi} \tag{7}$$

and

$$\omega_{LI} = \left\{ c + \frac{1-c}{1+\exp[-a(\theta_{LI} - b)]} \right\} \overline{\omega} \quad . \tag{8}$$

Evidently, $\theta_{HI} > \theta_{LI} \Leftrightarrow \omega_{HI} > \omega_{LI}$.

3.2 Innovative intelligence-biased technological change

The parameter *c* (the probability of solving problems by chance) in equation (6) will be basically common to all workers and technologies, constant, and relatively small. The remaining parameters *a* and *b* will change with some types of technological changes. If their values are changed by a technological change, ω_{HI} and ω_{LI} will also change by equations (7) and (8), but they may change in different ways.

3.2.1 Effect of a change in *a*

By equation (6),

$$\frac{d\omega}{da} = \frac{(1-c)\overline{\omega}(\theta - b)}{\exp[a(\theta - b)] + \exp[-a(\theta - b)] + 2} \quad . \tag{9}$$

Equation (9) indicates that $\frac{d\omega}{da}$ increases as *a* increases if $\theta > b$; conversely, $\frac{d\omega}{da}$ decreases as *a* increases if $\theta < b$. Because *b* is set at a level where most workers can use the technology properly, as discussed in Section 3.1.1, its value will be set relatively small, and thereby generally $\theta_{HI} > b > \theta_{LI}$. Therefore, as *a* increases, ω_{HI} increases but ω_{LI} decreases, which means that the importance of a worker's innovative intelligence (θ) in solving unexpected problems increases as *a* increases. Hence, an increase in *a* is advantageous for HI workers but disadvantageous for LI workers.

Note that if the value of *a* relative to the values of θ and *b* is sufficiently small, the effect of $\exp[a(\theta - b)] + \exp[-a(\theta - b)]$ in equation (9) is sufficiently smaller than that of $(\theta - b)$ in the numerator of equation (9) for a change in θ. In this case, if $\theta > b$, then for the larger θ, $\frac{d\omega}{da}$ increases to a greater extent as *a* increases. Conversely, if $\theta < b$, then for the smaller θ, $\frac{d\omega}{da}$ decreases to a greater extent as *a* increases. In this case, therefore, the property that an increase in *a* is advantageous for HI workers but disadvantageous for LI workers is amplified. Moreover, relatively small values of *a* are reasonable from the point of view of item response theory.

If the value of *a* is heterogeneous across technologies, therefore, the values of ω_{HI} and ω_{LI} vary depending on the characteristics of current technology *A* with regard to *a*. However, do technologies have heterogeneous values of *a*? They do, for the following reason. Suppose that there are 2 technologies; technologies 1 and 2. If technology 1 generates a larger number of varieties of minor unexpected problems than technology 2, workers' innovative intelligences will be more important for technology 1 than technology 2. That property means that technology 1 has larger values of *a* than technology 2 because the value of *a* is proportionate to the relative importance of worker's innovative intelligence. On the other hand, the number of varieties of minor unexpected problems a technology generates will not be common across technologies: that is, it will be basically heterogeneous across technologies. Therefore, the values of *a* will also be basically heterogeneous across technologies.

Regardless of the type of technology, a worker who has a relatively high innovative intelligence can use the technology more efficiently than a worker who has a relatively low innovative intelligence, so a worker with relatively high innovative intelligence is intrinsically in an advantageous position. In addition, if a technology has the property that it generates larger varieties of minor unexpected problems (i.e., has the larger value of *a*), the position becomes even more advantageous.

3.2.2 Effect of a change in *b*

The level of difficulty in using a technology (i.e., *b*) is set by the producer of the technology (or the producer of a machine or tool that embodies the technology), but *b* will not be set at a level where all workers can perfectly solve all unexpected problems generated by the technology because it is too costly to do so, as discussed in Section 3.1.1. The producer of the technology has to compromise and create an imperfect manual, which will be sufficiently useful for most, but not all, workers; therefore, some workers cannot use the technology sufficiently properly. Suppose that the difficulty *b* is set at a level at which the highest *h* ($1 > h > 0$) proportion of workers can solve unexpected problems at a rate above the probability *v* ($1 > v > 0$). Clearly, if *h* is smaller, *b* is larger, and vice versa. The value of *h* will be smaller if the number of possible varieties of rarely occurring minor incidents generated by a technology is larger, because the manual becomes more imperfect (Section 3.1.1).

By equation (6),

$$\frac{d\omega}{db} = -\frac{a(1-c)\overline{\omega}}{\exp[a(\theta-b)] + \exp[-a(\theta-b)] + 2} \quad ,$$

and thereby, for any θ,

$$\frac{d\omega}{db} < 0 \quad . \tag{10}$$

Inequality (10) indicates that an increase in *b* decreases both ω_{HI} and ω_{LI}. In addition, by the extreme value condition

$$\frac{d\left(\frac{d\omega}{db}\right)}{d\theta} = -a^2(1-c)\overline{\omega}\frac{\exp[a(\theta-b)] - \exp[-a(\theta-b)]}{\left\{\exp[a(\theta-b)] + \exp[-a(\theta-b)] + 2\right\}^2} = 0 \quad ,$$

when $b = \theta$, $\frac{d\omega}{db}(<0)$ is smallest (i.e., the negative effect of an increase in *b* is largest). As discussed in Section 3.2.1, because *b* is set at a level where most workers can use the technology properly, the value of *b* will be small. Hence, the value of θ when $b = \theta$ will generally be less than the average θ of all workers; furthermore it will be set close to θ, not to the average θ. Therefore, in general, the negative effect of an increase in *b* will be larger for LI workers than for HI workers. That is, as with *a*, the value of *b* is generally proportionate to the relative importance of a worker's innovative intelligence.

Because *b* and the importance of innovative intelligence are positively correlated, the values of *b* will be basically heterogeneous across technologies for the same reasons as for the case of *a*, and a technology that generates a relatively large number of varieties of minor unexpected problems will have a larger value of *b*. Therefore, as with *a*, the values of ω_{HI} and ω_{LI} will vary depending on the value of *b* corresponding to the current technology *A*.

In addition, because the effects of *a* and *b* have similar properties, it is highly likely that a technology that has a relatively large value of *a* also has a relatively large value of *b*.

3.2.3 IIBT and IIBTC

Because *a* and *b* are basically heterogeneous across technologies, technologies can be categorized depending on their values of *a* and *b*. However, as shown in Sections 3.2.1 and 3.2.2, a technology that has a relatively large value of *a* will probably also have a relatively large value of *b*. Hence, technologies can be categorized solely depending on their values of *a*. I call a technology an "innovation intelligence-biased technology" (IIBT) if the technology has a greater value of *a* than the average *a* of all technologies. In addition, I call an increase in the average *a* of all technologies in an economy an "innovation intelligence-biased technological change" (IIBTC).

What kind of technologies are IIBT? By its nature, IIBT generates a relatively large number of varieties of minor unexpected problems. The number of varieties of problems will increase as the number of possible different situations a technology will encounter becomes larger, because different situations will generally generate different varieties of problems. This implies that IIBTs are technologies that can be used in relatively more varied and diverse situations: that is, they are applicable to a relatively wide range of situations. Technologies that are closely related to information and communication technology (ICT) may be such technologies and thereby may belong to IIBT. The increasing prevalence of ICT throughout the economy in recent decades therefore may have caused IIBTC.

3.3 The increase in wage inequality and IIBTC

If a new technology is IIBT and causes IIBTC, ω_{HI} increases but ω_{LI} decreases. Thereby, the ratio $\frac{\omega_{HI}}{\omega_{LI}}$ increases. As shown in Section 2, wages are determined in the long run at the point satisfying $\frac{w_{HI}}{w_{LI}} = \frac{\omega_{HI}}{\omega_{LI}}$ (equation [4]). Thereby, $\frac{w_{HI}}{w_{LI}}$ will also increase if IIBTC occurs; that is, the inequality in wages between HI and LI workers will increase. IIBTC therefore increases wage inequality.

If IIBTC prevails over a certain period of time, wage inequality will increase during the period. Increases in wage inequality in many countries in recent decades may have occurred because IIBTC prevailed during this time period. If ICT is really an IIBT as argued in Section 3.2.3, IIBTC caused by the development and prevalence of ICT in recent decades may have caused increases in wage inequality.

However, even if IIBTC prevailed in many countries in recent decades, there is no guarantee that IIBTC will always prevail. There are many kinds of technologies, and new technologies cannot always be used in relatively more varied and diverse situations. The recent decades, during which ICT was substantially improved, may be an exceptional period. If anything, technological changes may be neutral on average with regard to workers' innovative intelligences, and the ratio $\frac{w_{HI}}{w_{LI}} = \frac{\omega_{HI}}{\omega_{LI}}$ (equation [4]) may be constant in the very long run.

4 CONCLUDING REMARKS

Explanations for recent increases in wage inequality based on SBTC have not been sufficiently supported empirically. In this paper, IIBTC was examined as a possible important source of increasing wage inequality. Workers' innovative intelligences are an important element in TFP, and they can be heterogeneous across workers. In addition, this heterogeneity will have great impacts on workers' wages. In this paper, I showed that the impacts on wages differ across heterogeneous workers depending on the characteristics of the technologies used for production.

IIBT is advantageous for workers with relatively high innovative intelligences and disadvantageous for workers with relatively low innovative intelligence. Hence, if IIBTC occurs, inequality in wages will increase among heterogeneous workers.

If IIBTC continues to prevail over a certain period of time, the inequality in wages between workers with higher and lower innovative intelligences will increase during the period. Recent decades may have been such a period, possibly because of rapid development of ICT. However, it is also true that IIBTC will not necessarily prevail in any given period.

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