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ABSTRACT

General Purpose Technology and Within-Group Inequality*

This Paper develops a theoretical model to analyse how a General Purpose Technology (GPT) shapes within-group wage inequality when workers are *ex ante* equal, but their adaptability to new technologies is subject to stochastic factors that are history dependent. It is argued that the diffusion of a GPT leverages the importance of these stochastic factors in three ways. First, a rise in the speed of embodied technological progress raises the market premium to workers adaptable to the leading-edge technology. Second, the generality of the technology raises the ability of adaptable workers to transfer recently acquired knowledge to new machines. Third, the generality of the technology reduces the cost of retooling old machines, which increases the demand for adaptable workers. In the model the rise in within-group inequality is mainly transitory and is mirrored by a rise in wage instability. The key predictions of the model are shown to be in line with some of the existing empirical evidence.

JEL Classification: E20, J30, O30
Keywords: general purpose technology, history-dependence, inequality, skill transferability, technological progress

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NON-TECHNICAL SUMMARY

Dramatic changes in wage distribution have recently taken place in the US economy. Wage inequality has grown rapidly over this period, reaching arguably the highest peak in the post-war era. Part of this increase in inequality is attributable to wage differentials between educational and experience groups, which have expanded at least since the late 1970s. But there has also been a large rise in wage inequality *within* groups of observationally equivalent workers. This rise in within-group inequality is a crucial feature of recent dynamics of the wage distribution not only in the US, but also in other countries where substantial changes in wage distribution have taken place, such as the UK and Canada.

Contemporaneously with dramatic changes in the wage structure, these same economies witnessed the arrival of a new *General Purpose Technology* (GPT) embodied in information and communication equipment. The GPT consists of a wave of major innovations, each one creating a new product or process that improves upon, but is closely related to, those created by other recent innovations. In 1970 only 14% of the equipment capital stock comprised information-processing goods, while in 1996 this share reached 25%. Besides its 'general nature', the other key feature of this technological wave has been the *speed* of quality improvements in the equipment embodying new technology. The seminal work by Gordon (1990) on quality-adjusted price indexes for production durable equipment goods documents extensive technological improvements in the past 50 years. A closer look at the data shows that the pace of improvement has accelerated since the mid-1970s. The lion's share of the decline in quality-adjusted price is obviously attributable to computers, communication equipment and other information processing goods.

The objective of this Paper is to develop a tractable dynamic general equilibrium model to analyse how the level of within-group wage inequality is affected by such a GPT, and to show that this model can account for a number of puzzling empirical regularities concerning the recent rise in inequality. Earnings are heterogeneous in the model because the ability to move towards better jobs and technologies is subject to stochastic factors that are history dependent: labour market history is scattered with stochastic events related to the luck of individuals, firms or industries. We argue that the rapid diffusion of a GPT leverages the importance of these stochastic factors, raising the premium to workers with no observable distinguishing characteristics other than their good fortune.

The mechanism of the model can be explained easily. In the benchmark economy workers are *ex ante* equal. Technological change takes place each period and is embodied in new machines. Wage inequality arises because some workers are fortunate enough to be adaptable to work with the most recent vintage of machines. Those who are adaptable two periods in a row earn an additional premium because they can employ skills on the new machines that were learned on last period's new machines. The diffusion of GPT raises inequality through three separate channels. First, it allows lucky workers to work on more productive machines. Second, because of its general nature, it raises the skill transferability of those who are adaptable twice in a row. Third, the same general nature permits old machines to be retooled more easily to work with new technology, thus amplifying the demand for adaptable workers.

The model can explain several dimensions of the rise in inequality, as we document throughout the Paper. In particular, the rise in within-group inequality in the model has a *transitory* nature and is mirrored by a rise in wage instability along individual labour market histories. These two features of our model find a rather strong support in the data, but existing theories largely fail to explain them.

1 Introduction

Important changes in the wage distribution have taken place in the US economy during the past 30 years. Wage inequality has grown rapidly over this period, reaching arguably the highest peak in the post-War era. For example, the ratio between the ninth and first deciles of the weekly wage distribution for males rose by 70% between 1970 and 1993.[1] Part of this increase in inequality is attributable to wage differentials between educational and experience groups, which have expanded at least since the late 1970's. But there has also been a large rise in wage inequality *within* groups of observationally equivalent workers. This rise in within-group inequality is a crucial feature of recent dynamics of the wage distribution not only in the US, but also in other countries where substantial changes in the wage distribution have taken place, such as the UK and Canada.[2]

Contemporaneously with dramatic changes in the wage structure, these same economies witnessed the arrival of a new *General Purpose Technology* (GPT) embodied in information and communication equipment.[3] The GPT consists of a wave of major innovations, each one creating a new product or process that improves upon, but is closely related to, those created by other recent innovations.[4] In 1970 only 14% of the equipment capital stock comprised information processing goods, while in 1996 this share reached 25%.[5] Accordingly, a recent survey by the Bureau of Labour Statistics concludes that the impact of computers has been *"...extensive because the technology, network systems, and software is similar across firms and*

[1]From Gottschalk (1997).

[2]For the UK, Gosling, Machin and Meghir (1998) report that "*like in the US, an important aspect of rising inequality is increased within-group wage dispersion*". For Canada, Baker and Solon (1999) write that "*the increase in Canadian earnings inequality has occurred mainly within education groups*".

[3]The term "General Purpose Technology" was coined by Bresnahan and Trajtenberg (1995). See Helpman and Trajtenberg (1998) for a collection of articles dealing with the role of GPTs in the growth process.

[4]In 1971 the first microprocessor and the first floppy disk were made commercially available, in 1973 Internet technology was developed, in 1975 the first mass produced personal computer (PC) was launched, and in 1979 the first modem was introduced, linking the PC technology to Internet. (From "Chronology of Computing" in the *Financial Times* Information Technology Review, October 6, 1999).

[5]These figures are taken from Katz and Herman (1997).

industries. This is in contrast to technological innovations in the past, which often affected specific occupations and industries (for example, machine tool automation only involved production jobs in manufacturing). Computer technology is versatile and affects many unrelated industries and almost every job category".[6]

Besides its "general nature", the other key feature of this technological wave has been the *speed* of quality improvements in the equipment embodying new technology. The seminal work by Gordon (1990) on quality-adjusted price indexes for production durable equipment goods documents extensive technological improvements in the past 50 years. A closer look at the data shows that the pace of improvement has accelerated since the mid 1970's. Greenwood and Yorukoglu (1997) use Gordon's data to show that the growth rate of *embodied* technical change was 3% on average between 1954 and 1974 and 4% on average between 1974 and 1984. Hornstein and Krusell (1996) and Krusell, Ohanian, Ríos-Rull and Violante (1998) extend the series until 1992 and reach a similar conclusion. The lion's share of the decline in quality-adjusted price is obviously attributable to computers, communication equipment other information processing goods: in the period 1985-1996 the quality-adjusted price indexes for memory chips and microprocessors declined at an annual rate of 20%, and 35% respectively, numbers which were just not imaginable thirty years ago.[7]

The objective of this paper is to develop a tractable dynamic general equilibrium model to analyze how the level of within-group wage inequality is affected by such a GPT[8], and to show that this model can account for a number of puzzling empirical regularities concerning the recent rise in inequality. Earnings are heterogeneous in the model because the ability to move towards better jobs and technologies is subject to stochastic factors that are history dependent: labour market history is scattered with stochastic events related to the luck of individuals, firms or industries. We argue that the rapid diffusion of a GPT leverages the importance of these stochastic factors, raising the premium to workers with no observable distinguishing characteristics other than their good fortune.

[6]From McConnell (1996), page 5.

[7]These numbers are taken from Grimm (1998).

[8]We are thus focusing attention on "idea-generating" GPTs, that is on technological breakthroughs which themselves generate a whole set of new ideas (or "secondary innovations") which require suitably adapted labor in order to be implemented.

The mechanism of the model can be explained easily. In the benchmark economy workers are *ex-ante* equal. Technological change takes place each period and is embodied in new machines. Wage inequality arises because some workers are fortunate enough to be adaptable to work with the most recent vintage of machines. Those who are adaptable two periods in a row earn an additional premium because they can employ skills on the new machines that were learned on last period's new machines. The diffusion of GPT raises inequality through three separate channels. First, it allows lucky workers to work on more productive machines. Second, because of its general nature, it raises the skill transferability of those who are adaptable twice in a row. Third, the same general nature permits old machines to be retooled more easily to work with new technology, thus amplifying the demand for adaptable workers.

The model can explain several dimensions of the rise in inequality, as we document throughout the paper. In particular, the rise in within-group inequality in the model has a *transitory* nature and is mirrored by a rise in wage instability along individual labour market histories. These two features of our model find a rather strong support in the data, but existing theories largely fail to explain them[9]. Indeed, a most common explanation for the widening of inequality within groups is that a shift in demand for skills would have increased the returns to permanent unobservable skills, such as innate ability. A variety of models in the literature can be traced back to this mechanism. For example, Galor and Moav (1999), and Rubinstein and Tsiddon (1999) contend that technological progress changes the nature of occupations, jobs and tasks to be performed. Innate ability helps in adapting to this new work environment, therefore a technological transition raises returns to ability and increases within-group inequality. In Caselli (1999) some workers are endowed with lower learning costs than others and will be those who can extract the higher wage premium from a new technological paradigm which requires acquisition of new knowledge to be implemented. In Lloyd-Ellis (1999), workers are ex-ante heterogeneous in their capacity to absorb new technology-specific skills. Wage in-

[9]An exception is Violante (1998) which develops a model with multiple vintages of capital and technology specific skills where learning rate on the job and transferability rate across jobs depend on the speed of technical change. The model, solved numerically and calibrated to the US economy, is a quantitative exercise. Our paper is complementary to Violante's: it develops a more general theoretical framework, which is analytically tractable, and derives a number of qualitative empirical implications.

equality rises when the rate at which technologies are introduced exceeds the rate at which they are absorbed because of increased competition for technologically mobile labour. Heckman, Lochner and Taber (1998) model innate skills as ability to learn and to invest in general human capital. They can explain rising inequality within low-education groups (but not within highly educated workers) because individuals of different ability levels respond differently to the same shocks and invest differently. Finally, Acemoglu (1997) in the context of a search model, and Jovanovic (1997) within an optimal assignment model show that a technological shock can drive up inequality through a higher positive covariance in the equilibrium assignment of workers with different ability to technologies of different quality.

All these models of within-group wage inequality rely entirely on *ex-ante* fixed differences in innate abilities across individuals. But if a rise in the returns to innate ability had been the dominant force behind the recent increase in within-group inequality, then one should have observed highly persistent shifts in individual wage profiles, and therefore lower wage instability and lower earnings mobility along individual labour market histories, as workers would tend to become more stratified on the basis of their innate skill dimensions. On the other hand, if transitory shocks were at work, one would expect larger mobility and higher wage instability. Needless to say, from the point of view of policy analysis it is important to know whether the observed increase in within-group inequality is affecting the permanent or the temporary component of income: indeed, higher mobility within groups might actually be perceived as a good thing, whilst higher long-run inequality may be perceived as detrimental to economic stability and growth.[10] As it turns out, recent empirical papers (e.g Gottschalk and Moffitt (1993) and Gittleman and Joyce (1996) for the US, Baker and Solon (1999) for Canada, Dickens (1999) for the UK, and Blundell and Preston (1999) for both the US and the UK) show, first that earnings mobility has not fallen whereas wage instability has increased during the past two decades, and second that transitory shocks might account for up to half of the observed increase in overall inequality and for most of the increase in within-group inequality.

The rest of the paper is organized as follows. Section 2 describes the economic environment and the stationary competitive equilibrium. Section 3 analyzes the baseline model in which all workers are ex ante equal, and capital is putty-clay.

[10]E.g., see Alesina and Rodrik (1994).

Section 4 shows how this model can be used to account for several empirical facts. Section 5 extends the model to allow for flexible capital adjustment. In Section 6 we extend the baseline model to incorporate ex-ante heterogeneity, with two different educational groups, in order to contrast the evolutions of within- versus between-group wage inequality. Section 7 concludes the paper.

2 The Economic Environment

2.1 Technology

Time is discrete, and indexed by t. Firms produce a good that can be used for consumption or for investment (machines). There is only one kind of consumption good, but each period an exogenous innovation occurs that allows a new improved vintage of machine to be produced. At any date only machines of the most recent vintage ("leading-edge" machines) can be produced.[11] Thus output at date t is:

$$y_t = c_t + k_t,$$

where c_t denotes the amount produced of the consumption good and k_t denotes the number of machines produced of vintage t.

Output is produced using labour and machines. Each machine lasts for two periods, with no depreciation taking place after the first period.[12] Thus at any date t there are two producing sectors; firms in sector 0 use leading-edge machines, while firms in sector 1 use "mature" machines (machines of vintage $t-1$). [13] The production function in each sector is Cobb-Douglas with constant returns to scale. The (labour-augmenting) productivity parameter in sector 0 at date t is $A_t = (1+\gamma)^t$, where $\gamma > 0$ is the constant, exogenous rate of labour-augmenting technological progress. The productivity parameter in sector 1 at date t is $(1+\eta)\,A_{t-1}$, where $\eta > 0$ is the constant, exogenous rate of learning by doing.

It is prohibitively costly to retool mature machines so as to transform them into leading-edge machines.[14] Thus the number of mature machines used in sector 1 at t

[11]This assumption is relaxed in Section 5 below.

[12]Our results generalize to the case of partial physical depreciation after one period.

[13]This particular assumption is also made by Galor and Tsiddon (1997), although in the context of a model of wage inequality based upon differences in innate ability and in parental human capital.

[14]This assumption is also relaxed in Section 5 below.

is k_{t-1}, and the aggregate production function is:

$$y_t = (A_t x_{0t})^{1-\alpha} k_t^\alpha + ((1+\eta) A_{t-1} x_{1t})^{1-\alpha} k_{t-1}^\alpha, \qquad t = 1, 2, ... \tag{1}$$

where x_{it} is the labour input used in sector i, $i = 0, 1$, and $0 < \alpha < 1$.

2.2 Preferences and Endowments

The economy is populated by a continuum of ex-ante identical, infinitely-lived individuals of mass 1. Perfect risk-sharing markets yield the same consumption profile for each individual, whose utility depends only on that profile, with unitary elasticity of intertemporal substitution:[15]

$$U = \sum_{t=1}^{\infty} \beta^{t-1} \ln c_t, \qquad 0 < \beta < 1.$$

Each individual is endowed with a unit of labour services at each date, and supplies it inelastically to one sector. Let n_{ij} denote the measure of individuals supplying labour to sector i this period, after having supplied sector j last period. The supply of labour to sector 1 is then:

$$x_1 = n_{01} + n_{11}. \tag{2}$$

An individual that worked in sector 0 last period acquired some knowledge that can be transferred to the leading edge this period; accordingly this individual's unit of labour services can provide $1 + \tau$ units of labour input to sector 0 this period, where $\tau \in [0, \eta]$ is an exogenous "transferability" parameter. Accordingly, the supply of labour to sector 0 is:

$$x_0 = (1+\tau)n_{00} + n_{10}. \tag{3}$$

Any individual can work in sector 1 where production takes place with mature machines. But not everyone can work in sector 0. Specifically, someone who worked in sector i last period has a probability σ_i of being able to work in sector 0 this period, $i = 0, 1$. The probabilities σ_0 and σ_1 are exogenous constants reflecting the stochastic forces determining a person's adaptability to the latest innovation. Assume $\sigma_1 \leq \sigma_0$, so that experience on a more recent vintage improves the ability

[15] Our results generalize to any constant elasticity of substitution.

to work in a new technological environment, and hence increases the likelihood of being productive on the leading edge machines.

The law of large numbers implies that no more than a fraction σ_0 (σ_1) of the labour force currently employed on leading-edge (mature) machines can be productively employed by firms operating leading-edge machines next period. More formally, the following *aggregate adaptability constraints* apply:

$$\left.\begin{aligned} n_{00} &\leq \sigma_0(n_{00}+n_{10}), \\ n_{10} &\leq \sigma_1(n_{01}+n_{11}) \end{aligned}\right\} \tag{AC}$$

2.3 Commentary

Our specification with respect to learning-by-doing and transferability reflects some implicit assumptions concerning technological knowledge. Thus the fact that everyone's labour services are equally productive in sector 1, whether or not they are experienced with that vintage of machine, reflects the assumption that it is the owners of the machines, or firms, that are learning, rather than the workers, and what they are learning is "organizational knowledge" on how best to employ workers on their machines. This view of learning by doing accords with the study by Bahk and Gort (1993), who show that, after controlling for quality of capital and labour, the productivity of a plant still rises for several years after its birth.

When a particular kind of machine is new however, firms still don't know how to exploit its full potential, and a worker who has experience with a similar machine may be able to operate the machine more efficiently than a worker without such experience. But the knowledge gained from experience on a very old vintage does not help much in this respect.[16] Hence our specification that workers coming to sector 0 from sector 0 carry some extra skills, but not workers coming to sector 0 from sector 1. The requirement that $\tau < \eta$ reflects the assumption that prior experience on similar machines is not as valuable as is long experience on identical machines.

The transferability parameter reflects the "generality" of technological knowledge. An economy where $\tau = 0$ is one in which subsequent innovations are fundamentally different from each other, hence knowledge is completely specific to a

[16] The last two sentences apply to the vintage model of learning by doing presented by Jovanovic and Nyarko (1996).

particular innovation. The opposite extreme where $\tau = \eta$ corresponds to an economy in which technological knowledge is completely general; knowledge acquired through experience with the previous vintage is fully transferable on the new generation of machines.[17]

As explained above, our assumption of history-dependent and stochastic individual adaptability rates differs sharply with the standard assumption in the literature of a fixed skill component which fully determines each worker's ability to work with a new vintage (as in Caselli, Galor and Moav, LLoyd-Ellis, etc.). Our model is general enough, however, to encompass an innate ability model, a model with random *iid* adaptability shocks and every degree of persistence in between. When $\sigma_0 = 1$ and $\sigma_1 = 0$, the initial assignment of workers to vintages repeats forever at the individual level, as an innate ability model would predict. When $\sigma_0 = \sigma_1 = \sigma$ the adaptability rate at the individual level is not history dependent, but purely *iid* over time. The intermediate case of $1 > \sigma_0 > \sigma_1 > 0$ generates history dependence in the likelihood that any worker can operate a leading-edge machine. This general approach allows us to analyze whether the diffusion of a *GPT* generates more or less inequality according to the degree of persistence of individual adaptability parameters.

Finally, a remark on the relationship between σ and τ. The parameters σ_0 and σ_1 are indexes of the *extensive* adaptability margin of an economy, as they determine how many "bodies" the labour market is able to match productively with the latest vintage. The parameter τ is an index of the *intensive* margin, as it determines how much skill each adaptable worker can productively transfer to the latest vintage. Interestingly, it will turn out that σ and τ have contrasting effects on inequality.

2.4 Decisions of Workers and Firms and Stationary Equilibrium

We focus attention on a steady-state general competitive equilibrium with complete markets, in which the labour flows n_{ij} are all constant from one period to the next; output, consumption and machinery all grow at the rate of technological progress γ;

[17] In the model of Chari and Hopenhayn (1991), knowledge is also vintage-specific, but it is embodied in workers (η is attached to the worker, not the firm) and it is fully specific, so non-transferable across vintages ($\tau = 0$). Moreover, their focus is on technology diffusion, rather than on inequality.

the real rate of interest r is constant; the real wage rate w_{it} in each sector i grows at the rate γ; and future values of all these variables are perfectly foreseen. The real rate of interest is governed by the steady-state Euler equation:

$$\frac{1}{1+r} = \beta \frac{c_t}{c_{t+1}} = \beta \frac{1}{1+\gamma}. \tag{4}$$

Let $\omega_i = w_{it}/A_t$ denote the steady-state productivity-adjusted wage in each sector i. Since firms are perfectly competitive, their aggregate input-output sequence $\{k_t, x_{0t}, x_{1t}, y_t\}_{t=1}^{\infty}$ must maximize the present value of aggregate profits:

$$\sum_{t=1}^{\infty} \left(\frac{1}{1+r}\right)^{t-1} (y_t - k_t - A_t \omega_0 x_{0t} - A_t \omega_1 x_{1t})$$

subject to (1), with k_0 given. The first-order conditions for profit-maximization imply that the relative wage in sector 0 is given by the ratio of marginal products:[18]

$$\frac{\omega_0}{\omega_1} = \frac{1+\gamma}{(1+\eta)^{1-\alpha}} \left(\frac{x_0}{x_1}\right)^{-\alpha}. \tag{5}$$

Since an individual who has worked in the leading-edge sector 0 for two periods in a row provides $(1+\tau)$ units of labour on his current job, that individual's productivity-adjusted wage is:

$$\omega_{00} = (1+\tau)\,\omega_0 \tag{6}$$

A worker's only labour-supply decision is whether to work in sector 0 or sector 1. This decision is made on the basis of wealth-maximization. Wealth equals the expected present value of lifetime wages, which is $V_{1,t} = A_t v_1$ for an individual working in sector 1 this period and $V_{i0,t} = A_t v_{i0}$ for an individual working in sector 0 this period who worked in sector i last period. Productivity-adjusted wealth v obeys the Bellman equations:

$$\begin{aligned} v_{00} &= \omega_{00} + \beta\{v_1 + \sigma_0 (v_{00} - v_1)^+\} \\ v_{10} &= \omega_0 + \beta\{v_1 + \sigma_0 (v_{00} - v_1)^+\} \\ v_1 &= \omega_1 + \beta\{v_1 + \sigma_1 (v_{10} - v_1)^+\} \end{aligned}$$

[18] The first-order conditions with respect to x_{0t} and x_{1t} are:

$$\omega_0 = (1-\alpha)\,(A_t x_{0t}/k_t)^{-\alpha}$$

and

$$\omega_1 = (1-\alpha)\,\frac{(1+\eta)^{1-\alpha}}{1+\gamma}\,(A_{t-1} x_{1t}/k_{t-1})^{-\alpha}.$$

Equation (5) follows from these and the stationarity condition that x_{0t}, x_{1t} and k_t/A_t be constant.

where the notation x^+ indicates the maximum of x and 0, and where we have made use of the Euler equation (4) determining the rate of interest. So, for example, a worker coming from sector 0 to sector 0 earns a productivity-adjusted wage ω_{00} and has a guaranteed continuation value of $(1+\gamma)\, v_1$, since working in sector 1 is always an option. With probability σ_0 the worker will have the option of continuing in sector 0 next period, which will be exercised if $v_{00} > v_1$.

Wealth-maximization by individual workers subject to the adaptability constraints (AC) implies the complementary inequalities:

$$\begin{array}{lll} 0 & \leq n_{00} & \text{with} = \text{if} \quad v_1 > v_{00} \\ n_{00} & \leq \sigma_0 \left(n_{00} + n_{10}\right) & \text{with} = \text{if} \quad v_1 < v_{00} \\ 0 & \leq n_{10} & \text{with} = \text{if} \quad v_1 > v_{10} \\ n_{10} & \leq \sigma_1 \left(n_{01} + n_{11}\right) & \text{with} = \text{if} \quad v_1 < v_{10} \end{array}$$

So, for example, if $v_1 < v_{00}$ then everyone who worked in sector 0 last period and can do so this period will choose to do so.

It is useful to highlight the economic factors behind the workers' mobility decisions. The choice of moving onto a new technology involves a trade-off: in terms of current pay-off, a new technology guarantees higher efficiency of capital (by a factor γ), but lower knowledge and experience on the new technology. As for the continuation value, being on a new technology always gives the worker a higher adaptability rate, and the option of larger future skill transferability.

Labour-market clearing requires full employment:

$$n_{00} + n_{10} + n_{01} + n_{11} = 1. \tag{7}$$

Furthermore, in a steady state the flows of labour into and out of sector 1 must be equal:

$$n_{01} = n_{10}. \tag{8}$$

3 Equilibrium within-group inequality

We measure inequality by the ratio between the highest and the lowest wage in the economy:

$$R_\omega = \frac{\max\left\{\omega_{00}, \omega_0, \omega_1\right\}}{\min\left\{\omega_{00}, \omega_0, \omega_1\right\}}$$

This wage ratio index R_ω has the advantage of being simple to characterize and of behaving in the vast majority of the cases similarly to other more common measures of inequality. In Section 3.2 we report a comparison between the R_ω index, the variance of log-wages (V_ω), and the 90/10 percentile wage ratio (D_ω) and we show that all our conclusions are robust to using these alternative measures of inequality.

The equilibrium condition (6) determines the relative wage ω_{00}/ω_0 of the two kinds of worker in sector 0. A complete description of all relative wages can thus be obtained by determining the relative wage ω_0/ω_1 between the two sectors. Equation (5) describes a "relative demand curve" relating ω_0/ω_1 to the relative quantity x_0/x_1. We determine ω_0/ω_1 by putting (5) together with a "relative supply curve," which we now proceed to construct on the basis of the previous Section's analysis.

First, note that individuals who worked in sector 1 last period will be indifferent between the two sectors this period if the relative wage ω_0/ω_1 equals:

$$\Omega = \frac{1}{1+\beta\sigma_0\tau},$$

for then $v_1 = v_{10}$. In this case, workers coming from sector 0 last period will strictly prefer to stay in sector 0, since $v_{00} = v_{10}+\tau\omega_0 > v_{10}$, so their adaptability constraint will be binding. By the same reasoning, when $\omega_0/\omega_1 > \Omega$, every worker will strictly prefer to work in sector 0, and both adaptability constraints will be binding. In this case, the relative supply x_0/x_1 equals:[19]

$$\chi = \frac{\sigma_1}{1-\sigma_0}\left(1+\sigma_0\tau\right). \tag{9}$$

Thus the relative supply curve has the reverse-L shape depicted in Figure 1. When the relative wage falls below Ω, workers coming from sector 1 strictly prefer to stay there, so that the steady-state flow into sector 0 is 0, which implies $x_0 = 0$.[20] When the relative wages equals Ω then wealth-maximization allows the fraction of workers from sector 1 that flow into sector 0 to be anything between 0 and σ_1, which is consistent with any relative supply between 0 and χ.

Define Φ as the relative wage along the relative demand curve when the relative

[19]With both adaptability constraints binding, $n_{10} = \sigma_1\left(n_{01}+n_{11}\right)$ and $n_{00} = \sigma_0\left(n_{00}+n_{10}\right)$. These two equations and the two labour market equilibrium conditions (7) and (8) can be solved for the four n_{ij}'s. Substituting the solutions into relationships (2) and (3) yields (9).

[20]That is, together with (7) and (8), $n_{10} = 0$ implies $n_{00} = 0$ and therefore, by (3), $x_0 = 0$.

supply is χ:

$$\Phi = \frac{(1+\gamma)}{(1+\eta)^{1-\alpha}}\left[\frac{(1-\sigma_0)}{\sigma_1(1+\sigma_0\tau)}\right]^{\alpha}$$

If $\Phi \geq \Omega$ then both adaptability constraints bind and $\omega_0/\omega_1 = \Phi$, as illustrated by demand curves D_a and D_b in Figure 1. Otherwise $\omega_0/\omega_1 = \Omega$. Thus:

$$\omega_0/\omega_1 = \max\{\Omega, \Phi\}. \tag{10}$$

The maximal wage is always ω_{00}, because otherwise wages in sector 1 would dominate those in sector 0 and the relative supply x_0/x_1 would be zero.[21] When $\Phi \geq 1$, then the minimal wage is ω_1 and $R_\omega = \omega_{00}/\omega_1 = (\omega_{00}/\omega_0)(\omega_0/\omega_1) = (1+\tau)\Phi$. When $\Phi < 1$, then, since $\Omega < 1$, the minimal wage is always ω_0 and $R_\omega = \omega_{00}/\omega_0 = (1+\tau)$. Putting these results together and using straightforward differentiation yields:

Proposition 1 *In the basic model,*

1. The wage ratio index (R_ω) in steady-state equilibrium is given by:

$$R_\omega = (1+\tau)\max\{1, \Phi\}.$$

where Φ is defined above.

2. Moreover:

$$\frac{\partial R_\omega}{\partial \tau} > 0, \quad \frac{\partial R_\omega}{\partial \gamma} \geq 0, \quad \frac{\partial^2 R_\omega}{\partial \gamma \partial \tau} \geq 0, \quad \frac{\partial R_\omega}{\partial \sigma_i} \leq 0, \quad \frac{\partial R_\omega}{\partial \eta} \leq 0.$$

In particular, if γ is small enough relative to η then $R_\omega = 1+\tau$. In this region of the parameter space, any increase in γ will affect inequality between workers on different vintages, but it will leave the maximal wage spread unaffected, which in turn occurs *within* sector 0; thus R_ω will be insensitive to the rate of technological progress. However, when γ is large then $R_\omega = (1+\tau)\Phi$. In this region any increase in γ will raise the maximal wage spread, which now occurs *between* sectors, so R_ω will be sensitive to changes in γ. An increase in τ will always raise R_w because it always raises the premium earned by the highest paid workers, namely those transferring skills from the previous leading edge to the current leading edge. Figure 2 provides a graphical representation of R_ω as a function of the pair (γ, τ), and clearly shows the two regions.

[21] More formally, $\omega_{00}/\omega_0 = 1+\tau > 1$ and $\omega_{00}/\omega_1 = (\omega_{00}/\omega_0)(\omega_0/\omega_1) = (1+\tau)(\omega_0/\omega_1) \geq (1+\tau)\Omega = (1+\tau)/(1+\beta\sigma_0\tau) > 1$.

Thus, equilibrium within-group wage inequality:

1. increases with the rate of embodied technical progress γ: the higher γ, the bigger the wedge between workers that can adapt quickly to new innovations and those who cannot. Note that the positive effect of faster technological progress on inequality is leveraged by the level of transferability τ;

2. decreases with the adaptability rates σ_i: the higher σ_i, the bigger the potential supply of workers that can adapt to new innovations and therefore the smaller the premium earned by these workers;

3. increases overall with the rate of transferability τ, even though the expression for R_ω in Proposition 1 uncovers two counteracting effects when both adaptability constraints bind and $\omega_0/\omega_1 = \Phi$. The multiplicative term $(1+\tau)$ reveals a *direct* effect for given labour supply: the higher τ the greater the comparative advantage of moving from leading edge to leading edge. The term in the denominator $(1+\sigma_0\tau)$ captures an *indirect* general equilibrium effect: the higher τ, the bigger the supply of labour in the leading edge sector (i.e. the larger the ratio x_0/x_1) which in turn tends to lower the relative wage of these workers and therefore the ratio R_ω. By simple differentiation, it is easy to see that the direct effect of τ always dominates.

4. decreases with the rate of learning-by-doing η: the higher η the more knowledge is cumulated about mature machines, which reduces the wage handicap of workers that cannot operate leading-edge machines.

3.1 Individual persistence in adaptability and inequality

One interesting question one can ask using our model is: what is the relationship between persistence in adaptability at the individual level and aggregate inequality? Or, how does individual persistence in adaptability affect the magnitude of the rise in within-group inequality, when the economy finds itself in the sensitive region of the parameter space?

Consider the two parameters σ_0 and σ_1. As argued above, $\sigma_0 = 1$ and $\sigma_1 = 0$ correspond to an innate ability model where initial conditions matter forever. On the contrary, when $\sigma_0 = \sigma_1$ history dependence in mobility options disappears.

To analyze the pure effect of persistence, we need to perform comparative statics on σ_0 and σ_1 assuming that the aggregate number of adaptable workers remains unchanged. The latter is simply equal to $n_{10} + n_{00} = \frac{\sigma_1}{1-\sigma_0+\sigma_1}N$, which implies that the ratio $\frac{\sigma_1}{1-\sigma_0}$ must be constant. When we decrease persistence, by reducing σ_0 keeping the ratio $\frac{\sigma_1}{1-\sigma_0}$ fixed, inequality measured by R_ω unambiguously rises. It is also easy to see that lower persistence accelerates the rise in inequality due to an increase in γ or/and in τ. This result is explained by the fact that as σ_0 gets closer to σ_1, the fraction of "low transferability" workers among movers rises, hence less skills are being transferred on to new technologies and the general equilibrium effect intrinsic in the denominator of Φ is downplayed, which clearly rises inequality.

This is an interesting result because, as mentioned in the introduction, the bulk of the literature based on increasing returns to innate ability implicitly assumes $\sigma_0 = 1$ and $\sigma_1 = 0$. We show here that these models ignore an important mechanism associated with the randomness and history dependence in individual adaptability, and consequently they tend to underestimate the effect of technological changes on within-group inequality.

3.2 Alternative measures of inequality

It is important to verify that the results in Proposition 1 do not hinge upon our particular measure of inequality, namely the wage ratio index R_ω, but that these results hold true for alternative (and more general) measures of inequality. We thus also consider the variance of log-wages (V_ω) and the $90 - 10$ log wage differential (D_ω). Since it is prohibitive to obtain simple closed forms for V_ω and D_ω in order to do analytic comparative statics, we have performed a number of simulations on the model to check the robustness of our conclusions.

The key results of these simulations are plotted in panels (1)-(6) of Figure 3. For these simulations, we have chosen parameter values that we regard as reasonable.[22] Since we assumed that machines depreciate in 2 periods, a consistent choice of the length of the period would be 5 years. The capital share parameter α is set to .3, and the discount factor β to .98 on an annual basis, implying an annual rate of return on capital of 5% when γ is 3% per year. In the benchmark case the learning

[22]This is not meant to be a calibration, but simply a numerical simulation to check the robustness of our conclusions in Proposition 1.

rate η is set to .22, which corresponds to a yearly measure of returns to experience of 4%, a number within the range estimated in the literature. For the transferable knowledge τ, we take a baseline value of 10% (roughly half of the learning rate η), and for the adaptability rates, we assume $\sigma_0 = \sigma_1 = .5$. We shall explore the joint behaviour of R_ω, V_ω, and D_ω for values of γ ranging from 0 to 7% per year, for values of η ranging from .1 to .3, for values of τ in the interval between 0 and .22, and for values of σ between .3 and .7. In the panels of Figure 3, we have changed the parameters one at the time with respect to the benchmark.

First, notice that V_ω increases with γ always at a faster rate than R_ω and D_ω. Second, as expected, V_ω does not have a flat region with respect to γ, however the simulations of Figure 3 show that in that same insensitive region of low values of γ, V_ω tends to grow more slowly than elsewhere.[23] Third, only in the case of very large aggregate adaptability is the behaviour of V_ω different from that displayed by the other two measures, as the latter then become unaffected by faster technical change, while V_ω keeps rising with γ. Fourth, as can be seen in Figure 3, in all our numerical simulations the behaviours of R_ω and D_ω coincide almost perfectly. Based upon this observed similarity, focusing on R_ω does not seem to involve any major loss of generality or insight.

3.3 GPT and the rise in within-group inequality

Analyzed through our benchmark model, the diffusion of a new GPT can be seen as having at least three distinct effects. First, it accelerates the rate of technological change *embodied* in equipment investment (higher γ). Next, because of its "general nature", it makes successive vintages of capital more similar to each other; thus it increases skill transferability towards new technologies (higher τ) and the adaptability of workers to new vintages (higher σ_i).[24] According to Proposition 1, two of these three effects work towards increasing inequality, whereas the effect of increased adaptability works towards reducing it.

[23]It should be said that for some extreme parametrization it is possible to generate, within this region of low γ, small declines in V_ω. The reason is that, as soon as the economy switches from $v_{10} < v_1$ to $v_{10} > v_1$, the wage ω_1 which is the intermediate wage, starts falling and gets increasingly closer to ω_0, thereby reducing wage heterogeneity in the economy. This effect is not captured by the wage ratio index R_ω, since the intermediate wage is irrelevant for such measure.

[24]A fourth effect, working through the relationship between GPT diffusion and capital retooling, is analyzed in Section 5.3 below.

Whilst the overall effect cannot be determined *a priori*, the only effect leading to lower inequality (higher σ_i), disappears in the parameter region where maximal inequality occurs *within* rather than *between* sectors. Specifically, it follows from Proposition 1 that when $\Phi < 1$, that is when:

$$\left(\frac{\sigma_1 (1 + \tau\sigma_0)}{1 - \sigma_0}\right)^{\alpha} \geq \frac{1 + \gamma}{(1 + \eta)^{1-\alpha}}, \tag{11}$$

then an increase in either of the σ_i's has no effect on R_ω: the maximal wage spread then occurs *within* the leading-edge sector 0, and therefore it remains unaffected by the mobility of workers between sectors.

In fact, equation (11) determines an upper bound $\overline{\sigma} < 1$ such that whenever σ_0 is bigger than $\overline{\sigma}$, then increased mobility has no effect on R_ω. Since there is no such limit on the range of parameter values over which an increase in transferability (τ) as a positive effect on inequality, an overall negative effect of GPT on inequality can occur only if mobility is initially sufficiently small that it satisfies (11).[25] Moreover, the larger τ the smaller $\overline{\sigma}$, and therefore the less likely it is that the overall effect from the diffusion of a new GPT on inequality will be negative.

4 Empirical predictions

Whilst the contribution of this paper is theoretical, our model generates a few empirical predictions, some of which distinguishes it from other models of wage inequality.[26]

1) *Within-group inequality increases in the rate of embodied technical change* γ.

The positive relationship pointed out in Proposition 1 between the level of within-group inequality and the parameter γ, is in line with the evidence, clear in the aggregate time-series, of a positive correlation between residual inequality and the rate of diffusion of information technologies, or the rate of *embodied* technical change[27].

[25]However, notice that a rise in γ would increase the upper bound $\overline{\sigma}$.

[26]The predictions in this Section only concern determinants of within-group inequality. In Section 5 we derive additional predictions on the comparative behaviour of within- and between-group inequality.

[27]For evidence and theoretical explanations on the fact that embodied technical progress has accelerated during a period of (disembodied) productivity slowdown, see Comin (1999).

2) *Wage volatility along individual labour market histories and cross-sectional within-group inequality behave similarly.*

One stark prediction of this model, which again distinguishes our approach from other models of residual inequality based upon changes in the returns to innate ability, is that whenever cross-sectional inequality rises, so does wage volatility along the history of individual workers. More specifically, since workers are ex-ante identical and the heterogeneity due to limited adaptability is stochastic and *iid* across individuals, the equilibrium variance of wages across workers is conceptually equivalent to the variance of wages that the ex-ante representative agent faces along her labour market history.

Our prediction that the instability of the individual wage profiles should increase during a technological transition during which the two parameters γ and τ rise, is in line with the findings of Gottschalk and Moffitt (1994), Gittleman and Joyce (1996), Dickens (1999) and Baker and Solon (1999) who document a rise in earnings instability along individual labour market histories during the past two decades, respectively in the US, the UK, and Canada. This rise in turn explains between one third and one half of the aggregate (the sum of between and within-group) rise in cross-sectional wage inequality.

3) *Within-group inequality is largely transitory.*

Recent econometric work by Blundell and Preston (1999) based on household data on consumption and income for the US and the UK, shows that the within-group component of wage inequality is largely *transitory,* in the sense that the authors find little evidence of any systematic growth in the variance of permanent income (i.e. consumption) shocks within educational groups over the past two decades. It is the between-group component that captures most of the increase in permanent income inequality.[28]

[28]Their result confirms the findings in Gottschalk and Moffitt (1994) for the US who obtain that, within groups, the transitory component explains from 60% (for high-school graduates) up to 80% (for college graduate) of the total increase in the variance of earnings. Dickens (1999) also reaches similar conclusions for the UK, where the transitory component accounts for the entire rise in within-group inequality among highly-skilled occupations, but a much smaller fraction among low-skilled.

In our model, the permanent component of income has a deterministic time trend, equal to $(1+\gamma)^t$ times the average productivity-adjusted wage, but cross-sectional variance is equal to zero. Note however, that the variance in permanent income across individuals would become strictly positive if there were some innate characteristics (e.g, differences in η's, σ's or in τ's) that generate a premium for a subset of individuals independently of the technology. We explore such extensions in Section 6. Note finally that *consumption* inequality cannot be analyzed in our baseline model where we have assumed perfect financial markets, and where therefore all the inequality is insurable by assumption. Whether these shocks are fully insurable or not in reality is difficult to say, although to the extent that they are temporary, there should be various ways for workers to partially insure against them (such as precautionary savings, intra-family transfers, formal borrowing, unemployment insurance, etc.).

5 Within-Group Inequality with Flexible Capital Adjustment

In this section, we relax the putty-clay assumption of the baseline model. We do it in two steps. First, we allow firms to retool their old capital and convert it into capital embodying the leading-edge technology. Firms might have the incentive to do so when adaptable labor is relatively abundant. Second, we allow firms to revive the old capital, and invest in old technologies, which might happen if adaptable labour is particularly scarce. As one can expect, retooling and reviving have opposite effects on the relative demand for adaptable labor, hence on within-group inequality. In the last part of the section we argue that the diffusion of a new *GPT* should make retooling (reviving) more (less) likely to happen and accelerate the rise in inequality.

5.1 Retooling of Old Capital

Suppose that after a machine has been used for one period a firm may convert it into $(1-\delta)$ leading-edge machines, where $\delta \in [0,1]$ is the exogenous cost of retooling. Although a retooled machine at t embodies the leading-edge productivity parameter A_t, it is unlike a newly-produced leading-edge machines in that it will fully depreciate at the end of the period. Let k_{it} be the number of machines used in sector i at t

and d_t be the number of mature machines that are retooled (into $(1-\delta)\,d_t$ leading-edge machines) at t. Then k_{1t} equals the number of newly-produced leading-edge machines at $t-1$ minus the number of mature machines retooled at t:

$$k_{1t} = k_{0t-1} - (1-\delta)\,d_{t-1} - d_t, \qquad t = 1, 2, ... \tag{12}$$

and the aggregate production function is:

$$y_t = (A_t x_{0t})^{1-\alpha}\, k_{0t}^{\alpha} + ((1+\eta)\,A_{t-1} x_{1t})^{1-\alpha}\, k_{1t}^{\alpha}, \qquad t = 1, 2, ... \tag{13}$$

In equilibrium the sequence $\{k_{0t}, k_{1t}, d_t, x_{0t}, x_{1t}, y_t\}_{t=1}^{\infty}$ must maximize the present value of aggregate profits:

$$\sum_{t=1}^{\infty} \left(\frac{1}{1+r}\right)^{t-1} (y_t - k_{0t} - (1-\delta)\,d_t - A_t\omega_0 x_{0t} - A_t\omega_1 x_{1t})$$

subject to (12), (13) and a non-negativity constraint on each d_t.

The introduction of retooling does not change the relative supply curve of Figure 1, but it does change the relative demand curve. Specifically, there is a critical relative wage:

$$\Phi^{ret} = \frac{1+\gamma}{(1+\eta)^{1-\alpha}}\,(1-\delta)^{\frac{\alpha}{1-\alpha}} \tag{14}$$

such that if $\omega_0/\omega_1 \geq \Phi^{ret}$ then firms will choose not to retool any mature machines and the relative demand curve will continue to be defined by equation (5), but once ω_0/ω_1 falls to the level Φ^{ret}, retooling will occur and increase in the relative input of leading-edge labour will induce a proportional increase in the steady-state supply of leading-edge machines, with no change in relative wages.[29] That is, the

[29]The first-order conditions for profit-maximization with respect to x_{0t} and x_{1t} imply:

$$\frac{\omega_0}{\omega_1} = \frac{1+\gamma}{(1+\eta)^{1-\alpha}} \left(\frac{x_0/\kappa_0}{x_1/\kappa_1}\right)^{-\alpha},$$

where $\kappa_0 = k_{0t}/A_t$ and $\kappa_1 = k_{1t}/A_{t-1}$, both constant in a steady-state. From (12) and the non-negativity constraint on d_t, $\kappa_0 \geq \kappa_1$, with equality if no retooling takes place. Thus:

$$\frac{\omega_0}{\omega_1} \geq \frac{1+\gamma}{(1+\eta)^{1-\alpha}} \left(\frac{x_0}{x_1}\right)^{-\alpha}, \text{ with equality if no retooling takes place.}$$

The first-order (Kuhn-Tucker) conditions with respect to d_t and k_t can be solved to yield:

$$\frac{\omega_0}{\omega_1} \geq \Phi^{ret}, \text{with equality if retooling takes place.}$$

relative-demand curve will now be:

$$\frac{\omega_0}{\omega_1} = \max\left\{\frac{1+\gamma}{(1+\eta)^{1-\alpha}}\left(\frac{x_0}{x_1}\right)^{-\alpha}, \Phi^{ret}\right\}$$

as illustrated in Figure 4.

If, as in the case depicted in Figure 4, $\Phi^{ret} > \max\{\Phi, \Omega\}$, then in equilibrium retooling will take place, both adaptability constraints will be binding and $\omega_0/\omega_1 = \Phi^{ret.}$ Otherwise, the relative wage ω_0/ω_1 will equal $\max\{\Phi, \Omega\}$, as before. Thus:

$$\omega_0/\omega_1 = \max\left\{\Omega, \Phi, \Phi^{ret}\right\}, \tag{15}$$

and the same logic that led from (10) to Proposition 1 now leads from (15) to:

Proposition 2 *When retooling is an option:*
1. The wage ratio index (R_ω) in steady-state equilibrium is given by:

$$R_\omega = (1+\tau)\max\left\{1, \Phi, \Phi^{ret}\right\}.$$

where Φ and Φ^{ret} are defined above.
2. Moreover:

$$\begin{array}{llllll} \dfrac{\partial R_\omega}{\partial \tau} & > 0, & \dfrac{\partial R_\omega}{\partial \gamma} \geq 0, & \dfrac{\partial^2 R_\omega}{\partial \gamma \partial \tau} \geq 0, & \dfrac{\partial R_\omega}{\partial \sigma_i} \leq 0, & \dfrac{\partial R_\omega}{\partial \eta} \leq 0, \\ \dfrac{\partial R_\omega}{\partial \delta} & \leq 0, & \dfrac{\partial^2 R_\omega}{\partial \tau \partial \delta} \leq 0, & \dfrac{\partial^2 R_\omega}{\partial \gamma \partial \delta} \leq 0. & & \end{array}$$

Thus transferability, speed, adaptability and learning by doing have the same qualitative effects as before on inequality. The cost of retooling now has a negative effect on inequality. This is because a fall in δ encourages firms to employ more capital with adaptable workers who are already earning the maximum wage, and correspondingly less capital to those (in sector 1) already earning the minimum wage.

Furthermore, the effects of retooling reinforce the effects of transferability and the speed of technological change. Consider, for example, an increase in τ, in the case where retooling is taking place and both adaptability constraints are binding (that is, $\Phi^{ret} = \max\{1, \Phi, \Phi^{ret}\}$). Then the general equilibrium effect that we saw operating in the benchmark model (see item 3 in the discussion following Proposition 1) which tended to moderate the increase in inequality will no longer operate; the increase in relative labour input to sector 0 workers will lead not to a dampening of relative wages in sector 0 but to a proportional increase in the number of machines employed in sector 0.

5.2 Reviving of Old Technology

In this section we relax the assumption that only leading-edge machines can be produced. Intuitively, this should reduce the relative demand for adaptable workers and therefore their relative wage in steady-state equilibrium. In other words, allowing firms to revive old technologies has the opposite effect from that of allowing old machines to be retooled using new technologies, namely it *decreases* wage inequality. Allowing for capital revival also introduces the interesting possibility that three instead of two subsequent vintages be operated at the same time.

Let k_t denote the production of new machines (leading-edge plus mature) at t. Let d_t be the number of mature machines retooled and e_t be the number of mature machines produced at t. There is now a second sector, namely sector 2, in which very mature machines (two-period old vintage) are used. Anyone can work in this subsector, just as anyone can work in sector 1 where mature machines are used. Thus workers in each of these sectors must receive the same wage ω_1 in a competitive equilibrium. Let k_{0t}, k_{1t}, k_{2t} and x_{0t}, x_{1t}, x_{2t} denote the inputs of machines and labour to the three sectors. Then:

$$k_{0t} = k_t + (1-\delta)\, d_t - e_t, \qquad t = 1, 2, ... \tag{16}$$

$$k_{1t} = k_{t-1} - e_{t-1} + e_t - d_t, \qquad t = 1, 2, ... \tag{17}$$

$$k_{2t} = e_{t-1}, \qquad t = 1, 2, ... \tag{18}$$

and the aggregate production function is:

$$y_t = (A_t x_{0t})^{1-\alpha} k_{0t}^{\alpha} + ((1+\eta)\, A_{t-1} x_{1t})^{1-\alpha} k_{1t}^{\alpha} + ((1+\eta)\, A_{t-2} x_{2t})^{1-\alpha} k_{2t}^{\alpha}, \tag{19}$$

The sequence $\{x_{0t}, x_{1t}, x_{2t}, k_{0t}, k_{1t}, k_{2t}, k_t, d_t, e_t, y_t\}_{t=1}^{\infty}$ must maximize the present value of aggregate profits:

$$\sum_{t=1}^{\infty} \left(\frac{1}{1+r}\right)^{t-1} (y_t - k_t - A_t \omega_0 x_{0t} - A_t \omega_1 (x_{1t} + x_{2t}))$$

subject to (16) − (19) and non-negativity constraints on each d_t and e_t.

As in the case where retooling but not reviving was an option, retooling will take place once the relative wage ω_0/ω_1 has fallen to Φ^{ret}, as defined by (14). But now reviving will take place once the relative wage has risen to:[30]

$$\Phi^{rev} = \frac{1+\gamma}{(1+\eta)^{1-\alpha}} \left(1 + \frac{\beta}{1+\gamma}\left((1+\gamma)^{\frac{\alpha-1}{\alpha}} - 1\right)\right)^{\frac{\alpha}{\alpha-1}}.$$

Notice that:

$$\Phi^{rev} > \frac{1+\gamma}{(1+\eta)^{1-\alpha}} > \Phi^{ret}.$$

When the relative wage lies between Φ^{rev} and Φ^{ret} the demand for labor continues to be given by equation (5). Thus the complete relative-demand schedule is as shown in Figure 5.

Assume that $\Phi^{rev} > \Omega$. Then there will exist a stationary equilibrium with a positive relative supply x_0/x_1. Reasoning as before, we have:

Proposition 3 *When both retooling and reviving are options:*

1. *Equilibrium within-group inequality is:*

$$R_\omega = (1+\tau)\max\{1, \Phi^{ret}, \min(\Phi, \Phi^{rev})\}.$$

2. *Moreover:*

$$\frac{\partial R_\omega}{\partial \tau} > 0, \quad \frac{\partial R_\omega}{\partial \gamma} \geq 0, \quad \frac{\partial^2 R_\omega}{\partial \gamma \partial \tau} \geq 0, \quad \frac{\partial R_\omega}{\partial \sigma_i} \leq 0, \quad \frac{\partial R_\omega}{\partial \eta} \leq 0.$$

Comparison of points (1) in Propositions 2 and 3 shows that if the possibility of reviving has any effect on inequality it is a negative one. This is because diverting resources from producing new leading-edge machines to producing new mature machines increases the potential demand for the non-adaptable labour who receive the minimum wage when both adaptability constraints bind. However, introducing reviving does not change the qualitative comparative statics results, thus the effects of a *GPT* diffusion highlighted for the benchmark model still hold true. In the next section we discuss some additional channels through which *GPT* can impact inequality in the augmented model.

[30]The first-order conditions for profit-maximization with respect to $k_t, k_{0t}, k_{1t}, k_{2t}$ and e_t can be solved to yield:

$$\frac{\omega_0}{\omega_1} \leq \Phi^{rev}, \text{ with equality if reviving takes place.}$$

5.3 The Impact of GPT on Capital Adjustment

The augmented model allows us to highlight two other possible effects of *GPT*, beyond those listed in Section 3.3 that would lead to rising inequality. First, an increase in the general nature of technology might decrease the cost of retooling machines (lower δ). Second, if γ and τ are sufficiently large during the acceleration phase in the diffusion of a new GPT, then $\Phi > \Phi^{rev}$, so that old vintages will not be produced. Thus, whilst an acceleration in the diffusion of a new GPT encourages the retooling of old machines, it also discourages the reviving of old technologies, thereby inducing a magnified increase in within-group wage inequality in comparison to the baseline case in which neither retooling nor reviving were not allowed.

Moreover, the augmented model provides us with two additional reasons for thinking that the only possible negative effect of a GPT on inequality, i.e. the one working through increased adaptability σ_i, will be limited. Specifically, it follows from Proposition 2 and Proposition 3 that only when:

$$\max\left\{(1-\delta)^{\frac{\alpha}{\alpha-1}}, \frac{1+\gamma}{(1+\eta)^{1-\alpha}}\right\} \geq \left(\frac{\sigma_1(1+\tau\sigma_0)}{1-\sigma_0}\right)^{\alpha} \geq \left(1+\frac{\beta}{1+\gamma}\left((1+\gamma)^{\frac{\alpha-1}{\alpha}}-1\right)\right)^{\frac{\alpha}{1-\alpha}} \tag{20}$$

then an increase in either of the σ_i's lowers R_ω. Given any values of the other parameters, equation (11) places an upper bound $\overline{\sigma} < 1$ and a lower bound $\underline{\sigma} > 0$ on σ_0, beyond which adaptability has no further effect on inequality. First, as shown by (11) this factor is limited by the possibility that maximal inequality occurs within rather than between sectors. Moreover, (20) shows that it is also limited by the possibility of retooling and reviving. For very large values of σ_i adaptable labor is abundant, and firms retool old capital into new technologies. An increase in σ_i in this range generates an downward pressure on inequality which is completely offset by a rise in the capital stock employed with adaptable labor, through additional retooled machines. For small values of σ_i firms will produce old vintages of machines because the labour cost of working with leading-edge machines is too high. An increase in σ_i in this range leads to an increase in the steady-state relative supply of adapted workers, but, as in the case where retooling takes place, the increase will result not in a change in the relative wage but in a proportional increase in the number of machines employed with adapted workers, this time because of reduced production of new mature (revived) machines.

6 Equilibrium between-group inequality

Our framework is flexible enough to include two types of workers: educated workers (type e) and uneducated workers (type u). But how should we relate the level of education with the parameters of the model? We do it in two ways. First, based upon the seminal work of Nelson and Phelps (1966) according to whom "*educated people make good innovators, so that education speeds the process of technological diffusion*", we assume that more educated workers are more easily adaptable to new technologies. Indeed, there is broad evidence that the share of high-education employment in high-tech firms and industries is systematically larger. Second, based upon the extensive empirical work on wage changes upon separation (see, among others, Rhum (1987), or Swaim and Podgursky (1989)) that has shown that the latter are smaller for workers with higher level of education, we assume that more educated workers' knowledge is more transferable. Formally, in terms of the parameters of our model, more educated workers have larger values of adaptability σ and of skill-transferability τ.

To simplify the analysis, we assume that the adaptability parameter of each type of worker is history-independent: $\sigma_0^i = \sigma_1^i = \sigma^i$, $i = e, u$, with $\sigma^e > \sigma^u$, and that type u workers cannot transfer any knowledge at all from previous leading edge to current leading edge: $\tau^e > \tau^u = 0$. To simplify further, suppose that retooling is no longer an option. Denote by f the educated fraction of the population, which we keep exogenous throughout the analysis.[31]

Under these assumptions the relative demand for labor in the two sectors is again given by equation (5). All workers in sector 1 receive ω_1, all workers coming from sector 1 to sector 0 receive ω_0, and workers coming from sector 0 to sector 0 receive $\omega_{00} = (1 + \tau^e)$ if they are educated but only ω_0 if uneducated.

By the same logic as before, educated workers coming from sector 1 will be indifferent between working in the two sectors this period when the relative wage

[31] We abstract from the possibility of imperfect substitutability between the two types of workers. We are aware that our assumption of perfect substitutability is extreme, but here our objective is to highlight another source of between-group inequality, above and beyond pure skill-biased technical change as in Katz and Murphy (1992) or capital-skill complementarity in production as in Krusell et al. (1999).

equals:

$$\Omega^e = \frac{1}{1+\beta\sigma^e\tau^e}.$$

Uneducated workers will prefer whichever sector has the highest base wage, because they transfer no skills. Thus when $\Omega^e < \omega_0/\omega_1 < 1$ both adaptability constraints of educated workers bind but all uneducated workers choose to work in sector 1, so the relative supply x_0/x_1 is:

$$\widetilde{\chi} = \frac{f(1+\tau^e)\sigma^e}{1-\sigma^e f},$$

and when $\omega_0/\omega_1 > 1$ all four adaptability constraints (applying to educated and uneducated workers coming from sectors 0 and 1) bind, so the relative supply is:

$$\widehat{\chi} = \frac{f(1+\tau^e)\sigma^e + (1-f)\sigma^u}{f(1-\sigma^e)+(1-f)(1-\sigma^u)}.$$

Therefore the relative supply curve will be as indicated by the step function in Figure 6.

To simplify even further, assume γ is large enough that educated individuals always prefer to work in sector 0; i.e., the relative demand curve cuts above the first step on the relative supply curve, so that $\omega_0/\omega_1 > \Omega^e$. Let $\widetilde{\Phi}$ denote the height of the relative demand curve at the relative supply $\widetilde{\chi}$:

$$\widetilde{\Phi} = \frac{(1+\gamma)}{(1+\eta)^{1-\alpha}}\left[\frac{1-f\sigma^e}{f(1+\tau^e)\sigma^e}\right]^\alpha,$$

and let $\widehat{\Phi}$ denote the height of the relative demand curve at the relative supply $\widehat{\chi}$:

$$\widehat{\Phi} = \frac{(1+\gamma)}{(1+\eta)^{1-\alpha}}\left[\frac{f(1-\sigma^e)+(1-f)(1-\sigma^u)}{f(1+\tau^e)\sigma^e+(1-f)\sigma^u}\right]^\alpha < \widetilde{\Phi}.$$

From examination of the demand and supply curves:

$$\omega_0/\omega_1 = \left\{\begin{array}{ll} \widehat{\Phi} & \text{if } \widehat{\Phi} > 1, \\ \min\left\{\widetilde{\Phi}, 1\right\} & \text{if } \widehat{\Phi} \le 1 \end{array}\right\}. \tag{21}$$

Let $\overline{\omega}^i$ denote the average productivity-adjusted wage within group $i = e, u$, and let $\Pi_\omega = \overline{\omega}^e/\overline{\omega}^u$ denote the educational premium. Then:

Proposition 4 *When there are two classes of workers:*

1. *Within-group inequality in each class is:*

$$R_{\omega}^{e}=\left(1+\tau^{e}\right)\max\left\{1,\widehat{\Phi}\right\}, \qquad R_{\omega}^{u}=\max\left\{1,\widehat{\Phi}\right\}.$$

2. *The equilibrium wage premium in the economy is:*

$$\Pi_{\omega}=\begin{cases}1-\sigma^{e}+\sigma^{e}\left(1+\tau^{e}\sigma^{e}\right)\min\left\{\widetilde{\Phi},1\right\}, & \text{if } \widehat{\Phi}\leq 1\\ \dfrac{1-\sigma^{e}+\sigma^{e}\left(1+\tau^{e}\sigma^{e}\right)\widehat{\Phi}}{1-\sigma^{u}+\sigma^{u}\widehat{\Phi}}, & \text{if } \widehat{\Phi}>1\end{cases}$$

3. *Moreover:*

$$\frac{\partial\Pi_{\omega}}{\partial\gamma}\geq 0;\quad \frac{\partial\Pi_{\omega}}{\partial f}\leq 0;\ \text{and}\ \frac{\partial R_{\omega}^{i}}{\partial f}\leq 0,\ \text{with equality whenever}\ \widehat{\Phi}<1<\widetilde{\Phi}.$$

Proof: When $\widehat{\Phi}>1$, then $R_{\omega}^{u}=\omega_0/\omega_1=\widehat{\Phi}$ and $R_{\omega}^{e}=\omega_{00}^{e}/\omega_1=\left(1+\tau^{e}\right)\widehat{\Phi}$. When $\widehat{\Phi}\leq 1$, then $R_{\omega}^{e}=\omega_{00}^{e}/\omega_0=\left(1+\tau^{e}\right)$. Also, when $\widehat{\Phi}\leq 1$, then either when $\omega_0/\omega_1=1$, or else $\omega_0/\omega_1<1$ but no uneducated worker chooses to work in the sector 0; in either case all uneducated workers receive the same wage, so that $R_{\omega}^{u}=1$. This proves part 1.

The average wage of educated workers is:

$$\left.\begin{aligned}\overline{\omega}^{e}&=\left(\sigma^{e}\right)^{2}\omega_{00}^{e}+\sigma^{e}\left(1-\sigma^{e}\right)\omega_0+\left(1-\sigma^{e}\right)\omega_1\\&=\sigma^{e}\left(1+\tau^{e}\sigma^{e}\right)\omega_0+\left(1-\sigma^{e}\right)\omega_1\end{aligned}\right\}\tag{22}$$

and the average wage of uneducated workers is:

$$\overline{\omega}^{u}=\left\{\begin{array}{ll}\sigma^{u}\omega_0+\left(1-\sigma^{u}\right)\omega_1 & \text{if}\ \ \widehat{\Phi}>1,\\ \omega_1 & \text{if}\ \ \widehat{\Phi}\leq 1.\end{array}\right\}\tag{23}$$

Part 2 follows from (21), (22) and (23). Part 3 follows from differentiation. ■

The first and obvious implication of Proposition 4 is that, to the extent that they have more transferable skills ($\tau^{e}>\tau^{u}=0$), within-group inequality is higher for educated workers. In addition, the above analysis yields a number of new interesting insights and predictions, in particular:

1) *An increase in the supply of educated labour may decrease between-group inequality, while at the same time be neutral on within-group inequality.*

An increase in f, the fraction of educated labour force, whilst always reducing the educational premium, has interesting effects on within-group inequality. If $\widehat{\Phi} < 1 < \widetilde{\Phi}$, increasing f has no effect on R_ω, whereas if $\widehat{\Phi} > 1$ or $\widetilde{\Phi} < 1$, then a larger fraction of educated workers tends to shrink within-group inequality in each group. The reason is related to the negative supply effects of highly educated workers on wages: these are relatively more adaptable than uneducated workers, hence an increase in f implies that more labour, in efficiency units, is being reallocated from old to new technologies, thereby reducing both, the wage differential and within-group inequality. It should be noted though, that even in this last case an aggregate index of residual inequality, weighted by the shares of the two educational group might *increase* as f rises, because of a *compositional effect*, since $R_\omega^e > R_\omega^u$.

This contrasting pattern in the dynamics of between and within-group inequality, has been observed in the US economy in the mid and late 70's, when a sudden acceleration of supply of educated workers took place, with the result of depressing temporarily the educational premium, but without any impact on within-group inequality, which continued to rise.[32]

2) *The educational premium is higher in industries with faster technological progress (higher γ)*

If one accepts that the diffusion of new information GPT has increased γ, then proposition 3 implies that this process will have raised, both within-group inequality and also the wage premium. Allen (1996) finds that differences in returns to education are indeed strongly correlated with some measures of technological progress across industries. In particular, the educational premium is higher in industries with the largest share of high-tech capital[33].

3) *In a between/within-plant decomposition of wage variance, the within-plant component is increasing in τ* and σ.

[32]This sudden rise in the educated labour force was most likely due to exogenous factors, such as the attempt to avoid the Vietnam-War draft through college enrollment, and the fact that baby-boomers entered the labour force in those years.

[33]Here, it might be worth emphasizing again the fact that our framework is not inconsistent with the measured productivity slowdown that started in the 70s. For example, if we superimposed to the model a further source of total factor productivity, neutral across vintages, none of our results on inequality would be affected by a slowdown in this productivity factor. In fact, as recently shown by Comin (1999), productivity slowdown has overlapped with the acceleration in the pace of *embodied* technical change, meanwhile the rate of *disembodied* technical change has gone down.

If we interpret, as we just did, the parameter τ^i as being related to the level of education, then an implication of our theory would be that in a between/within plant (or, equivalently, sector) decomposition of the wage variance, the within fraction should be much larger for more educated workers. Interestingly, Davis and Haltiwanger (1991) exploit the LRD plant level dataset to perform a decomposition of log-hourly wage variance in the manufacturing industries in the US between 1975 and 1986. They find that only 15% of the wage variance of production workers can be attributable to the within-plant component, while this magnitude reaches almost 55% for non-production workers.[34] Moreover, in our model, higher adaptability increases the fraction of the wage variance within plants (since the number of workers in new plants with large within-plant wage inequality increases with σ), thus reinforcing our conclusion.

To conclude this Section, let us just point out that the above extension can be reinterpreted as a model involving two groups of workers with the same level of education, but with different innate abilities which reflect in different levels of adaptability and skill transferability. In such a hybrid model, the rise in wage inequality within-groups would be partly transitory and partly permanent.

7 Concluding Remarks

In this paper we have developed a simple dynamic general equilibrium model to analyze how the diffusion of a new GPT can affect the evolution of within-group wage inequality, in particular through its effects on the speed of embodied technological change, on the transferability of skills across sectors, and on the cost of retooling old machines to work with new technologies. We showed that this model could help explain several puzzling facts about the recent rise in inequality. In particular, our explanation for within-group inequality based upon random adaptability and divergent labor market histories, could account for the facts: (i) that within-group inequality tends to be more transitory than between-group inequality (Blundell-Preston (1999)); (ii) that the variability of individual earnings has increased during the past two decades (Gottshalk-Moffitt (1998)); (iv) and that *between-group* and

[34]Their data also show a strong correlation between production/non-production classifications and education-based classifications, as production workers tend to be, on average, much less educated.

within-group inequality, have followed different evolutions, both in the mid-seventies and during the late 1990s where between-group inequality has gone down whilst within-group inequality has remained essentially unchanged.

Our framework is sufficiently simple that it can easily be used or extended in several interesting directions. A first extension would look at policy implications: to the extent that within-group inequality is temporary, growth-enhancing policies aimed at improving the adaptability of workers and capital, should be seriously considered even if such policies may result in an increase in within-group inequality, so long as they do not deteriorate the distribution of permanent income. In particular, it would be interesting to analyze how different organizations of education will affect the parameters τ, σ, and f in our framework, and thereby our measures of within-group and between-group inequality. For example, should we privilege higher education or secondary education, where presumably the former would directly contribute to raising γ and τ whereas the latter would tend to raise σ and η?

A second extension would be to endogenize the size of technological improvements, i.e. γ, as a function of the other parameters of the model. This should enrich somewhat our previous analysis: very preliminary analysis of the optimal choice of γ by new plants suggests that the equilibrium level of γ should increase both with respect to τ and with respect to η. In other words, endogenizing γ reinforces the direct positive effect of τ whereas it tends to offset the direct negative effects of η on wage inequality.

Also interesting would be to introduce unemployment into our framework, particularly when analyzing plants' retooling decisions. Whilst an increase in the rate of embodied technical progress γ would tend to shorten the average life of capital equipment, and therefore to reduce wage inequality between workers on old and new lines, a higher γ might also result in a higher rate of unemployment and therefore in a higher degree of overall inequality in the economy.

Finally, our framework can be used as a starting point for empirical research on the determinants of within-group wage inequality. Industry-level data could be used to analyze the cross-industry correlation between residual inequality and available measures of technological progress (age of capital, TFP, R&D expenditures, computer use, etc.), thereby capturing the effects of our parameter γ. Measuring skill transferability and its role in shaping inequality is more challenging. One possible strategy would be to proxy skill transferability through the average wage change upon separation for workers who move within industries, and then analyze the correlation of this measure with industry-level residual inequality.

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Figure 1: Relative Supply and Demand in the benchmark economy

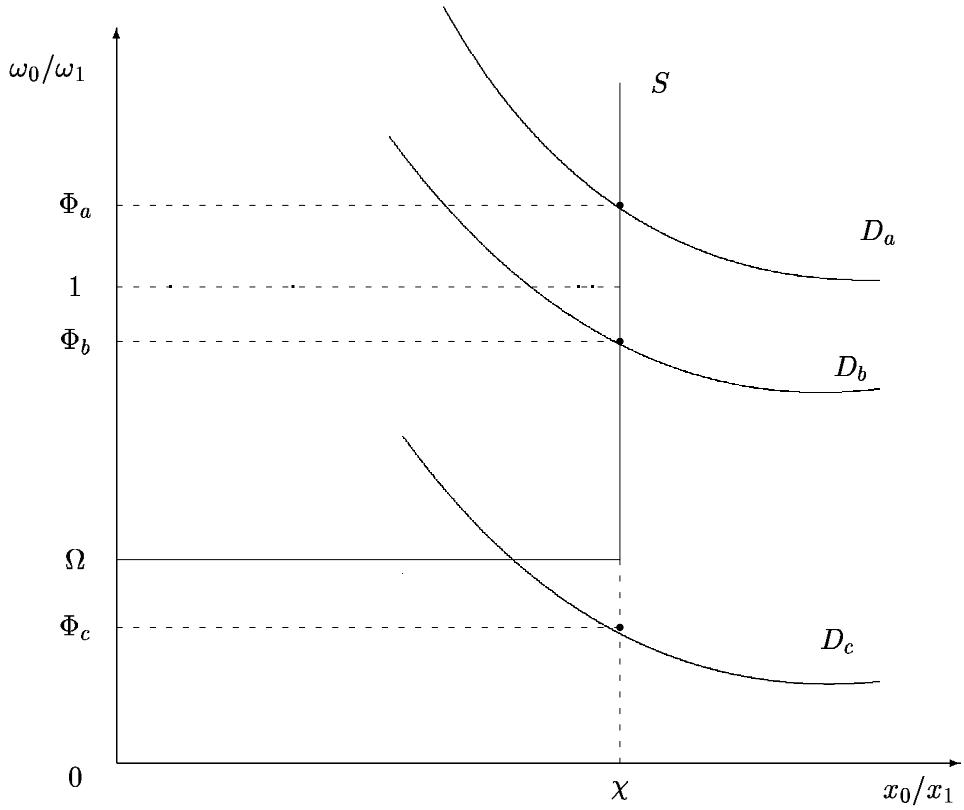

Figure 2: Within-Group Inequality as a function of γ and τ

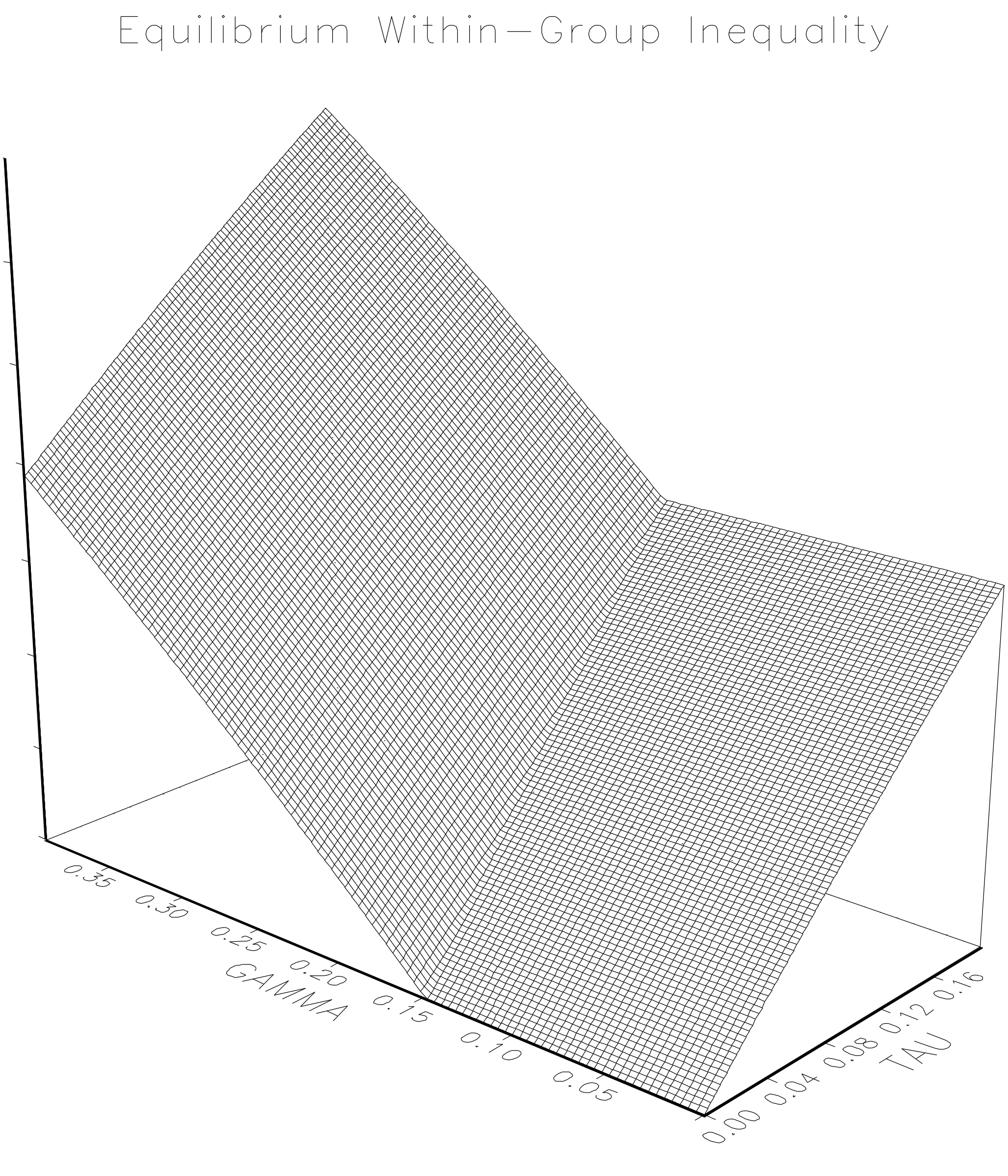

Figure 3: Sensitivity analysis in the benchmark model

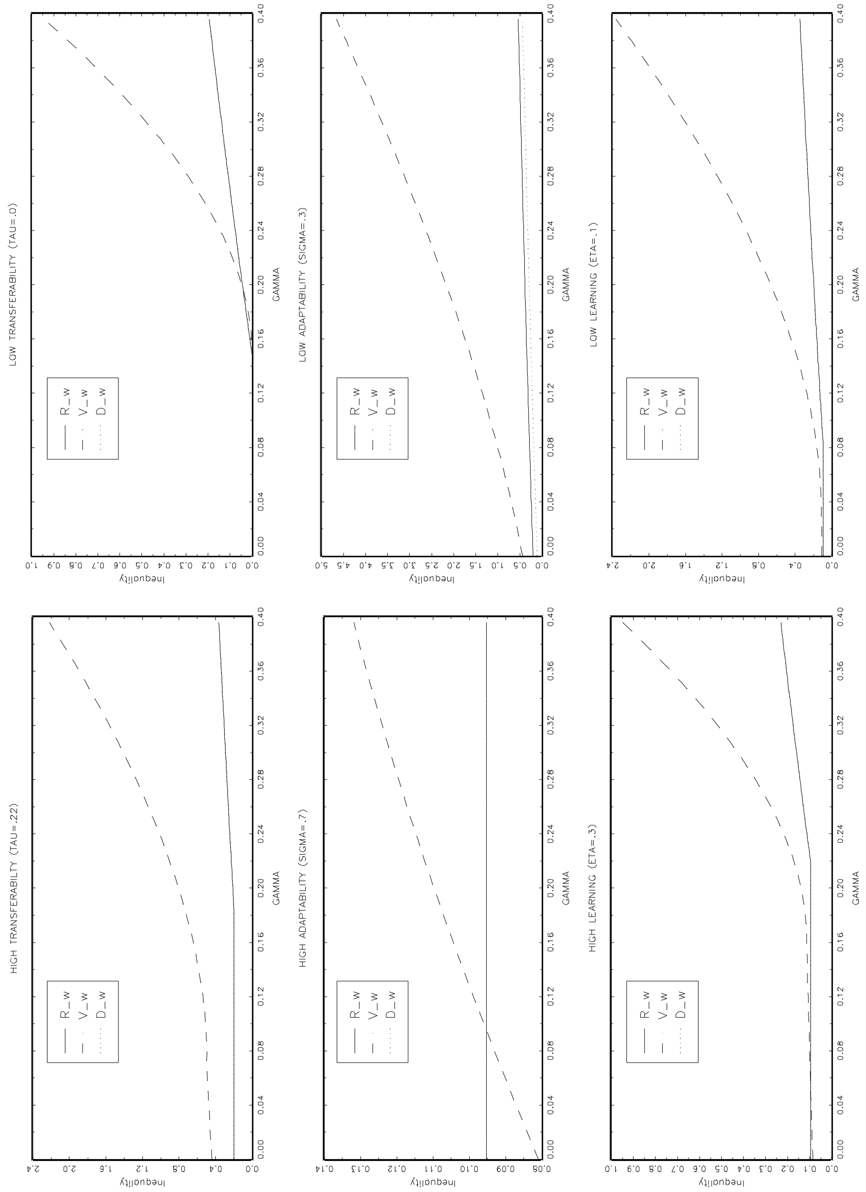

Figure 4: Relative Supply and Demand in the economy with retooling

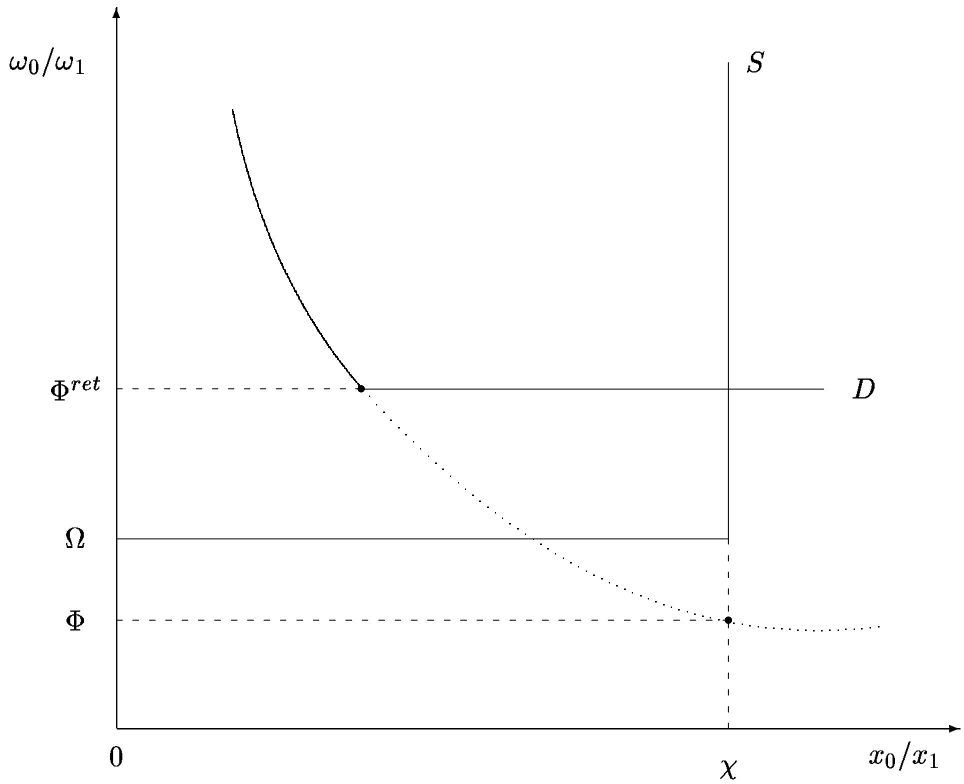

Figure 5: Relative Supply and Demand in the economy with retooling and reviving

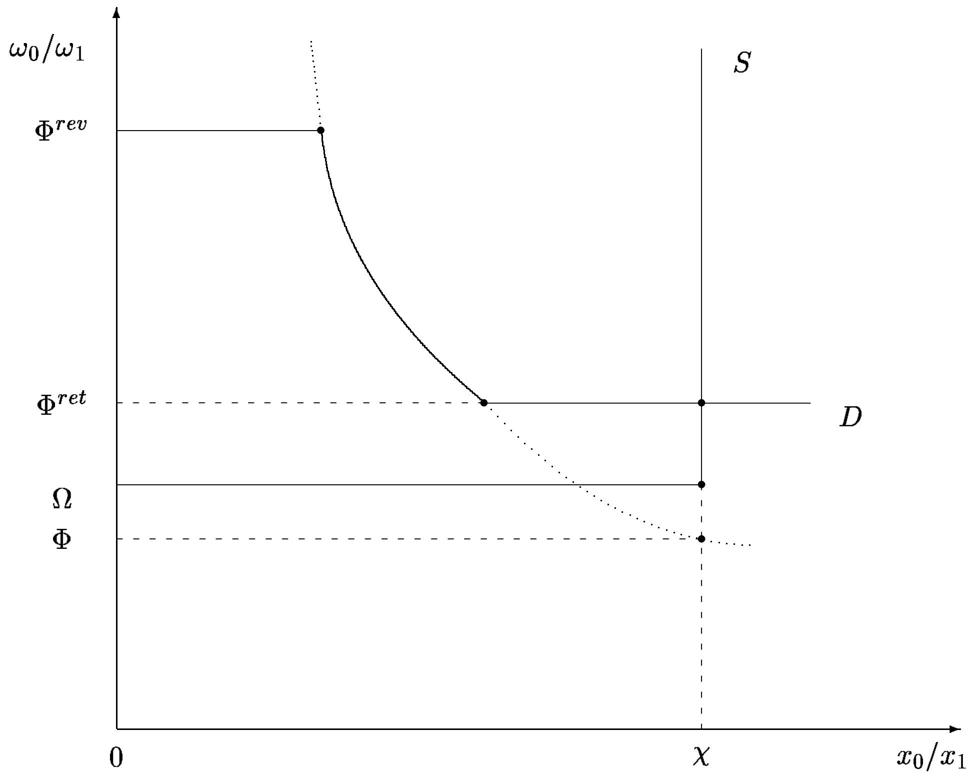

Figure 6: Relative Supply and Demand in the economy with two groups of workers