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ABSTRACT

Technological Acceleration, Skill Transferability and the Rise in Residual Inequality*

This Paper provides an interpretation for the recent rise in residual wage inequality, which is consistent with the empirical observation that a sizeable part of this increase has a transitory nature, a feature that eludes standard models based on *ex ante* heterogeneity in ability. In the model an acceleration in the rate of quality-improvement of equipment, like the one observed from the early 1970s, reduces workers' capacity to transfer skills from old to new machines. This force generates a rise in the cross-sectional variance of skills, and therefore of wages. Through calibration, the Paper shows that this mechanism can account for 30% of the surge in residual inequality in the US economy (or for most of its transitory component). Two key implications of the theory – faster within-job wage growth and larger wage losses upon displacement – find empirical support in the data.

JEL Classification: E24, J31, O30
Keywords: earnings instability, skill transferability, technological acceleration, wage inequality, wage loss upon displacement

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NON-TECHNICAL SUMMARY

During the past 30 years, the US wage distribution has undergone prominent changes: wage inequality has greatly increased over this period. Part of this rise in inequality is attributable to expanding wage differentials between educational and experience groups. Measurable characteristics such as education and experience can, however, explain at most half of the total surge in wage inequality: the majority of the increase in US wage inequality is *residual*, i.e. due to unobserved attributes of workers belonging to the same educational or demographic group.

It is this particular dimension of the recent changes in the wage distribution across a number of countries that still poses a major puzzle to labour and macro economists. What are its causes? Are the same forces that have expanded between group differentials also at work within groups?

The conventional view of the existing literature is that this phenomenon is the result of an increase in the return to *ability*, a term which is meant to capture some permanent (model specific) attribute driving the *ex ante* unobserved heterogeneity among observationally similar workers. All these models relying entirely on *ex ante* fixed differences in abilities across individuals have a stark empirical implication: the rise in residual inequality should be extremely persistent because workers would tend to become more stratified in the wage distribution on the basis of their innate skill dimension. The empirical literature, however, has often challenged this implication. One of the key empirical findings is that a sizeable part of the sharp rise in residual inequality is attributable to higher individual wage volatility which, in turn, reflects factors that are of a very temporary nature.

This Paper offers an alternative theory for rising residual inequality consistent with the above observations and, through a calibration exercise, it explores its quantitative importance. The theory is based upon the dynamics of (post-schooling) skill accumulation along the labour market history of *ex ante* identical workers. We can label this approach the *Skill Dynamics Hypothesis* (SDH) to distinguish it from the *Innate Ability Hypothesis* (IAH), as well as to stress that the key features of the theory are the transitory shocks occurring during the labour market experience of workers, and not, as posited by the IAH, those permanent factors which are predetermined upon entry in the labour market.

The two crucial – and closely related – ingredients of the model are the technological acceleration, and vintage-specific skills. A technological acceleration, like the one observed from the early 1970s, indicates that technology incorporates new features at a faster rate, these new features require the performance of new tasks, thus less skills are transferable across successive vintages of machines. The result is that the typical labour market history of the worker involves lower average skills (but skills of a younger vintage), larger wage losses upon separation and higher wage growth on the job. These forces generate a temporary decline in the real wage and a rise in the cross-sectional variance of skills. Increased mobility of workers (who respond to the shock by tracking closer to the leading edge) counteracts the above forces, but when the rise in mobility is not too large, the model predicts a surge in residual wage inequality.

We use our calibrated model economy for a *quantitative* study of the US economy. We show that a technological acceleration of the magnitude we observed in the past 25 years can account for just below 30% of the rise in residual inequality in the US, or for the bulk of the increase in its transitory component. The transitional dynamics of the calibrated model are also able to generate a slowdown in real wage growth that explains around 34% of the difference between wage growth in the data and long-run trend growth in the 15 years following the shock.

Finally, let us remark that the emphasis we gave to the *Skill Dynamics Hypothesis vis-à-vis* the *Innate Ability Hypothesis* is not just semantics, but it has profound policy implications. Insofar as we are interested in reducing inequality, models in the first class call for interventions that allow the disadvantaged (or unlucky) workers to rebuild their skill level, especially the *vintage* of their knowledge. Models in the second class suggest that the intervention should be targeted much earlier in the life of an individual, possibly during childhood when the crucial components of cognitive ability are being formed.

1 Introduction

During the past 30 years, the US wage distribution has undergone prominent changes. Wage inequality has greatly increased over this period, reaching arguably the highest peak in half-century: the ratio between the ninth and first deciles of the weekly log-wage distribution for males rose by 40% between 1963 and 1995 (Katz and Autor [1999], Figure 1). Part of this rise in inequality is attributable to expanding wage differentials between educational and experience groups.[1] However, measurable characteristics such as education and experience can explain at most half of the total surge in wage inequality. Juhn, Murphy and Pierce [1992] conclude that the majority of the increase in US wage inequality is *residual*, i.e. due to unobserved attributes of workers belonging to the same educational or demographic group. This rise in residual (or within-group) inequality is a crucial feature of the recent dynamics of the wage distribution not only in the US, but also in other countries where remarkable changes in the wage structure have taken place, such as the UK and Canada.[2] It is this particular dimension of the recent changes in the wage distribution across a number of countries that still poses a major puzzle to labor and macro economists. What are its causes? Are the same forces that have expanded between group differentials also at work within groups?

The conventional view of the existing literature is that this phenomenon is the result of an increase in the return to *ability*, a term which is meant to capture some permanent (model specific) attribute driving the ex-ante unobserved heterogeneity among observationally similar workers. A variety of models in the literature can be traced back to this mechanism, that we will call the *Innate Ability Hypothesis* (IAH). Acemoglu [1999] proposes a model where firms search for workers endowed with different skill levels in a frictional labor market. An increase in skill-based technical change (or in the supply of skills) induces firms to switch from creating "middling" jobs towards creating separate jobs for each skill type. This in turn leads to higher inequality. Galor and Moav [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.

[1] Katz and Autor [1999] document that the wage premium for college graduates relative to high-school graduates increased by 28%, and the wage ratio between workers with 25-35 years of experience and workers with 5 years of experience expanded by 12% in the same period.

[2] Gosling, Machin and Meghir [1998] report that an important aspect of rising inequality in the UK is increased within-group wage dispersion. Baker and Solon [1999] argue that the increase in Canadian earnings inequality has occurred mainly within education groups.

Heckman, Lochner and Taber [1998] model innate skills as ability to learn on the job. They explain rising residual inequality because individuals with different ability levels respond differently to the same shocks and devote diverging amounts of time to learning. 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. Similarly, in Lloyd-Ellis [1999], workers are ex-ante heterogeneous in their capacity to absorb new technology-specific skills. Wage inequality rises when the rate at which technologies are introduced exceeds the rate at which they are absorbed because of increased competition for "technologically mobile" labor.

All these models relying entirely on *ex-ante* fixed differences in abilities across individuals have a stark empirical implication: the rise in residual inequality should be extremely persistent because workers would tend to become more stratified in the wage distribution on the basis of their innate skill dimension. However, starting from the work by Gottschalk and Moffitt [1994, 1995], the empirical literature has often challenged this implication. Using PSID data, Gottshalk and Moffitt [1994] decompose the increase in within-group inequality into a temporary and a permanent component and find that the rise in earnings instability due to transitory shocks is as large as the rise in the permanent component from 1970 to 1987.[3] Gittleman and Joyce [1996] use matched cross-sections from the CPS to examine changes in earnings mobility from 1967 to 1991. They conclude, in agreement with Gottschalk and Moffitt, that short-term earnings mobility did not decline over the period. Blundell and Preston [1999] exploit income and consumption information from the CEX for the period 1980-1995 and conclude that there was only a minor upward trend in consumption inequality within educational groups, suggesting that the bulk of rising residual income inequality is largely insurable, therefore fairly transitory.[4]

The lesson one should draw from this literature is that a sizeable part of the sharp rise in residual inequality is attributable to higher individual wage volatility which, in turn, reflects factors that are of a very temporary nature. Although all the above empirical

[3] There are some dissenting opinions on the exact fraction accounted for by the transitory component. For example, Katz [1994] and Baker and Solon [1999] argue that Gottschalk and Moffit's methodology tends to understate the permanent factor. However, even more sophisticated analysis reach similar conclusions of substantial contributions of both components.

[4] Baker and Solon [1999] report that the rise in Canadian inequality has stemmed from upward trends in both the temporary and the permanent component, with the permanent component playing a somewhat larger role. Dickens [2000] studies the dynamic structure of male wages in the UK for 1975-1995 and concludes that the transitory component explains about half of the rise in inequality. The findings of Blundell and Preston [1999] for the UK are similar to those for the US.

papers conclude with an appeal to devote more attention to the sources of these transitory factors, virtually no attempt has been made to construct theoretical models that could explain this crucial aspect of the data.

This paper offers an alternative theory for rising residual inequality consistent with the above observations and, through a calibration exercise, it explores its quantitative importance. The theory is based upon the dynamics of (post-schooling) skill accumulation along the labor market history of ex-ante identical workers. We can label this approach the *Skill Dynamics Hypothesis* (SDH) to distinguish it from the IAH, as well as to stress that the key features of the theory are the transitory shocks occurring during the labor market experience of workers, and not, as posited by the IAH, those permanent factors which are predetermined upon entry in the labor market.

1.1 An Overview of the Model and the Results

The two crucial –and closely related– ingredients of the model are the technological acceleration, and vintage-specific skills. The seminal work by Gordon [1990] on quality-adjusted price indexes for production durable equipment 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, Rios-Rull and Violante [2000] extend the series until 1992 using different methodologies and reach a similar conclusion.[5]

The role of the technological acceleration in shaping *between-group* inequality has been emphasized for example by Krusell et al. [2000]: the observed acceleration in capital-embodied technical change, together with a moderate degree of capital-skill complementarity in production can generate a rise in the educational premium comparable to the data. In this paper we argue that the technological acceleration can also induce a rise in *within-group* inequality when the specificity of skills is linked to the vintage of the technology. An important advantage of the "acceleration approach" for the quantitative study of rising inequality is that it allows us to tie down the source of the shock in the economy in terms of one parameter –the speed of embodied technical change– which can

[5] The lion's share of this acceleration is obviously attributable to computers, communication equipment and other information processing goods. Grimm [1998] for example documents that 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.

be measured through *independent* data. In contrast, in the other existing models which formalize the rise in residual inequality, the source of the shock (i.e. skill-biased technical change) is unobservable or measured directly from the rise of inequality itself.

The second key feature of the theory is that skills are vintage-specific.[6] Extensive empirical work shows that skills cumulated in the labor market have a large specific component. First, there is evidence of significant returns to tenure, and second, workers are subject to substantial and persistent wage losses upon displacement. Both facts suggest that the knowledge cumulated on the job can only be *partially transferred* to new occupations. Accumulation and transferability of specific knowledge represent important determinants of individual wages, so they should be regarded as potential sources of changes in cross-sectional wage inequality.

We associate the specificity of skills to their vintage: the amount of skills which are transferable by a worker moving between jobs is proportional to the *technological distance* between the two machines, i.e. the vintage differential weighted by the speed of embodied technical change. This is a plausible assumption when technological speed is measured, as we do, from *quality-adjusted* relative price of equipment because such a measure captures precisely the speed of improvements in quality, richness and complexity of the technology. A technological acceleration indicates that technology incorporates new features at a faster rate, these new features require performing new tasks, thus less skills are transferable across successive vintages of machines.[7,8]

The economic mechanism in the model can be easily explained. Ex-ante identical workers face a frictional labor market where they search for jobs (machines). Machines

[6]The same assumption of vintage human capital is present in Chari and Hopenhayn [1991], and Jovanovic and Nyarko [1996], but in both papers the emphasis is on how imperfect skill transferability can affect the endogenous adoption and diffusion of technologies, whilst here we abstract from these issues and instead focus on inequality.

[7]Gordon [1990] provides a wealth of examples of quality improvement in equipment requiring a set of new tasks in the associated jobs. In the aircraft industry, in the 70's new avionics were introduced that provided a safer but more complex navigation system. In the 80's completely computerized cockpits appeared with sophisticated self-diagnosis capabilities. In the telephone industry, around the mid 70's electromechanical telephone switchboards were replaced by more sophisticated and flexible electronic switching equipment with larger programming possibilities (e.g. the first system could only send the call through a fixed path and return a busy signal if it was unavailable; with the second, employees have some limited ability to reprogram the path and reroute the call). In the software industry, since the early 80's, every new version of a software is equipped with new features. Those users who remain attached to an old version are often unfamiliar with many features of the new one.

[8]Some authors have pointed out that the recent wave of innovations has a particularly versatile nature and can be applied across virtually every sector and job category in the economy. Aghion, Howitt and Violante [2000] provide a theoretical framework, consistent with the SDH, where the emphasis is on the fact that such *general purpose* nature of the recent technological wave could have increased skill transferability across industries, and study its effect on wage inequality.

embody different vintages of technology, and the productivity of the leading edge machine advances exogenously at a constant rate. In every period workers choose whether to keep the current match with the machine or separate and search for a new match. When matched, workers learn vintage-specific skills. When moving, they can only partially transfer their skills across machines: the amount of skills they can transfer depends on the technological distance between machines, hence it is decreasing in the speed of technology. A technological acceleration implies that workers have less ability to transfer skills from old to new machines. As a consequence, the typical labor market history of the worker involves lower average skills (but skills of a younger vintage), larger wage losses upon separation and higher wage growth on the job. These forces generate a temporary decline in real wage growth and a rise in the cross-sectional variance of skills and wages, the latter essentially through increased earnings instability. The change in the mobility decisions of workers (who respond to the acceleration by tracking closer the leading edge) counteracts the above forces. The overall effect on wage inequality is, in general, ambiguous and its assessment requires a quantitative study.

The quantitative analysis shows that this mechanism can account for 30% of the rise in the residual variance of log-wages, or for almost 90% of the rise in its transitory component. Moreover, along the transition, the model economy produces a slowdown in real wage growth in the 15 years immediately following the shock which can explain 34% of the slowdown in wage growth (relative to trend) in the data from 1973 to 1989. Two sharp empirical predictions of the model are the rise in within-job wage growth and in wage losses upon displacement. Using data from the *Panel Study of Income Dynamics*, we show that the average wage loss for displaced workers (1 year after the separation) increased by around 10% and wage growth on the job increased by 1.5% per year from the 70's to the 80's.

The plan for the rest of the paper is as follows. Section 2 presents the general model used in the quantitative analysis. Section 3 presents a stylized version of the model that delivers transparently some of the key features of the theory. Section 4 describes the calibration of the model and illustrates the main results of the quantitative analysis. Section 5 confronts some testable implications of the theory against the data. Section 6 concludes the paper.

2 The Economy

Preferences and Technology

The discrete time economy is populated by a measure one of infinitely lived, risk-neutral workers and a larger continuum of infinitely lived, risk-neutral potential entrepreneurs, all discounting the future at rate β. In the rest of the paper we assume that β equals the inverse of the rate of return $(1+r)$.

In any period a worker can be either unemployed $(s = u)$ or employed $(s = e)$, thus $s \in \mathcal{S} \equiv \{u, e\}$. Entrepreneurs can create production opportunities (firms). A firm corresponds to a job which can be either matched with a worker $(s = e)$ or vacant $(s = u)$. Creating a production opportunity requires embedding the current leading edge technology into a machine and gives the right to claim the associated profits (output minus the payment to rented labor) from production. The leading edge technology in the economy advances exogenously at rate $\gamma > 0$. We normalize the productivity of the newest machine to 1 so that a technology of age $j \in \mathcal{J} \equiv \{0, 1, ..., J\}$ has productivity factor $(1+\gamma)^{-j}$. The parameter γ is therefore a measure of the speed at which the quality of machine-embodied technology improves over time.[9] We denote by $m(s, j)$ the measure of firms of type (s, j).

A firm needs a site to produce and there is a measure one of sites available in the economy, which can be rented for the duration of the production opportunity by paying upfront the price q, determined in equilibrium. The production opportunity lasts until the machine breaks down. With probability $(1-\delta)$ a machine survives between periods and its age j increases deterministically by one unit of time, until the maximum age J at which the machine breaks down with certainty.

Each machine of age j matched with a worker with efficiency units $z \in \mathcal{Z} \equiv [z_0, Z]$ generates output according to the production technology $y(j, z) = (1+\gamma)^{-\theta j}(\kappa + z)$, where $\kappa > 0$ is the labor input of the self-employed entrepreneur. Hence, rented labor services are not strictly indispensable for production and, even when vacant, capital can always produce $\overline{y}(j) = (1+\gamma)^{-\theta j}\kappa$ with the self-employment of the entrepreneur. This alternative represents an outside option for the firm when the match with the worker fails.

[9] We are implicitly assuming that the amount of capital in each machine is normalized to 1. This choice entails no loss of generality, because as long as the choice of capital has to be made prior to entering the labor market and is irreversible, it does not affect relative wages, which are the focus of this paper.

Search and Bargaining

Idle workers search for vacant machines in a frictional labor market. Search is random and every idle worker makes always one contact with a vacant machine before the next production cycle so searching does not require to be unemployed for an entire period.[10] If the contact is rejected both parties spend one full period unmatched. Conditional on making a contact, a worker's probability of meeting a machine of age j is $\alpha(j) = \frac{m(0,j)}{m(0)}$, i.e. the fraction of vacant machines of type j out of the total number of vacant machines.

When an idle machine and a worker meet, the pair has match-specific rents to share and will bargain over output. We assume that utility is transferable and the bargaining game follows the rules of Rubinstein [1982] and Shaked and Sutton [1984] so that workers get a fraction ξ of output, unless the outside option is binding for one of the parties, in which case that party will get exactly the flow value of her outside option. If this is enough to guarantee a positive surplus, the match goes on, otherwise the pair separates efficiently.[11] The wage rate within a match is renegotiated at the beginning of each period.

Skill Accumulation and Transferability

Skills are assumed to be *vintage-specific:* each worker is indexed by a two-dimensional skill bundle (j, z) where z defines how productive she is in operating technology of age j. In other words, the skill level z can be interpreted as the number of tasks she is able to perform on technology j: to operate a technology at its best, one must be able to perform Z tasks.

The level of knowledge z evolves differently according to the employment status of a worker. Every period an employed worker can cumulate new knowledge through learning-by-doing with probability λ. Upon learning, her skills are increased by a fixed amount η (i.e. the worker learns to perform η additional tasks), until level Z. An unemployed worker suffers only from obsolescence of skills (because knowledge ages relative to the frontier technology), but her ability to perform those tasks is not affected, thus z does not change.

A worker with skill bundle (j, z) who is transiting out of unemployment to move towards a machine of age j' can carry her knowledge on the new job according to the

[10]This assumption is made purely for calibration purposes, as explained in Section 4, Footnote 25. None of the results depend on it.

[11]This bargaining rule has three advantage over the usual Nash bargaining often used in matching models. First, some authors argue that it has better microfoundations in search environments (Acemoglu [1996]). Second, it has also stronger experimental support (Binmore, Shaked and Sutton [1989]). Last, in our environment it allows to derive the useful wage variance decomposition in (2).

transferability function:

$$z' = T(j, z, j') = \begin{cases} \min\left\{z_0, z(1+\gamma)^{\tau(j'-j)}\right\} & if\ j' < j \\ z & otherwise. \end{cases} \tag{1}$$

This function has the property that the fraction of skills that can be carried from an old onto a newer machine is proportional to the *technological distance* between the two machines, through a factor $\tau \geq 0$. The presence of the term γ in the transferability technology is crucial: the rate of quality improvement of capital-embodied technologies determines the degree by which the new one is different, more complex and richer than the previous generation. A higher γ reduces skill transferability in the economy. Obviously, at least z_0 can be transferred on newer machines. Moreover, we assume that when workers move to older technologies, they can transfer all their knowledge.[12]

The vintage j of skills increases deterministically every period by one unit of time for all employed and unemployed workers until age J. When a worker of type (j, z) is transiting out of unemployment to work on a machine of age j' his age index takes immediately the value of the current machine, independently of her past realizations of j. In other words, we allow for history dependence in the skill level z, but not in j.[13]

The *two-dimensional* skill bundle and the transferability function represent the key modeling innovations of this paper. The index j of the skill bundle allows to capture an aspect of the labor market that is absent from one-dimensional skill models: the market value of the skills of an experienced worker with high z can be inferior to that of a novice worker with low z when the vintage of knowledge of the novice worker is more recent.[14] The transferability function allows to link explicitly the rate of quality-improvement in capital goods γ with the wage distribution. By determining the skill losses upon separation, the transferability function affects the cross sectional skill distribution

[12] Alternatively, we could have assumed that even when moving to older machines, some skills are lost because knowledge has a machine-specific component. However, we could also have assumed that knowledge z on technology j is equivalent to $z' > z$ on a machine of age $j' > j$. We opted for an intermediate assumption.

[13] We make this approximation mainly for computational reasons, since keeping track of the past $j's$ of the worker would enlarge substantially the dimensionality of the problem. An example can help clarify the consequences of this assumption. Consider a worker whose labor market history (in terms of vintages of technologies) is $0-3-2$ and compare her to a worker whose history is $4-3-2$. In the second separation, the first worker loses the same fraction of skills as the second, even though in the first period she worked on exactly the same technology (vintage 0 becomes vintage 2 after 2 periods). This is because past $j's$ do not matter. However, her superior history is translated in a higher expected level of z at the end of the two transitions since in the first separation she transfers more skills than the second worker.

[14] For example, on newly created jobs in the printing industry a skilled manual typesetter could be less productive than a novice electronic compositor. Similarly, on newly created jobs in the software industry an experienced Basic programmer can be less productive than a young Java programmer, and so on.

and the mobility decisions of workers, and impacts directly on the equilibrium wage distribution.

Timeline of the Economy

Having described the environment, we now briefly summarize the timing of the events in the economy. In the beginning of each period new machines enter the economy in place of those depreciated and continuing pairs decide whether to keep the match alive or separate. Random matching takes place. Newly formed pairs decide whether to stay together or part. Matched pairs engage in production activities and income is distributed. At the end of the period a fraction of machines break down, the technology of surviving machines and the skills of surviving workers age by one unit of time. The outcome of learning-by-doing for employed workers is revealed. The next period begins.

The aggregate state of the economy is the distribution of workers across states $\mu(s,j,z)$ defined over all the subsets of the state space $\{\mathcal{S}\times\mathcal{J}\times\mathcal{Z}\}$, representing a snapshot of the economy taken just before the search stage.[15] The value functions will be defined at this same stage.

2.1 Stationary Equilibrium

Since the model has been stationarized, a steady-state equilibrium corresponds to a balanced growth path for the original model. In order to emphasize the key mechanism of our theory, based on the skill dynamics and the mobility decisions of workers, we have chosen to restrict the set of stationary equilibria of the model. The main result permitting to do so is stated in Lemma 1 below.[16]

Lemma 1 *If $(1-\xi)Z \leq \xi\kappa$, then the wage function for all continuing pairs is $w(j,z) = (1+\gamma)^{-\theta j} z$. The separation decision is always taken by the worker and is jointly efficient.*

The main virtue of embracing the parametric restriction in Lemma 1 is that it allows to greatly simplify the computation of the equilibrium and the interpretation of the results, without losing excessive generality. Computation is simplified because one needs to keep track only of the workers' side of the economy. Generality is maintained because the

[15] Since the age distribution of machines $m(j)$ is exogenous, the measure of vacant machines of each age j, $m(0,j)$ is a by-product of the measure of employement on technology j, i.e. $m(0,j) = m(j) - \mu(1,j)$, where $\mu(1,j) = \sum_{z\in\mathcal{Z}} \mu(1,j,z)$. Thus, we do not need to keep track of $m(s,j)$ explicitly.

[16] All proofs are in the Appendix.

firm acts optimally and the separation decision is jointly efficient.[17] The interpretation of the results are very intuitive in light of a decomposition of the log-wage variance which can only be derived thank to that particular wage determination mechanism where the wage is always a multiplicative function of technology and skills. By taking logs of the wage rule $w(j,z)$ and computing the variance with respect to the equilibrium employment distribution, we obtain:

$$var(\widetilde{w}) = \theta^2\gamma^2 var(j) + var(\widetilde{z}) - 2\theta\gamma cov(\widetilde{z}, j), \tag{2}$$

where we have taken log-approximations of the type $\log(1+x) \simeq x$ and expressed logarithms of the variables with the "$\sim$" symbol. The variance of log-wages is the sum of three components: variance of technologies, variance of skills and covariance between skills and the age of technologies. In the rest of the paper we will use extensively this decomposition to interpret some properties of the equilibrium and to assess the quantitative importance of the economic forces at work.

Hereafter, we concentrate our attention on the worker's side of the economy. The decision problem of the employed worker is:

$$\begin{aligned} V(j,z) = \quad & w(j,z) + \widehat{\beta}\left[(1-\delta)\,\lambda \max\left\{V(j+1, z+\eta), U(j+1, z+\eta)\right\}\right. \\ & +(1-\delta)\,(1-\lambda)\max\left\{V(j+1,z), U(j+1,z)\right\} \\ & \left.+\delta\left\{\lambda U(j+1, z+\eta) + (1-\lambda)\, U(j+1,z)\right\}\right], \end{aligned} \tag{3}$$

where we have used the shorter notation $\widehat{\beta}$ for $\beta\,(1+\gamma)^{\theta}$. Employed workers –upon continuing life of their machine– decide whether to stay or to quit in order to search for a better job opportunity. We denote the discrete decision rule implicit in the value function above as $\chi_e(j,z) \in \{0,1\}$ where $\chi_e(j,z) = 1$ if the decision involves a separation.

The decision problem of the unemployed worker is:

$$U(j,z) = \quad \textstyle\sum_{j' \in \mathcal{J}} \alpha(j') \max\left\{V\left(j', T(j,z,j')\right), \widehat{\beta} U(j+1,z)\right\}. \tag{4}$$

Unemployed workers, upon meeting with a machine, decide whether to accept the job offer or to keep searching in the next period. We denote the discrete decision rule implicit in the value function above as $\chi_u(j,z,j') \in \{0,1\}$, with the same convention as for χ_e.

[17] Lemma 1 also implies that the equilibrium price q of a productive opportunity equals the discounted present value of the profits accruing to a new machine, i.e. $q = \sum_{j=0}^{J}\left[\frac{(1-\delta)}{(1+r)}\right]^{j}\kappa$. Since the price q is sunk once the machine enters the labor market, and given that the scrap value of capital at every age is zero, it is never optimal for a firm to exit before J, and q does not affect the wage distribution. Without loss of generality, we can ignore q in the description of the equilibrium.

We can define a *stationary equilibrium* for this economy as a pair of decision rules $\{\chi_e(j,z), \chi_u(j,z,j')\}$, value functions $\{V(j,z), U(j,z)\}$, wages $w(j,z)$, meeting probabilities $\alpha(j)$, and a time-invariant distributions of workers $\mu(s,j,z)$, such that:

- in each active pair (j,z), the wage is $w(j,z) = (1+\gamma)^{-\theta j} z$,
- the probability for an unemployed worker to meet a vacant machine of type j is $\alpha(j) = \frac{m(0,j)}{m(0)}$, where $m(0,j) = m(j) - \mu(1,j)$,
- given the wage rule and the meeting probabilities, the policy functions $\{\chi_e(j,z), \chi_u(j,z,j')\}$ solve the dynamic maximization problem of the worker described in (3) and (4) and $\{V(j,z), U(j,z)\}$ are the associated value functions,
- for any triple $(\mathcal{S}^*, \mathcal{J}^*, \mathcal{Z}^*) \in \{\mathcal{S} \times \mathcal{J} \times \mathcal{Z}\}$, μ satisfies $\mu(\mathcal{S}^*, \mathcal{J}^*, \mathcal{Z}^*) = Q(\mathcal{S}^*, \mathcal{J}^*, \mathcal{Z}^*)(\mu)$.

Notice that the last condition requires the derivation of the fixed point of the function Q mapping this period workers' distribution into next period distribution.[18] By satisfying the above functional equation, the stationary equilibrium measure μ guarantees the consistency of the individual decisions with the aggregate functions that the individual takes as given in the economy, i.e. the vector $\alpha(j)$ of contact rates and the wage rule $w(j,z)$.

3 A Stylized Version of the Economy

In this section we present a stylized version of our model with a fully analytical solution in order to illustrate intuitively some properties of the equilibrium of the richer model used for the quantitative analysis.[19] We need to make two simplifying assumptions to obtain a tractable model.

First, we assume that machines are productive only for 2 periods and do not depreciate in the first period of life ($\delta = 0$), but fully depreciate at the end of the second period. It follows that every period the economy is populated by active machines (and workers with skills) of age $j \in \{0,1\}$. Second, we assume that skills cumulated through learning-by-doing depreciate fully after one period. This implies that, irrespectively of the skill level at the beginning of the period, at the end of the period the skill level of the worker will be

[18] This transition function is constructed from the contact rates, the transferability function, the learning probability, the surviving rate and the agents' optimal separation rules. The Appendix contains a full description of the transition function Q.

[19] This section draws partially from the theoretical model in Aghion, Howitt and Violante [2000].

z_0 if she did not learn (or if she was unemployed) and $Z = (z_0 + \eta)$ if she was employed and learned. These two assumptions maintain analytical tractability and, at the same time, they are just enough to generate a vintage model with history-dependence in the skill level, two crucial ingredients of the richer model used for the quantitative analysis.

In this stylized model there is no unemployment since all contacts translate immediately into productive matches.[20] This is not necessarily true in the general model, and we will return to this issue in Section 4.

We normalize z_0 to 1 and, to simplify the notation, denote the individual state of the worker by the triple (i, j, j'), where i is the outcome of learning-by-doing in the previous period with $i = H$ if learning took place (with probability λ), and $i = L$ otherwise. The index j (j') denotes the age of the previous (current) technology the worker was (is) matched to. Overall, we have six skill levels and six wage rates in the economy. The skill levels are:

$$\begin{array}{lll} z_{H01} = (1+\eta), & z_{H00} = z_{H11}(1+\eta)(1+\gamma)^{-\tau}, & z_{H10} = (1+\eta)(1+\gamma)^{-2\tau}, \\ z_{L01} = 1, & z_{L00} = z_{L11} = (1+\gamma)^{-\tau}, & z_{L10} = (1+\gamma)^{-2\tau}. \end{array} \tag{5}$$

The corresponding productivity-adjusted wage rates are simply given by $w_{ij0} = z_{ij0}$ and $w_{ij1} = z_{ij1}(1+\gamma)^{-\theta}$ as established by Lemma 1. The value functions in (3) and (4) simplify to:

$$\begin{aligned} V_{i01} &= w_{i01} + \widehat{\beta}\left[\lambda U_{H1} + (1-\lambda) U_{L1}\right], \\ V_{i11} &= w_{i11} + \widehat{\beta}\left[\lambda U_{H1} + (1-\lambda) U_{L1}\right], \\ V_{i00} &= w_{i00} + \widehat{\beta}\left[\lambda \max\left\{V_{H01}, U_{H0}\right\} + (1-\lambda) \max\left\{V_{L01}, U_{L0}\right\}\right], \\ V_{i10} &= w_{i10} + \widehat{\beta}\left[\lambda \max\left\{V_{H01}, U_{H0}\right\} + (1-\lambda) \max\left\{V_{L01}, U_{L0}\right\}\right], \\ U_{ij} &= \alpha V_{ij0} + (1-\alpha) V_{ij1}, \end{aligned}$$

where $i \in \{H, L\}$, $j \in \{0, 1\}$, and α denotes the probability of meeting a new machine.

3.1 Optimal Separation Decisions

Because all contacts translate into matches and matches on old machines break down exogenously with certainty, the only decision we need to characterize is the separation decision for workers on new technologies, which we denote by $\chi_i \in \{0, 1\}$, $i \in \{H, L\}$.

[20] If an unemployed worker accepts a job offer on the worst technology available (age 1), at the end of the period the continuation value of such job is equal to the continuation value of turning down the offer. Thus, as long as wages are non-negative, even the worst job offer will always be preferred to remaining idle.

The trade-off involved in this choice is simple. Searching yields the chance to find a job on a leading edge machine. In terms of current period payoff, on the leading edge machine workers can transfer less of their skills, but the productivity of the new machine is higher, so the current gain of moving has ambiguous sign. In terms of continuation value, moving to a new machine is always better, as future ability to transfer skills will be higher. Indeed, $V_{i00} > V_{i10}$ and $V_{i01} > V_{i11}$ which means that for any given vacancy contacted, holding younger skills is strictly better.

The following Lemma characterizes the optimal separation decision for workers with high (type H) and low (type L) skills as a function of the parameters τ and θ.

Lemma 2 *For $\tau \leq \theta$, then $\chi_i = 1$ always. For $\tau > \theta$, if $\chi_H = 1$ then $\chi_L = 1$.*

The results of this Lemma are very intuitive. For $\tau \leq \theta$, skill transferability is high and the current period gain of moving to a new machine (the first term of $(A1)$) is strictly positive. A fortiori, a separation is always optimal because the continuation value (the second term of $(A1)$) is decreasing in the age of skills. A more articulated solution arises when $\tau > \theta$ because the current payoff from moving is negative. In this case, a skilled worker of type H is affected more severely by the skill loss implied by moving to the youngest vintage, so he will be less willing to separate than an unskilled worker of type L.

In the rest of this section we focus on the more articulated case $\tau > \theta$. It descends from Lemma 2 that for $\tau > \theta$ the model has potentially 3 types of stationary equilibria: $(E1)$ where none of the workers separate from technologies of age 0, $(E2)$ where L workers separate, but H workers do not, and $(E3)$ where all workers separate every period.

In this stylized model, despite the absence of search externalities linked to changes in the aggregate number of unmatched parties (unemployed workers make always one contact), there are externalities due to the two-sided heterogeneity arising from composition effects in the pool of vacancies and unemployed workers. As illustrated by Sattinger [1995], such externalities often lead to multiple steady-states, and it is easy to show that for some parametrization this is indeed the case in our simple economy. The exhaustive characterization of the stationary equilibria in terms of different regions of the parameter space is lengthy and cumbersome, and lies beyond the scope of this section. However, we can easily prove one result that is useful in the rest of the paper and gives the intuition on how an increase in γ can induce a switch to a steady-state with higher mobility.

Lemma 3 *There exists a value $\overline{\gamma}$ such that for $\gamma > \overline{\gamma}$, $(E3)$ is always a stationary equilibrium, and $(E1)$ is never a stationary equilibrium.*

The key consequence of Lemma 3 is that as the rate of quality-improvement of machines increases, workers tend to bring forward their separation decision. This result is related to the intertemporal trade-off intrinsic in the separation decision. Choosing to remain on an old vintage improves the current wage, but worsens future wages because in the next period the worker will have older knowledge, with poor degree of transferability. As γ goes up, the expected future wage loss from holding old skills increase faster than the current wage gain and is discounted at the higher effective rate $\widehat{\beta}$. Workers tend to separate more often in order to track closer the leading edge because young skills are more valuable when γ is large.

3.2 Equilibrium Wage Inequality

To characterize equilibrium wage inequality in the three steady-states of the model we use the log-wage variance decomposition outlined in equation (2). Note that all the wage inequality in this economy is *residual*, since workers are ex-ante equal. For this same reason, inequality is not the result of heterogeneous levels of innate ability, but it is due to how differently the labor market histories of workers unfold. It is the combination of the degree of skill transferability, stochastic factors (learning and luck in the meeting process) and workers' mobility decisions that determine how widely wages can span in equilibrium.[21]

Lemma 4 *In each steady-state, an increase in γ that does not change the separation decision raises $var(\widetilde{z})$, $cov(\widetilde{z}, j)$ and $var(\widetilde{w})$. The magnitude of the increase is proportional to τ. An increase in γ that changes the separation decision has ambiguous effects on $var(\widetilde{w})$.*

The variance of skills is increasing in γ since a higher γ reduces the skill transferability of the bottom end workers (type $L10$), while not affecting the skill level of the top end workers (type $H01$). The covariance between skills and age of technology is also increasing in γ, a force that restrains inequality because it worsens the equilibrium sorting in the economy. The reason is that a larger γ reduces the skills of workers moving to the

[21]Following the log-wage decomposition in (2), in the next Lemma we take log-approximations of the type $\log(1 + x) \simeq x$ and express logarithms of the variables with the "$\sim$" symbol.

new technology relatively more than the skills of workers moving to (or staying on) old technologies. Overall, when the decision rules do not change, inequality is unambiguously increasing in γ: for $\tau > \theta$ the rise in skill heterogeneity dominates the fall in the covariance component.[22]

Consider now an arbitrarily small increase in γ that changes the mobility decisions of workers: in switching across types of steady-states the variance of wages falls. Once again, the variance of skills and the covariance component move in opposite direction, and for $\tau > \theta$ the fall of the skill variance dominates. This result is explained by the discrete change in the employment distribution. Imagine switching from $(E1)$ to $(E2)$. Since the workforce on the newest technology is no longer composed exclusively by workers of type $i10$ moving from the old machines, but also by type L workers moving from newer machines —hence endowed with better ability to transfer skills— the equilibrium sorting of skills across technologies improves and the covariance falls. However, the same change in the separation decision reduces the variance of skills as it moves some mass from the lower tail to the middle of the skill distribution: at the top end of the skill range, type $H01$ who had mass $\lambda/2$ has now measure $\lambda/\left[2(2-\lambda)\right]$ and symmetrically, at the bottom end, type $L10$ who had mass $(1-\lambda)/2$ has now measure $(1-\lambda)/\left[2(2-\lambda)\right]$.

The conclusion we should draw from Lemma 4 is that the faster rate of quality-improvement in capital has two effects. First, through reduced skill transferability it tends to increase wage inequality. However, workers respond to the shock by anticipating their separation in order to maintain their skills younger and shelter themselves from large skill losses. This force contributes to reducing inequality. A necessary condition for the first effect to dominate is $\tau > \theta$, but at the end of the day what force will be paramount is a quantitative question.

3.3 Individual Earnings Instability

An alternative interpretation of the effect of a larger γ on inequality is obtained by analyzing how wage growth within job $\Delta\widetilde{w}^S$ (i.e. for workers who stay on the same machine) and wage losses upon displacement $\Delta\widetilde{w}^M$ (i.e. for movers from machines of age 1) depend on γ. Cross-sectional wage inequality in this model is equivalent to the variability of wages over time: the rate at which the wage rate grows on the job and the size of the wage losses upon job change represent the two main sources of wage variability

[22]The variance of vintages of machines is unaffected so the increase in γ raises technological heterogeneity mechanically. However, even in absence of this force, the variance of wages would be increasing in γ.

along individual work histories.

Lemma 5 *In each steady-state, an increase in* γ *that does not change the separation decision raises both* $\Delta\widetilde{w}^S$ *and* $\Delta\widetilde{w}^M$*. An increase in* γ *that changes the separation decision has ambiguous effects on* $\Delta\widetilde{w}^S$ *and* $\Delta\widetilde{w}^M$*.*

For given separation decisions, the result on the relationship between γ and wage losses upon displacement derives directly from the specification of the transferability function. Clearly, as workers anticipate their separation decisions, they reduce their skill losses.

The result on wage growth is less straightforward. Wage growth for stayers is entirely determined by skill growth, so by the learning process. The key reason for faster wage growth on the job is that the average skill level of workers on machines of age 0 falls with γ due to lower transferability. In the next period, the skill level of these workers is either 1 or $(1+\eta)$. Both values are unaffected by γ, so wage growth increases.[23]

We conclude once again that, barring strong effects originating from the change in the separation decisions, a technological acceleration induces more volatile labor market histories where job changing entails large skill losses on average, but when on the job workers move on the steeper portion of their learning curve.

3.4 The Transitional Dynamics of Average Wage

It is immediate to show that the stationarized average log-level of skills is $(\eta - \gamma\tau)$ in all three steady-states, thus it falls unambiguously when γ increases. This opens the interesting possibility that in the model the average wage could decrease along the transition following a technological acceleration. Suppose that at time t the economy is in steady-state with $\gamma = \gamma_L$ (and with the productivity of the new machine normalized to 1). The average log-wage is then $\widetilde{W}_t = \lambda\eta - \tau\gamma_L - \theta\gamma_L/2$, independently of χ_i. Suppose now that γ rises to γ_H and the decision rules do not change. Then, after simple algebra one can determine that next period the average log-wage is

$$\widetilde{W}_{t+1} = \lambda\eta + \frac{\theta\gamma_H}{2} - \frac{\tau}{2}(\gamma_L + \gamma_H) = \widetilde{W}_t - \frac{\tau}{2}(\gamma_L - \gamma_H) + \frac{\theta}{2}(\gamma_L + \gamma_H).$$

[23] This result is more general than it seems at first sight, in that it does not depend on the assumption of "short memory" in the skill level. Consider a worker with skill level z in the more general model of Section 2. Upon learning, her skill level becomes $(z+\eta)$, otherwise it remains z, hence once again the expected skill growth will be larger if z is smaller. The result depends only on the concavity (i.e. the decreasing returns) of the learning function, in the sense that the marginal gain from learning at lower skill levels is higher than at higher skill levels. This is a common and natural assumption, well supported by the empirical literature on learning curves, experience and tenure profiles.

We conclude that if $(\gamma_H - \gamma_L) / (\gamma_L + \gamma_H) > \theta/\tau$ (thus, for τ large enough or for a rise in γ large enough), then the average wage could decrease along the transition, notwithstanding the technological acceleration.[24] This result fits well with the finding that the average real wage in the US has decreased in the early to late 70's and has been stagnant in the 80's (see Murphy and Welch [1992], Table 1), but once again the magnitude of the wage fall predicted by the model is a quantitative issue.

4 The Quantitative Analysis

Despite its ability to highlight the key mechanism at work, the stylized model is far too simple to be useful in approaching the data. Its main shortcoming is that physical and human capital are assumed to fully depreciate after two periods for analytical tractability. This assumption is very restrictive when looking at actual economies where several vintages of technologies are active at the same time, and where workers' human capital depends on their entire work experience.

In the rest of the paper, we will use a calibrated version of the full scale model presented in Section 2 in order to measure how much of the increase in residual wage inequality can be attributed to this mechanism. The first step is to calibrate the initial steady-state of the model economy to the US economy in the period before the technological acceleration. The second step is to compute numerically the new steady state of the model economy under the faster rate of embodied technical change and analyze the change in residual wage inequality. Finally, we compute the transitional dynamics to study to what extent the model generates, along the transition path, a slowdown in average wage growth.

4.1 Calibration

The model contains 10 parameters to calibrate, $\{\gamma_L, \gamma_H, \theta, \beta, \kappa, J, \lambda, \tau, Z, \delta\}$. The period of the model is chosen to be six months.[25] The speed of capital-embodied technical change is the key parameter of the model. Following a large literature, we measure this parameter

[24] This example generalizes immediately to the case where $\chi_i = 1$ for $i \in \{H, L\}$ and to the case where χ_H changes from 0 to 1. The general conclusion is that for τ or $(\gamma_H - \gamma_L)$ large enough, the average wage could fall.

[25] This is a compromise between two contrasting requirements. On the one hand, we need to model the fact that a handful of very old vintages are always active in the economy. For this purpose, in order to keep the vintage grid small and mantain a reasonably sized state space, we would like to use a long time period (e.g. 1 year). On the other hand, to deal with labor mobility, we would like to have a much shorter time period (e.g. 1 quarter).

through the quality-adjusted relative price of equipment.[26] The data produced by Gordon [1990] and extended by Krusell et al. [2000] are available from 1947 to 1992. Since our data on wage inequality start in the early 60's, we only use the period 1960-1992. It has been documented that the acceleration has taken place in the early to mid 70's (see for example Hornstein and Krusell [1998]). Moreover, the yearly relative price series shows a clear outlier in 1974. For these reasons, to calculate γ before and after the acceleration, we split the sample in two periods, 1960-1973 and 1975-1992, and we dummy out 1974. The results, shown in Table 1, suggest to use a pre-acceleration value $\gamma_L = 3.5\%$ and a post-acceleration value $\gamma_H = 4.8\%$. In the numerical experiment, the technological acceleration of the past 25 years will be modeled as a rise from γ_L to γ_H.[27]

TABLE 1

Relative Price of Equipment Regression

Dep. variable: growth of quality-adjusted relative price of equipment

Variable	Coefficient	Std. Error	t-Statistic
c_{60-73}	-.0349	.0049	-7.064
c_{75-92}	-.0477	.0043	-10.97
d_{74}	.1099	.0019	5.75
Nobs = 33,	$\overline{R}^2$ = .588,	D.W. = 1.556,	F-stat. = 21.43.

Note: Data on quality-adjusted relative price of equipment from Krusell et al. [2000]. Sample: 1960-1992.

Murphy and Welch [1992] report that average wage has grown at a rate of 2.4% per year in the period 1963-1973. Given the calibrated value of γ_L and the expression for the wage function in Lemma 1, we set $\theta = .7$ to match average wage growth before the acceleration. We set the discount factor $\beta = .964$ to obtain an average annual rate of return of 5%, and the skill level of the entrepreneur $\kappa = 5$ to match a labor share of .68, as commonly used in the Real Business Cycle literature (see Cooley [1995]). We set the maximum operating age of a machine J to 28 (14 years) so that the average age of an active machine in the economy is 7.7 years, the average age of equipment in the US economy in the period 1960-1973.[28]

The lower bound for the skill level z_0 representing the minimum amount of transferable skills is normalized to 1. The upper bound Z is chosen so that the equilibrium variance of log-wages in the model matches the corresponding value in the data. The model is not

[26] In this one good economy the price of a machine relative to consumption, not quality-adjusted, equals 1. However, the quality-adjusted price falls at rate γ over time.

[27] In the section on sensitivity analysis, we experiment with a wider range for the parameter γ.

[28] This number is obtained from Table A.6 in *Fixed Reproducible Tangible Wealth in the US 1925-1989*, a publication of the Bureau of the Economic Analysis [1994]. See also Yorukoglu [1996] for a similar calculation.

designed to capture inequality in wages stemming from educational differentials and innate ability (as workers are ex-ante identical) or experience (as workers are infinitely lived). The residual component of inequality with respect to these factors — what is sometimes called in this literature *transitory* component of inequality, or earnings instability— is the target of the calibration. Gottschalk and Moffitt [1994] calculate that the variance of the transitory component of weekly wages before 1974 equals .051. Since they only use data from 1970, this average is only based on 4 data points. To verify whether this number is robust to the inclusion of the earlier years, we use the Current Population Survey (CPS) March Annual Demographic Files (1964-1999) and compute a comparable number for the period (1963-1973) in two steps.[29] First, we compute log weekly wages for each individual/year in the sample and we regressed them on a set of four educational dummies (high school dropouts, high-school graduates, workers with some college and college graduates), a quartic in age, years of education and an interaction term of age and years of education. The variance of the residuals of this regression is plotted in Figure 1.[30] Second, we use Gottschalk and Moffitt's calculation of the transitory component: they report that the transitory component accounted always for around *one third* of total residual inequality in log-weekly wages in the entire period 1970-1987 (see their Table 2, page 233). When we apply this same fraction to our average index of residual inequality from 1963 to 1973, we obtain a value for the variance of log wages of .055. As a target value for the calibration of the model's inequality in the first steady-state we choose the midpoint of these two estimates, .053, which requires to set $Z = 20$. Finally, notice that the CPS data imply a rise of the transitory variance up to .089 in the late 90's, so a rise of around 68% in 25 years. To be successful, the model should generate a comparable increase across steady-states.

The parameter δ is the failure rates of machines and determines the fraction of employment who separates exogenously every period. We choose $\delta = .05$ so that the total separation rate (layoffs plus quits) in the model is 16.6%, the annual separation rate from employment to unemployment in the data between 1960 and 1973 (Blanchard and Di-

[29]The sample is constructed by selecting white males between 18 and 60 years old, who worked full time at least 14 weeks in the past year, who are not self-employed and not union members. Weekly earnings are constructed as annual earnings divided by weeks worked. To deal with the issue of the tails of the distribution, we followed Katz and Murphy [1992]. First, we excluded workers with real weekly earnings below $67 in 1982 dollars (equivalent to 50% of the 1982 real minimum wage based on a 40-hour workweek). To deflate wages we used the Urban CPI (1982=100). Second, workers with topcoded earnings were inputed an annual wage income equal 1.45 times the annual topcode amount.

[30]The computed pattern in the residual wage variance over the sample period mirrors very closely that reported by Katz and Autor [1999, Table 5].

amond [1990]). We calibrate the probability of learning by doing λ to match the wage growth within-job in the data. Topel [1991] reports that at the average experience level, wage growth within job is 3% in the period 1967-1982, which implies a value of $\lambda = .345$.[31] The transferability parameter τ is chosen to match the average wage loss upon exogenous separation. Topel [1991, Table 1] reports a fall of approximately 22% in the wage of laid-off workers with 6-10 years of tenure who are re-employed within 1 year. Jacobson et al. [1993] calculate that the wage of laid-off workers is roughly 17% below their pre-displacement wage after 6 months for individually laid off workers and roughly 30% for mass layoffs. We set $\tau = 1.90$ to reproduce a mean wage loss of 23% in the model (the average of those 3 statistics) for workers displaced after an exogenous break up of their machine who are reemployed after 1 model period (i.e. 6 months).[32] The calibration procedure is summarized in Table 2.[33]

TABLE 2
Summary of Calibration

Parameters	Moment to match (yearly average)	Source
$\gamma_L = .036$	growth of rel. price of equipment (< 1974)	Krusell et al. [2000]
$\gamma_H = .048$	growth of rel. price of equipment (> 1974)	Krusell et al. [2000]
$\theta = .7$	growth of real average wage $= .024$	Murphy-Welch [1992]
$\beta = .964$	rate of return on capital $= .05$	Cooley [1995]
$\kappa = 5$	labor share $= .68$	Cooley [1995]
$J = 28$	average age of equipment $= 7.7$	Bureau of Economic Analysis [1994]
$\lambda = .345$	wage growth within job $= .03$	Topel [1991]
$\tau = 1.90$	wage loss upon layoff $= .23$	Jacobson et. al [1993], Topel [1991]
$Z = 20$	transitory residual wage variance $= .053$	CPS data, Gottschalk-Moffitt [1994]
$\delta = .05$	separation rate from employment $= .166$	Blanchard-Diamond [1990]

4.2 Steady-State Results

In order to understand the results it is useful to analyze how workers change their separation decisions in response to the shock. Figure 2 shows the optimal age of separation by skill level and confirms two features of the stylized model of Section 3. First, in the simulated economy unskilled workers separate earlier (as established by Lemma 2).

[31] The points of the skill grid $[1, 20]$ are equidistant so that the learning-by-doing function is concave as the data suggest for tenure and experience profiles: for low skill levels the expected percentage skill gain is higher than for high skill levels.

[32] In the sensitivity analysis we experiment with a wide range of values for λ and τ.

[33] Technically, the calibration procedure is executed in two steps. First, we set $\{\gamma_L, \gamma_H, \alpha, \beta\}$ as they can be calibrated to independent observations. Second, we set contemporaneously the last 6 parameters so that the remaining 6 "equilibrium moments" of the model economy in the steady-state with γ_L match their data counterpart.

Second, a technological acceleration induces workers to track closer the leading edge in order to avoid large skill losses, with the unskilled workers being the more sensitive to the shock (as established in Lemma 3). As we have emphasized in Section 3, this change in the separation decision has an important impact on the results because it constitutes a force leading towards a reduction of inequality, contrasting the direct effect of lower skill transferability.

The main results of the numerical experiment are shown in Table 3. The variance of log wages increases from .053 to .085, a rise of 60% compared to 68% in the data. The model can replicate 88% of the surge in the transitory component, thus it explains just below 30% of the total increase in residual inequality in the US since the early 70's. We will use the variance decomposition outlined in (2) as a guide to interpret the economic forces at work in the simulations.

TABLE 3

Results of the Numerical Experiment

	Variance of log wages DATA	Variance of log wages MODEL	Variance of technologies	Variance of skills	Covariance component	Within Job component	Between Job component
γ_L =.035	.053	.053	.008	.085	-.038	.052	.054
γ_H =.048	.089	.085	.014	.145	-.074	.084	.094
	Average age of capital	Average skill level	Average log wage	Wage growth within-job	Wage loss upon layoff	Separation rate	Long-term unemployment
γ_L =.035	7.700	11.086	2.177	.030	-.230	.166	.019
γ_H =.048	7.448	8.595	1.837	.044	-.305	.171	.027

The first component of the wage variance is technological heterogeneity. Here two effects come into play to explain the consequences of the shock. Because separation decisions are taken earlier, the age distribution of employed machines shifts to the left (the average age falls by 3 months) and becomes slightly less disperse, as evident from Figure 3, panel (3). However, the rise in γ means that the technological distance between machines of any successive age group increases, which fosters technological heterogeneity across jobs in the economy. The net result in general depends on the calibration: in our economy technological heterogeneity increases from .008 to .014, contributing only mildly to the increase in residual inequality.

The second component, skill heterogeneity, rises substantially between steady-states from .085 to .145. The skill distribution, plotted in panel (2) displays a clear shift to the left, due mainly to the lower skill transferability which reduces the average skill level in the economy by one third, from 11.1 to 8.6. As explained in Section 3, one way to interpret the changes in the model's cross-sectional skill heterogeneity is to map them into changes in the individual variability of skills. The latter is essentially determined by skill growth on the job and skill transferability across jobs. Table 3 shows that the model predicts a rise in within-job wage growth of 1.4% and a fall of wage change upon layoff of more than 7%. Intuitively, lower transferability moves mass of the skill distribution from the center to the lower tail, while the faster wage growth moves mass from the center to the upper tail. Clearly, the first effect is quantitatively stronger, but both combine into a dramatic rise of skill heterogeneity.

The third component is the covariance between the skill level and the productivity of technologies. In the initial steady-state the covariance is negative, indicating that the highest skilled workers tend to be matched with older (and less productive) capital. This is a natural feature of our economy, given that workers need to spend time on the machine to cumulate skills, and given that less skills are transferable on the youngest machines. On top of this, the decision rules reinforce this pattern: unskilled workers separate earlier and more often than skilled workers.

Panel (4) shows the contours of the employment distribution in both steady-states. In the new steady-state, the contours move to the left, and twist slightly clockwise to indicate a stronger negative covariance between skill level and productivity of capital. In fact, with faster rate of quality-improvement, the covariance falls even further indicating that new technologies are now associated with workers holding even lower skills. This effect contributes to lower inequality.

Like in the stylized model, the variance of skills and the covariance component move in opposite directions, but the change in the decision rules of the workers is not strong enough and inequality increases. This can also be seen from Table 3 showing that the model predicts only a small rise in the separation rate, from .166 to .171 per year, suggesting that the forces counteracting the direct effect of lower skill transferability are quantitatively weak. The (normalized) wage distribution is plotted in panel (1) of Figure 3. The higher variance is mirrored by the fatter tails, especially the lower tail.

Another interesting result of the simulations is that the rate of long-term unemployment (longer than 6 months) in the economy increases slightly. When unemployed, workers tend to accept job offers on young machines and reject jobs on old machines because the former are relatively more productive and guarantee higher future transferability. The rise in γ reinforces both channels and unemployed workers become more demanding and reject a larger fraction of job offers (on old capital), which tends to increase the average duration of unemployment in the economy.

Finally, we replicated the within-job and between-job wage variance decomposition in Gottschalk and Moffitt by dividing our workers between movers and stayers and computing the change in the log-wage variance for both types separately. The results are in line with their empirical findings (see their Table 4, page 239): the increase of inequality is almost equally split between the two groups, with a slightly larger change for movers.

4.2.1 An Experiment with Two Educational Group

An important empirical finding in Gottschalk and Moffitt [1994] that represents a challenging test for our model is that the variance of transitory earnings increased much more markedly for low-educated workers than for high educated ones, and a disproportionate fraction of this increase is accounted for by the between-job component. Can our model replicate these facts? To answer this question, we have chosen to calibrate the model to two different educational groups, high-school dropouts and college graduates. We interpret the educational level as a different combination of ability to transfer skills (the value of τ) and ability to learn (the value of λ), while leaving all the other parameters unchanged.

To calibrate the pair (τ, λ) for each type, we used two data points: a measure of residual wage inequality and the magnitude of wage loss upon layoff for each group of workers.[34] In the 70's the average number of years of education was about 12.5 for males, with an average of 8.5 years for high-school dropouts and 16.5 for college graduates. Swaim and Podgursky [1989] report that every additional year of education reduces wage losses upon displacement by 3% on average for males (Table 2, page 44). Keeping 23% as our benchmark value for the average wage loss upon displacement in the entire economy implies an average wage loss of 35% for high-school dropouts and 11% for college graduates. To match these numbers we set respectively τ to 2.50 and 1.37. Matching wage dispersion required setting λ to .28 and .17, respectively.[35]

[34] The objective of the exercise is comparing within-job and between-job components of wage inequality in the model with those computed by Gottschalk and Moffitt. Since their measure of wage inequality is the variance of annual earnings, for consistency we match directly their numbers.

[35] Both numbers for λ are lower than in the benchmark case, because the measure of wage dispersion matched here is larger for both groups, since it refers to annual earnings, not weekly wages. With our parametrization, a higher value for wage dispersion required a lower λ (see the sensitivity analysis section below).

TABLE 4

Results of Numerical Experiment for Two Educational Groups

	Variance of log wages		Within Job component		Between Job component	
High-School Dropouts						
	DATA	MODEL	DATA	MODEL	DATA	MODEL
γ_L =.035	.106	.106	.042	.102	.157	.113
γ_H =.048	.208	.175	.064	.166	.289	.216
College Graduates						
	Variance of log wages		Within Job component		Between Job component	
	DATA	MODEL	DATA	MODEL	DATA	MODEL
γ_L =.035	.065	.065	.040	.063	.098	.073
γ_H =.048	.093	.087	.050	.083	.114	.108

Note: The data are taken from Gottschalk and Moffitt [1994], Table 4, page 239.

The results of this experiment are reported in Table 4. The model is consistent with the data in generating a large increase in inequality for high-school dropouts (65% vis-a-vis 96% in the data) and a moderate rise for college graduates (34% vis-a-vis 43% in the data). The lower skill transferability of poorly educated workers, associated in the model to a higher value of τ, exacerbates the effects of a rise in γ and amplifies the rise in inequality for this group (a result contained implicitly in Lemma 4). It follows that in the model most of the rise in inequality for high-school dropouts is accounted for by the between-job component which captures wage changes upon displacement. For college graduates the rise is equally split between the two components which is what the data suggest as well.

Despite this success, the model systematically overestimates the importance of the within job component, especially for low-educated workers. In other words, in the model the variability of wages on the job due to the stochastic learning process is larger than in the data.[36]

4.2.2 Sensitivity Analysis

We have performed a sensitivity analysis on the variance of log wages with respect to three key parameters in the model, γ, τ, and λ. Figure 4 shows that all the three components of

[36] This was not the case in the benchmark experiment. One explanation could be that the data refer to changes in the variance of annual earnings which are affected both by weeks worked and by weekly wages. In the model there is no variation is weeks worked, and it is natural to conjecture that such variation is much more important in the between-job component than in employment spells where the worker is staying continuously with the same employer.

residual inequality are monotone in γ in the range $[.025, .055]$ which includes the calibrated values. Reasonable deviations from our calibrated values for γ_L and γ_H would not change substantially our quantitative findings. The model predicts that a further acceleration in the rate of quality-improvement in the years to come would lead to an additional increase in residual inequality.

Figure 5 shows how the three components of wage variance, and wage variance itself change with τ in the two steady-states. The range for τ is set to $\pm 20\%$ of the calibrated value 1.9. Also in this case, each component is well behaved. Not surprisingly, skill heterogeneity rises and the covariance component falls as suggested in the analytical derivations of Section 3. Overall, the rise in wage inequality is stronger for τ large, but not substantially. For example, when $\tau = 1.5$ inequality rises by 60% and when $\tau = 2.5$ it rises by 67%.

The results on λ showed in Figure 6 are somewhat more interesting, as the stylized model has ambiguous predictions on how λ shapes inequality. We have analyzed a very large range of values spanning the interval $[.1, .7]$. The main findings are that, given our parametrization, inequality is falling in λ and that the rise in inequality associated to a technological acceleration is more pronounced for low values of λ. These results come from the observation that the higher is the learning rate, the more the skill distribution becomes massed towards its upper bound. The skill variance falls and the covariance between age and skills decreases because workers learn faster and consequently they are much more likely to hold high-skills on young vintages. In other words, a technological acceleration that reduces skill transferability does not have a significant effect on the skill distribution since the fast learning process realigns quickly the differences between the more and the less lucky workers in the economy.

4.3 Transitional Dynamics

In this section we focus on the transitional dynamics of the economy between the two steady-states in order to assess to what extent the reduced skill transferability, and the associated fall in workers' average skill level, contributed to the slowdown in wage growth observed in the data since the mid 70's.

To initiate the transition, we start the economy in the steady-state with γ_L and assume that unexpectedly, the speed of capital embodied technical change rises to γ_H. This is equivalent to a sudden trend break in the series of relative-prices of equipment, as the data suggest. The key step in computing the transition is to generalize the transferability function in (1) to the case in which $\gamma(t)$ changes over time, since in a nonstationary environment the technological distance between two machines of age j and $j' < j$ at time t depends on the past values $\gamma(t-j), ..., \gamma(t-j')$. Hence:

$$T(j, z, j', t) = \begin{cases} \min\left\{z_0, z\left[\prod_{i=j}^{j'} \gamma(t-i)\right]^{-\tau}\right\} & if\ j' < j \\ z & otherwise. \end{cases} \tag{6}$$

The rest of the computation of the transition is straightforward.[37]

Given the values of γ_L, γ_H, and θ, the model yields an initial long-run growth rate in average wage of .024 and predicts a trend growth rate of .033 per year in the final steady-state. Figure 7 displays the transitional dynamics of wage growth in the model economy. In the 10 years following the shock wage growth falls considerably and then it picks up again, but it does not cross back the old trend until 20 years later, while it takes around 60 years to get close to the new long-run growth rate. Intuitively, the technological acceleration creates a workforce with skills of a younger vintage, but of smaller magnitude. Despite the more productive capital, labor productivity is lower on average, thus wage (and output) growth slows down temporarily.

Quantitatively, in the 15 years following the transition, annualized average wage growth is .0198, hence .0132 points below its long-run trend. In the calibration, we have placed our shock in the early 70's. Murphy and Welch [1992] calculate that annualized wage growth in the 15 years from 1973 to 1989 was $-.0055$, hence .0385 points below trend. Thus, the model can explain approximately 34% of the wage growth slowdown in the period immediately following the technological acceleration.

5 Empirical Evidence

The simulations of the model economy show clearly that the main source of rising residual inequality is an increase in the skill variance due to lower skill transferability and higher within-job wage growth. In the steady-state with faster rate of quality improvement in machines the typical labor market history implies larger earnings losses upon displacement and, because workers' skill level is lower on average, higher wage growth within jobs (see Figure 8). In this section we provide evidence that the data support this mechanism.

[37] Technically, we set T to a large number and we start from a guess of a time path for the contact probabilities $\left\{\alpha^0(j,t)\right\}_{t=0}^T$. Next, we obtain the implied time sequence for the value functions $\left\{V^0(t), U^0(t)\right\}_{t=0}^T$ and the associated decision rules $\left\{\chi_e^0(t), \chi_u^0(t)\right\}_{t=0}^T$. Next, we use the decision rules to obtain a time-path for the measure $\left\{\mu^0(t)\right\}_{t=0}^T$ which generates a new sequence of meeting probabilities $\left\{\alpha^1(j,t)\right\}_{t=0}^T$. We continue until convergence is reached.

We use 22 waves from the *Panel Study of Income Dynamics* (PSID), from 1970 to 1991.[38] The objective of the empirical analysis is to analyze wage losses upon displacement and wage growth on the job in the early part (the 70's) and in the late part (the 80's) of the sample. This requires to identify job separations, a difficult task in the PSID: since there are no employer codes associated to workers' records, separations need to be inferred from other survey questions. We use three different methodologies to verify the sensitivity of our findings to the chosen criterion. The key variables for the analysis are wages, employment status, "reason for separation from previous employer" and "months in current position".[39]

The first and most obvious way of identifying a permanent layoff is to consider all workers who are unemployed at the time of the survey and report as "reason for separation" either being fired or plant closing. We then follow these workers in the successive waves and, if they are employed and report no separation, we measure their wages and compare them with the last wage before the unemployment spell. This method surely captures genuine layoffs, but it is quite conservative since it is likely to record only separations associated to relatively long unemployment spells. Therefore, it should provide a lower bound for the number of involuntary separations and an upper bound for the magnitude of wage losses upon displacement. We call this method, method (a).

The second approach is to use the question on the "reason for separation" alone, without requiring the worker to be unemployed at the time of the survey. Whoever answers that the "reason for separation from previous employer" is a permanent layoff or plant closing is followed in the next waves and as long as she is employed and reports no separation, her wage is recorded and compared to the last wage before the separation. We call this method, method (b). This method captures a larger number of genuine separations than the previous one, but it is also likely to record some spurious ones. In particular it presents three types of problems. First, prior to 1984 the question on "reasons for separation" was elicited only if the respondents indicated that they had been in their present position for less than 12 months, hence errors in position tenure responses might transmit to this question as well. Second, between 1984 and 1987 this question was skipped only if the respondents indicated that they had been in their present position at least since January of the previous year, which on average is more than 12 months given that interviews are generally administered between March and May. Thus, in this

[38]The first two years of the survey (1968-1969) are excluded because earnings are bracketed.

[39]The Appendix in Polsky [1999] reports the exact wording of the questions in each year of the survey.

period separations might be artificially inflated. Third, until 1984 the position tenure response exhibited substantial "heaping" at 12 months due to rounding by the survey's respondents. This, once again, could underestimate measured separations before 1984 compared to the later years.[40]

The third approach we explore is to use the response to "months in current position" and compare it to the time elapsed since the last interview. When the former is lower than the latter, a separation is recorded. Conditional on this definition of separation, we used the "reason for separation" to identify layoffs and plant closures. Moreover, to avoid the heaping problem described earlier, the data prior to 1984 have been deheaped following the methodology used by Diebold, Neumark and Polsky [1997][41]. We call this method, method (c). Although this approach uses more survey information and eliminates the heaping problem, it presents different drawbacks. First, until 1974 the tenure variable was coded in intervals, which clearly leads to measurement errors in the calculation of separations. Second, the tenure variable refers to "positions" not employers, so a job change within the same company could be wrongly identified as a separation.[42] This method should therefore provide a lower bound to wage losses upon separation.

The baseline sample is constructed by selecting white males head of households between 18 and 60 years old, who are not self-employed and not union members and do not reside abroad or in Alaska and Hawaii. We also exclude the low-income oversample. In every year we subtract to each individual wage observation its annual mean to avoid contaminating the results with cyclical changes in productivity that are absent from the model.

We apply the three methods outlined above on two 11 year sub-periods, 1970-1980 and 1981-1991. As expected, we find that method (a) is the one capturing the lowest number of separations, and method (b) the most inclusive. In particular the (involuntary) separation rates from employment were 1.85% and 2.12% for method (a), 6.19% and 8.51% for method (b), 2.45% and 3.14% for method (c), in the two periods.[43]

[40] Valletta [1999] uses this methodology to identify separations and presents a more thorough discussion of the associated measurement problems.

[41] I thank Dan Polsky for providing his deheaping programs.

[42] For example, as pointed out by Brown and Light [1992] position tenure is not highly correlated with employer tenure. Using the "reason for separation" to bring in additional information is useful, but does not solve the problem completely: 1) a worker may perceive a job change within the firm as a layoff from his old job, and 2) a worker might be moved to another job within the same firm because a firm's plant closed down. An alternative method which is sometimes employed in the literature but that we do not explore here would be to use the variable "months with current employer". However, also this method is plagued with inconsistencies. See Polsky [1999] for details.

[43] Consistently with the existing literature we find a significant increase in separation only with method

Table 5 presents the estimates of wage losses upon displacement with the three different methods $(a),(b),(c)$. Column 1 is the baseline sample, column 2 includes also self-employed, column 3 includes also unionized workers, column 4 restricts the sample to prime-aged males between 25 and 50, and column 5 restricts the sample to Manufacturing industries only. First of all, as expected, method (a) yields the highest point estimates of mean wage losses and method (c) the lowest. Strikingly, independently of the method, and of the sample selection, in all cases the initial wage losses upon displacement (i.e. 1 year after layoff) in the 80's are larger than in the 70's. Method (a) yields very few observations, so the estimates are imprecise, but in most of the columns for methods (b) and (c) the differences are statistically significant at 5% level, an important exception being prime-aged males (column 4).

Another strong pattern emerging form the data is that, once the worker accepts a new job, she recovers her losses more quickly in the 80's than in the 70's. After 5 years wage growth is never statistically different between the 70's and the 80's even though the initial losses are far larger in the 80's. This finding represents preliminary evidence in favor of wage growth within job being faster in the 80's, however to establish this fact we should look at the larger sample of all job stayers.

Table 6 presents the estimates of wage growth within job with two different methods, since (a) and (b) essentially imply the same criterion to select job stayers. Given the larger sample, now we can split the period into 4 subperiods. Once again, independently of the method and of the sample cut, the result is unambiguous: wage growth within job is higher in the 80's than in the 70's and the difference between the first and the last interval is always statistically significant at 5% level. In most of the cases wage growth increases smoothly across the four periods, except for columns (b) and (c) where the estimate for the period 81-86 is the largest.[44] Similarly to our earlier findings on wage losses upon displacement, the evidence is slightly weaker for prime-aged males.

Overall, we can conclude that the dimensions of the data we looked at do not contradict the key mechanism of the theory. The model predicts that a technological acceleration would increase earnings instability along labor market histories through larger wage losses upon displacement and faster recovery on the job, two features that emerged fairly robustly from the PSID data we analyzed.[45]

(b)—used for example by Gottschalk and Moffitt [1994]— who report a rise in job instability.

[44] Admittedly, demeaning individual wages might not exclude entirely business cycle effects, in which case this result could depend on the fact that the period 81-86 is the only one of the four intervals with a very short and mild recession, whilst all other intervals contain prolonged recession episodes.

[45] Polsky [1999] is the only paper we are aware of that analyzes changes in wage growth for movers and

6 Conclusions

In their 1992 survey on rising earnings inequality Levy and Murnane concluded that the most important unresolved puzzle concerned the reasons for two decades of trend towards higher residual inequality. Eight years later in his survey Acemoglu [2000] still states that one of the biggest area of future research is the determinants of residual inequality and calls for theories with sharper empirical predictions.

In this paper we contribute to this ongoing debate in three ways. First, we suggest a new mechanism to interpret the surge in residual inequality based on *vintage-specific* skills. We argue that an acceleration in the rate of quality-improvement of equipment, like the one observed from the early 70's, implies that workers have less ability to transfer skills from old to new machines. The result is that the typical labor market history of the worker involves lower average skills (but skills of a younger vintage), larger wage losses upon separation and higher wage growth on the job. These forces generate a temporary decline in the real wage and a rise in the cross-sectional variance of skills. Increased mobility of workers (who respond to the shock by tracking closer the leading edge) counteracts the above forces, but when the rise in mobility is not too large, the model predicts a surge in residual wage inequality.

It is important to remark that the increased inequality in the model comes about through a rise in *earnings instability*, a feature of the data that has been documented for the US, the UK and Canada. Standard explanations of rising inequality based on ex-ante heterogeneity in innate ability and on the complementarity between ability and new technologies can only predict inequality which is very permanent in its nature, failing to match a crucial dimension of the data.

Second, while all the existing models are purely theoretical, we use our calibrated model economy for a *quantitative* study of the US economy. We show that a technological acceleration of the magnitude we observed in the past 25 years can account for just below 30% of the rise in residual inequality in the US, or for the bulk of the increase in its transitory component. The transitional dynamics of the calibrated model are also able to generate a slowdown in real wage growth that explains around 34% of the difference

stayers. His analysis uses PSID data and focuses on prime-aged males between 1976-1981 and 1986-1991. His main conclusion is that the consequences of job losses are worse in the 80's. He also reports that the point estimate of average wage growth within job for stayers is lower in the 80's, but the difference is not significant. Our results in column (4c) which uses his same method and a similar sample cut, also confirm that the difference in wage growth between the two periods above is not statistically different from zero.

between wage growth in the data and long-run trend growth in the 15 years following the shock.

Third, we showed that the model has two sharp empirical predictions: larger wage losses upon displacement and faster wage growth on the job. We have used individual panel data from PSID to document that the data do not contradict the theory on these two dimensions.

The theory and the quantitative analysis developed in this paper have two major limitations. In order to focus on the –often neglected– transitory component of inequality, we have intentionally ruled out ex-ante heterogeneity in ability. The model can be naturally extended to include workers which are ex-ante different in their ability to learn (λ) or to transfer skills (τ), or both. One could calibrate the distribution of these parameters in the population to match the cross-sectional wage distribution (or the distribution of wage growth on the job and wage losses upon separation), and then repeat the same thought experiment we did.[46] As a result, both components of inequality will rise. In particular, the increase in the permanent component will be associated to the change in the average wage for each type (λ, τ) of worker in the economy (i.e. the fixed effect of the Gottschalk and Moffitt decomposition).

Second, although we have emphasized the transitory nature of the earnings fluctuations in our model, the interesting issue from a welfare perspective is how *insurable* these shocks are. If they are not so easily insurable, then in terms of individual welfare there is little difference between the sources of inequality. In our model workers are risk-neutral, so any speculation on welfare and insurance would be far-fetched. However, our mechanism can be easily embedded into an economy with risk-averse workers and, given a set of assumptions on the degree of market incompleteness, one could study the impact on the distribution of consumption and on welfare.

Finally, let us remark that the emphasis we gave to the *Skill Dynamics Hypothesis* vis-a-vis the *Innate Ability Hypothesis* is not just semantics, but it has profound policy implications. Insofar as we are interested in reducing inequality, models in the first class call for interventions that allow the disadvantaged (or unlucky) workers to rebuild their skill level, especially the *vintage* of their knowledge. Models in the second class suggest that the intervention should be targeted much earlier in the life of an individual, possibly during childhood when the crucial components of cognitive ability are being formed.

[46] We have somehow explored this extension in the experiment with two educational groups summarized in Table 4.

Appendix

Proof of Lemma 1

Proof. Recall that the income accruing to the entrepreneur of an idle firm of type j is $\overline{y}(j) = (1+\gamma)^{-\theta j}\kappa$. If $\kappa \geq (1-\xi)(\kappa + Z)$, the outside option of the firm is always binding in the bargaining game, no matter how skilled the worker is, thus the bargaining rule specifies that the firm will always command the flow value of its alternative payoff. Moreover, since $\overline{y}(j)$ is decreasing in j, the worker will have to guarantee exactly $\overline{y}(j)$ to the firm each period. The worker is the residual claimant on output and her wage is $w(j,z) = y(j,z) - \overline{y}(j)$, which is her marginal value product and yields the expression above. It follows naturally that a firm is always indifferent about separating, but a worker in general is not, hence it is always the worker to take the separation decision and such a decision is jointly efficient. ■

The determination of the transition function Q

We define the transition function in two steps. First for employed workers, next for unemployed. We use the notation $I\{\cdot\}$ for the indicator function.

$$\begin{aligned}
\mu(e,\mathcal{J}^*,\mathcal{Z}^*) = \;& (1-\delta)\lambda \textstyle\sum_{j,z} \mu(e,j,z)\left[1-\chi_e(j+1,z+\eta)\right] I\{j+1 \in \mathcal{J}^*, z+\eta \in \mathcal{Z}^*\} \\
+\;& (1-\delta)(1-\lambda) \textstyle\sum_{j,z} \mu(e,j,z)\left[1-\chi_e(j+1,z)\right] I\{j+1 \in \mathcal{J}^*, z \in \mathcal{Z}^*\} \\
+\;& (1-\delta) \textstyle\sum_{j,z,j'} \mu(u,j,z)\alpha(j')\left[1-\chi_u(j,z,j')\right]\{\lambda\left[1-\chi_e(j'+1,T(j,z,j')+\eta)\right] \\
& I\{j'+1 \in \mathcal{J}^*, T(j,z,j')+\eta \in \mathcal{Z}^*\} + (1-\lambda)\left[1-\chi_e(j'+1,T(j,z,j'))\right] \\
& I\{j'+1 \in \mathcal{J}^*, T(j,z,j') \in \mathcal{Z}^*\}\}.
\end{aligned}$$

$$\begin{aligned}
\mu(u,\mathcal{J}^*,\mathcal{Z}^*) = \;& \lambda \textstyle\sum_{j,z} \mu(e,j,z)\left[\delta + (1-\delta)\chi_e(j+1,z+\eta)\right] I\{j+1 \in \mathcal{J}^*, z+\eta \in \mathcal{Z}^*\} \\
+\;& (1-\lambda) \textstyle\sum_{j,z} \mu(e,j,z)\left[\delta + (1-\delta)\chi_e(j+1,z)\right] I\{j+1 \in \mathcal{J}^*, z \in \mathcal{Z}^*\} \\
+\;& \textstyle\sum_{j,z,j'} \mu(u,j,z)\alpha(j')\chi_u(j,z,j') I\{j+1 \in \mathcal{J}^*, z \in \mathcal{Z}^*\} \\
+\;& \delta \textstyle\sum_{j,z,j'} \mu(u,j,z)\alpha(j')\left[1-\chi_u(j,z,j')\right]\{\lambda I\{j'+1 \in \mathcal{J}^*, T(j,z,j')+\eta \in \mathcal{Z}^*\} \\
& + (1-\lambda) I\{j'+1 \in \mathcal{J}^*, T(j,z,j') \in \mathcal{Z}^*\}\} \\
+\;& (1-\delta) \textstyle\sum_{j,z,j'} \mu(u,j,z)\alpha(j')\left[1-\chi_u(j,z,j')\right]\{\lambda\chi_e(j'+1,T(j,z,j')+\eta) \\
& I\{j'+1 \in \mathcal{J}^*, T(j,z,j')+\eta \in \mathcal{Z}^*\} + (1-\lambda)\chi_e(j'+1,T(j,z,j')) \\
& I\{j'+1 \in \mathcal{J}^*, T(j,z,j') \in \mathcal{Z}^*\}\}.
\end{aligned}$$

Proof of Lemma 2

Proof. Workers of type i choose to separate if and only if $V_{i01} > U_{i0}$ which is equivalent to $V_{i00} > V_{i01}$, a condition that can be written as

$$(w_{i00} - w_{i01}) + \widehat{\beta}\left\{\lambda\left[\max\left\{V_{H01}, U_{H0}\right\} - U_{H1}\right] + (1-\lambda)\left[\max\left\{V_{L01}, U_{L0}\right\} - U_{L1}\right]\right\} > 0 \tag{A1}$$

The second term of $(A1)$, the term multiplied by $\widehat{\beta}$, is always positive. If $\tau \leq \theta$ the first term is positive, which proves the first point of the Lemma. If $\tau > \theta$ the first term is negative. In this case $(w_{H00} - w_{H01}) = (1+\eta)(w_{L00} - w_{L01}) < (w_{L00} - w_{L01}) < 0$ which establishes the second point. ■

Proof of Lemma 3

Proof. Consider first the condition for the separation of type H workers, $V_{H00} > V_{H01}$, given that L workers separate. This condition is a special case of $(A1)$ and can be written as

$$\begin{aligned}(w_{H00} - w_{H01}) + \; & \widehat{\beta}\left\{\lambda\left[\alpha\left(w_{H00} - w_{H10}\right) + (1-\alpha)\left(w_{H01} - w_{H11}\right)\right] + \right.\\ & \left.(1-\lambda)\left[\alpha\left(w_{L00} - w_{L10}\right) + (1-\alpha)\left(w_{L01} - w_{L11}\right)\right]\right\} > 0.\end{aligned}$$

By substituting (5) in the above expression, it is immediate to see that as $\gamma \to \infty$ the difference $(V_{H00} - V_{H01})$ tends to $\beta(1+\eta\lambda)(1-\alpha) = \beta(1+\eta\lambda)/2 > 0$, since $\alpha = 1/2$ in the equilibrium with full workers' mobility. The individual decisions are consistent with the aggregate matching rate α, so for γ large enough $(E3)$ is always a stationary equilibrium. Consider now the decision of type L workers, given that type H workers do not separate. They will decide *not* to separate –as required by the steady-state with no mobility $(E3)$– if and only if $V_{L00} < V_{L01}$. After some algebra, the difference $(V_{L00} - V_{L01})$ can be re-expressed as:

$$w_{L00} - w_{L01} + \frac{\widehat{\beta}(1+\eta\lambda)}{\left(1+\widehat{\beta}\right)}\left(w_{L01} - w_{L10}\right).$$

Using (5) one can show that as $\gamma \to \infty$ the difference $(V_{L00} - V_{L01})$ approaches zero from above, hence for γ large enough $(E3)$ is never a steady-state. ■

Proof of Lemma 4

Proof. The first step of the proof is to obtain the equilibrium contact rate and employment distribution. Next, one can compute the equilibrium wage distribution.

Given the decision rules, it is straightforward to derive the equilibrium contact rate α. In steady-state $(E1)$ no worker separates from the new machines, hence for workers displaced from old machines $\alpha = 1$. In steady-state $(E2)$ only L workers move from machines of age 0, so the total number of vacancies is $(2-\lambda)/2$ of which $1/2$ are on new machines implying $\alpha = 1/(2-\lambda)$. In steady-state $(E3)$ every worker separates every period, so $\alpha = 1/2$. Given the contact rate, the decision rules, and the learning rate, it is easy to obtain the equivalent of the transition function Q for our stylized economy. Below, we derive Q for type H workers. For type L workers it is sufficient to substitute $(1-\lambda)$ for λ and χ_L for χ_H. Notice that $1/2$ is the measure of workers on each vintage of capital.

$$\begin{aligned}
\mu_{H01} &= \lambda\left[(1-\chi_H)+\chi_H(1-\alpha)\right]\frac{1}{2},\\
\mu_{H00} &= \lambda\chi_H\alpha\frac{1}{2},\\
\mu_{H10} &= \lambda\alpha\frac{1}{2},\\
\mu_{H11} &= \lambda(1-\alpha)\frac{1}{2}.
\end{aligned}$$

In steady-state $(E1)$ the implied equilibrium distribution is $\mu_{H00} = \mu_{H11} = \mu_{L00} = \mu_{L11} = 0$, $\mu_{H10} = \mu_{H01} = \lambda/2$, and $\mu_{L10} = \mu_{L01} = (1-\lambda)/2$. In steady-state $(E2)$ the equilibrium distribution for type H workers is given by $\mu_{H00} = 0$, $\mu_{H10} = \lambda/\left[2(2-\lambda)\right]$, $\mu_{H11} = \lambda(1-\lambda)/\left[2(2-\lambda)\right]$, $\mu_{H01} = \lambda/2$. The equilibrium distribution for type L workers is given by $\mu_{L00} = \mu_{L10} = (1-\lambda)/\left[2(2-\lambda)\right]$, $\mu_{L11} = \mu_{L01} = (1-\lambda)^2/\left[2(2-\lambda)\right]$. In steady-state $(E3)$, the equilibrium distribution of workers across machines is given by $\mu_{H00} = \mu_{H11} = \mu_{H11} = \mu_{H10} = \lambda/4$ and $\mu_{L00} = \mu_{L11} = \mu_{L11} = \mu_{L10} = (1-\lambda)/4$.

At this point we can use the skill levels in (5) and the corresponding wage rates to obtain the equilibrium variance of log-wages and its three components in the three steady-states. The proof is purely algebraic, so we omit it.

In $(E1)$:

$$\begin{aligned}
&var(\widetilde{w}) = \lambda(1-\lambda)\eta^2 + \gamma^2\left[\frac{\theta^2}{4} + \tau(\tau-\theta)\right]\\
&and\\
&var(j) = 1/4,\ var(\widetilde{z}) = \lambda(1-\lambda)\eta^2 + \gamma^2\tau^2,\ cov(\widetilde{z},j) = \frac{\gamma\tau}{2}.
\end{aligned}$$

In $(E2)$:

$$\begin{aligned}
&var(\widetilde{w}) = \lambda(1-\lambda)\eta^2 + \gamma^2\left[\frac{\theta^2}{4} + \frac{1}{2}\tau(\tau-\theta)\right] + \frac{\gamma\lambda(\tau-\theta)}{2(2-\lambda)}\left[\tau\gamma + 2\eta(1-\lambda)\right]\\
&and\\
&var(j) = 1/4,\quad var(\widetilde{z}) = \lambda(1-\lambda)\eta^2 + \frac{\gamma^2\tau^2}{2} + \frac{\gamma\lambda\tau}{2(2-\lambda)}\left[\tau\gamma + 2\eta(1-\lambda)\right],\\
&cov(\widetilde{z},j) = \frac{\gamma\tau}{4} + \frac{\lambda}{4(2-\lambda)}\left[\tau\gamma + 2\eta(1-\lambda)\right].
\end{aligned}$$

In $(E3)$:

$$
\begin{aligned}
&var(\widetilde{w}) = \lambda(1-\lambda)\eta^2 + \gamma^2 \left[\frac{\theta^2}{4} + \frac{1}{2}\tau(\tau-\theta)\right] \\
&and \\
&var(j) = 1/4, \quad var(\widetilde{z}) = \lambda(1-\lambda)\eta^2 + \frac{\gamma^2\tau^2}{2}, \quad cov(\widetilde{z}, j) = \frac{\gamma\tau}{4}.
\end{aligned}
$$

By simple inspection, it is clear that within each type of stationary equilibrium, $var(\widetilde{z}), cov(\widetilde{z}, j)$ and $var(\widetilde{w})$ are increasing in γ and this derivative is increasing in τ. However, an increase of γ that triggers a switch across types of steady-state has ambiguous effects on $var(\widetilde{w})$. ■

Proof of Lemma 5

Proof. We compute average wage growth for stayers by measuring the change in log wage for all workers who are on vintage 1 in the current period and last period did not separate. Symmetrically, we define as average wage loss upon displacement the average log wage change for all workers who were displaced exogenously from vintage 1 last period. We present the details of the calculation only for steady-state $(E1)$, as it is straightforward to extend it to the other cases. Average wage growth on the job is obtained as

$$
\begin{aligned}
\Delta\widetilde{w}^S = \frac{1}{2} \quad &\{\mu_{H10}\left[\lambda\left(z_{H01} - z_{H10}\right) + (1-\lambda)\left(z_{L01} - z_{H10}\right)\right] \\
&+ \mu_{L10}\left[\lambda\left(z_{H01} - z_{L10}\right) + (1-\lambda)\left(z_{L01} - z_{L10}\right)\right]\},
\end{aligned}
$$

which using (5) becomes $\Delta\widetilde{w}^S = 2\tau\gamma$. Average wage loss is obtained as:

$$
\begin{aligned}
\Delta\widetilde{w}^M = \frac{1}{2} \quad &\{\mu_{H01}\left[\lambda\left(z_{H10} + 2\theta\gamma - z_{H01}\right) + (1-\lambda)\left(z_{L10} + 2\theta\gamma - z_{H01}\right)\right] \\
&+ \mu_{L01}\left[\lambda\left(z_{H10} + 2\theta\gamma - z_{L01}\right) + (1-\lambda)\left(z_{L10} + 2\theta\gamma - z_{L01}\right)\right]\},
\end{aligned}
$$

which using (5) becomes $\Delta\widetilde{w}^M = -2\left(\tau-\theta\right)\gamma$. Similarly, in steady-state $(E2)$, $\Delta\widetilde{w}^S = 2\tau\gamma - (1-\lambda)\eta$ and $\Delta\widetilde{w}^M = -\left(\tau-\theta\right)\gamma - \left[\lambda\left(1-\lambda\right)\eta + \left(\tau\lambda-\theta\right)\gamma\right]/(2-\lambda)$. In steady-state $(E3)$ with full mobility $\Delta\widetilde{w}^M = -\left(\tau-\theta\right)\gamma$ and $\Delta\widetilde{w}^S$ is not defined. By inspection, it is clear that all these magnitudes are increasing in γ. However, when a rise in γ induces a change in the decision rules the results are ambiguous. ■

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TABLE 5

Wage Losses Upon Displacement

Years after	(1a)		(2a)		(3a)		(4a)		(5a)	
Separation	70-80	81-91	70-80	81-91	70-80	81-91	70-80	81-91	70-80	81-91
1	-.269	-.483	-.288	-.476	-.299	-.465	-.428	-.493	-.373	-.491
	(.067)	(.052)	(.064)	(.049)	(.057)	(.046)	(.092)	(.058)	(.109)	(.077)
2	.103	.062	.042	.001	.128	.048	.024	.069	.066	-.091
	(.057)	(.058)	(.054)	(.056)	(.051)	(.054)	(.067)	(.067)	(.078)	(.086)
3	.098	.071	.006	.009	.116	.137	.097	.082	.212	-.037
	(.068)	(.068)	(.069)	(.068)	(.055)	(.061)	(.063)	(.080)	(.075)	(.099)
4	.190	.151	.127	.119	.195	.187	.179	.209	.387	.015
	(.069)	(.074)	(.072)	(.073)	(.060)	(.066)	(.086)	(.086)	(.072)	(.096)
5	.269	.199	.095	.164	.226	.243	.249	.332	.313	.028
	(.102)	(.123)	(.087)	(.121)	(.084)	(.102)	(.121)	(.137)	(.105)	(.135)
Sample Size	621	866	697	1000	817	1043	367	690	314	372

Years after	(1b)		(2b)		(3b)		(4b)		(5b)	
Separation	70-80	81-91	70-80	81-91	70-80	81-91	70-80	81-91	70-80	81-91
1	.005	-.116	-.001	-.097	-.021	-.144	-.099	-.135	.002	-.102
	(.019)	(.017)	(.019)	(.015)	(.018)	(.015)	(.022)	(.019)	(.024)	(.022)
2	.191	-.095	.130	-.116	.123	-.108	.133	-.092	.071	-.114
	(.038)	(.034)	(.035)	(.032)	(.033)	(.029)	(.047)	(.040)	(.052)	(.049)
3	.269	.104	.200	.064	.245	.094	.264	.146	.161	-.061
	(.046)	(.038)	(.040)	(.038)	(.036)	(.033)	(.052)	(.045)	(.056)	(.047)
4	.349	.186	.266	.147	.265	.189	.328	.213	.163	.087
	(.048)	(.054)	(.042)	(.052)	(.035)	(.040)	(.064)	(.063)	(.055)	(.085)
5	.270	.289	.208	.276	.267	.278	.266	.301	.291	.139
	(.050)	(.068)	(.047)	(.065)	(.044)	(.053)	(.058)	(.079)	(.063)	(.083)
Sample Size	2960	3858	3329	4421	3813	4630	1822	2938	1623	1916

Years after	(1c)		(2c)		(3c)		(4c)		(5c)	
Separation	70-80	81-91	70-80	81-91	70-80	81-91	70-80	81-91	70-80	81-91
1	.089	-.046	.092	-.056	.048	-.070	-.019	-.036	.056	-.026
	(.025)	(.021)	(.024)	(.020)	(.023)	(.018)	(.028)	(.020)	(.030)	(.028)
2	.199	.033	.198	.017	.169	.017	.109	.029	.148	.046
	(.034)	(.034)	(.032)	(.033)	(.029)	(.028)	(.033)	(.038)	(.042)	(.055)
3	.254	.075	.258	.072	.229	.068	.195	.054	.310	.082
	(.039)	(.044)	(.038)	(.043)	(.035)	(.034)	(.038)	(.045)	(.064)	(.057)
4	.297	.159	.298	.133	.200	.116	.278	.134	.304	.225
	(.047)	(.061)	(.046)	(.060)	(.034)	(.041)	(.046)	(.061)	(.089)	(.085)
5	.274	.174	.291	.220	.229	.150	.276	.120	.189	.254
	(.052)	(.076)	(.051)	(.075)	(.040)	(.054)	(.056)	(.070)	(.100)	(.108)
Sample Size	1585	1650	1710	1802	2203	2126	1004	1269	869	806

Note: Author's computations on PSID data. The suffix a), b), and c) refer to the methods used to identify involuntary separation. Column (1) is the benchmark case, (2) includes also self-employed, (3) includes also unionized workers, (4) includes only prime-aged males, (5) includes only Manufacturing. Standard deviation of the mean in parenthesis.

TABLE 6

Wage Growth Within Job

	(1b)	(2b)	(3b)	(4b)	(5b)	(1c)	(2c)	(3c)	(4c)	(5c)
70-75	.031	.031	.031	.035	.027	.038	.034	.038	.043	.037
	(.002)	(.002)	(.002)	(.003)	(.003)	(.002)	(.002)	(.002)	(.002)	(.003)
75-80	.041	.044	.033	.045	.038	.044	.042	.035	.053	.046
	(.002)	(.002)	(.002)	(.003)	(.003)	(.002)	(.002)	(.002)	(.002)	(.003)
81-86	.050	.049	.043	.057	.052	.051	.052	.043	.060	.053
	(.002)	(.002)	(.002)	(.003)	(.003)	(.002)	(.002)	(.002)	(.002)	(.003)
86-91	.051	.054	.045	.051	.046	.057	.056	.048	.054	.049
	(.002)	(.002)	(.002)	(.002)	(.003)	(.002)	(.002)	(.002)	(.002)	(.003)
Sample Size	29141	34633	39103	22241	15543	29499	30704	39588	22684	15854

Note: Author's computations on PSID data. The suffix b) and c) refer to the methods used to identify involuntary separations. Column (1) is the benchmark case, (2) includes also self-employed, (3) includes also unionized workers, (4) includes only prime-aged males, (5) includes only Manufacturing. Standard deviation of the mean in parenthesis.

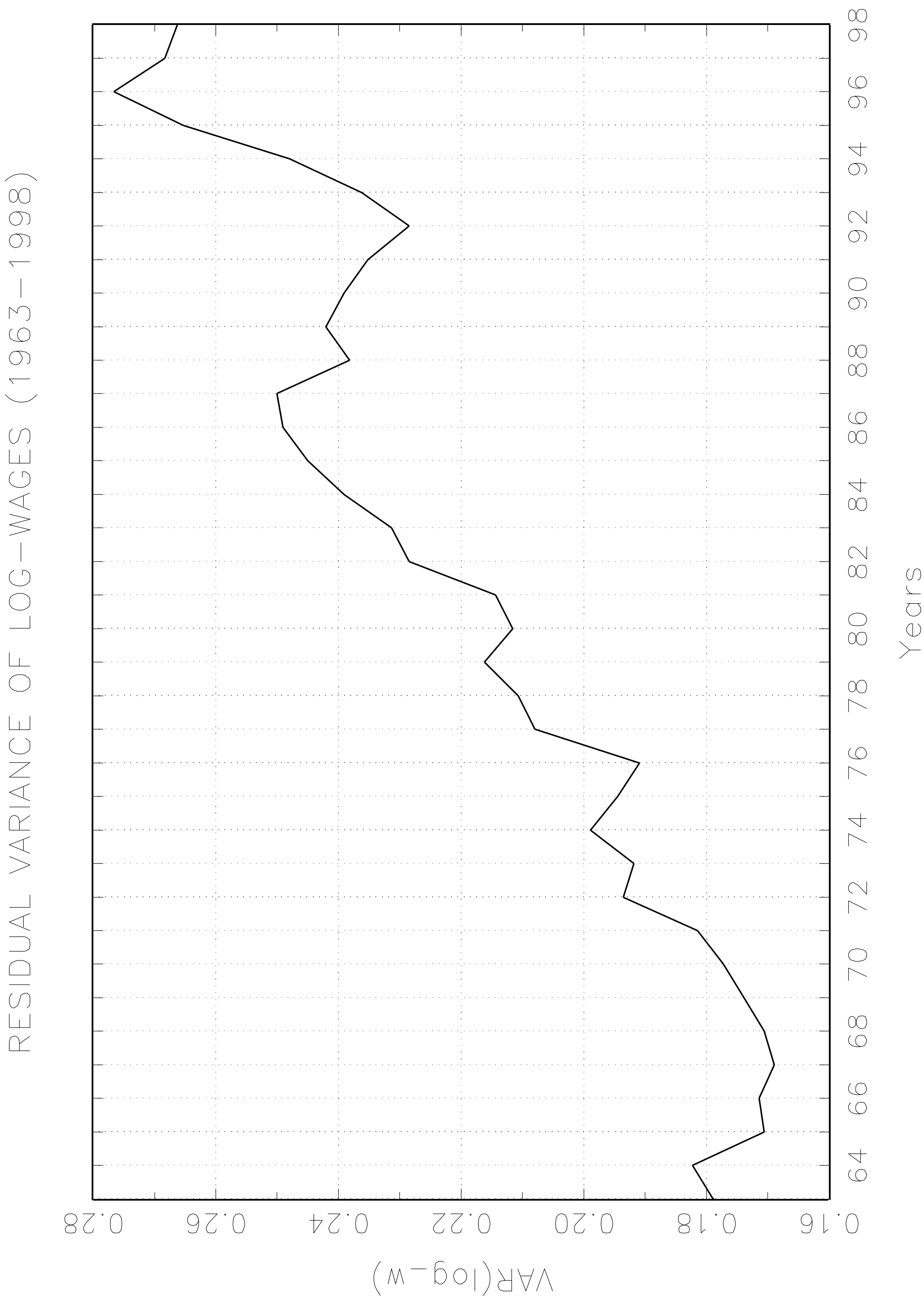

Figure 1: Residual Variance of Log Wages (1963-1998). Source: Author's computation from the Current Population Survey, March Annual Demographic Files

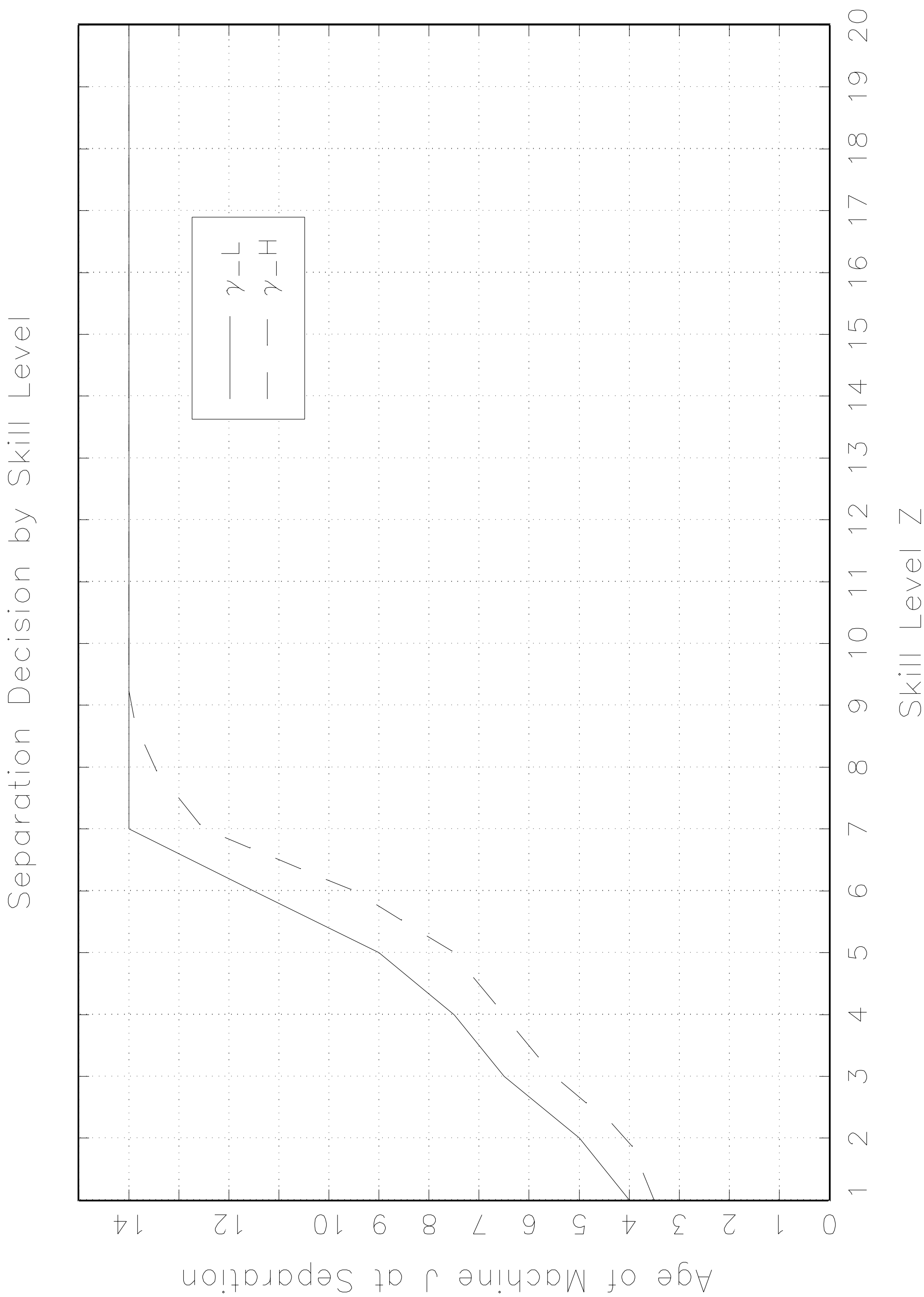

Figure 2: Separation Decisions in the Model Economy

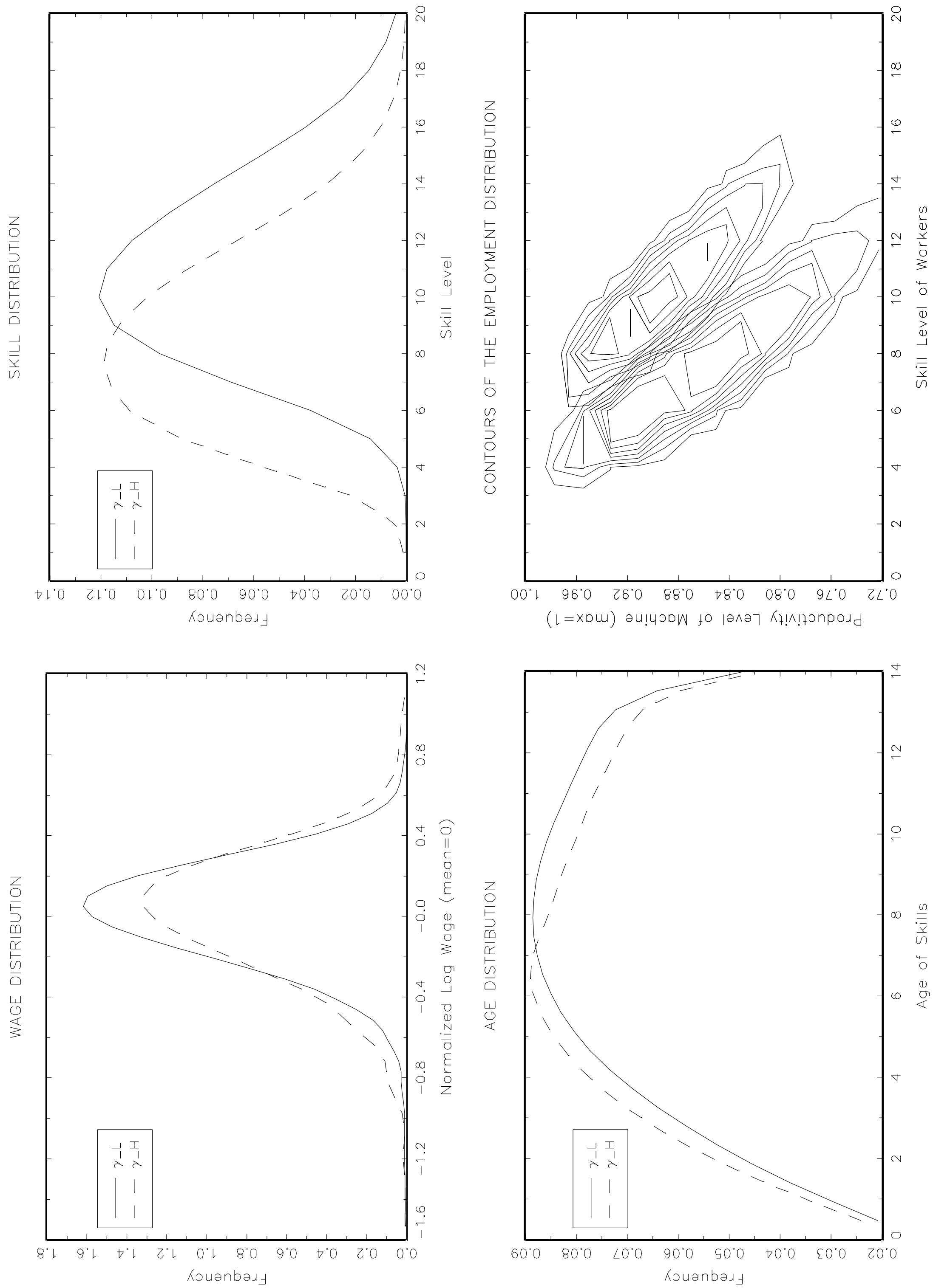

Figure 3: The Equilibrium Wage Distribution and the Wage Variance Components

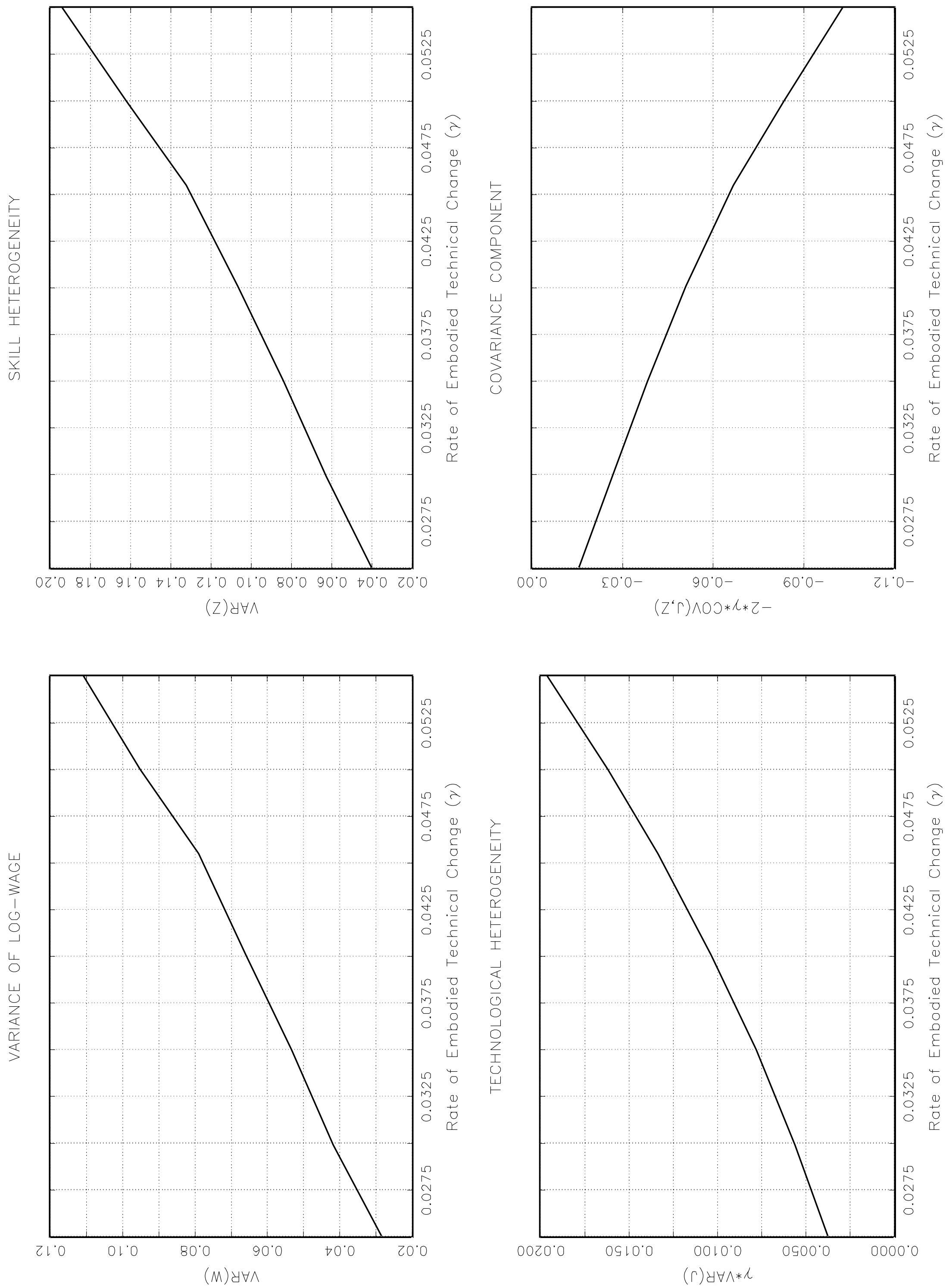

Figure 4: Sensitivity Analysis with respect to γ

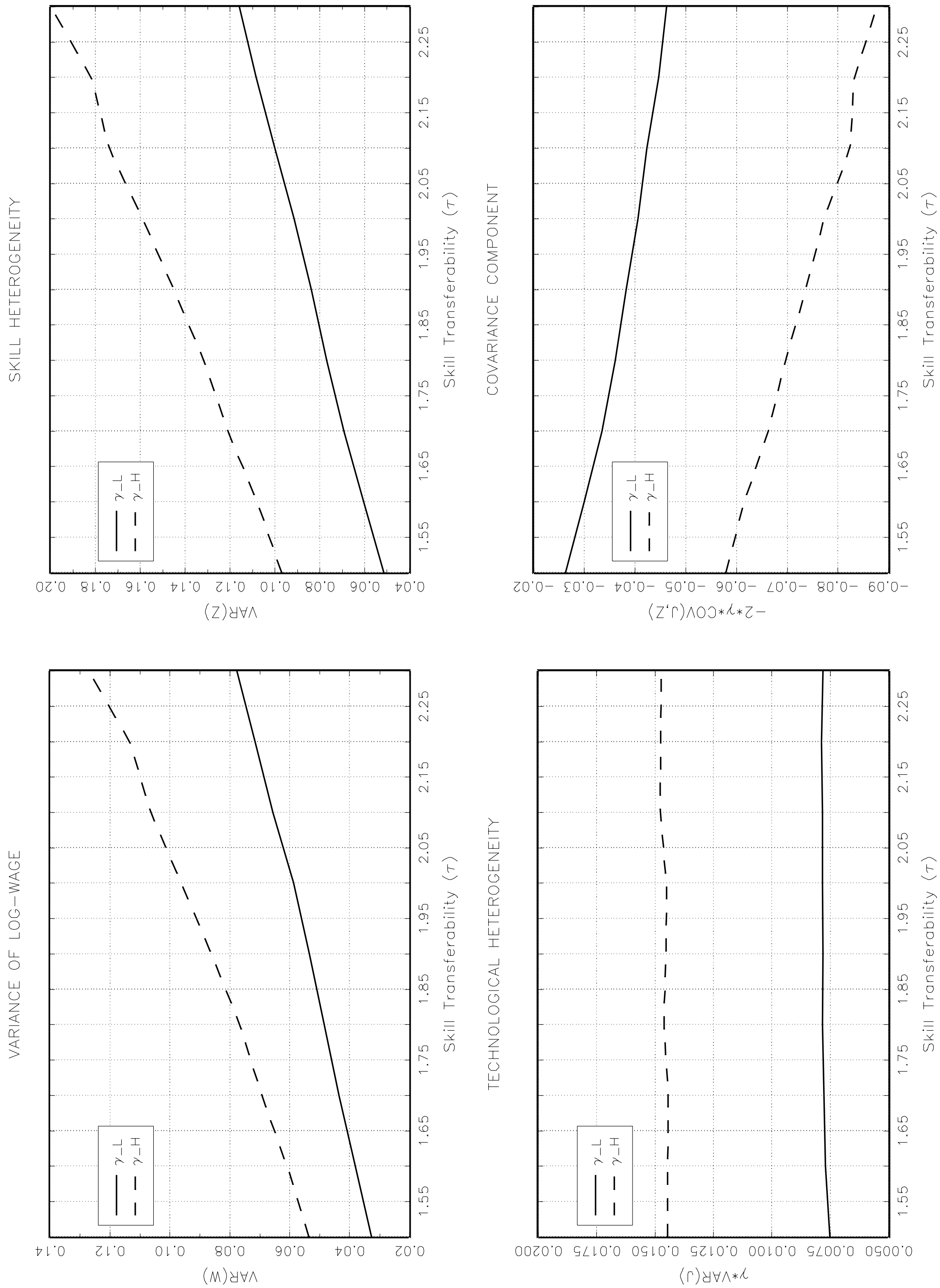

Figure 5: Sensitivity Analysis with respect to τ

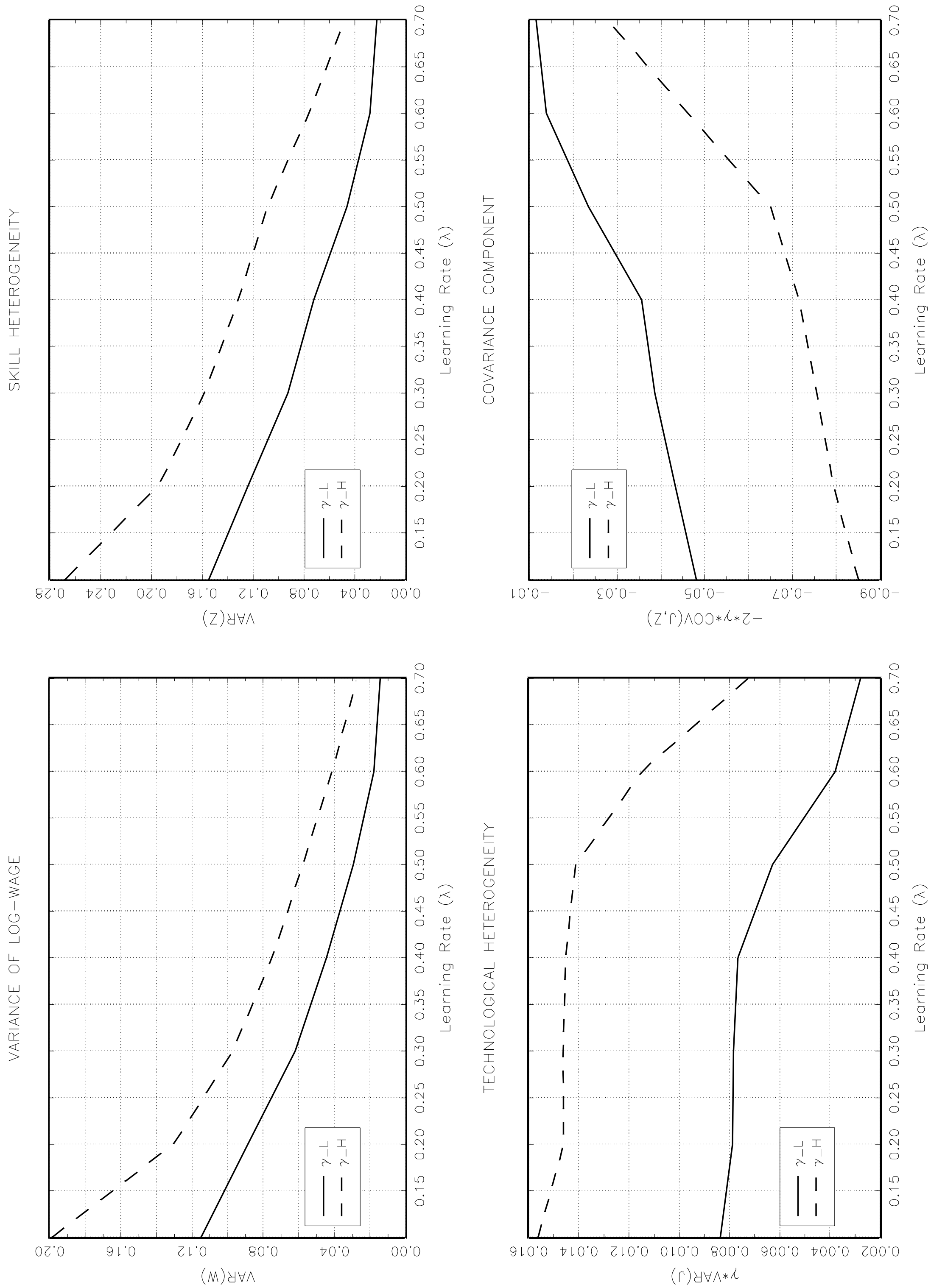

Figure 6: Sensitivity Analysis with respect to λ

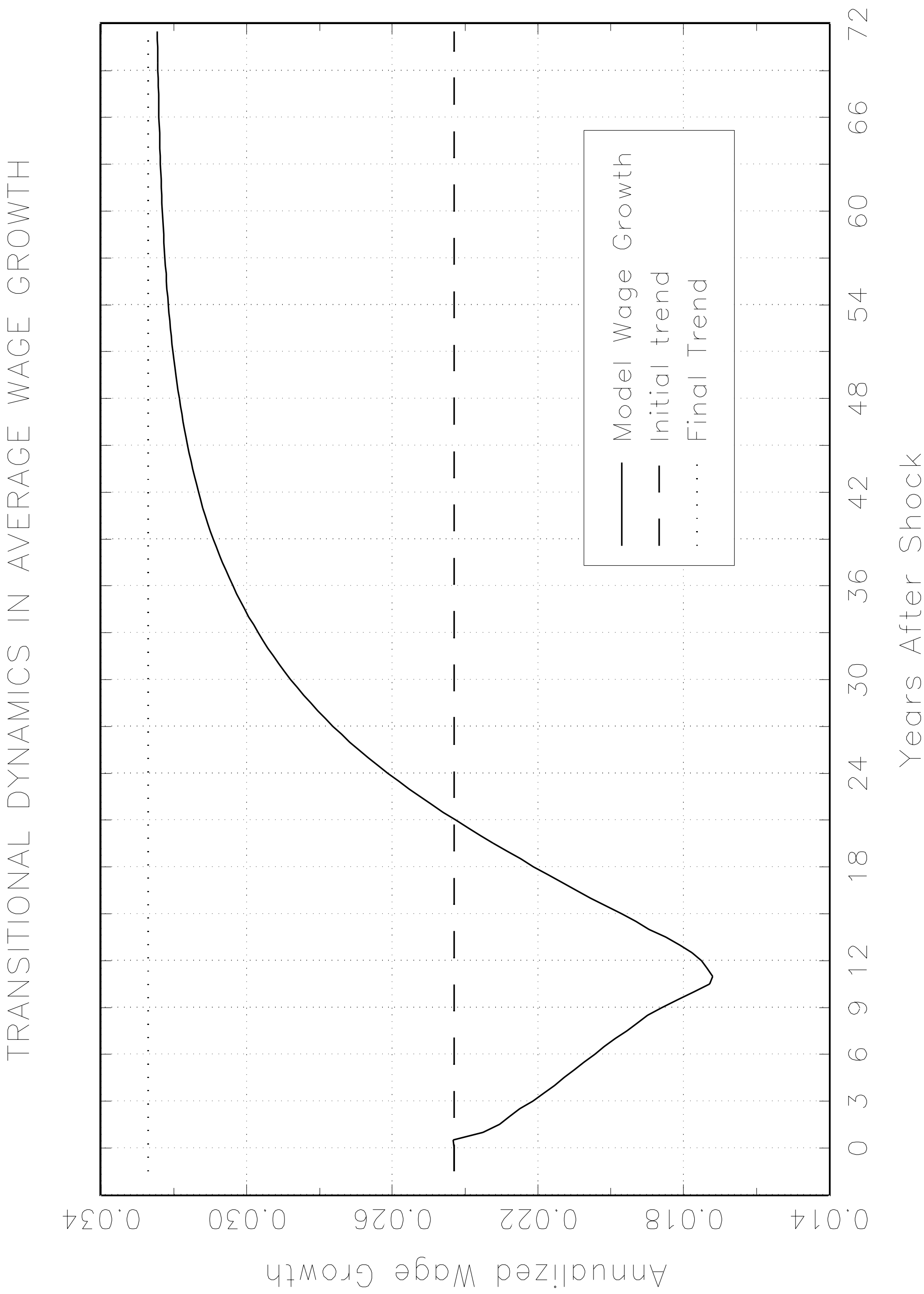

Figure 7: Average Wage Growth in the Transitional Dynamics of the Model Economy

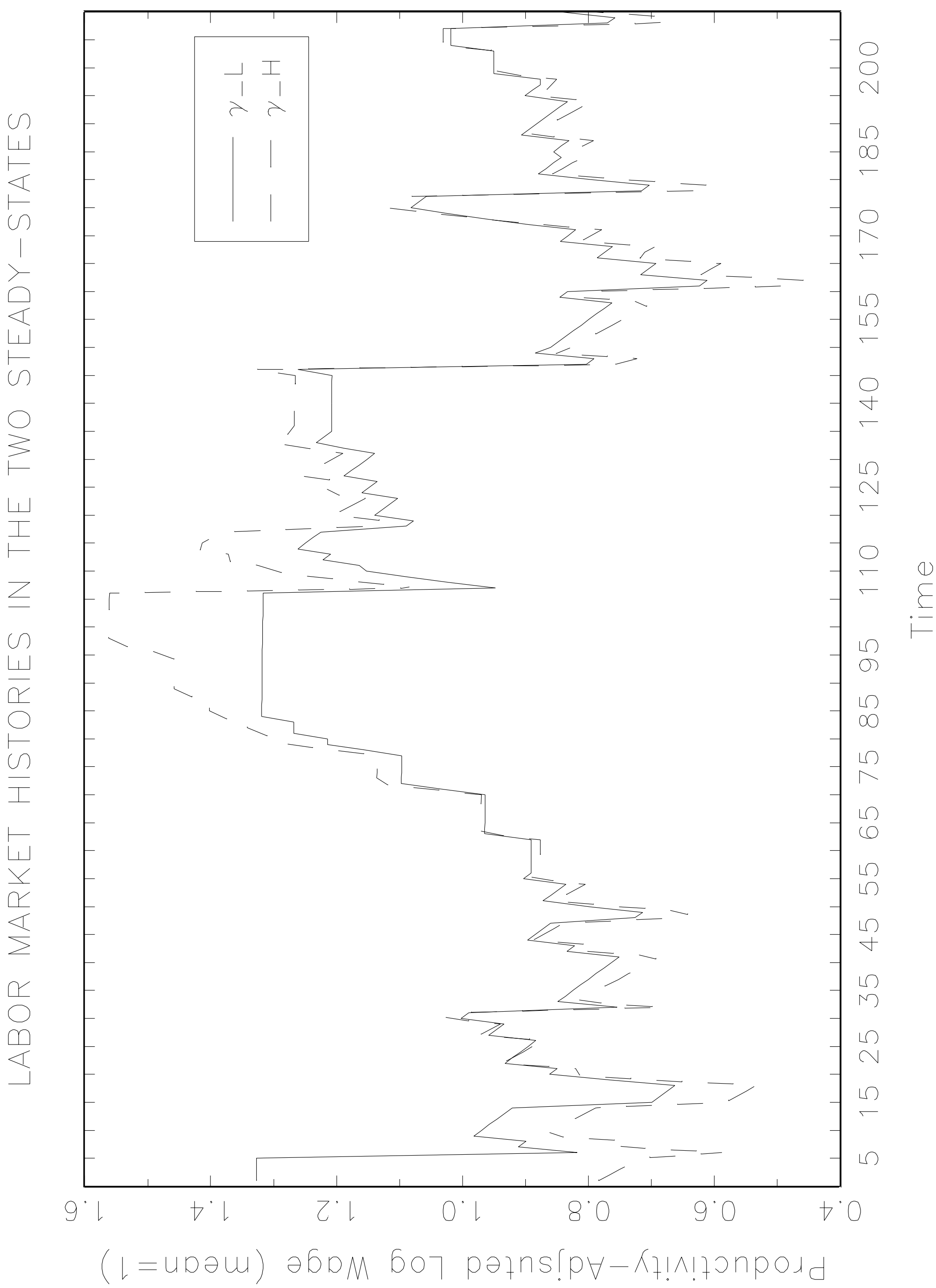

Figure 8: Wage Instability in a Typical Labor Market History in the Two Steady-States