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

Giovanni L. Violante

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ABSTRACT

This paper provides a quantitative theory for the recent rise in residual wage inequality 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. An acceleration in the rate of quality-improvement of equipment, like the one observed from the early 70's, increases the productivity/quality differentials across machines (jobs). In a frictional labor market, this force translates into higher wage dispersion even among ex-ante equal workers. With vintage-human capital, the acceleration reduces workers' capacity to transfer skills from old to new machines, generating 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 percent of the surge in residual inequality in the U.S. 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: Wage Inequality, Skill Transferability, Technological Acceleration, Earnings Instability, Wage Loss Upon Displacement.

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I Introduction

During the past 30 years, the U.S. 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 percent 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 [1993] conclude that the majority of the increase in U.S. 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 U.S., but also in other countries where remarkable changes in the wage structure have taken place, such as the U.K. 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. 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. Galor and Moav [2000] contend that technological progress changes the nature of occupations, jobs and tasks to be performed.

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

[2] Gosling, Machin and Meghir [2000] report that an important aspect of rising inequality in the U.K. is increased within-group wage dispersion. Baker and Solon [1999] argue that the increase in Canadian earnings inequality has occurred mainly within education groups.

Innate ability helps in adapting to this new work environment, therefore a technological transition raises returns to ability and increases within-group inequality.[3]

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.[4] 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.[5]

The lesson one should draw from this literature is that a sizeable part of the 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 papers conclude with an appeal to devote more attention to the sources of these transitory factors, virtually no attempt has been made to investigate further empirically and theoretically this crucial aspect of the data.

[3]Other notable examples are Heckman, Lochner and Taber [1998], and Lloyd-Ellis [1999]. Clearly, not all existing papers claim that wage inequality among observationally similar workers reflects ability differentials. For example, Acemoglu [1998] develops a model where such unobserved skills may not be ability differences. Gould, Moav and Weinberg [2000] is another attempt to distinguish transitory from permanent components of inequality.

[4]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.

[5]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 U.K. are similar to those for the U.S..

A A Deeper Look at the Data

The first contribution of this paper is an empirical analysis of the sources of the rise in earnings instability. The increased variability of individual earnings could be potentially linked to two sources: more frequent separations and/or, for a given turnover rate, more volatile dynamics of wages on the job and between jobs. A large body of recent work on labor turnover in the U.S., based on various datasets, does not find any significant increase in separation rates.[6] Thus, we focus on the second source. Our findings, based on the *Panel Study of Income Dynamics* (PSID), show that the average wage loss for displaced workers (one year after the separation) increased by around 10 percent and wage growth on the job increased by 1.5 percent per year from the 70's to the 80's. Although there are several possible factors responsible for these trends, in the paper we focus on one classical determinant of wage dynamics: specific skills.[7] The existence of significant returns to tenure (over and above experience) and of persistent wage losses upon displacement suggest that knowledge cumulated on the job has a large specific component. Accumulation and transferability of specific human capital represent important determinants of individual wages, so they should be regarded as potential sources of wage variability.

B An Overview of the Model

The second contribution of the paper is to offer an alternative theory for rising residual inequality consistent with the above observations. The three crucial ingredients of the model are the technological acceleration, labor market frictions, 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] show that in the original Gordon's data the growth rate of *embodied* technical change is 3 percent on average between 1954 and 1974 and 4 percent 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. The role of the technological acceleration in shaping *between-group* inequality has been studied for example by Autor, Katz and Krueger [1998]

[6]See Wanner and Neumark [1999] and Neumark [2000] for an overview of the literature.

[7]The "institutional explanations" of rising inequality are a serious alternative candidate. Deunionization and the erosion of the minimum wage could have easily led to larger wage instability on the job and between jobs. See DiNardo et al. [1996] and Lee [1999] for an empirical analysis of the role of these two factors for the increase in residual wage inequality.

in relation to computer prices, and Krusell et al. [2000] in relation to equipment prices as a whole.[8] In this paper we argue that the technological acceleration can also induce a rise in *within-group* inequality.

The first economic mechanism in the model is based on labor market frictions. Our starting point is an economy where ex-ante identical workers are matched randomly with jobs (machines). Machines embody different vintages of technology, and the productivity of the leading edge machine advances exogenously at a constant rate. In the wake of an acceleration in embodied technical change, the productivity gap between machines of different vintages increases. Since the labor market is not competitive, workers receive wages proportional to the productivity of their machine. Therefore, the technological acceleration raises wage dispersion between workers.

Although this intuitive mechanism can qualitatively explain the rise in residual inequality (and in wage instability), it has little to say about wage growth on the job and wage losses upon separations. To try to match these additional features of the data, we need to model explicitly the dynamics of workers' specific human capital. 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.[9]

The second mechanism of the model is based precisely on vintage-specific human capital. Consider the same model as before where, when matched, workers learn vintage-specific skills and, when separating, they can only partially transfer their skills across machines. A technological acceleration has two effects. First, it reduces skill transfer-

[8] It is useful to recall that, as emphasized by Katz and Murphy [1992], a satisfactory explanation of the rise in educational wage differentials in the 80's and 90's requires, besides a technologically driven increase in the demand for skilled labor, also a deceleration in the supply of skills.

[9] 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 telephone industry, around the mid 70's electromechanical telephone switchboards were replaced by more sophisticated and flexible electronic switching equipment with larger programming possibilities. 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.

ability thereby increasing wage losses upon separation. Second, it reduces the average skill level of workers who find themselves, on average, on the steeper region of a concave learning curve, which in turn implies higher wage growth on the job. These forces also tend to raise the cross-sectional variance of skills and wages, the latter essentially through increased earnings instability. Finally, during the transition to the new steady-state, notwithstanding the technological acceleration, the fall in the average skill level of the workforce can generate a temporary slowdown in average wage growth.

C How Much Does the Model Account?

The third contribution of the paper is to explore the quantitative importance of these economic mechanisms through a calibration exercise on a full-scale model. The quantitative analysis shows that our mechanism can account for 30 percent of the rise in the residual variance of log-wages, or for almost 90 percent of the rise in its transitory component. Along the transition to the new steady-state, the model economy produces a slowdown in real wage growth in the 15 years immediately following the shock which can explain one third of the slowdown in wage growth (relative to trend) in the data from 1973 to 1989. Finally, the model has quantitative implications for changes in wage growth on the job and wage losses upon displacement which are roughly in line with the evidence.

The plan for the rest of the paper is as follows. Section II presents the empirical evidence on changes in wage growth on the job and wage losses upon displacement. Section III presents a stylized model that contains the key features of the theory. Section IV lays out the more general model used in the quantitative analysis, describes the calibration of the model and illustrates the main results of the simulations. Section V concludes the paper.

II Empirical Analysis of Wage Instability

In this section we use data from the *Panel Study of Income Dynamics* (PSID) to investigate the extent to which the rise in earnings instability in the U.S. can be attributed to changes in the wage dynamics on the job and between jobs. The objective of the empirical analysis is to analyze wage losses upon displacement and wage growth on the job in the early part (the 1970's) and in the late part (the 1980'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. Besides wages and employment status, the key variables for the analysis are provided by two useful survey questions: one asking the "reason for separation from previous employer" and the other asking the number of "months in current position".

We use three different methodologies to verify the sensitivity of our findings to the chosen criterion.[10] 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. We call this method, method (a). The second approach, method (b), uses 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 on the same job, her wage is recorded and compared to the last wage before the separation. 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. This is method (c).

We apply the three methods outlined above on two 11 year sub-periods, 1970-1980 and 1981-1991. Table I presents the estimates of wage losses upon displacement. Wages are hourly earnings computed as annual earnings divided by annual hours worked. Wage losses are computed as the difference between the hourly wage on the new job N years after separation and the last wage earned before separation. Strikingly, independently of the method, and of the sample selection, in all cases the initial wage losses upon displacement (i.e. one year after layoff) in the 1980's are roughly 10 percent larger than in the 1970'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 percent level.[11] Another strong pattern emerging from the data is that, once the worker finds a new job, she recovers her losses more quickly in the 1980's than in the 1970's. After 5 years of continuous tenure, wage growth is never statistically different

[10] The Data Appendix provides a detailed discussion of the three methods and information on the sample selection procedure.

[11] For prime-aged males (column 4) the size of the initial wage loss is not statistically different between the 1970's and the 1980's, but the wage loss is more persistent in the 1980's: 2 years after separation, wage losses are significantly different in case (b).

between the 1970's and the 1980's even though the initial wage losses are far larger in the 1980's. This finding represents preliminary evidence in favor of wage growth within job being faster in the 1980's. To establish this fact more firmly we look at the larger sample of all job stayers, i.e. workers who do not separate.

Table II presents the estimates of wage growth within job for stayers. We use two different methods to identify stayers. First, we consider all workers who are employed in two consecutive periods and, when answering the question on "reason for separation", do not report any separation. This method essentially selects all those workers who do *not* separate (either voluntarily or involuntarily) according to criterion (b) above.[12] Second, we use method (c) outlined above to identify all separations (again, both voluntary and involuntary), and we retain in the sample all workers who do *not* separate according to this criterion.

Given the larger sample, now we can split the period into 4 subperiods. Independently of the method and of the sample cut, the result is unambiguous: wage growth within job is approximately 1.5 percent higher in the 1980's than in the 1970's and the difference between the first and the last interval is always statistically significant at 5 percent level. In most cases wage growth increases smoothly over the sample period, except for columns (b) and (c) where the estimate for 1981-1986 is the largest. Similarly to our earlier findings on wage losses upon displacement, the evidence is slightly weaker for prime-aged males.[13]

In the next section, we present a simple theoretical framework to explain the rise in the transitory component of residual wage inequality originating from the described changes in individual wage instability.

III A Stylized Model

Consider an economy populated by a measure one of infinitely lived, risk-neutral workers and by the same measure of jobs. Jobs are machines embodying a given technology. The technological frontier advances every period at rate $\gamma > 0$. The machines have a productive life of two periods and do not depreciate after the first period. Each machine

[12] All the separations identified through criterion (a) are captured by (b) as well.

[13] Polsky [1999] is the only paper we are aware of that analyzes changes in wage growth for movers and 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 1980'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.

of age $j \in \{0,1\}$ matched with a worker produces (stationarized) output $y_j = (1+\gamma)^{-\theta j} z$, where z represents the skill level of the workers. Workers are ex-ante equal, and we begin by assuming that there are no skill dynamics, so z is the same for all workers.

The labor market is frictional, i.e. workers separated from their jobs face a random search technology to re-match with a vacant machine. We postulate that the bilateral monopoly problem between firm and worker is solved by a rent sharing mechanism that sets wages to be a constant fraction ξ of current output, where ξ is a measure of the bargaining power of workers. This –admittedly reduced-form– wage setting rule allows tractability as well as a decomposition of wage inequality particularly useful in the interpretation of the results. In section IV we show how such wage rule can arise, under some conditions, from a general bargaining game between firm and worker.

Let V_j denote the value of a worker employed on capital of age j, and U denote the value of an unemployed worker. We obtain that $V_0 = w_0 + \widehat{\beta} \max\{V_1, U\}$, $V_1 = w_1 + \widehat{\beta} U$, and $U = \alpha V_0 + (1-\alpha) V_1$, where $\widehat{\beta}$ is the productivity-adjusted discount factor and α is the probability of meeting a new machine in the search process, i.e. the fraction of vacant machines embodying the leading-edge technology.[14] The only decision we need to characterize is the separation decision for workers on new technologies, which we denote by $\chi \in \{0,1\}$, where $\chi = 1$ indicates a separation. It is immediate to see that $V_1 < U$ since $w_0 > w_1$. Thus $\chi = 1$, and there is always an equal fraction of idle new and old machines, or $\alpha = 1/2$.

We now study how equilibrium wage inequality in this economy is affected by a technological acceleration. Let us take log-approximations of the type $\log(1+x) \simeq x$ and express logarithms of the variables with the "$\sim$" symbol. It is convenient to measure the degree of inequality in the economy through the variance of log wages, $var(\widetilde{w})$, and simple algebra delivers the result that $var(\widetilde{w}) = \dfrac{\theta^2\gamma^2}{4}$, which is increasing in γ. Intuitively, in this economy all the heterogeneity is generated by technological differentials across machines. A technological acceleration amplifies the productivity gaps between jobs and, in a non-competitive labor markets where individual wages are linked to individual output, it raises wage dispersion even among ex-ante equal workers. This increase in wage inequality is mirrored by a rise in wage instability along the lifetime of each worker: given a certain amount of labor turnover, larger cross-sectional productivity differences translate into more volatile individual wage profiles.

[14] Note that, for simplicity, we have assumed that a worker who separates does not have to sit out an entire period before searching again.

However, it is easy to see that this simple model cannot explain the facts of section II: it predicts zero wage growth within job and wage changes upon exogenous separation (i.e. for workers on the old machines) which are always positive and increase in the speed of technology γ: workers displaced by old firms will improve upon their past wage because of the persistent growth in the productivity of capital. This result also implies that the average wage in this economy increases monotonically along the transition between steady-states, a prediction at odds with the dynamics of the U.S. average real wage which has fallen in the early to late 70's and has been stagnant in the 80's (see Murphy and Welch [1992], Table 1). We conclude that, without explicitly modeling the process of human capital accumulation on the job and transferability across jobs, this simple model is unable to match some key features of the recent rise in wage inequality.[15]

A Wage Inequality with Vintage Human Capital

We now augment the previous model with the feature that skills are *vintage-specific.* Every period employed workers cumulate, through learning-by-doing, knowledge about the technology they are matched with. We normalize the amount of specific skills cumulated after every employment spell to 1, so that the learning curve of the workers is concave, i.e. learning is faster for workers with lower initial skills.

A worker on a machine of age j who, next period, moves on a machine of age j' can carry on the new job a fraction of the cumulated skills equal to $z_{jj'}$ determined by the transferability function

$$z_{jj'} = (1+\gamma)^{\tau[j'-(j+1)]} . \tag{1}$$

This function has the property that the fraction of skills that can be transferred 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. As a result, we have three skill levels in the economy:

$$z_{01} = 1, \quad z_{00} = z_{11} = (1+\gamma)^{-\tau}, \quad z_{10} = (1+\gamma)^{-2\tau}, \tag{2}$$

[15] With more than 2 vintages and exogenous separations at each vintage level, the model is capable, under stringent conditions, of generating average wage losses upon displacement which increase with γ. Nevertheless, it still predicts no changes in wage growth within job and a rise in the level of average wage.

and the corresponding productivity-adjusted wage rates are $w_{ij} = \xi z_{ij} (1+\gamma)^{-\theta j}$, $i, j \in \{0,1\}$. The value functions for the workers become $V_{j1} = w_{j1} + \widehat{\beta} U_1$, $V_{j0} = w_{j0} + \widehat{\beta} \max\{V_{01}, U_0\}$, and $U_j = \alpha V_{j0} + (1-\alpha) V_{j1}$, where $j \in \{0,1\}$.

In contrast with the previous model, now the separation decision for workers on new technologies involves a trade-off. 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, $V_{0j} > V_{1j}$ and $U_0 > U_1$ which means that, for any given vacancy contacted, holding younger skills is strictly better. The following Lemma characterizes the optimal separation decision for workers as a function of the parameters of the model.[16]

LEMMA 1. If $\tau \leq \theta$, then $\chi = 1$ always. If $\tau > \theta$, there exists a value $\overline{\gamma}$ such that, for $\gamma > \overline{\gamma}$, $\chi = 1$.

The results of this Lemma are 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 always positive. A more articulated solution arises when $\tau > \theta$ because the current payoff from moving is negative. In this case, as the rate of quality-improvement of machines γ 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 the old vintage improves the current wage, but worsens future skill transferability and future wages. As γ goes up, the expected future wage loss from holding old skills increases faster than the current wage gain and is discounted at the higher productivity-adjusted 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.

It descends from Lemma 1 that the model has two types of stationary equilibria: $(E1)$ where workers only separate from technologies of age 1, and $(E2)$ where workers choose to separate also from new technologies. In what follows, we will characterize wage inequality in the two steady-states of the model. The interpretation of the results will be intuitive in light of the following decomposition of the log-wage variance which can be derived thank to our wage determination mechanism where the wage is a multiplicative function

[16] All the proofs are in the Theoretical Appendix.

of technology and skills. By taking logs of the wage rule and computing the variance with respect to the equilibrium employment distribution, we obtain:

$$\text{(3)} \qquad \mathrm{var}(\widetilde{w}) = \theta^2\gamma^2\mathrm{var}(j) + \mathrm{var}(\widetilde{z}) - 2\theta\gamma\mathrm{cov}(\widetilde{z}, j).$$

The variance of log-wages is given by the sum of three components: variance of technologies (which was the sole component in the previous model), variance of skills and covariance between skills and the age of technologies. 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: the combination of technological heterogeneity, skill dynamics and random matching determines how widely wages can span in equilibrium. The next Lemma fully describes how the different components of equilibrium inequality respond to a technological acceleration:

LEMMA 2. In each steady-state, an increase in γ raises both $\mathrm{var}(\widetilde{z})$ and $\mathrm{cov}(\widetilde{z}, j)$. If $\tau > \theta$, then $\mathrm{var}(\widetilde{w})$ increases. An increase in γ that changes the separation decision has ambiguous effects on $\mathrm{var}(\widetilde{w})$.

Intuitively, the variance of skills is increasing in γ since a higher γ reduces the skill transferability of the bottom end workers (type 10), while not affecting the skill level of the top end workers (type 01). 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 new technology relatively more than the skills of workers moving to (or staying on) old technologies. Notice also that although the variance of vintages of machines $\mathrm{var}(\widetilde{j})$ is unaffected, the increase in γ raises technological heterogeneity in the economy. This was the key economic force at work in the previous model.

For $\tau > \theta$, when the separation rule does not change, inequality is unambiguously increasing in γ because the rise in skill heterogeneity dominates the rise in the covariance component. Consider now an arbitrarily small increase in γ that changes the mobility decisions of workers. In switching between steady-states the variance of wages falls. This result is explained by the discrete change in the employment distribution across steady-states. Since in $(E2)$ the workforce on the new technology is no longer composed exclusively by workers of type 10 moving from the old machines, but also by workers moving from new 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 (bottom) end of the skill range, workers of type 01 (10) who had mass 1/2 in ($E1$), have now measure 1/4 in the equilibrium with full mobility ($E2$). Once again, the variance of skills and the covariance component move in the same direction, and for $\tau > \theta$ the fall of the skill variance dominates.

The conclusion we should draw from Lemma 2 is that the faster rate of quality-improvement in capital has two effects. First, the reduced skill transferability tends to increase skill heterogeneity and cross-sectional residual wage inequality. However, workers could 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. The overall effect is ambiguous and, ultimately, what force will be paramount is a quantitative question.

B Individual Earnings Instability

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 separation represent two key sources of wage variability along individual work histories. Therefore, 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.

LEMMA 3. In each steady-state, an increase in γ raises $\Delta\widetilde{w}^S$. For $\tau > \theta$, it raises also $\Delta\widetilde{w}^M$. 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. A worker that moves from an old to a young machine gains in terms of increased productivity of capital, but loses in terms of human capital specific to that technology. Evidently, the higher is τ compared to θ, the larger this loss will be. As workers anticipate their separation decisions, they hold younger vintages of skills on average and therefore can reduce their average skill losses.

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 following period, the skill level of stayers is 1 which is unaffected by γ. Altogether, wage growth within job increases with γ. The result depends only on the concavity of the learning function, which is a common and natural assumption, well supported by the vast empirical literature on learning curves, experience and tenure profiles.

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 and employed workers move on the steeper portion of their learning curve.

C The Transitional Dynamics of Average Wage

It is immediate to show that the stationarized average log-level of skills is $(-\tau\gamma)$ in both 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 $\widetilde{W}_t = -\tau\gamma_L - \theta\gamma_L/2$, independently of χ. Suppose now that γ rises to γ_H. Then, after simple algebra one can determine that next period the average log-wage is

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

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, in spite of the technological acceleration. This result fits well with the actual pattern of the average real wage in the U.S., but once again the magnitude of the wage fall predicted by the model is a quantitative issue.

IV The Quantitative Analysis

As we have emphasized, an increase in γ that induces a higher turnover rate of workers puts in motion a force that in equilibrium restrains inequality. For this reason, qualitatively, the overall impact of a technological acceleration in the model is ambiguous and only a quantitative analysis can shed light on which force, empirically, is dominant. The stylized model was designed to highlight the key economic mechanisms at work, but it is far too simple to be useful in approaching the data. In particular, to maintain analytical tractability, physical capital was assumed to fully depreciate after two periods and human capital accumulation was modeled as a deterministic process with short memory (one period). These assumptions are quite 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 what follows, we present the full scale version of the model in section III in order to develop a framework rich enough to measure how much of the increase in residual wage inequality in the data can be attributed to our mechanism.

A The Full Scale Model

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 using the discount factor β.

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 $(1+\gamma)^{-j}$. [17] 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 fully depreciates 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 $y(j, z) = (1+\gamma)^{-\theta j} (\kappa + z)$,

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

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.

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.[18] 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 $\alpha(j) = \dfrac{m(0,j)}{m(0)}$, 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.[19] The wage rate within a match is renegotiated each period.

Skills are assumed to be *vintage-specific:* each worker is indexed by a two-dimensional skill bundle (j, z) where z defines how productive the worker is in operating technology of age j. In other words, the skill level z can be interpreted as the number of tasks one 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. This implies a concave learning-by-doing function. 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

[18] This assumption is made purely for calibration purposes, as explained in Footnote 24. None of the results depend on it.

[19] 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 (3).

knowledge on the new job according to the transferability function:

$$z' = T(j, z, j') = \begin{cases} \min\left\{z_0, z(1+\gamma)^{\tau[j'-(j+1)]}\right\} & if\ j' < j+1 \\ z & \text{otherwise.} \end{cases} \tag{4}$$

This function generalizes (1) in two ways: first, at least z_0 can be transferred on newer machines; second, we assume that when workers move to older technologies, they can transfer all their knowledge.[20]

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.[21]

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

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 depreciate, the technology of surviving

[20] 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.

[21] 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. See Violante [2000] for a more articulated discussion of this issue.

[22] 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.

machines and the skills of 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.[23] The value functions will be defined at this same stage.

B 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 focus on 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 the next Lemma.

LEMMA 4. *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 4 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.[24] Generality is maintained because the firm acts optimally and the separation decision is jointly efficient. Moreover, thank to that particular wage determination mechanism, we can use extensively the wage variance decomposition (3) 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

[23] 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 employment 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.

[24] Note that the price q is sunk once the machine enters the labor market. 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.

decision problem of the employed worker is:

$$V(j,z) = w(j,z) + \widehat{\beta}\left[(1-\delta)\lambda \max\left\{V(j+1,z+\eta), U(j+1,z+\eta)\right\}\right. \\ + (1-\delta)(1-\lambda)\max\left\{V(j+1,z), U(j+1,z)\right\} \\ \left. +\delta\left\{\lambda U(j+1,z+\eta) + (1-\lambda)U(j+1,z)\right\}\right], \tag{5}$$

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:

$$U(j,z) = \sum_{j' \in \mathcal{J}} \alpha(j') \max\left\{V\left(j', T(j,z,j')\right), \widehat{\beta} U(j+1,z)\right\}. \tag{6}$$

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. The Theoretical Appendix contains a formal definition of the stationary equilibrium.

C 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 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 1960's, we only use the period 1960-1992. It has been documented that the acceleration has taken place in the early to mid 1970's (see for example Hornstein and Krusell [1996]). 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 suggest to use a pre-acceleration value $\gamma_L = 3.5$ percent and a post-acceleration

[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 maintain 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).

[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.

value $\gamma_H = 4.8$ percent. In the numerical experiment, the technological acceleration of the past 25 years will be modeled as a rise from γ_L to γ_H.

Murphy and Welch [1992] report that average wage has grown at a rate of 2.4 percent 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 percent, 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 U.S. economy in the period 1960-1973.[27]

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 designed to capture inequality in wages due to educational differentials and innate ability (as workers are ex-ante identical) or experience (as workers are infinitely lived). The target of the calibration is the *transitory* component of residual inequality. We compute this number in two steps. First, we use the Current Population Survey (CPS) March Annual Demographic Files (1964-1999) to calculate a number for residual inequality for the period 1963-1973.[28] We regress log weekly wages for each individual/year in the sample 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.[29] Second, we use Gottschalk and Moffitt's calculation of the transitory component: they report that the transitory component accounted always for roughly 30 percent of total residual inequality in log-weekly wages in the entire period

[27] 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.

[28] 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. 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 percent 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.

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

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 .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 percent 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 percent, the annual separation rate from employment to unemployment in the data between 1960 and 1973 (Blanchard and Diamond [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 percent in the period 1967-1982, which implies a value of $\lambda = .345$. 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 percent 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 percent below their pre-displacement wage after 6 months for individually laid off workers and roughly 30 percent for mass layoffs. We set $\tau = 1.90$ to reproduce a mean wage loss of 23 percent in the model (the average of those 3 statistics) for workers displaced after an exogenous break up of their machine who are re-employed after 1 model period (i.e. 6 months).[30] The calibration procedure is summarized in Table III. Section IV.E reports the results of the sensitivity analysis with respect to three key parameters of the model: γ, λ, and τ.

D *Steady-State Results*

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

The first component of the wage variance is technological heterogeneity. Here two

[30] Our calculations in Tables I and II are in agreement with the numbers used for the calibration.

effects come into play to explain the impact of the shock. 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. However, the change in workers' separation decisions in response to the shock has a counteracting effect. The simulations confirm the result of the stylized model whereby a technological acceleration induces workers to track closer the leading edge jobs in order to avoid large skill losses. Because separation decisions are taken earlier, the age distribution of employed machines shifts to the left (the average age falls by 3 months, from 7.7 to 7.45 years) and becomes slightly less disperse, as evident from Figure 2, panel (3). In our economy technological heterogeneity increases from .008 to .014, contributing 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) of Figure 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 III.B, 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 IV shows that the model predicts a rise in within-job wage growth of about 1.4 percent and a fall of wage change upon layoff of approximately 7 percent. Both numbers are very much in line with the facts documented in section II. As suggested by the stylized model, lower transferability across jobs and faster skill growth on the job combine into more volatile skill profiles.

The third component is the covariance between the skill level and the age of technologies. As in the stylized model, the covariance is positive, 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 fewer skills are transferable on the youngest machines. The way the separation decision χ_e depends on the skill level z reinforces this pattern: unskilled workers separate earlier and more often than skilled workers. The reason is that highly skilled workers are affected more severely by the skill loss implied by moving to a younger vintage, so they are less willing to separate than unskilled workers.[31]

Panel (4) shows the contours of the employment distribution in both steady-states.

[31] Violante [2000] extends the stylized model of section III.A to allow for stochastic learning and two skill levels (high and low). In this extended model, it can be proved formally that low-skilled workers separate earlier than high-skilled.

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. This effect contributes to lower inequality. Similarly to the stylized model, the changes in the variance of skills and the covariance component tend to offset each other, but the switch in the separation decision is not strong enough and inequality increases in the new steady state. This can also be seen from Table IV where it appears 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 2. The higher variance is mirrored by the fatter tails, especially the lower tail.[32]

E 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. Reasonable deviations from our calibrated values for γ_L and γ_H do 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: for $\gamma = .055$, the long-run level of residual inequality would rise to .11. Each component of the wage variance is well behaved also with respect to small changes in τ. Overall, the rise in wage inequality is stronger for τ large, but not substantially. For example, when $\tau = 2.5$ (with corresponding average wage loss of 34 percent in the steady state with γ_L) it rises by 67 percent, compared to 60 percent in the baseline.

The results on λ are somewhat more interesting, as this parameter is absent from the stylized model of section III. We have analyzed a 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. The intuition is that, for λ large, the fast learning process realigns quickly the differences between the more and the less lucky workers in the economy. As a consequence, a technological acceleration that reduces skill transferability does not have a strong effect on the skill distribution.[33]

[32] We also 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.

[33] Violante [2000] contains a more detailed discussion of the sensitivity analysis.

F Transitional Dynamics

In this section we focus on the transitional dynamics of the economy between the two steady-states. Besides our interest on the dynamic path of wage inequality, we also want 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 progress jumps 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 (4) to the case in which $\gamma(t)$ changes over time, since in a non-stationary 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:

$$(7) \qquad T(j,z,j',t) = \begin{cases} \min\left\{ z_0, z\left[\prod_{i=j'}^{j} \gamma(t-i)\right]^{-\tau} \right\} & if\ j' < j+1 \\ z & otherwise. \end{cases}$$

The rest of the computation of the transition is straightforward.[34]

Wage inequality rises monotonically along the transition, albeit at a slightly slower pace than in the data: 25 years after the shock the model predicts a level of residual wage inequality around .078, compared to its long-run level of .086 and its value in the data, which is .089 in the late 90's. The slow convergence in the model is, at least partially, due to the infinitely-lived-agents assumption. With overlapping generations, every period there is always a fraction of the population whose skill level is re-initialized, and this would speed up the convergence process to the higher level of inequality.

We now turn to average wage growth. 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 3 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. Intuitively, the technological acceleration creates a workforce with skills of

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

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 percent of the wage growth slowdown in the period immediately following the technological acceleration.

V Conclusions

This paper offers a theory to interpret the recent surge in residual inequality. We have argued that an acceleration in the rate of quality-improvement of equipment, like the one observed from the early 70's, increases the productivity/quality differentials across machines (jobs). In a non-competitive labor market, this force translates into higher wage dispersion even among ex-ante equal workers. With vintage-human capital, the acceleration reduces workers' capacity to transfer skills from old to new machines, generating a rise in the cross-sectional variance of skills, and therefore of wages. Two implications of the theory –faster within job wage growth and larger wage losses upon displacement– receive empirical support.

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 U.S., the U.K. 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 this crucial dimension of the data. We can label our 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 our 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. The emphasis we give to the SDH vis-a-vis the IAH 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.

In the second part of the paper, we have used our calibrated model for a *quantitative* study of the U.S. economy. An important advantage of the "technological 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 be measured through *independent* price data. In contrast, in many 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. We show that a technological acceleration of the magnitude observed in the past 25 years can account for just below 30 percent of the rise in residual inequality in the U.S., 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 one third of the difference between wage growth in the data and long-run trend growth in the 15 years following the shock.

The theory and the quantitative analysis developed in this paper have at least three limitations. First, although the distinction between transitory and permanent nature of earnings fluctuations is important, the crucial issue from a welfare perspective is how *insurable* these shocks are. If they are not easily insurable, 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.

Second, in this paper we argue that a technological acceleration reduces skill transferability in the economy. It has been suggested elsewhere that the recent information technology innovations have a particularly versatile nature and can be applied across virtually every sector and job category in the economy. This could have increased skill transferability across some industries. We do not address this issue in the paper. Aghion, Howitt and Violante [2000] provide a theoretical framework, consistent with the SDH, where the emphasis is on the general purpose nature of the recent technological wave and study its effect on wage inequality.

Third, the focus of the analysis being inequality, we have sidestepped the implications of the model for unemployment. Although our economy of section III has not been calibrated to match this dimension of the data, an interesting result of the simulations is that the model generates an increase in the long-term (more than 6 months) unemployment rate from 1.9 percent in the old steady state to 2.7 percent after the shock. Given the fuzzy distinction between long-term unemployment and nonparticipation, the closest data counterpart of the number generated by the model is, arguably, nonemployment. Murphy and Topel [1997] report that nonemployment for males rose from 7 percent to 12 percent from the early 70's to the late 90's. The model's prediction goes therefore in the right direction, but the increase explained is quantitatively modest. A satisfactory study of the impact of the faster skill obsolescence related to the technological acceleration on the rise in male nonemployment requires to model explicitly labor supply choices. This is beyond the scope of the current paper, but it represents a promising avenue of research.

Data Appendix

All the calculations in section II are based on 22 waves from the *Panel Study of Income Dynamics* (PSID) from 1970 to 1991. The first two years of the survey (1968-1969) are excluded because earnings are bracketed. The baseline sample is constructed by selecting white males head of households between 18 and 60 years old, who are not self-employed, not union members and do not reside abroad or in Alaska and Hawaii. We also exclude the low-income oversample, but we retain part-time workers. Excluding part-timers from the calculations does not result in any substantive change in the results. Column 1 in Tables I and II 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.

The definition of wages that we use is hourly wages, computed as annual earnings divided by total hours worked for the preceding year. For job changers (Table I), this is presumably an average of the wage in every job weighted by the portion of the year spent in each. Thus it is not the ideal wage measure for our purposes, but arguably the best that can be calculated consistently for the whole sample period.[35] Moreover, the fact that the *level* of the initial wage loss might be underestimated due the wage definition does not necessarily affects our conclusions which are based on a comparison between the 1970's and the 1980's. Finally, to deal with outliers, in every year we exclude hourly wages below 50% of the current minimum wage and wages beyond the 99th percentile of the distribution for the baseline sample.

Before computing the entries for Tables I and II, to each individual wage observation in any given year in samples 1 to 5, we subtract the average hourly wage of the corresponding sample in that year to control for cyclical variations in aggregate total factor productivity (i.e. productivity changes which are not embodied in physical or human capital) that are absent from the model. Admittedly, we might also involuntarily eliminate some of the aggregate growth effect of embodied technical change. We opted for demeaning the data primarily because we feared that the large variance of business cycle effects could obscure the more structural forces we are interested in. It turns out that the conclusions of section II would be essentially unchanged were the data not demeaned.

To construct the data for Table I, we identify all workers who report a layoff in a given survey-year and are re-employed when interviewed in the next survey. Each column

[35] The PSID contains also a direct measure of hourly wages on the current job, but it is unavailable before 1975 and it is truncated prior to 1978.

contains the difference between the average hourly wage in the year of separation and the current hourly wage paid in the re-employment job N years after the calendar year of the original separation ($N = 1, 2, ..., 5$), as long as the worker stays on that same job.

Some remarks on the three methods used to identify separations are in order. Method (a) 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.

Method (b) includes a larger number of genuine separations. However, it is subject to three potential problems due to the fact that the survey designers have changed slightly the wording of the question asking the "reason for separation from previous employer" over the years.[36] First, prior to 1984 this question 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 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.[37]

In applying method (c), 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][38]. 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.[39] This method should therefore provide a lower bound to wage losses upon separation.

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

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

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

[39]For example, as pointed out by Brown and Light [1992] position tenure is not highly correlated with employer tenure. 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.

As expected from the discussion above, we find that method (a) is the one capturing the lowest number of separations, and method (b) is the most inclusive. In particular the (involuntary) separation rates from employment were 1.85 percent and 2.12 percent for method (a), 6.19 percent and 8.51 percent for method (b), 2.45 percent and 3.14 percent for method (c), in the two periods.[40] Moreover, method (a) yields the highest point estimates of mean wage losses and method (c) the lowest.

[40] Consistently with the existing literature we find a significant increase in separation only with method (b)—used for example by Gottschalk and Moffitt [1994]— who report a rise in job instability.

Theoretical Appendix

Proof of Lemma 1. Workers choose to separate if and only if $V_{01} > U_0$ which is equivalent to:

$$V_{00} > V_{01} \Leftrightarrow (w_{00} - w_{01}) + \widehat{\beta}\,(V_{01} - U_1) > 0 \tag{A1}$$

The second term of $(A1)$ is always positive. If $\tau \leq \theta$ the first term is positive, which proves the first point of the Lemma. Consider now the case $\tau > \theta$. Suppose first that workers do not separate from new technologies, thus $\alpha = 1$. After simple algebra, the difference $(V_{00} - V_{01})$ can be re-expressed as:

$$w_{00} - w_{01} + \frac{\widehat{\beta}}{\left(1 + \widehat{\beta}\right)}\,(w_{01} - w_{10})\,.$$

Using (2) one can show that as $\gamma \to \infty$ the difference $(V_{00} - V_{01})$ approaches zero from above, hence for γ large enough we find a contradiction. Suppose now that workers separate from new technologies, thus $\alpha = 1/2$. In this case, the difference $(V_{00} - V_{01})$ can be written as:

$$w_{00} - w_{01} + \frac{\widehat{\beta}}{2}\left[(w_{00} - w_{10}) + (w_{01} - w_{11})\right],$$

which, as $\gamma \to \infty$, converges to $\dfrac{\beta}{2} > 0$ confirming that, for γ large enough, workers choose optimally to separate.

Proof of Lemma 2. The first step of the proof is to obtain the equilibrium contact rate α and the 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 $(E2)$ every worker separates every period, so $\alpha = 1/2$. Given the contact rate and the decision rule, it is easy to obtain the employment distribution below. Let μ_{ij} denote the measure of workers on technology j who last period were on technology i and notice that $1/2$ is the measure of workers on each vintage of capital. Then:

$$\begin{aligned}
\mu_{01} &= \left[(1-\chi) + \chi\,(1-\alpha)\right]\frac{1}{2},\\
\mu_{00} &= \chi\alpha\frac{1}{2},\\
\mu_{10} &= \alpha\frac{1}{2},\\
\mu_{11} &= (1-\alpha)\,\frac{1}{2}.
\end{aligned}$$

In steady-state $(E1)$ with $\chi = 0$ the implied equilibrium distribution of workers across machines is $\mu_{00} = \mu_{11} = 0$, $\mu_{10} = \mu_{01} = 1/2$. In steady-state $(E2)$, where $\chi = 1$, the equilibrium distribution is given by $\mu_{00} = \mu_{11} = \mu_{11} = \mu_{10} = 1/4$. At this point we can use the skill levels in (2) and the corresponding wage rates to obtain the equilibrium variance of log-wages and its three components in the two steady-states. The proof is purely algebraic, so we omit it.

In $(E1)$:

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

In $(E2)$:

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

By simple inspection, it is clear that within each type of stationary equilibrium, $var(\widetilde{z})$ and $cov(\widetilde{z}, j)$ are increasing in γ. Altogether, $var(\widetilde{w})$ is increasing in γ if $\tau > \theta$. However, a rise of γ that triggers a switch from $(E1)$ to $(E2)$ has ambiguous effects on $var(\widetilde{w})$.

Proof of Lemma 3. We compute average wage growth for stayers by measuring the change in log wage for all those workers who stay on the same technology for two consecutive periods. 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. Average wage growth on the job in the two steady-states is given by:

$$(E1): \quad \Delta\widetilde{w}^S = \widetilde{z}_{01} - \widetilde{z}_{10} = 2\tau\gamma$$

$$(E2): \quad \Delta\widetilde{w}^S = \frac{1}{2}\left[(\widetilde{z}_{01} - \widetilde{z}_{10}) + (\widetilde{z}_{01} - \widetilde{z}_{00})\right] = \frac{3}{2}\tau\gamma.$$

Average wage loss upon layoff in in the two steady-states is given by:

$$(E1): \quad \Delta\widetilde{w}^M = (\widetilde{w}_{10} + \theta\gamma) - \widetilde{w}_{01} = -2(\tau - \theta)\gamma$$

$$(E2): \quad \Delta\widetilde{w}^M = \frac{1}{4}\left[(\widetilde{w}_{10} + \theta\gamma - \widetilde{w}_{11}) + (\widetilde{w}_{10} + \theta\gamma - \widetilde{w}_{01}) + (\widetilde{w}_{11} + \theta\gamma - \widetilde{w}_{01}) + \theta\gamma\right]$$

Thus, in steady-state $(E2)$, $\Delta\widetilde{w}^M = -\frac{3}{2}(\tau - \theta)\gamma$. The conclusion of Lemma 3 follows immediately.

Proof of Lemma 4. Recall that the (growth-adjusted) income accruing to the entrepreneur of an idle firm of age j is equal to $\overline{y}(j) = (1+\gamma)^{-\theta j}\kappa$. It follows that 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 $\overline{y}(j)$. 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 in Lemma 4. 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.

Definition of stationary equilibrium.

A stationary equilibrium for this economy is 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 $\alpha(j) = \dfrac{m(0,j)}{m(0)}$, 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 (5) and (6) 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 $\mu(\mathcal{S}^*, \mathcal{J}^*, \mathcal{Z}^*) = Q(\mathcal{S}^*, \mathcal{J}^*, \mathcal{Z}^*)(\mu)$.

The last condition requires the derivation of the fixed point of the function Q mapping this period workers' distribution into next period distribution. This transition function is constructed from the contact rates, the transferability function, the learning probability, the depreciation rate and the agents' optimal separation rules. 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. The full description of the transition function Q follows below.

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.

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

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

UNIVERSITY COLLEGE LONDON, INSTITUTE OF FISCAL STUDIES, AND CENTRE FOR ECONOMIC POLICY RESEARCH

References

Acemoglu, Daron,"A Microfoundation for Social Increasing Returns in Human Capital Accumulation," *Quarterly Journal of Economics*, 111 (1996), 779-804.

—, "Why Do New Technologies Complement Skills? Directed Technical Change and Wage Inequality," *Quarterly Journal of Economics*, 113 (1998), 1055-1090.

—, "Changes in Unemployment and Wage Inequality: An Alternative Theory and Some Evidence," *American Economic Review*, 89 (1999),1259-78.

Aghion, Philippe, Peter Howitt and Giovanni L. Violante, "General Purpose Technology and Within-Group Wage Inequality," CEPR working paper n. 2474, 2000.

Autor, David, Lawrence Katz and Alan Krueger, "Computing Inequality: Have Computers Changed the Labor Market?," *Quarterly Journal of Economics* 113 (1998), 1169-1213.

Baker, Micheal and Gary Solon, "Earnings Dynamics and Inequality among Canadian Men, 1976-1992: Evidence from Longitudinal Tax Records", NBER working paper 7370, 1999.

Binmore, Ken, Avner Shaked and John Sutton, "An Outside Option Experiment," *Quarterly Journal of Economics*, 104 (1989), 753-770.

Blanchard, Olivier and Peter Diamond, "The Cyclical Behavior of the Gross Flows of U.S. Workers," *Brookings Papers of Economic Activity*, 2 (1990), 85-143.

Blundell, Richard and Ian Preston, "Inequality and Uncertainty: Short-Run Uncertainty and Permanent Inequality in the U.S. and Britain," mimeo, University College London, 1999.

Brown James, and Audrey Light, "Interpreting Panel Data on Job Tenure," *Journal of Labor Economics* 10 (1992), 219-257.

Bureau of Economic Analysis, "Fixed Reproducible Tangible Wealth in the United States, 1925-1989," U.S. Department of Commerce: Washington D.C. (1994).
Caselli, Francesco, "Technological Revolutions," *American Economic Review*, 89 (1999), 78-102.

Cooley, Tom (ed.), *Frontier of Business Cycle Research*, Princeton University Press, 1995.

Diebold, Francis, David Neumark and Daniel Polsky, "Job Stability in the United States," *Journal of Labor Economics*, 15 (1997), 206-233.

Dickens, Richard, "The Evolution of Individual Male Earnings in Great Britain: 1975-1995," *Economic Journal*, 110 (2000), 27-49.

DiNardo John, Nicole Fortin, and Thomas Lemieux, "Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semi-parametric Approach," *Econometrica*, 64 (1996), 1001-1044.

Galor, Oded and Omer Moav, "Ability Biased Technological Transition, Wage Inequality Within and Across Groups, and Economic Growth," *Quarterly Journal of Economics*, 115 (2000), 469-497.

Gittleman, Maury and Mary Joyce, "Earnings Mobility and Long-Run Inequality: An Analysis Using Matched CPS Data," *Industrial Relations*, 35 (1996), 180-197.

Gordon, Robert. J., *The Measurement of Durable Good Prices*, NBER Monograph Series, University of Chicago Press, 1990.

Gosling, Amanda, Steve Machin and Costas Meghir, "The Changing Distribution of Male Wages in the UK," *Review of Economic Studies*, 67 (2000), 635-666.

Gottschalk, Peter and Robert Moffitt, “The Growth of Earnings Instability in the U.S. Labor Market,” *Brookings Papers of Economic Activity*, 2 (1994), 217-272.

Gottschalk, Peter and Robert Moffitt, “Trends in the Autocovariance Structure of Earnings in the U.S.: 1969- 1987,” mimeo, Johns Hopkins University, 1995.

Gould, Eric, Omer Moav and Bruce Weinberg, “Precautionary Demand for Education, Inequality and Technological Progress,” mimeo, The Hebrew University of Jerusalem, 2000.

Greenwood Jeremy and Mehmet Yorukoglu, “1974”, *Carnegie-Rochester Conference Series on Public Policy*, 46 (1997), 49-96.

Heckman, James, Lance Lochner and Christopher Taber, “Explaining Rising Wage Inequality: Explorations with a Dynamic General Equilibrium Model of Labor Earnings with Heterogeneous Agents,” *Review of Economic Dynamics*, 1 (1998), 1-58.

Hornstein, Andreas and Per Krusell, “Can Technology Improvements Cause Productivity Slowdowns?,” *NBER Macroeconomics Annual*, (1996), 209-259.

Jacobson, Louis, Robert LaLonde and Daniel Sullivan, “Earnings Losses of Displaced Workers,” *American Economic Review*, 83 (1993), 685-709.

Juhn, Chinui, Kevin Murphy and Brooks Pierce, “Wage Inequality and the Rise in Returns to Skill,” *Journal of Political Economy*, 101 (1993), 410-442.

Katz, Lawrence, “Comments and Discussion” for “The Growth of Earnings Instability in the U.S. Labor Market,” by Peter Gottschalk and Robert Moffitt, *Brookings Papers on Economic Activity*, 2 (1994), 255-261.

Katz, Lawrence and David Autor, “Changes in the Wage Structure and Earnings Inequality,” chapter 26, Volume 3, in *Handbook of Labor Economics*, (edited by Orley Ashenfelter and David Card), 1999.

Katz, Lawrence and Kevin Murphy, “Changes in Relative Wages, 1963-1987: Supply and Demand Factors,” *Quarterly Journal of Economics*, 107 (1992), 35-78.

Krusell, Per, Lee Ohanian, José-Victor Rios-Rull and Giovanni L. Violante, “Capital Skill Complementarity and Inequality: A Macroeconomic Analysis,” *Econometrica*, 68 (2000), 1029-1054.

Lee, David, “Wage Inequality in the U.S. During the 1980s: Rising Dispersion or Falling Minimum Wage?,” *Quarterly Journal of Economics*, 114 (1999), 977-1023.

LLoyd-Ellis, Huw, “Endogenous Technological Change and Wage Inequality,” *American Economic Review*, 89 (1999), 47-77.

Murphy, Kevin and Robert Topel, “Unemployment and Nonemployment,” *American Economic Review Papers and Proceedings*, 87 (1997), 295-300.

Murphy, Kevin and Finis Welch, “The Structure of Wages,” *Quarterly Journal of Economics*, 107 (1992), 285-326.

Neumark, David, “Changes in Job Stability and Job Security: A Collective Effort to Untangle, Reconcile and Interpret the Evidence,” NBER working paper 7472, 2000.

Polsky, Daniel, “Changing Consequences of Job Separation in the United States,” *Industrial and Labor Relations Review*, 52 (1999), 565-580.

Rubinstein, Ariel, “Perfect Equilibrium in a Bargaining Model,” *Econometrica*, 50 (1982), 97-109.

Shaked, Avner and John Sutton, “Involuntary Unemployment as a Perfect Equilibrium in a Bargaining Model, ” *Econometrica,* 52 (1984), 1351-1364.

Topel, Robert, “Specific Capital, Mobility, and Wages: Wages Rise with Job Seniority,” *Journal of Political Economy*, 99 (1991), 145-177.

Valletta, Robert, “Declining Job Security,” *Journal of Labor Economics*, 17 (1999), S170-S197.

Violante, Giovanni L., “Technological Acceleration, Skill Transferability and the Rise in Residual Wage Inequality,” University College London Discussion Paper 19-2000, (2000).

Wanner, Eric and David Neumark, “Preface,” Journal of Labor Economics, 17 (1999), Siii-Siv.

Yorukoglu, Mehmet, “The Information Technology Productivity Paradox,” *Review of Economic Dynamics*, 1 (1998), 551-592.

TABLE I

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. Wages are hourly wages computed as annual earnings divided by hours worked. Each column reports the difference between the current wage and the last wage before separation for workers who, after a job loss, are re-employed within one year and are continuously employed for N years after separation, $N = 1, 2, ..., 5$. The suffix a), b), and c) refer to the methods used to identify involuntary separation. Method a) identifies job losses through the question "reason for separation" and in addition requires the worker to be unemployed at the time of the survey. Method b) is based on the same question, but does not require the worker to be unemployed. Method c) identifies a job changer whenever the "months on current position" are less than the time elapsed since the last interview and uses the "reason for separation" to distinguish job losses from quits. Column (1) is the benchmark case. The benchmark sample includes white males head of households between 18 and 60 years old, who are not self-employed, not union members and do not reside abroad or in Alaska and Hawaii. Column (2) includes also self-employed, (3) includes also unionized workers, (4) includes only prime-aged males, (5) includes only Manufacturing. We always exclude the low-income oversample. To each individual wage observation in a given year, we subtract the annual mean wage for the corresponding sample. Standard errors are reported in parenthesis. See the main text for more details.

TABLE II
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. Wages are hourly wages computed as annual earnings divided by hours worked. Each column reports the annual wage growth for stayers. The suffix b) and c) refer to the methods used to identify job stayers. Method b) identifies job stayers as those who do not report any separation when answering the question "reason for separation". Method c) identifies a job stayer if the "months on current position" are higher than the time elapsed since the last interview. Column (1) is the benchmark case. The benchmark sample includes white males head of households between 18 and 60 years old, who are not self-employed, not union members and do not reside abroad or in Alaska and Hawaii. Column (2) includes also self-employed, (3) includes also unionized workers, (4) includes only prime-aged males, (5) includes only Manufacturing. We always exclude the low-income oversample. To each individual wage observation in a given year, we subtract the annual mean wage for the corresponding sample. Standard errors are reported in parenthesis. See the main text for more details.

TABLE III
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]

TABLE IV

Results of the Numerical Experiment

	Variance of log wages DATA	Variance of log wages MODEL	Variance of technologies	Variance of skills	Covariance component
γ_L =.035	.053	.053	.008	.085	-.038
γ_H =.048	.089	.085	.014	.145	-.074

	Average age of capital	Average skill level	Wage growth within-job	Wage loss upon layoff	Separation rate
γ_L =.035	7.700	11.086	.030	-.230	.166
γ_H =.048	7.448	8.595	.044	-.305	.171

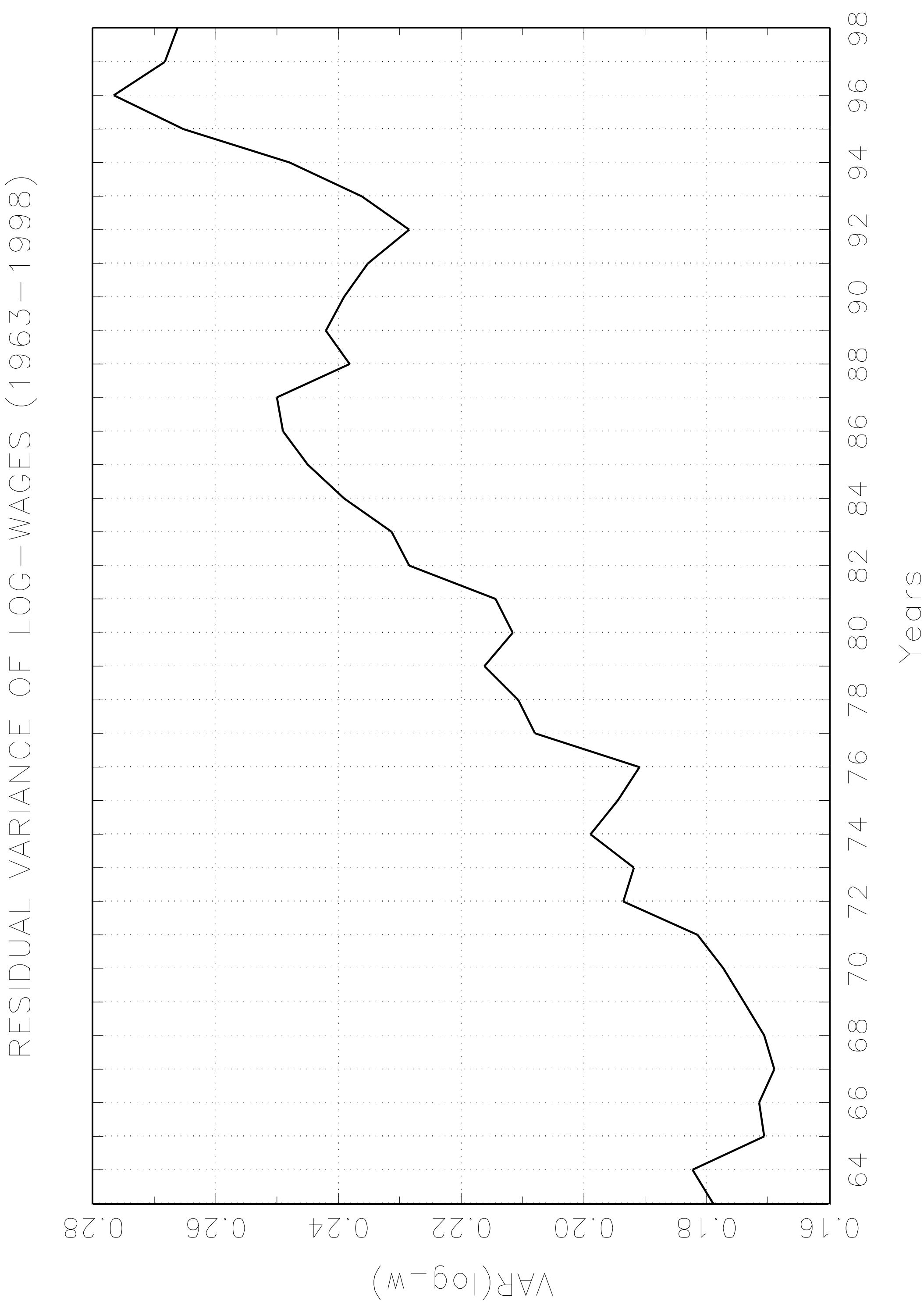

Figure I: Residual Variance of Log Wages (1963-1998). Source: Author's computation from the Current Population Survey, March Annual Demographic Files

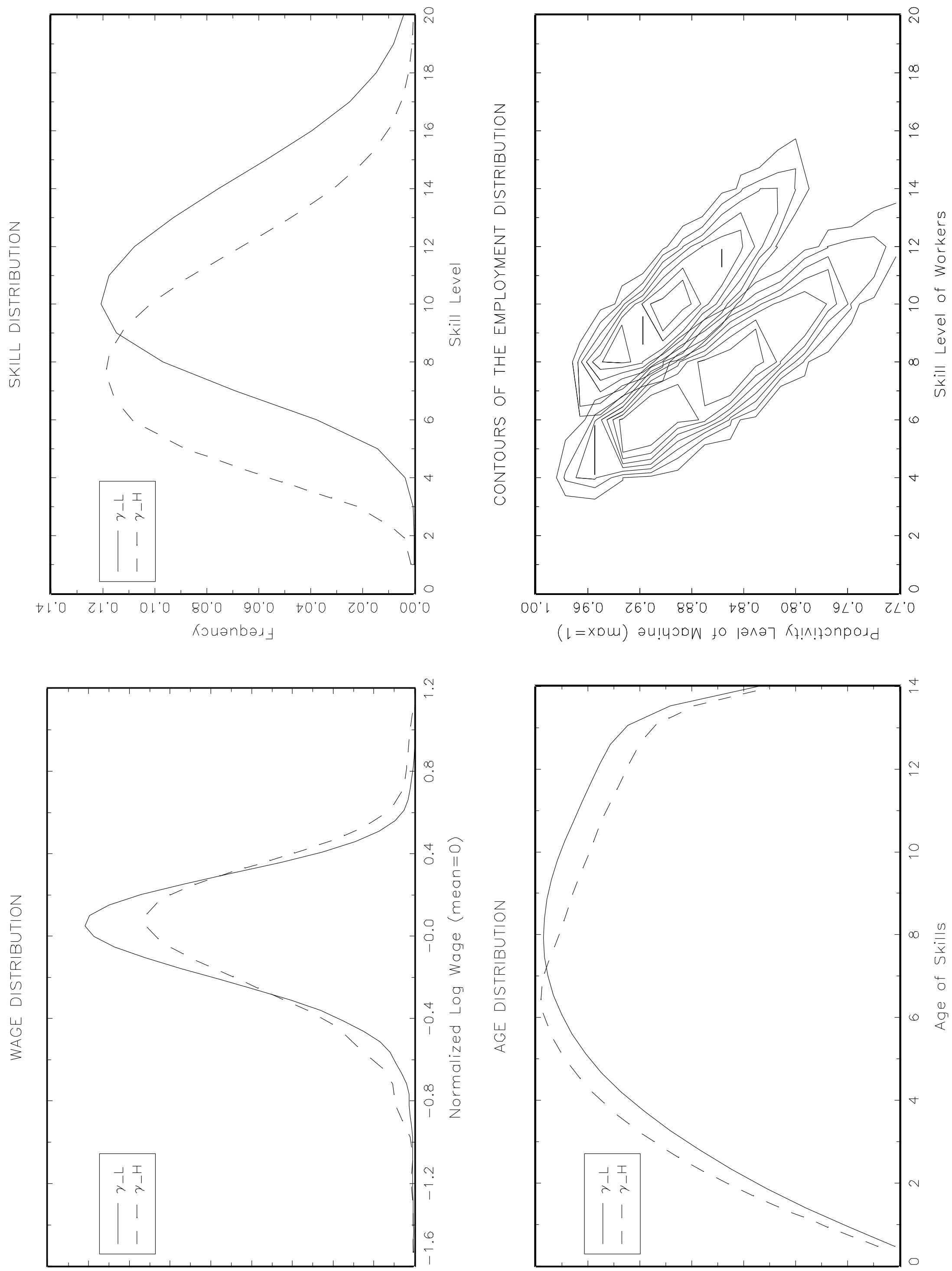

Figure II: The Equilibrium Wage Distribution and the Wage Variance Components

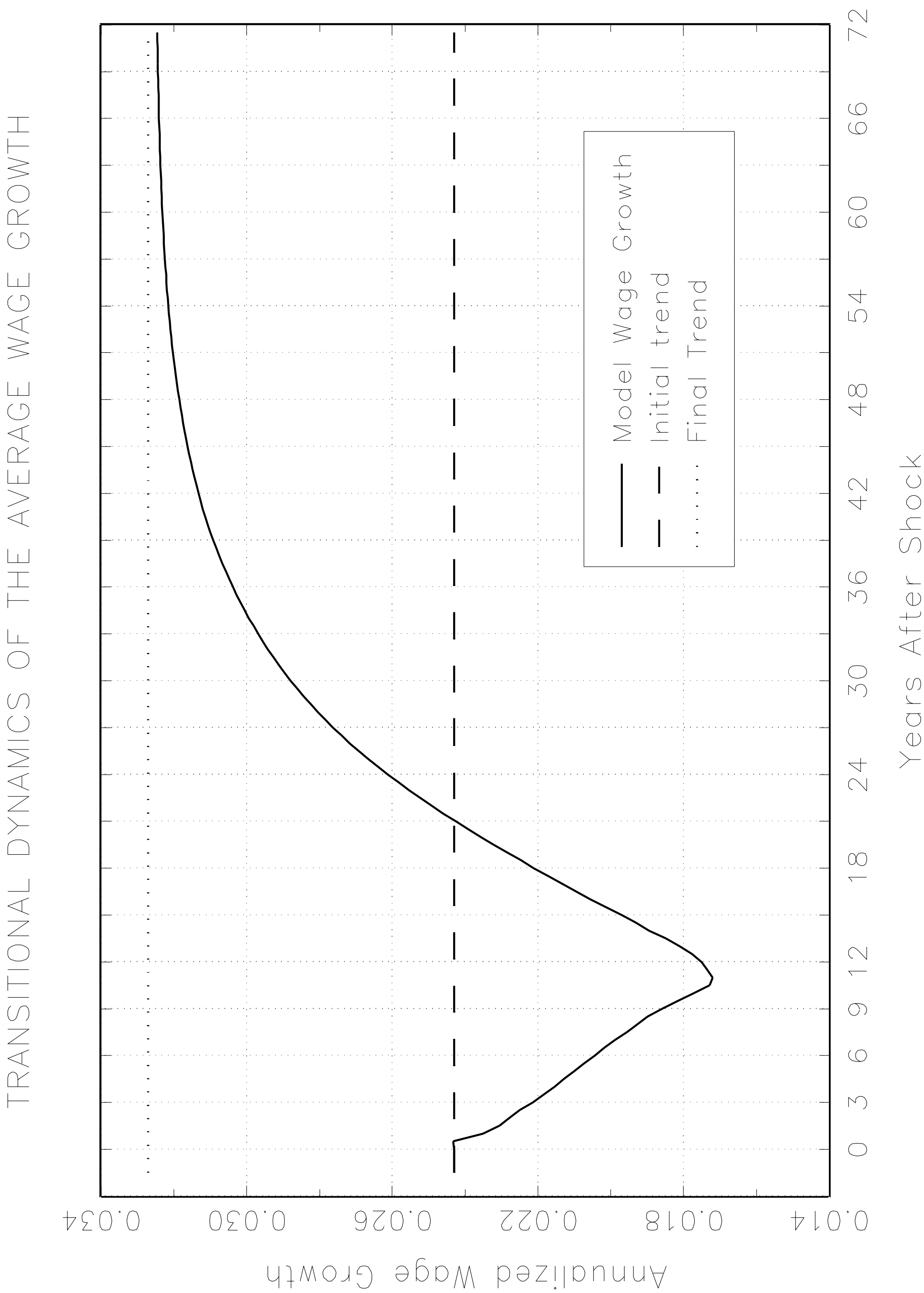

Figure III: Average Wage Growth in the Transitional Dynamics of the Model Economy