# Experience and Technology Adoption

May 2002

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Vintage human capital models imply that young workers will be the primary adopters and beneficiaries of new technologies. Because technological progress in general, and computers in particular, may be skill-biased and because human capital increases over the lifecycle, technological change may favor experienced workers. This paper estimates the relationship between experience and technology adoption and the effect of technological change on the returns to experience. Estimates indicate that technological change is an important explanation for changes in experience premia. We find a complementarity between existing human capital and computer adoption and provide evidence that young workers are better able to adapt to new technologies. Our estimates also shed light on creative destruction models of the productivity slowdown.

The author is grateful for comments from and discussions with Susan Athey, David Autor, Gary Becker, Lex Borghans, David Galenson, Eric Gould, Masanori Hashimoto, Peter Howitt, Ken Judd, Steve Levitt, Lance Lochner, Stephen Machin, Kevin Murphy, Derek Neal, Yona Rubenstein, Jim Spletzer, Robert Topel, Bas ter Weel, Yoram Weiss, Finis Welch and seminar participants at the Hoover Institution, Maastricht University ROA/SKOPE, Northwestern University, the Society of Labor Economists 2001, Stanford University (Economics Department), Econometrics in Tel Aviv 2001, Clemson University, Ohio State University, the University of Chicago, the 2002 AEA Meetings, the 2002 NBER Summer Institute, Duke University, Indiana University, Purdue University, and Concordia University but retains sole responsibility for all errors. The author gratefully acknowledges the support of the Hoover Institution, where this paper was written, and the National Science Foundation through SES-0095776.

JEL Codes: J31, J24, O30.

**Experience and Technology Adoption**

## I. Introduction

Based on vintage human capital models, economists generally argue that young workers are the primary adopters and beneficiaries of new technologies. On the other hand, research has indicated that technological progress is generally biased toward skill, and this certainly appears to be true for the recent episode of technological change surrounding computers.[1] Because human capital increases with experienced, the skill-biasedness of technological change would tend to favor more experienced workers. The effects of technological changes on different experience groups will therefore depend on the interplay between skill-bias and vintage effects.

This paper develops and estimates a new model of technology adoption and estimates the effects of technological change on the returns to experience. The model is a human capital accumulation model with two technologies, old and new. Workers choose which technology to use and accumulate skills specific to that technology. The vintage human argument that young workers are the first to adopt new technologies is predicated on the assumptions that human capital with an old technology is imperfectly transferable to new technologies and that young workers have longer to recoup any fixed cost of adoption. While adopting a new technology may render some skills with the previous technology obsolete, we emphasize that a new technology may complement existing skills.[2] To capture these effects, the model includes an estimable complementarity-

[1] See Goldin and Katz [1998]; Murphy, Riddell, and Romer [1998]; and Acemoglu [2002] for discussions of skill-bias over the long term.

[2] Autor, Levy, and Murnane [2001] argue that computers have generally been used to automate routine or repetitive cognitive and manual tasks, placing greater emphasis on troubleshooting and problem solving. A worker who had developed skills in a range of tasks, including some that are computerized, would find the skills that were computerized obsolete, but their existing skills with the other tasks might become more valuable. Borghans and Ter Weel [2001b] provide conditions under which workers with higher wages or opportunity costs of time will be provided computers by their employers, even if there is no complementarity between skill and computers. Because more experienced workers have more skills, they may receive computers as a time savings device, so long as vintage effects do not lower their productivity

transferability parameter, which determines how old-technology skills affect the initial stock of new-technology skills for people who adopt.

We measure technology adoption using computer use at work from the October Current Populations Surveys (CPS) computer use supplements. In contrast to existing work, we find considerable lifecycle variation in computer use and that the lifecycle pattern differs markedly by education.[3] Among college graduate men, young workers have adopted computers most intensively. At lower levels of education, however we find that more experienced workers are most likely to use computers. CPS earnings data indicate that experience premia have narrowed among more educated workers but increased among less educated workers.[4] Cross-industry regressions show that in industries with the greatest increases in computer use, the returns to experience have increased among high school graduates but declined among college graduates. Thus, a range of evidence indicates that among high school graduates computers have complemented experienced workers and that among college graduates they have complemented young workers.

The impact of technological change on workers at different levels of experience has implications for a broad range of phenomena. First, it can contribute to our understanding of the wage effects of recent technological changes. Research has investigated these effects on a variety of skill dimensions, including education, occupation, gender, race, and ability, either measured or unmeasured.[5] One prominent

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with them.

[3] Aggregating over education groups, Krueger [1993]; Autor, Katz, and Krueger [2000] and Freidberg [2000] find that computer use is quite flat over most of the career.

[4] This pattern is consistent with results in Katz and Murphy [1992] and Card and Lemieux [2000].

[5] Bound and Johnson [1992]; Krueger [1993]; Machin and Van Reenen [1998]; and Autor, Katz, and Krueger [2000] focus on the returns to education. Berman, Bound, and Grilliches [1994] study occupational differences. Looking across gender groups, Weinberg [2000] finds that computers have shifted the demand from physical to non-physical skills. Murnane, Willet, and Levy [1995] study the returns to measured cognitive ability, while Juhn, Murphy, and Pierce [1993] use residual inequality as a proxy for ability. Gottschalk and Moffitt [1994] note that much of the recent increase in residual inequality is transitory, leading to researchers to focus on the stochastic elements of technological change. Gould,

dimension that has received only limited attention is experience.[6] In fact, Card and DiNardo [2002] suggest that the increase in returns to experience among college graduates represents a challenge to the literature on skill-biased technological change. Unlike most variables that have received attention (e.g. education and ability), which are largely fixed over the career, in estimating the effect of technological change on experience premia it is important to account for changes in current investment.

Our results also shed light on vintage human capital models. Researchers have relied on vintage effects as an explanation for a range of phenomena.[7] Despite this, and notwithstanding Grilliches' [1957] well-known work, studies of the effect of experience on technology adoption are rare.[8] In contrast to most models, which argue that new technologies uniformly benefit young workers, we find evidence that new technologies can both complement existing skills and can be adopted first by workers that have experience with the old technology (Jovanovic and Nyarko [1996] consider this possibility). Researchers generally argue that schooling and experience play different roles in using new technologies, with new technologies complementing education (Welch [1970], Bartel and Lichtenberg [1987]), but substituting for experience for vintage

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Moav, and Weinberg [2001] consider both the returns to education and inequality within education groups. Looking across occupations, Gould [2002] shows the increased importance of (unobserved) general ability. Katz and Murphy [1992] and Doms, Dunne, and Troske [1997] consider a wide range of ability dimensions. Galor and Moav [2000] develop a theoretical model to show how technological change may favor higher ability workers.

[6] Heckman, Lochner, and Taber [1998] show that trends in the returns to education can affect observed experience premia through their effects on time spend in current production, but do not consider the effect of technological change on the returns to experience. Allen's [2001] results are consistent with ours.

[7] For example, Chari and Hopenhayn [1991] explain the slow pace at which new technologies diffuse in terms of vintage. In their model diffusion is slowed by the presence of a stock of workers with skills that are specific an old technology. Jovanovic and Nyarko [1996] show that imperfect transferability across technologies may generate technological lock in. Laing, Palivos, and Wang [1999] point to vintage as a determinant of educational attainment and wage compression. MacDonald and Weisbach [2001] explain the skewedness of the wage distribution on the basis of vintage human capital.

[8] Freidberg [1999] considers the relationship between retirement and computer adoption. Diamond [1980], studies the adoption of cliometrics among economic historians. Mulligan and Sala-i-Martin [2000] find little effect of age on adoption of new financial instruments. Bartel and Sicherman [1993, 1998] study the effect of technological change on retirement decisions and worker training. Aghion, Howitt, and Violante [2000] and Violante [2000] model the transferability of skills from one technology to later technologies.

reasons. Our results refine this understanding, indicating that the benefits of schooling are particularly strong at the beginning of the career, presumably because of the emphasis on abstract reasoning in school and the abstract nature of computer work. They also suggest the benefits of experience for people with less formal training (see Zuboff [1984]).

The findings presented can contribute to our understanding of life cycle productivity. A range of evidence indicates that young people find it easier to adapt to new technologies than older people and this seems consistent with casual observation.[9] To capture this possibility, we augment our model to allow an individual's productivity with a new technology to depend on his experience at the time he adopted the new technology. This approach represents a significant departure from traditional lifecycle models. The traditional economic approach focuses on life-cycle variations in the incentives to adopt new technologies given a stable production function.[10] We allow for life-cycle variations in the production function for new skills itself, which are likely to be particularly important during a period of rapid technological change. The possibility that people can switch to new technologies but find it increasingly difficult as they gain experience also constitutes a new form of vintage effect, which bridges some of the differences between vintage models of human and physical capital.[11] We present

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[9] Brynjolfsson, Renshaw, and Alstyne [1997] discuss the introduction of new technologies in a medical products plant. One goal of the redesign was to reduce the cost of switching production between products to allow greater flexibility. They found that workers who had grown accustomed to the old process had difficulty adjusting to the new system,

> Most workers continued to behave as if the paramount performance indicator was eliminating machine downtime. As a result, they avoided change-overs and kept the flexible machines running on the same product line almost as much as they had with designated equipment. Although this no longer increased the profitability of the factory or their individual pay, this and many other heuristics were too ingrained to overturn easily (p. 49).

Their discussion points to a negative effect of experience on productivity with the new technology that is distinct from traditional human capital considerations and which we model formally.

[10] See Ben-Porath [1967]; Mincer [1974]; Becker [1975]; and Weiss [1986] for a survey.

[11] Zeckhauser's [1968] model of vintage human capital assumes that technological progress generates ever-improving technologies. Individuals work with a technology for an optimally chosen period, acquiring

evidence that productivity with the new technology is highest for workers who adopted when young. Our findings in this area are consistent with research in cognitive psychology indicating that people are most adaptable when young (see Simonton [1988] on the psychological view; Galenson and Weinberg [2000, 2001] present econometric evidence).

Finally, proponents of creative destruction argue that computers represent a new general purpose technology (GPT) that has lead to the obsolescence of existing knowledge. A number of authors have argued that the productivity slowdown may have been caused by obsolescence of the existing stock of skills combined with greater time spent investing in new skills.[12] Our findings on this point are largely negative. While depreciation of skills with the old technology are found to increase after the introduction of the new technology, skills with the old technology are found to complement the new technology, and the amount of human capital devoted to investment declines at least in the short run. Overall, our estimates imply that creative destruction of human capital can not account for the trends in earnings in the data.

The next section discusses patterns in computer use and the returns to experience. Section III provides cross-industry evidence on the relationship between computer use and the returns to experience. Section IV develops the model. Identification and estimation are discussed in section V. Section VI presents estimates. Section VII

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skills specific to it, before switching to a new technology. The literature on vintage effects in physical capital, often assumes that once capital is put into place, new investments are impossible, so that productivity is fixed while the capital remains in use (see Cooley, Greenwood and Yorukoglu [1997]). The assumption that the capital stock cannot be adjusted is clearly untenable in the case of human capital, where ongoing investments are considerable. In the model proposed here, individuals endogenously switch technologies, but face greater costs at older ages. Empirical studies of vintage human capital have taken a much more limited approach. Weiss and Lillard [1978] and Neuman and Weiss [1995] assume that vintage affects only the rate of depreciation, because the introduction of new technologies causes existing skills to become obsolete. Other studies have assumed that vintage only affects the initial stock of human capital (see Rosen [1976]; Weiss and Lillard [1978] also discuss this approach).

[12] A variety of mechanisms have been proposed by Hornstein and Krusell [1996]; Greenwood and Yorukoglu [1997]; Howitt [1998]; Helpman and Rangel [1999]; Galor and Moav [2000]; and Violante [2000].

concludes.

## II. Patterns in Computer Use and Experience Premia

### *Computer Use*

We estimate the adoption of new technologies using data on computer use at work. Figure 1 shows the cross-sectional relationship between experience and computer use among men from 1984 to 1997, controlling for observable characteristics. Computer use rises considerably over the period, so the profiles for later years are above those for earlier years at all points. Computer use is considerably higher among college graduates (including those with additional education) than high school graduates (exactly). The shapes of the use-profiles also differ markedly by education, a fact which is not apparent from existing studies (see Krueger [1993]; Autor, Katz, and Krueger [1998]; and Freidberg [2001]), which aggregate over these groups causing the different lifecycle patterns to cancel one another. Among high school graduates, computer use is most prevalent among experienced workers, peaking among workers with between 20 and 30 years of potential experience.[13] For college educated workers, computer use is highest at the beginning of the career, falling considerably by older ages. In the earliest years computer use peaked at the time of labor market entry. In the later years computer use rises initially before turning down; controlling for occupation weakens this relationship. By the 1990s, with use among young college graduate men approaching 90% but continuing to rise among older workers, the profiles flatten.

It is worth noting that when use is fit with a probit, the profiles for the different years are essentially parallel, shifting out at close to a constant rate (see figures 3 and 5),

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[13] These are statements about the cross-sectional relationship between experience and computer use. For a given cohort, computer use increases monotonically over the lifecycle, reflecting improvement in computer technologies relative to non-computer technologies. The cross-sectional relationship provides an indication of the groups where the present discounted value of using is highest relative to the cost at a given point in time. Because the benefits of use are increasing over time and experienced workers have shorter careers, a positive cross-sectional relationship between experience and use indicates either that the costs are lower or that the current benefits of use are higher for experienced workers.

so the time-variation in shapes is due to non-linearities of a distribution function. Thus, the features to explain are the shapes of the profiles, not changes in the shapes. The model presented below is attractive for this purpose in that it generates essentially parallel profiles aside from the non-linearities implied by a distribution function.

Empirically, individuals who use computers in the work place are classified as having adopted a new technology. In some cases achieving proficiency with computers will require considerable investments in new skills, but in other cases learning to use a computer *per se* may not impose large costs.[14] Researchers have emphasized that the introduction of information technology is frequently linked to a cluster of complementary changes in work.[15] For example, a factory might introduce computers on the floor as part of a move toward an information-based production process. Thus, even if there is little cost to acquiring computer skills, workers will have to adjust to the new method of work (an example is Garicano [2001]). On the other hand, because adoption often involves a large scale re-engineering of work, the jobs of some people who do not work directly with computers are likely to have been affected by them.

***Experience Premia***

Figure 2 (solid line), shows the returns to experience among male high school and college graduates. Here too, the patterns differ across education groups. Among high school graduates, the returns to experience declined from 1959 through 1970, at which point they began rising through the mid-1980s. At the end of the sample, the returns to experience among high school graduate men are at their peaks over the 40-year period. Among college graduates, the experience premium declined during the 1960s, before rising through the mid-1970s. During the 1980s and 1990s the returns to experience

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[14] See discussions of the costs and returns to computer skills in Borghans and TerWeel [2001a] and Handel [2000].

[15] See Milgrom and Roberts [1990]; Bresnahan and Trajtenberg [1995]; Ichniowski, Shaw, and Prennushi [1997]; Caroli and Van Reenen [1999]; and Brynjolfsson and Hitt [2000].

among college graduate men declined, reaching a low at the end of the period.

To account for cohort-size effects and variations in labor market conditions, which may particularly affect new entrants to the labor market, figure 2 also shows the returns to experience adjusting for the age composition of the workforce and the unemployment rate (broken line)[16]. Demographic factors can account for virtually all changes in the returns to experience during the 1970s.[17] The aging of the high school graduate workforce, however cannot explain the increase in returns to experience among high school graduates since the late 1970s. The aging of the college graduate workforce did contribute to the reduction in returns to experience since the late 1970s; the adjusted series is flat during the 1980s with an increase and then a decline in the 1990s. The declining or constant returns to experience among college graduates not only contrasts with the large increase in returns to experience among high school graduates, but also the large increase in returns to skill along almost all other dimensions.

## III. Cross-Industry Evidence on Computer Use and the Returns to Experience

The preceding results suggest that technological change complements experience workers among high school graduates men and young workers among college graduate men. On the other had, it is conceivable that the observed patterns are spurious. To further probe the effect of technological change on the returns to experience, this section studies the cross-industry relationship between computer use and the returns to experience.

Our models are motivated by the assumption that experienced workers are imperfectly mobile across industries due to specific human capital and the assumption that workers receive at least a portion of the quasi-rents on their specific investments. If

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[16] See Freeman [1979]; Welch [1979]; and Berger [1985]; and Card and Lemieux [2000] on cohort size. Weinberg [2001] discusses labor market conditions.

[17] The decline in employment among young workers between 1959 and 1967, potentially linked to the Vietnam War, fully explains the decline in the experience premium among college graduates during this period and overexplains the decline among high school graduates.

among high school graduate men, technological change increases the demand for experienced workers, industries with greater technological change would see increases in the returns to experience.[18] If among college graduate men, technological change reduces the demand for experienced workers, the returns to experience should decline in industries with the most rapid technological change.

We run log earnings regressions including standard human capital variables and an interaction between experience and industry-level computer use as an explanatory variable. Separate regressions were run for high school graduate and college graduate men. The data are for 1984, 1989, 1993, and 1997, the years of the CPS computer use supplements. To control for economy-wide changes in the returns to experience, the models include year-specific quartics in potential experience. To control for differences and changes in wages across industries due to unobserved worker ability, efficiency wages, and demand shocks, the models include industry-year dummy variables. To control for time-invariant differences in the returns to experience across industries due, for example, to differences in human capital accumulation, the models include linear industry-specific experience effects. The inclusion of these effects ensures that our estimates are identified from differences across industries in the change in industry computer use.[19]

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[18] Consider a model with two-period-lived agents and industry-specific human capital. In the extreme, if experienced workers do not switch industries, an increase in the demand for experienced workers in an industry raises the (market clearing) wages of experienced workers in that industry. If young workers are freely mobile and the distribution of future wages is the same across industries then young workers will earn the same wages in all industries. Thus, the experience differential will increase. If worker's investments are purely firm-specific, if the wage of experienced workers are set by bargaining between firms and workers, technological change that increases the productivity of experienced workers, raises the cost to firms of losing experienced workers and leads them to pay higher wages. Again, if young workers are freely mobile and the distribution of future wages is the same in all industries, the wages of young workers will be the same in all industries and experience premia will be higher in industries with greater technological change. See Weinberg (2000) for an analysis.

[19] The model is more complicated than a traditional model with industry and time fixed effects because we are interested in the effect of one variable (computer use) on the effect of another variable (experience) on a third variable (log wages). Fixed effects models are often used to investigate the effect of one variable (e.g. computer use) on the mean of another variable (e.g. wages).

The estimates are reported in table 1. They show that in industries that experienced the most rapid increases in computer use, the returns to experience among high school graduate men increased. Mean industry computer use increased 21% among high school graduate men from 1984 to 1997, so this increase in computer use would have raised the return to one year of experience by .15% over this time period, or the return to 30 years of experience by 4.4%. Among college graduate men, mean industry computer use increased 29% from 1984 to 1997. This increase in computer use would have lowered the returns to one year of experience by .32%, and lowered the return to 30 years of experience by 9.6%.

One wants to be a bit cautious in interpreting these results as the causal effect of technological change on experience premia – for example they do not account for selection or changes in time devoted to investing in new human capital. Nevertheless, these estimates do indicate a link between computer use and experience differentials, in a way that is consistent with the cross-sectional patterns in computer use.

## IV. A Model

This section develops a model of technology adoption over the lifecycle that will serve as the basis for estimation. In the estimation, we employ psuedo panel data on earnings and computer use in the workplace. Thus the focus is on developing an estimable model of wages and technology adoption.

### *Setup of the Model*

We consider a risk neutral agent who maximizes the present discounted value (PDV) of his lifetime earnings. Let $x$ denote experience, $X$ denote the length of the career, $r$ denote the real interest rate, and $y(x)$ denote real earnings at experience level $x$.[20] The PDV of earnings from the beginning of the career is given by

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[20] For high school graduates $X$ is set to 47; it is set to 43 for college graduates, so retirement occurs at 65.

$$Y(0)=\int_0^X e^{-r\xi}y(\xi)d\xi\ .$$

The economy consists of two sectors, corresponding to the old and new technologies, which will be denoted by subscripts *O* and *N* respectively. Earnings with technology *i*, for someone at experience level *x* are $y_i(x)$. The PDV of earnings for a person at the beginning of his career who adopts the new technology at experience $x_A$ is

$$Y(0,x_A)=\int_0^{x_A} e^{-r\xi}y_O(\xi)d\xi+\int_{x_A}^X e^{-r\xi}y_N(\xi)d\xi\ . \qquad (1)$$

For comparability with prior research, earnings are assumed to follow the human capital model developed by Ben Porath [1967] within each technology. Let $h_i(x)$ denote the individual's stock of human capital with technology *i*; $s_i(x)$ denote the share of time devoted to human capital investment (as is common, we focus on time inputs); and $R_i(x)$ denote the real rental price per unit of human capital with technology *i*, all of which are functions of the individual's experience, *x*. The individual's earnings in sector *i* at experience level *x* are given by,

$$y_i(x)=R_i(x)h_i(x)[1-s_i(x)].$$

Let $\delta_i$ denote the depreciation rate of human capital in sector *i*, which combines both depreciation of human capital (e.g. from memory loss) and obsolescence induced by technological change. Within each sector, human capital evolves according to:

$$\dot{h}_i(x)=[s_i(x)h_i(x)]^\beta-\delta_i h_i(x).$$

In this expression, $\beta\in(0,1)$ gives the productivity of investments in human capital[21]. The individual chooses his investment path, $s_i(x)$, so as to maximize the PDV of his earnings.

We assume that the new technology is introduced in year $t_I$. For the estimation,

[21] The production function for human capital is assumed to be the same in both sectors. This formulation assumes that the production function reflects a constant feature of the learning process, which does not vary with the technology. When $\beta$ is allowed to differ, the estimates are often quite close, so this

we set $t_I = 1975$. While computers were available prior to the mid-1970s, researchers have argued that their impact was greatest beginning in the mid-1970s (e.g. Greenwood and Yorukoglu [1997]). After introduction in $t_I$, individuals have the option of switching from the old to the new technology at any point. Thus, everyone who entered the labor market before $t_I$, is assumed to work in the old sector until $t_I$. In $t_I$, they have the option of adopting the new technology immediately, adopting at some later point, or remaining with the old technology until the end of their career. Similarly, all individuals who enter in or after $t_I$ have the option of starting with either technology, and those who start with the old technology have the option of switching to the new one at any point or remaining with the old technology until the end of their careers.

The rental price of human capital changes over time. We estimate three productivity growth rates, $g_O$, the growth of the old technology before $t_I$; $g_{O'}$, the growth of the old technology after $t_I$; and, $g_N$, the growth rate of the new technology after it is introduced in $t_I$. (For the old technology, post-introduction variables are distinguished from pre-introduction variables with a prime, as in $h_{O'}(x)$ and $y_{O'}(x)$.) Thus, the introduction of the new technology is allowed to affect the rate of improvement of the old technology. The current analysis is partial equilibrium, focusing only on the labor market. Moreover, separate models will be estimated for specific education groups. So the $g_i$ should be interpreted as incorporating both technological progress, which may be biased between groups, and changes in the inputs of complementary and substitutable factors that affect the marginal product of labor. The $g_i$ can also capture network externalities that arise as the share of users increases in a reduced form manner. We also estimate three human capital depreciation rates, $\delta_O$, $\delta_{O'}$, and $\delta_N$, to capture the effect of

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assumption seems consistent with the data.

the new technology on the obsolescence rate of old-technology human capital.

Let *c* denote the cohort, or year the individual entered the labor market. The individual's experience at the time of introduction is given by $x_I = t_I - c$, which is allowed to take negative values for people who entered the labor market after introduction. The rental price in the old and new sectors when the individual is at experience *x* are given by,

$$R_O(x) = \begin{cases} R_O e^{(x-x_I)g_O} & \text{if } x < x_I \\ R_O e^{(x-x_I)g_{O'}} & \text{if } x > x_I \end{cases} \text{ and } R_N(x) = \begin{cases} 0 & \text{if } x < x_I \\ R_N e^{(x-x_I)g_N} & \text{if } x \geq x_I \end{cases},$$

where $R_O$ and $R_N$ denote the rental price in the old and new sectors in the base year, taken to be $t_I$. Presumably, the new technology exhibits greater productivity growth than the old technology, so the number of people who have adopted increases over time.

Here and below, three points in time will be arise repeatedly: the time of entry into the labor market or the cohort, *c*; the time or experience at which the new technology is introduced, $t_I$ and $x_I$, also referred to as the time or experience of introduction, which will vary across individuals as a function of their cohort; and the experience level at which the new technology is adopted, $x_A$, or more simply the "time" of adoption. We use of the identity $t = c + x$ to transfer from one set of variables to the other as appropriate.

***Introducing Technology Adoption***

The extent to which skills developed on the old technology are valuable with the new technology is an important determinant of the relationship between experience and adoption. The human capital of someone who adopts the new technology at experience *x* is $h_N(x) = h_{O'}(x)^\alpha$. In this formulation $\alpha$ reflects the complementarity-transferability of old sector skills to the new technology. The literature has emphasized the imperfect transferability of skills from old to new technologies. A value of $\alpha < 1$ reflects imperfect transferability (so long as $h_{O'}(x_I) > 1$). While less emphasized in the literature, when

$\alpha > 1$ the new technology complements existing skills.

Individuals are assumed to differ in terms of their productivity with the new technology relative to the old technology.[22] Let $\theta$ denote the individual's relative productivity with the new technology, which is assumed to depend on individual characteristics, *Z*, and a random component, $\varepsilon_\theta$, which is assumed to follow a log normal distribution. Formally, $\ln(\theta) = Z\Gamma + \varepsilon_\theta$, where $\varepsilon_\theta \sim N(0, \sigma_\theta)$. For simplicity, all people are assumed to have an equal productivity (of 1) in the old sector. The heterogeneity parameter, $\theta$, can also capture job-related differences in the importance of the new technology in a reduced form manner.

***Solution of the Model***

Given these assumptions, the individual's problem is to choose $x_A$, where $x_A \in [x_I, X]$ for people entering prior to introduction and $x_A \in [0, X]$ for people entering after introduction, $s_O(x)$ for $x \in [0, x_A]$, and $s_N(x)$ for $x \in [x_A, X]$ to maximize

$$Y(0, x_A) = \int_x^{x_A} e^{-r\xi + g_O \min[0, \xi - x_I] + g_{O'} \max[0, \xi - x_I]} R_O h_O(\xi)[1 - s_O(\xi)]d\xi$$
$$+ \theta \int_{x_A}^{X} e^{-r\xi + g_N(\xi - x_I)} R_N h_N(\xi)[1 - s_N(\xi)]d\xi$$

$$\textit{subject to } \dot{h}_i(x) = [h_i(x)s_i(x)]^\beta - \delta_i h_i(x), \;\; h_{O'}(x_I) = h_O(x_I), \;\; \textit{and } h_N(x_A) = h_{O'}(x_A)^\alpha .$$

Appendix A contains the solution to this optimization problem.

For people who will adopt the new technology, pre-adoption investment decisions depend on their expectations about adoption. For example, if skills in the old sector complement the new technology, $\alpha > 1$, then people who anticipate adopting in the future will spend more time investing prior to adoption. We assume that individuals who

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[22] Consistent with this assumption, recent work has argued that new technologies have emphasized a different set of skills than old technologies. Murnane, Willet, and Levy [1995] emphasize the increased importance of cognitive skills. Weinberg [2000] focuses on the de-emphasis of physical skills. In keeping with the selection model presented here, Gould [2002] estimates a multi-sector model of wage determination, and finds increased emphasis of general ability.

adopt the new technology do not adjust their human capital accumulation paths prior to adoption. This assumption has two components. First it implies that prior to the time of introduction, people did not anticipate the availability of the new technology. It is unlikely that many people realized the potential impact of information technology in the 1960s and early 1970s and adjusted their human capital accumulation paths in response to future adoption. We also assume that after introduction people follow the human capital accumulation path that would be optimal if they do not adopt the new technology. Even today it is not clear to what extent people anticipate adoption and adjust their skill investments. We have experimented with models in which people anticipate future adoption decisions and adjust their human capital accumulation paths accordingly. Unfortunately, this model exceeds computational limits.[23]

***Characterizing Adoption***

Let $y_{O'}(x,c)$ denote the earnings with the old technology after introduction for someone at experience level *x* in cohort *c*, following the optimal human capital accumulation path. Let $y_N(x,c,x_A,h_N(x_A))$ denote the earnings at experience level *x* for someone in cohort *c* with $\theta = 1$, who had a human capital stock of $h_N(x_A)$ when they adopted the new technology at $x_A$ and has since followed the optimal human capital accumulation path. Necessary conditions for the optimal time for an individual to adopt the new technology can be obtained by differentiating the individual's problem (1) with

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[23] As is shown below, the model implies a threshold value, $\theta^*(c,x)$, for each cohort and at each level of experience, such that people for whom $\theta$ exceeds the threshold will have adopted. In the model developed here there exists a simple formula for $\theta^*$ (see below). When human capital investments adjust in advance, no such formula exists, so a value of $\theta^*$ must be solved for as a fixed point by conjecturing a shadow value of human capital at adoption, $\lambda_O(x_A)$, then calculating $h_{O'}(x_A)$, which in turn implies a value for $\theta^*$. The whole procedure must be iterated until a fixed point is found. This is computationally burdensome because when wage profiles are estimated, it must be done at each point where the integrals are evaluated. One iteration of the present model takes approximately 1 minute on an Sun UltraSparc, compared to approximately 45 minutes for the model in which human capital investment is fully endogenous.

respect to $x_A$ to obtain

$$e^{-rx_A} y_{O'}(x_A, c) = -\theta \frac{\partial \int_{x_A}^{X} e^{-r\xi} y_N(\xi; c, x_A, h_N(x_A))}{\partial x_A}. \qquad (2)$$

An individual adopts at the point where earnings with the old technology equal the reduction in future earnings in the new sector from marginally delaying adoption.[24] Let $\tilde{\theta}^*(c, x_A)$ denote the value of $\theta$ that solves (2) for a given value of *c* and $x_A$,

$$\tilde{\theta}^*(c, x_A) = -\frac{e^{-rx_A} y_{O'}(x_A, c)}{\frac{\partial \int_{x_A}^{X} e^{-r\xi} y_N(\xi, c, x_A, h_N(x_A))}{\partial x_A}}.$$

Because the new technology is presumably improving relative to the old technology, $\tilde{\theta}^*(c, x_A)$ is decreasing in both arguments, implying that as time passes (either because people are in a later cohort or because they have more experience) people with lower values of $\theta$ find it optimal to adopt. Let $\tilde{x}_A(\theta, c)$ denote the optimal time of adoption for a given level of $\theta$ for someone in cohort *c*, which is the inverse of $\tilde{\theta}^*(c, x_A)$ for a given value of *c*. Here $\frac{\partial \tilde{x}_A}{\partial \theta} < 0$ and $\frac{\partial \tilde{x}_A}{\partial c} < 0$, so that people with higher values of $\theta$ adopt earlier, as do people in later cohorts, for a given value of $\theta$.

The individual's problem need not be globally concave in $x_A$, which complicates the adoption problem. The details are discussed in Appendix B. Accounting for this nonconvexity leaves intact the implication that there exists a critical value, $\theta^*(c, x_A)$, such that an individual adopts if and only if $\theta$ is greater than or equal to $\theta^*$. For a given cohort, more workers adopt as time passes (as the workers age), until some level of

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[24] The effect of delaying adoption on the PDV of earnings with the new technology includes the current earnings with the new technology, but also reflects the fact that delaying adoption (i) reduces the length of the career with the new technology, reducing the incentive to invest in new technology skills after adoption, and (ii) affects the initial level of new technology skills because it will be associated with a

experience, $\tilde{x}_A\left(\theta^{**}(c),c\right)$ at which point adoption for each cohort ceases.

***Characterizing Earnings***

In addition to an equation for technology adoption, we estimate a wage equation. Prior to introduction, all workers in a given cohort are identical. Until the time of introduction earnings evolve according to Ben Porath's model.

After introduction, determining implied earnings becomes more complicated because adoption decisions depend on $\theta$, which varies across the population. Calculating earnings involves integrating over the earnings of people who have already adopted and adding the earnings of people who have not yet adopted. At time, *t*, after introduction, the mean log earnings of cohort *c* workers is,

$$\begin{aligned}E\left[\ln(y_N)\middle|x,c\right]=&\int_{\theta^*(c,\max\{0,x_I\})}^{\infty}\ln\left(\theta y_N\left(x,c,\max\{0,x_A\},h_N\left(\max\{0,x_I\}\right)\right)\right)\phi\left(\frac{\theta}{\sigma_\theta}\right)d\theta\\&+\int_{\max\{0,x_I\}}^{x}\ln\left(\theta^*(c,x_A)y_N\left(x,c,x_A,h_N(x_A)\right)\right)\phi\left(\frac{\theta^*(c,x_A)}{\sigma_\theta}\right)\left|\frac{\partial\theta}{\partial x_A}(c,x_A)\right|dx_A\\&+\Phi\left(\frac{\theta^*(c,x)}{\sigma_\theta}\right)\ln\left(y_{O'}(x,c)\right)\end{aligned}$$

Here $\max\{0,x_I\}$ gives the experience level at which adoptions can first occur, which will either be at experience *0* (for cohorts that entered after introduction) or $x_I$ (for cohorts that entered before introduction). In general there will be a mass of workers who adopt at the first possible time (i.e. all those for whom $\theta>\theta^*(c,\max\{0,x_I\})$; the first term gives the earnings of these workers weighted by their density. The second term gives the earnings of workers who adopted at some point after entry or introduction but before $c+x$. Since within each cohort, the function $\theta^*(c,x)$ uniquely determines the value of $\theta$ for people who will adopt at *x*, the integration occurs over the experience at adoption, with $\theta$ being implied through a change of variables. The final term gives the earnings of

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change in the stock of old technology skills that are transferred.

people who have not adopted weighted by their mass. Explicit formulas for earnings are in appendix A.

## V. Identification and Estimation

### *Identification*

This section outlines the identification of the model. The next discusses estimation. It is worth considering what sources of variation are used to identify the parameters of the model. As is the case with any structural model, the specific parameter estimates will depend on the functional forms employed, but the basic implications of the data for the parameters should be general across a broad class of models. We have used Ben-Porath's model as the basis for our estimation because it is well understood and has been estimated often, augmenting it to incorporate multiple technologies and a complementarity between new technologies and old human capital to match the features of the data.

We have set two of the model's parameters *ex ante*, the interest rate, $r$, and the concavity of the human capital production function, $\beta$. In the case of the interest rate, reasonable information is available. We choose $r=.075$, an estimate which exceeds conventional estimates of the risk free interest rate, but is beneath the real rate of return on risky assets such as stocks. Existing studies that estimate structural human capital models often obtain high estimates of $r$ (see Brown 1976), which is also the case in the present model, when $r$ is estimated. We also set $\beta=.2$. Here existing studies have tended to estimate high values for $\beta$ (again see Brown 1976), but the present model, perhaps because it includes multiple sectors and the adoption equation, tends toward low estimates of $\beta$. Setting both parameters reduces computation time and improves inference for the other parameters, but the parameters of interest are not sensitive to these restrictions.

Our main interest is in the degree of complementarity or imperfect transferability of human capital across technologies, $\alpha$. This variable is particularly important for determining the relationship between experience and adoption. A general feature of human capital models, including Ben-Porath's model, is that human capital increases with experience, especially in the early years of the career. So when $\alpha>1$ ($\alpha<1$), the model predicts that adoption will increase (decrease), with the greatest effect at the beginning of the career as human capital is being accumulated. The parameter $\alpha$ also affects earnings – high values of $\alpha$ make post-1975 experience-earnings profiles steeper. The identification of the other parameters is discussed in Appendix C.

***Estimation***

The model consists of two equations, one for technology adoption and a second for wages. They are estimated in a two stage procedure to reduce computational requirements.

Let $Z_{i,x,t}$ denote the characteristics of the $i^{th}$ worker with experience $x$ in the sample in year $t$ and $Adopted_{i,x,t}$ denote his adoption status. Assuming that the random component of the individual's relative productivity, $\varepsilon_\theta$, is normally distributed implies

$$\Pr\left[Adopted \middle| x, Z_{i,x,c+x}\right] = \Pr\left[Z_{i,x,c+x}\Gamma_U + \varepsilon_\theta > \ln\left(\theta^*(c,x)\right)\right] = \Phi\left(\frac{Z_{i,c,c+x}\Gamma_U - \ln\left(\theta^*(c,x)\right)}{\sigma_\theta}\right)$$

$$= \Phi\left(\frac{1}{\sigma_\theta}\left[Z_{i,c,c+x}\Gamma_U + \ln\left(-\frac{\partial\int_x^X e^{-r\xi} y_N\left(\xi, c, x, h_N(x),\right)}{\partial x}\right) - \ln\left(e^{-rx} y_{O'}(x,c)\right)\right]\right) \quad \begin{matrix} where \\ t = c + x. \end{matrix}$$

In this formulation, an increase in $Z_{i,x,t}$ that raises the relative productivity with the new technology or an increase in the marginal cost of delaying adoption increase the probability of having adopted, while an increase in the earnings of non-adopters lowers the probability of adoption.

The first stage for the adoption equation is a probit model of adoption status on $Z_{i,x,t}$, and experience-year dummy variables (i.e. $t=1959$, $x=0$; $t=1959$, $x=1$; ...; $t=1967$,

$x=0$; ...)[25]

$$Use_{i,x,t} = \begin{cases} 0 \text{ if } Z_{i,x,t}\Gamma_U + \sum_{x,t} \nu_{x,t} I(\exp er = x, year = t) + \varepsilon_{U,i,x,t} < 0 \\ 1 \text{ if } Z_{i,x,t}\Gamma_U + \sum_{x,t} \nu_{x,t} I(\exp er = x, year = t) + \varepsilon_{U,i,x,t} \geq 0 \end{cases}$$

The dependent variables in a second stage are the coefficients on the dummy variables, $\nu_{x,t}$, for experience level *x* in year *t*.

In the case of the wage equation, in the first stage, the log weekly wage of individual *i* with *x* years of experience in the sample in year *t*, $w_{i,x,t}$ is regressed on his characteristics, $Z_{i,x,t}$ and the experience-year dummy variables,

$$w_{i,x,t} = Z_{i,x,t}\Gamma_W + \sum_{x,t} \omega_{x,t} I(\exp er = x, year = t) + \varepsilon_{wi,x,t}$$

In the second stage, the coefficients on the year-experience dummy variables, the $\omega_{x,t}$, are taken as the dependent variables.

The second stage is estimated by non-linear least squares. The criterion is,

$$\sum_{x,t} \eta^U_{x,t} \left( \nu_{x,t} - \frac{\ln(\theta^*(t-x,x))}{\sigma_\theta} \right)^2 + \sum_{x,t} \eta^W_{x,t} (\omega_{x,t} - E[\ln(y)|x, t-x])^2 \quad where\, c = t - x\,.$$

Here, $\nu_{x,t}$ and $\omega_{x,t}$ give the dummy variables from the first stage equations, and the second term in each expression gives the prediction of the model, as a function of the parameters. To account for heteroskedasticity, $\eta^U_{x,t}$ and $\eta^W_{x,t}$ give weights for the use and wage equations, equal to the square root of the number of observations in each cell. The data are described in Appendix D.

## VI. Results

### *High School Graduate Men*

The first two columns of Table 2 present parameter estimates for high school

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[25] The characteristics are dummy variables for years of education within broad education groups, and dummy variables for race, marital status, metropolitan residence, census division, and, depending on the specification, 14 occupation categories.

graduate men. Occupation controls are excluded in the first column and included in the second. The estimates are plausible. The fit of the model can best be seen by comparing the (de-meaned) dummy variables to which the computer use and wage equations were fit to the predicted values generated by the model. The top panel of figure 3 plots the computer use dummy variables, the $\nu_{x,t}$, along with the values predicted from the model. The model matches both the trend and lifecycle pattern in computer use, with use increasing in experience through the middle of the career and declining at the end of the career in a cross section.

The bottom panel plots individual earnings profiles for each year – the wage dummy variables, $\omega_{x,t}$ – along with the model's wage predictions. The model captures the levels of the profiles in different years as well as the shapes. The productivity growth rates play a large role in fitting the levels of the profiles – for high school graduate men, productivity is estimated to grow by 1.7% per year before 1975; after 1975 it is estimated to decline by 2.2% annually for non-users and to be flat for users. The negative productivity growth rate reflects the fact that technological change has been biased away from high school graduate men. The model also captures the rise in the returns to experience, with the predicted experience-earnings profiles stretching as the actual experience-earnings profiles stretch. Whereas the actual log wage differential between high school graduate men with 0-4 and 25-34 years of experience was .51 in 1972 rising to .63 in 1997, the estimates rise from .52 to .61. Two percentage points of the increase in the experience premium are due to changes in time devoted to investment, with the rest due to an increase in potential earnings for more experienced workers.

Another way to assess the model's predictions for earnings is to compare the actual and predicted lifecycle earnings for particular cohorts of workers. Figure 4 provides such a comparison. Actual life-cycle earnings paths for the period under investigation look little like the neat quadratic profiles described in the literature because the profiles for workers who entered before the mid-1970s show growth until that point and are then constant or decline. For example, real earnings peaked for cohort that entered in 1950 in the mid 1970s, half way through their careers. Despite their irregularity, the model fits the overall features of these lifecycle profiles well, although it under predicts earnings somewhat in the later years.

The model assumes that there are two economically distinct technologies with comparative advantage, different skill prices, different rates of productivity growth, and different human capital depreciation rates. One way of assessing the appropriateness of the model is to test whether the two post-1975 technologies are distinct. The tests, reported in the last row of the table, soundly reject the hypothesis of no difference between the technologies.[26] The estimates also imply a complementarity between the new technology and human capital with the old technology in that $\hat{\alpha} > 1$ and the difference is statistically significant. The inclusion of occupation controls reduces $\hat{\alpha}$ , because a high value for $\alpha$ implies adoption later in the career and when occupation is controlled adoption occurs earlier.

***College Graduate Men***

The second sets of columns of table 2 present results for college graduate men. Figure 5 presents actual and fitted values for computer use and wages. Again, the model captures the main features of both series. The computer use profiles reflect the increase in use over time and the decline in use with experience in a cross section, although they imply a rapid decline in use with experience at the beginning of the career, whereas the data show a smaller decline or even an initial increase. The model captures the levels and lifecycle patterns in wages well (bottom panel of figure 5). As indicated in figure 2, the trend in returns to experience among college graduates is small and the predicted profiles show little change. The model also matches the lifecycle earnings profiles shown in the lower panel of figure 4 even though actual earnings profiles looked little the canonical pictures. The model somewhat over predicts earnings in the very last years of the sample.

The coefficients are in the second set of columns of table 2. When occupation controls are excluded, $\hat{\alpha}$ is close to 1, but $\hat{\alpha} < 1$, when occupation controls are included, implying imperfect transferability. These results are sensible, because lowering $\alpha$ leads to earlier adoption and when occupation is controlled, use declines from the beginning of the career. The estimates also show high values for $g_N$, especially without occupation controls, and a large difference between $\delta_{O'}$ and $\delta_N$. These results arise because high growth and low depreciation make adoption particularly attractive to young workers. The fact that $\hat{\delta}_{O'} > \hat{\delta}_O$ and $\hat{\delta}_N < \hat{\delta}'_O$, implies that the introduction of the new technology raises obsolescence of old-technology human capital and new-technology human capital depreciates less rapidly than old-technology human capital. The $\chi^2$ tests (last row) soundly reject the hypothesis of no difference between the old and new technologies after introduction.

***Experience and Adaptability***

As indicated, there is evidence that younger individuals are more adaptable than older ones. To allow for this possibility, we augment the model by multiplying post-adoption productivity by the factor $e^{-\psi x_A}$. Thus, the individual's productivity with the new technology declines by $\psi$ for each year after labor market entry that the person adopts the new technology. Aside from this modification, the model remains as above. As noted, this modification represents a marked departure from traditional human capital models in assuming that the ability to acquire new skills varies over the lifecycle.

With this modification, the estimates for college graduate men that exclude occupation controls imply $\hat{\psi} = .004$ (s.e. .0015) and $\hat{\alpha} = 1.166$ (s.e. .074). Thus, when

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[26] This hypothesis imposes: $\alpha = 1$, $g_{O'} = g_N$, $\delta_{O'} = \delta_N$, $\sigma_\theta = 0$, and $R_O = R_N$.

this possibility is allowed, computers are found to complement human capital for college graduates (and the degree of complementarity is similar to that for high school graduates). The estimates indicate, that young college graduates are particularly productive with computers. Not surprisingly, including the additional parameter particularly improves the fit of the adoption equation (the variance of the error declines to .0011 from .0012). The improvement arises at the beginning of the career, with the augmented model implying that computer use is flat at the beginning of the career and then declines.[27] We interpret the large direct effect of experience among college graduates men as an indication that young college graduates are particularly proficient with new computer technologies, which seems consistent with obervation.

***Interpretation***

It is worth considering what might account for the difference in estimates for high school and college graduates. One source is Zuboff's [1984] study of technological change in paper mills. Zuboff's analysis suggests that, especially among less educated workers, existing knowledge may be important for learning new technologies. Prior to introduction of computer controls, experienced workers in two of the plants she observed had operated the plant based on hands-on techniques, such as smelling or feeling the pulp, developed with experience. Operating the new technology effectively required these workers to translate between the computer system and their hands on experiences with the equipment. While many of these workers' skills became obsolete, their existing knowledge helped these workers learn to work with the new computer system.

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[27] Both $\alpha$ and $\psi$ represent experience effects. $\alpha$, loads off of the human capital profile. A general feature of human capital models, including Ben-Porath's model, is that human capital accumulation is greatest in the early years of the life. So when $\alpha>1$ the model predicts that adoption will increase rapidly at the beginning of the career as human capital is being accumulated. By contrast, $\psi$ has a linear effect. When $\psi>0$, people who adopt the new technology when young have a comparative advantage with it relative to those who adopt later in their lives, so a high value of $\psi$ leads to greater adoption at young ages and less at older ages. Estimates with $\psi>0$ and $\alpha>1$ fit the computer use data well because $\psi>0$ can generate the large decline in use over most of the lifecycle, with $\alpha>1$ offsetting this effect at the beginning of the career when human capital is rising particularly rapidly.

In another factory, which was built from the outset based on computer operation, the workforce was more educated but younger than the others. These workers became effective primarily by developing a theoretical understanding of the production process, which was facilitated by the abstract nature of the computer-controlled system. Thus Zuboff's work suggests that just as experience helped less educated workers use the new technology, formal schooling was important for young educated workers.

***Productivity Levels***

Proponents of creative destruction argue that the productivity slowdown was generated by a reduction in time spent in current production while people invest in the new technology and by an increase in obsolescence of existing skills. These questions are difficult to answer without a structural model – obsolescence is unmeasurable and while some training activities are measurable (see Bartel and Sicherman 1998), much training may be difficult to measure. Assuming that wages reflect the value of the marginal product of labor, our model can shed light on these hypotheses in terms of their implications for changes in labor productivity.

Figure 6 plots the mean log wage and the mean of the predicted log wages for high school and college graduates in each year. The first columns of table 3 present these numbers. Mean log wages increased for high school graduates until the early 1970s and then declined through the end of the period. For college graduates, wages increased until the early 1970s, declined until the early 1980s and then rose through the end of the period. In both cases, the model captures the general features of the data. Not surprisingly, the model misses some of the transitory variations, such as low wages during the early-1980s recession.

We decompose the change in mean log wages after 1975 into two subcomponents,

$$E\left[\ln(y)\middle|x,c\right]=$$
$$\underbrace{\left(1-\Phi\left(\frac{\theta^*(x,c)}{\sigma_\theta}\right)\right)\left(\ln\frac{R_N}{R_O}+(g_N-g_O)(x-x_I)\right)+\Phi\left(\frac{\theta^*(x,c)}{\sigma_\theta}\right)(g_{O'}-g_O)(x-x_I)+\int_{\theta^*(x,c)}^{\infty}\ln(\theta)\phi\left(\frac{\theta}{\sigma_\theta}\right)d\theta}_{(1)}$$
$$\underbrace{+\int_{\theta^*(x,c)}^{\infty}\left[\ln(h_N(x)-q_N(x))-\ln(h_O(x)-q_O(x))\right]\phi\left(\frac{\theta}{\sigma_\theta}\right)d\theta+\Phi\left(\frac{\theta^*(x,c)}{\sigma_\theta}\right)\left[\begin{array}{r}\ln(h_{O'}(x)-q_{O'}(x))\\ -\ln(h_O(x)-q_O(x))\end{array}\right]}_{(2)}$$

The first component reflects productivity growth and selection on $\theta$. (These terms are intertwined because, as is typical in earnings models, the price of skill, $R_N$ , is not identified separately from the mean of the skill distribution, $\theta$, which was restricted to 0.) The second gives the difference in human capital stocks net of human capital devoted to investment after introduction versus before introduction.

The difference in human capital currently devoted to production can be further decomposed. For people who adopt the new technology at the time it is introduced or, for those entering the labor market after introduction and adopting immediately:

$$\ln(h_N(x)-q_N(x))-\ln(h_O(x)-q_O(x))\approx$$
$$\Bigg\{\underbrace{\left[h_{O'}(x_A)^\alpha-h_{O'}(x_A)\right]e^{-\delta_N(x-x_A)}}_{(2.1)}+\underbrace{h_{O'}(x_A)\left[e^{-\delta_N(x-x_A)}-e^{-\delta_O(x-x_A)}\right]+\int_{x_A}^{x}q_N(\xi)\left[e^{-\delta_N(x-x_A)}-e^{-\delta_O(x-x_A)}\right]d\xi}_{(2.2)}$$
$$\underbrace{+\int_{x_A}^{x}\left[q_N(\xi)-q_O(\xi)\right]e^{-\delta_O(x-x_A)}d\xi}_{(2.3)}-\underbrace{\left[q_N(\xi)-q_O(\xi)\right]}_{(2.4)}\Bigg\}\frac{1}{h_N(x)-q_N(x)}$$

The first term in this expression gives the effect of complementarity or imperfect transferability at the time of adoption on the human capital stock. The second term gives the effect of differences in depreciation between the new and old technologies, which affects the human capital stock at the time of adoption and all subsequent investments. The third term gives the effect of differences in lagged investment on the current human capital stock. The fourth term gives the difference in human capital currently devoted to investment. The expression for people who are still using the old technology after introduction is analogous, except the first term reflecting $\alpha$ is not present. The expression for people who do not adopt immediate (i.e. who work with the old technology after introduction and before adopting) is also analogous. In this case, $h_{O'}(x_A)$ include a term for human capital accumulated under the new technology after introduction.

The results of the decomposition are presented in the remaining columns of table 3. For high school graduates, the growth/selection component can more than account for the large decline in wages among high school graduates. This result is consistent with the low estimated productivity growth rates for high school graduates. The model shows that human capital inputs per high school graduate actually increased over this period. Most of the change is due to a decline in depreciation and to the complementarity between old-technology human capital and the new technology, which effectively raises human capital stocks. Because of the decline in productivity growth, high school graduates devote slightly less human capital to investment after introduction, which raises wages in the short run, but lowers them in the long run. Both effects turn out to be rather small.

Real productivity for college graduates dips immediately after introduction, before increasing in the long run. The estimates indicate that productivity grew for college graduates, but that human capital declined especially in the short run. The dip and subsequent increase in wages arises for two reasons. First, productivity growth is accelerating – it is higher for the new technology than the old technology and the share of people who have adopted increases over time. Second, human capital declines initially because depreciation with the old technology increases after the introduction of the new technology. Because depreciation with the new technology is lower, as more college graduates adopt, they are subject to lower depreciation and human capital increases. As with college graduates, there is little change in the amount of human capital devoted to investment. For college graduates, the estimates indicate weak imperfect transferability of human capital across technologies leading to small declines in human capital.

The decline in productivity is greatest for high school graduates. The data suggest that technologies have increased the importance of existing skills for this group, so perhaps it is not surprising that obsolescence turns out not to be the primary factor in the decline in their wages.

***Identification***

While our structural estimates have the advantage of allowing us to estimate parameters that have no direct empirical counterparts, they rely on specific assumptions in order to achieve identification. Figure 7 plots the pseudo-regressors for the computer use (panel a) and wage (panel b) equations to clarify how each parameter enters the model. The figures are for college graduate men without occupation controls and they include a direct effect of experience on adaptability, $\psi$. Estimates for high school graduates and the other models are similar. The first two panels are for $\alpha$ and $\psi$, which are of particular interest. Increasing $\alpha$ leads to an upward sloping adoption profile, with the greatest increase arising at the beginning of the career when human capital is growing most rapidly. Increasing $\psi$ leads to greater adoption at the beginning of the career, but reduces adoption later. The effect is close to linear. In figure 7b, increasing $\alpha$ makes experience profiles steeper, while increasing $\psi$ flattens them.[28] The other figures are also consistent with the discussion in the text and appendix.

## VII. Conclusion

This paper studies the relationship between experience and technology adoption and the effect of technological change on experience premia. In contrast to vintage models, we argue that new technologies may complement experience and be adopted first

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[28] These patterns are reversed in the very first years of the career. Immediately after adoption, earnings decline as people increase their human capital investments. As discussed above, increasing $\alpha$ reduces adoption at the beginning of the career, which increases observed earnings; increasing $\psi$ raises adoption, which raises observed earnings.

by experienced workers. Computer use, which we use to measure use of new technologies, increases in experience for less educated men, but declines in experience for more educated men. These patterns are echoed by recent trends in experience premia for both groups. Cross-industry earnings regressions also indicate that technological change has favored experienced workers among high school graduates and young workers among college graduates.

We develop a structural model of technology adoption and earnings, which can account for these patterns. In contrast to work that emphasizes imperfect transferability of skills across technologies, the estimates indicate that when workers adopt the new (computer) technology, a higher human capital stock with the old (non-computer) technology raises relative productivity with the new technology. There is some evidence that younger workers are better able to technological change. The results have implications for vintage human capital models and for creative destruction models of the productivity slowdown.

## Appendix A. Solution to the Human Capital Accumulation Problem

Working backwards, the Hamiltonian for someone who has already adopted the new technology is

$$H_N = \theta e^{-rx+g_N(x-x_I)} R_N h_N(x)[1-s_N(x)] + \lambda_N(x)\{[s_N(x)h_N(x)]^\beta - \delta_N h_N(x)\}.$$

The conditions for an optimum are $\lambda_N(X)=0$,

$$\frac{\partial H_N}{\partial s(x)} = -\theta_N e^{-rx+g_N(x-x_I)} R_N h_N(x) + \lambda_N(x)\beta s_N(x)^{\beta-1} h_N(x)^\beta = 0$$

$$-\frac{\partial H_N}{\partial h_N(x)} = -\theta e^{-rx+g_N(x-x_I)} R_N[1-s_N(x)] - \lambda_N(x)[\beta s_N(x)^\beta h_N(x)^{\beta-1} - \delta_N] = \dot{\lambda}_N(x).$$

Following Ben Porath [1967] it is possible to derive the law of motion

$\dot{\lambda}_N(x) - \delta_N \lambda_N(x) = -\theta R_N e^{-rx+g_N(x-x_I)}$ and show that

$$\lambda_N(x) = \frac{\theta R_N e^{-rx+g_N(x-x_I)}}{g_N - r - \delta_N}\left[e^{(g_N-r-\delta_N)(X-x)} - 1\right]$$

$$q_N(x) \equiv s_N(x)h_N(x) = \left[\frac{\beta}{\theta R_N e^{-rx+g_N(x-x_I)}}\lambda_N(x)\right]^{\frac{1}{1-\beta}} = \left\{\frac{\beta}{g_N - r - \delta_N}\left[e^{(g_N-r-\delta_N)(X-x)} - 1\right]\right\}^{\frac{1}{1-\beta}}$$

$$h_N(x) = h_N(x_A)e^{-\delta_N(x-x_A)} + \int_{x_A}^{x} q_N(x)^\beta e^{-\delta_N(x-\xi)} d\xi .$$

Earnings are

$$y_N(x,c,x_A,h_N(x_A)) = \theta R_N e^{(x-x_I)g_N}[h_N(x) - q_N(x)].$$

The solution to the individual's maximization problem for people using the old technology, either before or after introduction, is analogous. After introduction, for people who have not yet adopted, human capital evolves according to,

$$h_{O'}(x) = \begin{cases} h_0 e^{-\delta_{O'}x} + \int_0^x q_{O'}(x)^\beta e^{-\delta'_O \xi} d\xi & \textit{for people entering after } t_I \\ h_{O'}(x_I)e^{-\delta_{O'}(x-x_I)} + \int_{x_I}^x q_{O'}(x)^\beta e^{-\delta'_O \xi} d\xi & \textit{for people entering before } t_I \end{cases}.$$

where

$$q_{O'}(x) \equiv s_{O'}(x)h_{O'}(x) = \left[\frac{\beta}{R_O e^{-rx+g_{O'}(x-x_I)}}\lambda_{O'}(x)\right]^{\frac{1}{1-\beta}} = \left\{\frac{\beta}{g_{O'}-r-\delta_{O'}}\left[e^{(g_{O'}-r-\delta_{O'})(X-x)}-1\right]\right\}^{\frac{1}{1-\beta}}.$$

Earnings are $y_{O'}(x,c) = R_O e^{(x-x_I)g_{O'}}\left[h_{O'}(x) - q_{O'}(x)\right]$.

For people who entered prior to introduction, until the time of introduction human capital evolves according to,

$$h_{O'}(x) = h_0 e^{-\delta_O x} + \int_0^x q_O(x)^\beta e^{-\delta_O \xi} d\xi \;\; \forall x < x_I$$

where $h_{O'}(x_I) = h_O(x_I)$ and

$$q_O(x) \equiv s_O(x)h_O(x) = \left[\frac{\beta}{R_O e^{-rx+g_O(x-x_I)}}\lambda_O(x)\right]^{\frac{1}{1-\beta}} = \left\{\frac{\beta}{g_O-r-\delta_O}\left[e^{(g_O-r-\delta_O)(X-x)}-1\right]\right\}^{\frac{1}{1-\beta}}.$$

Earnings are $y_O(x,c) = R_O e^{(x-x_I)g_O}\left[h_O(x) - q_O(x)\right]$.

**Appendix B. Adoption Behavior**

As indicated, the individual's problem need not be globally concave in their optimal adoption time, $x_A$, so that for people with low values of $\theta$ it may be better not to adopt than to adopt at $\tilde{x}_A(\theta,c)$. Appendix figure 1 shows the PDV of lifetime earnings as a function of $x_A$ for a given cohort at three values of $\theta$. The necessary conditions identify the local maximum in all cases. Because of the non-concavity in $x_A$, the value of adopting at the local maximum may or may not exceed the value of never adopting, which is equivalent to adopting at *X*. As shown in appendix figure 1, there will exist a critical value $\theta^{**}(c)$, where the PDV of earnings for someone who adopts at $\tilde{x}_A(\theta^{**}(c),c)$ equals the PDV of earnings for someone who simply does not adopt. Because pre-adoption earnings do not depend on the adoption time, the critical value $\theta^{**}$, is where the PDV of earnings from $\tilde{x}_A(\theta^{**}(c),c)$ to the end of the career for someone who adopts at $\tilde{x}_A(\theta^{**}(c),c)$ equals the PDV of earnings from $\tilde{x}_A(\theta^{**}(c),c)$ to *X* for someone who does not adopt,

$$\theta^{**}(c)=\frac{\int_{\tilde{x}_A(\theta^{**}(c),c)}^{X} e^{-r\xi} y_{O'}(\xi,c)d\xi}{\int_{\tilde{x}_A(\theta^{**}(c),c)}^{X} e^{-r\xi} y_N(\xi,c,\tilde{x}_A(\theta^{**}(c),c),h_N(x_A))d\xi}.$$

For $\theta \geq \theta^{**}(c)$, the solution $\tilde{x}_A(\theta,c)$ to the first order conditions (2) represent a global maximum and characterize the optimal adoption time. For $\theta < \theta^{**}$, the solution $\tilde{x}_A(\theta,c)$ to the first order conditions (2) give a local optimum, but earnings are higher from never adopting.[29] Thus, for each cohort and each experience level there exists a critical value $\theta^*(c,x_A)=\max\{\tilde{\theta}^*(c,x_A),\theta^{**}(c)\}$ such that all individuals with values of $\theta$ greater than or equal to $\theta^*$ have adopted, while those with lower values of $\theta$ have not adopted. For a given cohort, more workers adopt as time passes (as the workers age), until $\tilde{x}_A(\theta^{**}(c),c)$ at which point adoption stops.[30]

**Appendix C. Identification**

The identification of the productivity growth parameters, $g_O$, $g_{O'}$, and $g_N$, is largely off of the time series in earnings for the specific education groups. Thus, high school graduate men experienced earnings growth before the mid-1970s and then earnings declines. The model matches these features of the data with a positive $g_O$ and lower or negative $g_{O'}$ and $g_N$. In order for computer use to increase over time, $g_N$ must

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[29] It is possible to show that $\tilde{x}_A(\theta^{**}(c),c)=\tilde{x}_A \;\forall c$. Put differently, all cohorts (except those that entered substantially before the new technology was introduced) stop adopting at the same experience level, although the critical value $\theta^{**}(c)$ is lower for later cohorts.

[30] A cohort that entered substantially before the new technology is introduced, may be past the experience at which the first order conditions for adoption apply (i.e. for $c < t_I - \tilde{x}_A$, $x_I > \tilde{x}_A(\theta^{**},c)$). In this case, there will be a group of workers whose values of $\theta$ are sufficiently high that their earnings from the time of introduction to the end of their careers are higher if they adopt immediately than if they never adopt. Individuals with sufficiently high values of $\theta$ exceed $\theta^{**}(c)$ adopt immediately, but no other workers in these cohorts adopt. The critical value is given by,

exceed $g_{O'}$, and the trend growth in computer use helps to identify this difference. The fraction of the workforce that has adopted increases over time, meaning that $g_{O'}$ has the largest effect on earnings shortly after 1975 while $g_N$ has a larger effect later.

The three depreciation rates govern the slopes of the (cross-sectional) experience-earnings profiles, with high depreciation flattening experience profiles.[31] As with the growth rates, $\delta_O$ is important before introduction.[32] Immediately after 1975, $\delta_{O'}$ is most important, but as a share of people who have adopted increases year by year $\delta_N$ becomes more important. The depreciation rates also affect adoption profiles. To see this consider that $\delta_N$ is likely to be low relative to $\delta_{O'}$ (and maybe $\delta_O$). A low rate of future depreciation with the new technology, generates an incentive to adopt the new technology; this effect is important for most of the career, but declines rapidly toward the end (just before retirement, future depreciation has no effect on adoption incentives).

The rental rates on human capital, $R_O$ and $R_N$, and the initial human capital stock, $h_0$, affect the level of earnings and much of the identification of these variables comes from fitting mean earnings. The ratio $R_N / R_O$ affects the relative productivity of the new and old technologies (but not the time trend in productivities), so some of the identification of this ratio comes from the level of adoption.[33] The initial human capital level, $h_0$, affects the level of earnings. In this model, where gross investments in human

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$$\theta^{**}(c) = \frac{\int_{x_I}^{X} e^{-r\xi} y_{O'}(\xi, c) d\xi}{\int_{x_I}^{X} e^{-r\xi} y_N(\xi, c, h_N(x_A)) d\xi}.$$

[31] While the first order effect of the productivity growth rates is on the change in earnings across time, a high productivity growth rate also steepens cross-sectional earnings profiles, by increasing the incentive to invest in human capital.

[32] It also affects experience-earnings profiles after introduction for people who entered before introduction because it affects their human capital stocks at the time of introduction.

[33] As is common in human capital models, the skill price $R_N$ is not identified separately from the mean of the skill distribution. We have restricted the mean of $\theta$ to be 0 and exclude an intercept from $Z$.

capital are independent of the current stock of human capital (the "neutrality assumption"), $h_0$ also affects the slope of experience-earnings profiles – a high $h_0$ raises human capital and earnings initially until the initial human capital stock depreciates. If $\alpha \neq 1$, $h_0$ also affects adoption. If existing human capital complements the new technology ($\alpha > 1$), then a higher $h_0$ raises adoption, and if $\alpha < 1$, then a higher $h_0$ lowers adoption. In either case, the effect is greatest at the beginning of the career, diminishing as the initial stock depreciates.

The amount of variation in comparative advantage with the new technology, $\sigma_\theta$, affects both the level and time-path of adoption. Conditional on the other parameters, when $\sigma_\theta$ is high there is considerable weight in the right tail of the relative productivity distribution leading to a high initial level of adoption, but since the density at any point is low, a smaller increase in adoption over time and less variation across experience groups at a point in time. More comparative advantage with the new technology also increases the scope for selection, which increases earnings after introduction, especially in the later years when more people have adopted.

Lastly, it is worth noting that the model implies that people who adopt the new technology have lower earnings in the years after adoption. This earnings decline arises endogenously as people spend more time accumulating human capital with the new technology. Thus, factors that increase adoption at, say the beginning of the career (lower values for $\alpha$ or $\delta_N$, or a higher value for $\delta_{O'}$) lead to earnings declines at the beginning of the career as adoption is increased.

**Appendix D. Data**

Technology adoption is measured using data on computer use at work from the Current Population Surveys (CPS), which contained questions on computer use in 1984, 1989, 1993, and 1997. The computer use samples included male high school graduates (exactly) and college graduates (or more) who were working or who held a job between the ages of 18 and 65.[34] Pooling data for all years, the high school graduate sample included 42,023 observations, while the college graduate sample included 32,183.

Data on weekly wages and hours worked were taken from the 1960 Census 1% Public Use Micro Samples (PUMS) and the March CPS Annual Demographic File from 1968 through 1998 at 5-year intervals. Earnings data for the cross-industry analysis were drawn from the 1985, 1990, 1994, and 1998 CPS, which covered the years in the computer supplements. In both data sets the data used correspond to the year before the survey. Separate wage and hours samples were used. The wage sample included male high school and college graduates between the ages of 18 and 65. The wage sample was restricted to people with high labor force attachment, defined as usually working full time, being in the labor force at least 40 weeks, and not working part year due to school or retirement.[35] The wage sample excluded respondents who were self-employed, who worked on a farm or without pay, or who had self-employment or farm income. Earnings were deflated using the CPI-U. The earnings of respondents with topcoded earnings were multiplied by 1.45.[36] Individuals with weekly wages less than $35 or greater than $5000 in 1982-1984=1 terms were eliminated from the sample, as were respondents with imputed earnings.[37] The 1960 Census and pre-1975 CPS reported weeks worked in bracketed intervals. When calculating weekly wages, respondents in each interval were

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[34] The education codes in the March CPS changed between 1991 and 1992 surveys. (The codes on the 1960 Census are comparable to those on the early CPS). Through 1991, individuals who had completed 12 years of schooling and not attended a 13th were classified as high school graduates, and those with 16 years of completed school or more were classified as college graduates. Afterwards high school graduates are identified, and respondents with a bachelors degree or higher were classified as college graduates. To adjust for changes in years of school among college graduates, regressions included dummy variables for each level of completed school or degree. In all analyses, experience was calculated as $\max\{0, \min\{age - school - 7, age - 17\}\}$.

[35] In the 1960 PUMS, the sample was restricted to people who worked at least 40 weeks, currently were working full time, and were not currently enrolled in school.

[36] Beginning in 1996, the CPS topcoded earners to the median value among topcoded respondents. These values were used.

[37] In 1960 Census individuals with imputed total income were deleted. Prior to 1975, the CPS only

assigned the mean weeks worked among respondents in the 1976-1980 March CPS who fell in the same intervals.

The hours sample, used to calculate the experience composition of the workforce, included all employed adult men between 18 and 65. On the post-1976 CPS annual hours were calculated as the product of weeks worked in the previous year and usual hours worked. The 1960 PUMS only contains data on weeks worked in 1959 (in bracketed intervals) and current hours (also bracketed). Respondents were assigned the mean annual hours among male respondents to the 1976-1980 March CPS who fell in the same intervals for weeks worked last year and current hours. In the 1968-1975 CPS, for people who were working at the time of the survey, annual hours in the previous year were calculated as the product of weeks worked last year (with values imputed for the brackets from the means in the 1976-1980 March CPS) and current hours. For respondents who were not working at the time of the survey, annual hours last year were computed as the product of weeks worked last year (with bracketed values imputed) and mean hours among men with the same full-time/part-time status. When calculating annual hours, CPS respondents were weighted by their March supplement weight.

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included allocation flags for family income. In these years, the family flag was used.

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Table 1. Industry computer use and the returns to experience.

| | HS Graduate Men | | College Graduate Men | |
|---|---|---|---|---|
| Experience*Computer use in industry | .007<br>(.003) | | -.011<br>(.005) | |
| Experience*Computer use among HS graduate men in industry | | .006<br>(.003) | | |
| Experience*Computer use among college graduate men in industry | | | | -.007<br>(.004) |
| $R^2$ | .346 | .346 | .327 | .327 |
| Observations | 101,343 | 101,343 | 68,541 | 68,541 |

Note. Sample pools data from 1984, 1989, 1993, and 1997. Models include controls for marital status; race; Hispanic background; urban residence; region of residence; year-specific quartics in experience; industry-year effects; and time-invariant, industry-specific, linear experience effects. College graduate sample includes college graduates and more education. Models for college graduates also include year-specific dummy variables for specific level of educational attainment.

Table 2. Estimates.

| | HS graduates | | College graduates | |
|---|---|---|---|---|
| $\alpha$, complementarity-transferability of old human capital to new technology | 1.156<br>(.034) | 1.048<br>(.016) | .962<br>(.030) | .872<br>(.047) |
| $g_O$, productivity growth rate of old technology before introduction | .017<br>(.0006) | .016<br>(.0006) | .010<br>(.001) | .012<br>(.0009) |
| $g_{O'}$, productivity growth rate of old technology after introduction | -.022<br>(.002) | -.014<br>(.001) | .008<br>(.001) | -.0006<br>(.002) |
| $g_N$, productivity growth rate of new technology | -.002<br>(.003) | -.008<br>(.002) | .048<br>(.009) | .038<br>(.004) |
| $\delta_O$, depreciation rate of old technology human capital before introduction | .135<br>(.006) | .126<br>(.005) | .126<br>(.007) | .090<br>(.006) |
| $\delta_{O'}$, depreciation rate of old technology human capital after introduction | .138<br>(.008) | .118<br>(.005) | .152<br>(.008) | .112<br>(.008) |
| $\delta_N$, depreciation rate of new technology human capital | .081<br>(.007) | .099<br>(.009) | .104<br>(.008) | .090<br>(.0009) |
| $\sigma_\theta$, standard deviation of relative productivity with new technology | .404<br>(.086) | .135<br>(.045) | .498<br>(.105) | .497<br>(.065) |
| $h_0$, initial human capital level with old technology | 4.12<br>(.220) | 4.63<br>(.236) | 4.39<br>(.284) | 7.060<br>(.582) |
| $R_O$, rental price of human capital with old technology at introduction | 64.7<br>(3.25) | 57.0<br>(2.65) | 82.1<br>(5.04) | 58.7<br>(4.55) |
| $R_N$, rental price human capital with new technology at introduction | 30.3<br>(4.16) | 35.0<br>(6.43) | 19.9<br>(5.73) | 27.9<br>(3.44) |
| Includes controls for occupation | no | yes | no | yes |
| Variance of error in 2nd stage computer use equation | .0011 | .0010 | .0012 | .011 |
| Variance of error in 2nd stage wage equation | .00016 | .00017 | .00028 | .00028 |
| $\chi^2(1)$ for $\delta_O = \delta'_O$ | .656 | 11.9 | 51.4 | 68.7 |
| $\chi^2(5)$ for equality of two sectors | 7931 | 4050 | 1014 | 8471 |

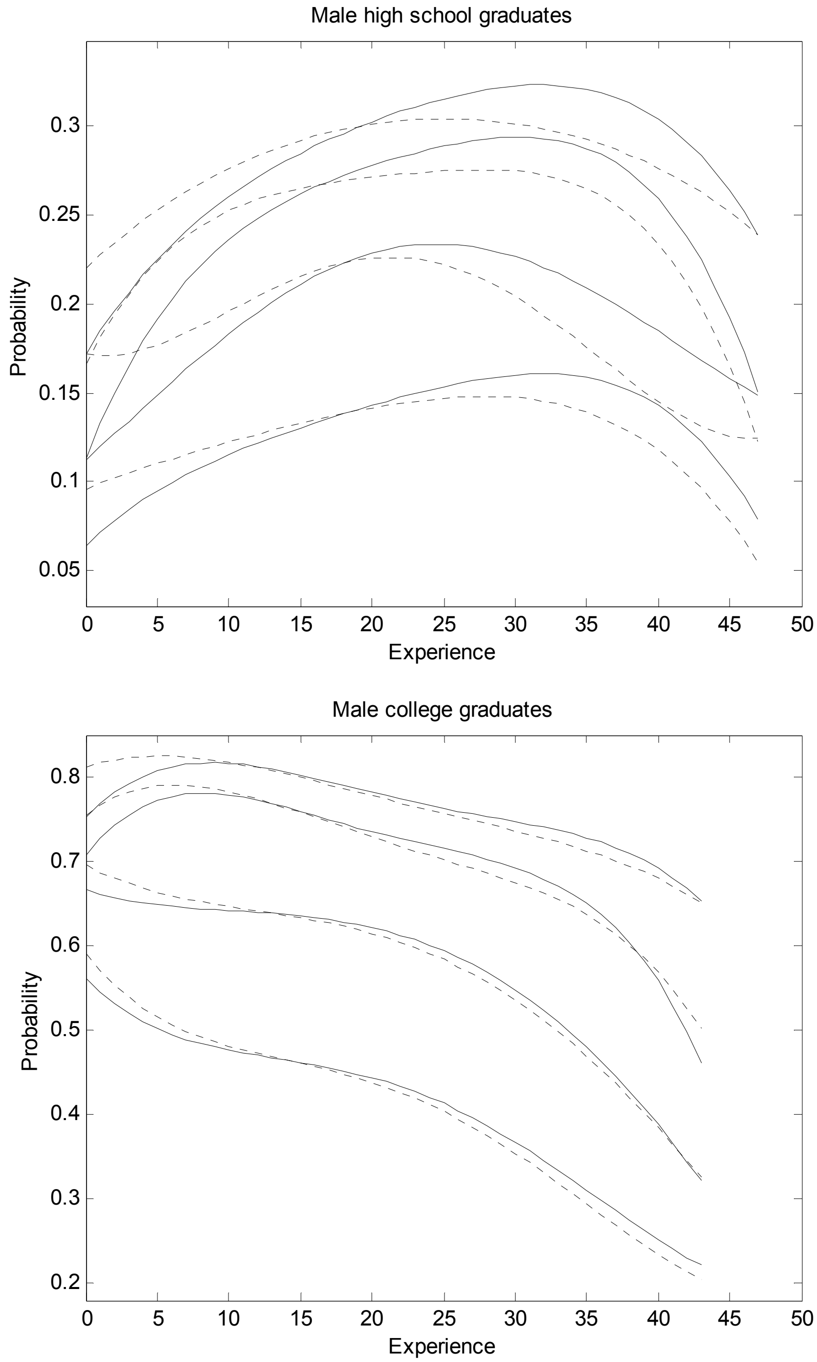
Note. Assymptotic standard errors reported in parentheses. Critical value at 5% level for $\chi^2(1)$ is 3.84 and for $\chi^2(5)$ is 11.07.

Table 3. Implied productivity and components of change in productivity.

| Year | Mean log wage | | Predicted difference from 1975 | Components of predicted difference | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Actual | Predicted | | Growth and selection | HC in current production | Components of change in HC in current production | | | | |
| | | | | | | Change in Investment | Change in HC stock | Components of change in HC stock | | |
| | | | | | | | | Depreciation | Complementarity / Transferability | Lagged investment |
| High school graduate men | | | | | | | | | | |
| 1959 | 5.64 | 5.66 | | | | | | | | |
| 1967 | 5.81 | 5.79 | | | | | | | | |
| 1972 | 5.93 | 5.88 | | | | | | | | |
| 1977 | 5.90 | 5.93 | .002 | -.097 | .099 | .017 | .068 | .011 | .069 | -.012 |
| 1982 | 5.78 | 5.84 | -.010 | -.212 | .122 | .013 | .086 | .040 | .075 | -.029 |
| 1987 | 5.76 | 5.76 | -.167 | -.324 | .159 | .008 | .119 | .075 | .081 | -.037 |
| 1992 | 5.68 | 5.70 | -.230 | -.429 | .202 | .002 | .159 | .117 | .084 | -.042 |
| 1997 | 5.67 | 5.65 | -.280 | -.525 | .248 | -.004 | .201 | .163 | .087 | -.048 |
| College graduate men | | | | | | | | | | |
| 1959 | 6.06 | 6.08 | | | | | | | | |
| 1967 | 6.14 | 6.15 | | | | | | | | |
| 1972 | 6.24 | 6.20 | | | | | | | | |
| 1977 | 6.20 | 6.20 | -.024 | .013 | -.038 | .019 | -.058 | -.048 | -.002 | -.008 |
| 1982 | 6.10 | 6.16 | -.067 | .050 | -.117 | .017 | -.142 | -.116 | -.003 | -.023 |
| 1987 | 6.16 | 6.17 | -.068 | .087 | -.145 | .011 | -.170 | -.133 | -.006 | -.031 |
| 1992 | 6.25 | 6.21 | -.019 | .127 | -.146 | .0001 | -.163 | -.117 | -.009 | -.037 |
| 1997 | 6.25 | 6.28 | .049 | .172 | -.127 | -.014 | -.131 | -.074 | -.014 | -.044 |

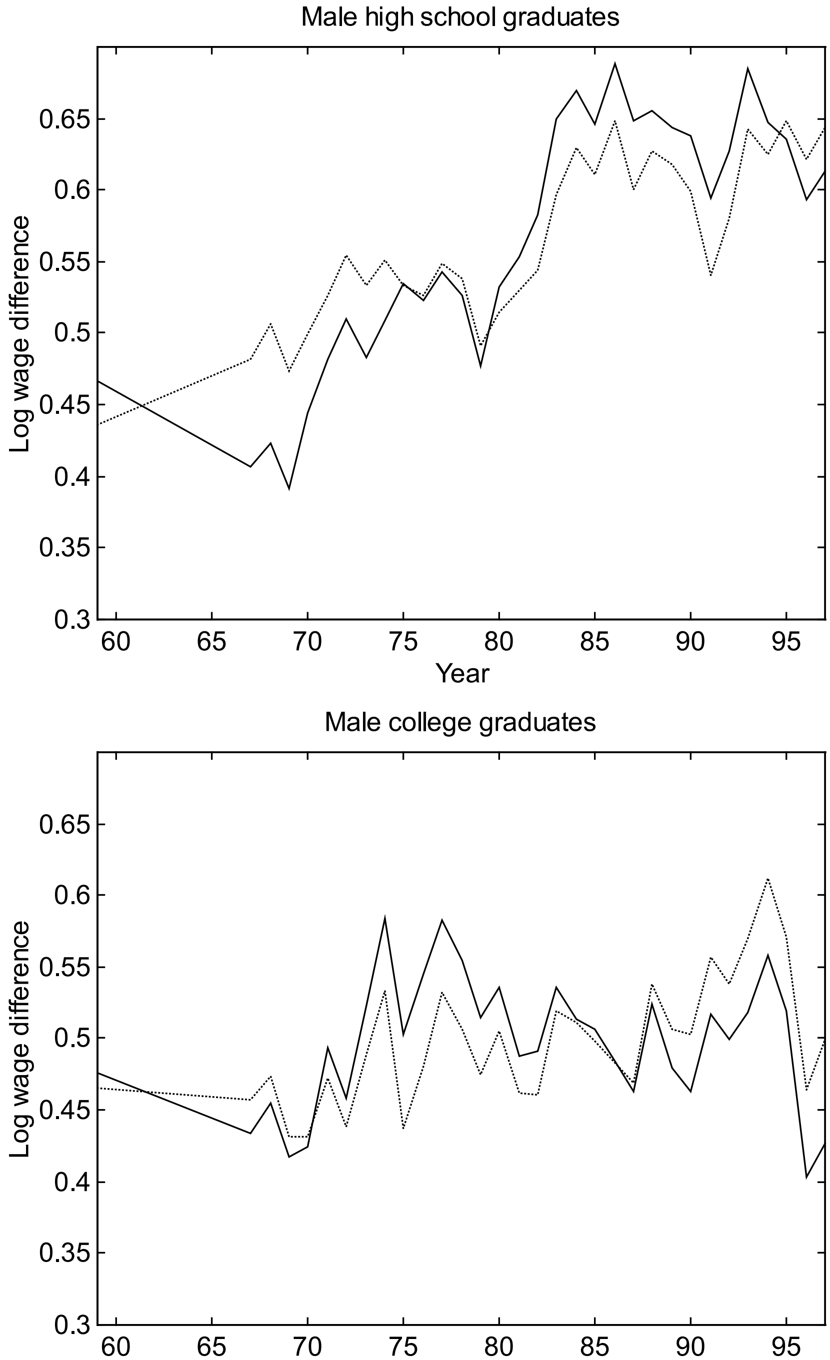
Note. Components of change in human capital in current production do not equal the change in human capital in current production because they approximate a log difference with a percentage change.

Figure 1. Probability of using a computer at work by experience for men, by education, 1984, 1997, 1993, 1997.



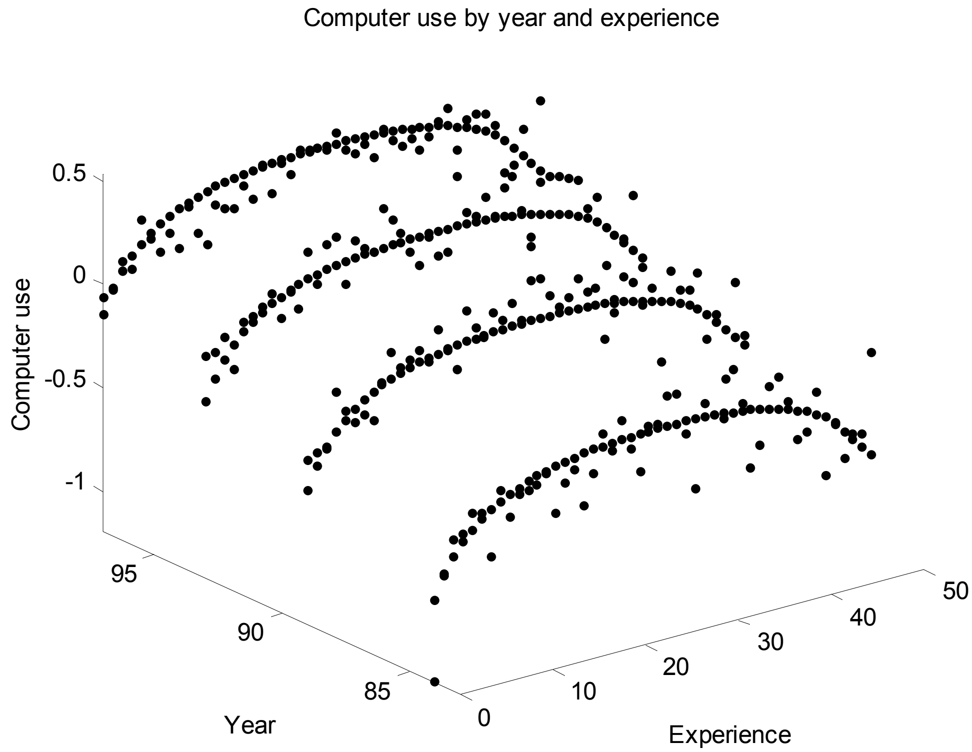

Note. Use profiles for later years above profiles for earlier years. Solid curves do not control for occupation, dashed curves control for 14 occupation categories. Probabilities predicted from a quartic in potential experience from linear probability models that control for years of education (among college graduates), marital status, race, urban residence, and region, and are evaluated at the mean characteristics in the group.

Figure 2. Returns to experience for men, by education, 1959-1997.




Note. Solid lines give log wage differential between workers with 25-34 and 0-4 years of potential experience. Dashed lines give log wage differential adjusted for share of workforce with 0-9 and 10-19 years of potential experience and civilian unemployment rate. Log wage differentials regression adjusted for years of education (among college graduates), marital status, race, urban residence, and region.

Figure 3. Actual and predicted values for male high school graduates.



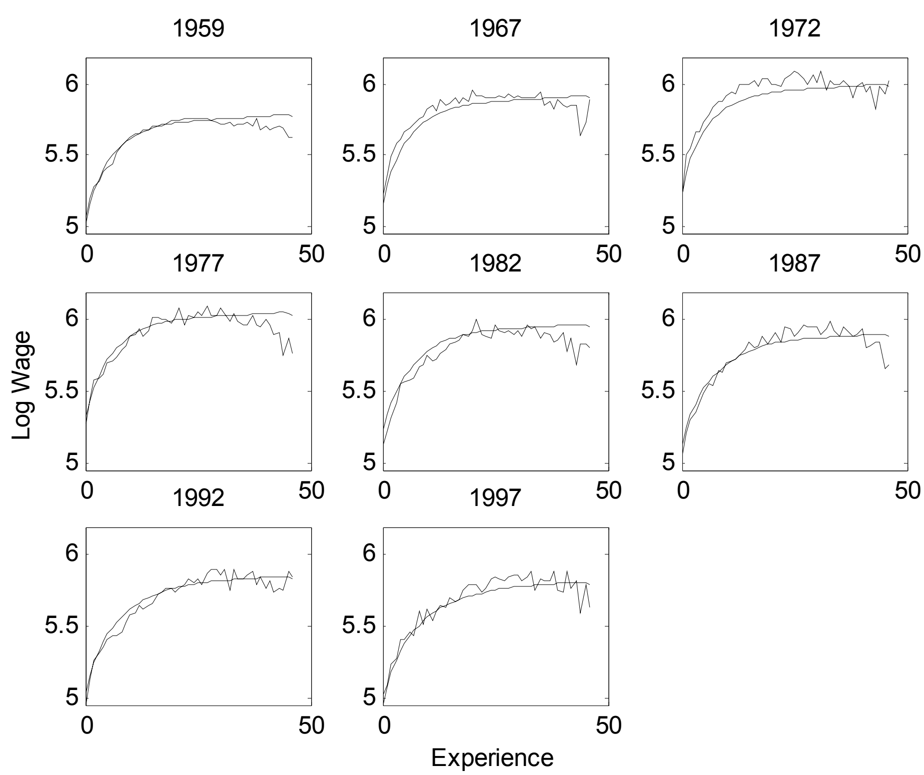
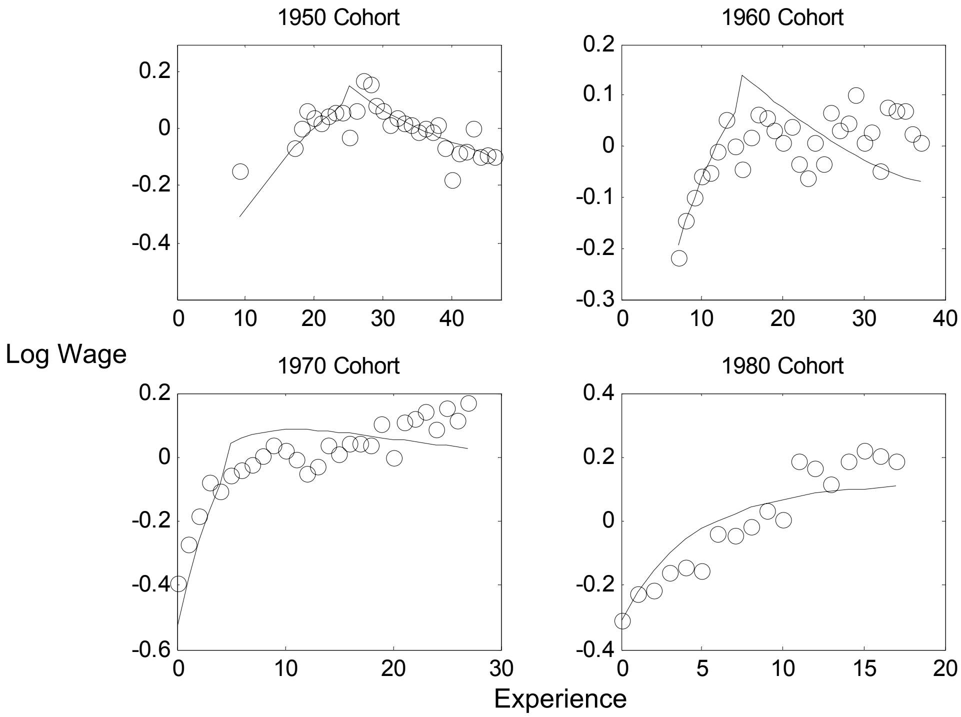
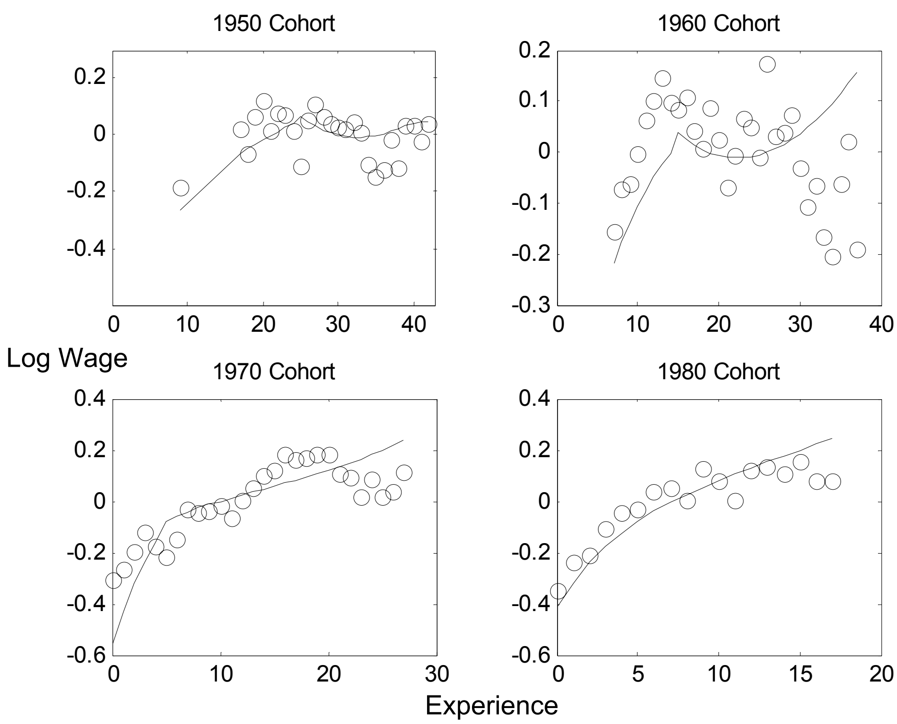



Figure 4. Actual and predicted lifecycle earnings by cohort.

A. High school graduate men.




B. College graduate men.




Note. Log wages and predicted values shown as deviations from mean.

Figure 5. Actual and predicted values for male college graduates.

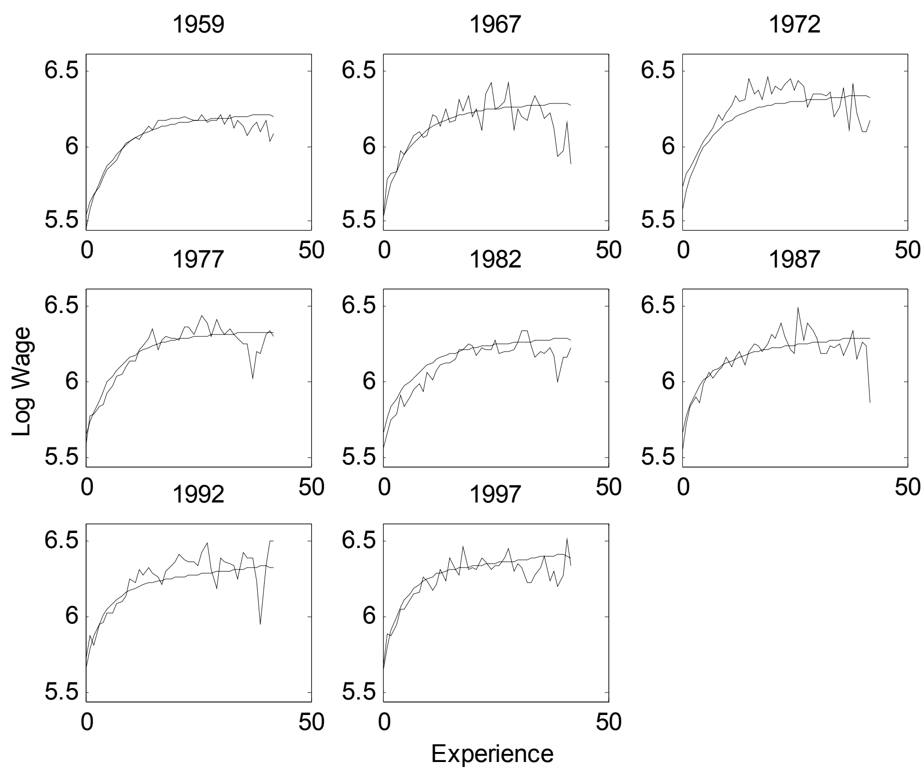
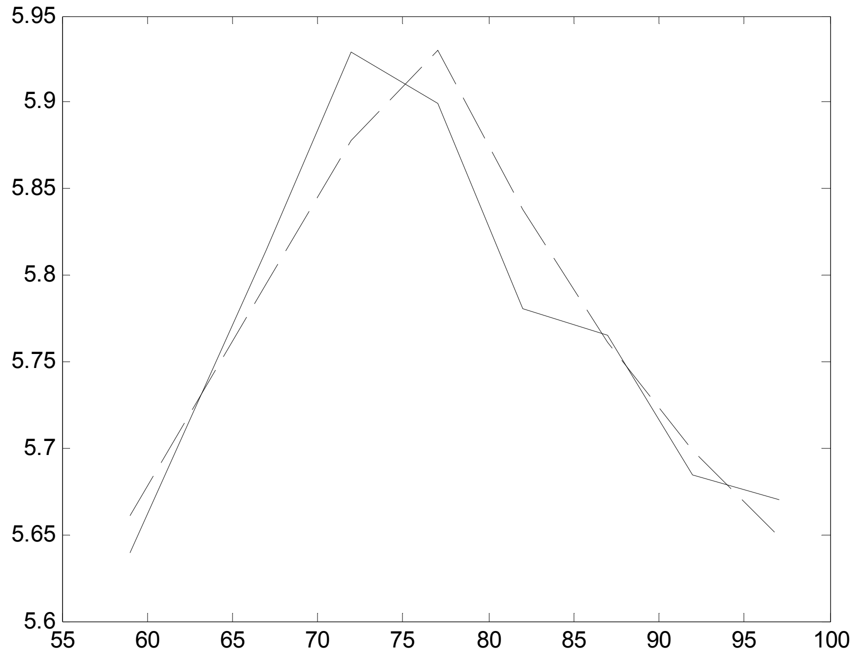
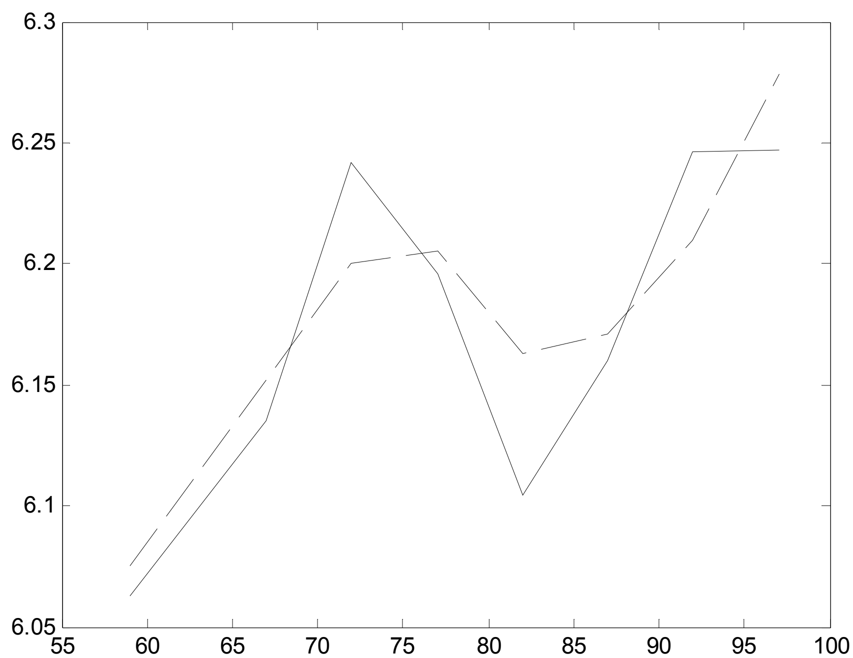



Figure 6. Actual and predicted mean log wages by year.
A. High school graduate men.

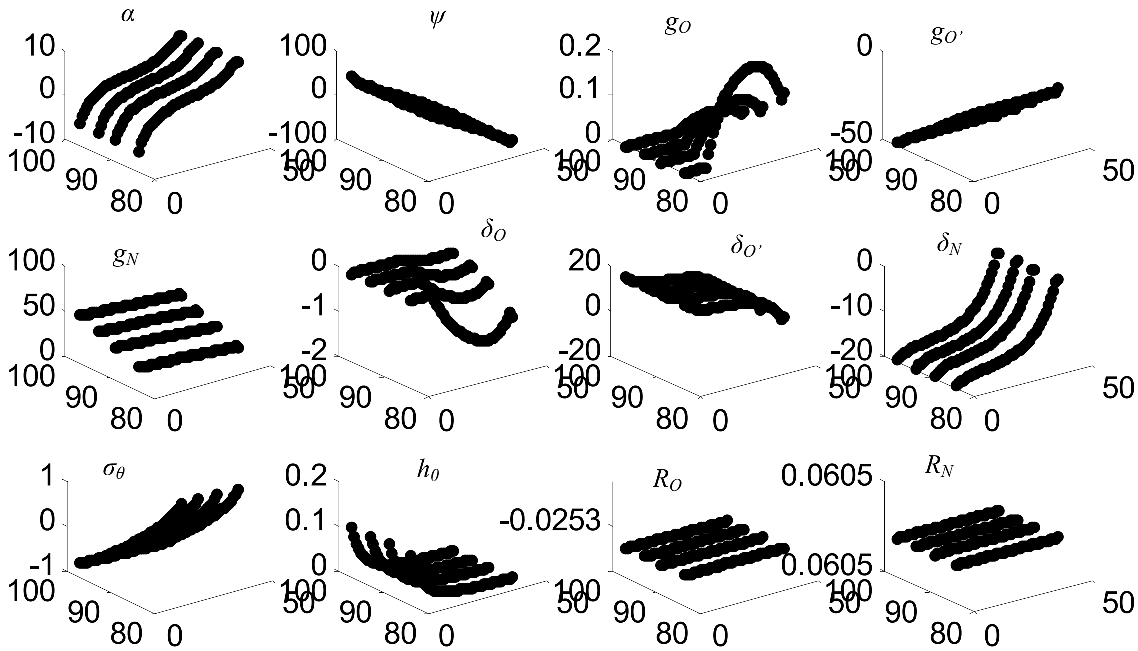



B. College graduate men.



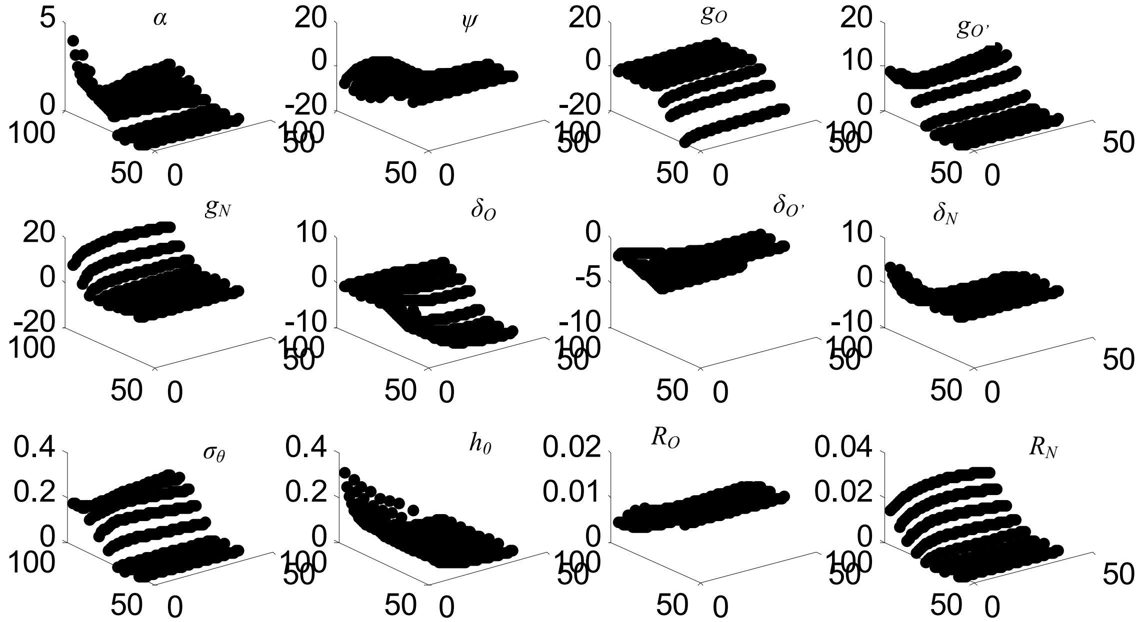

Note. Solid line plots the data; broken line plots the predictions of the model. Estimates from models without occupation controls.

Figure 7. Pseudo-regressors for college graduate men.
A. Computer use equation.



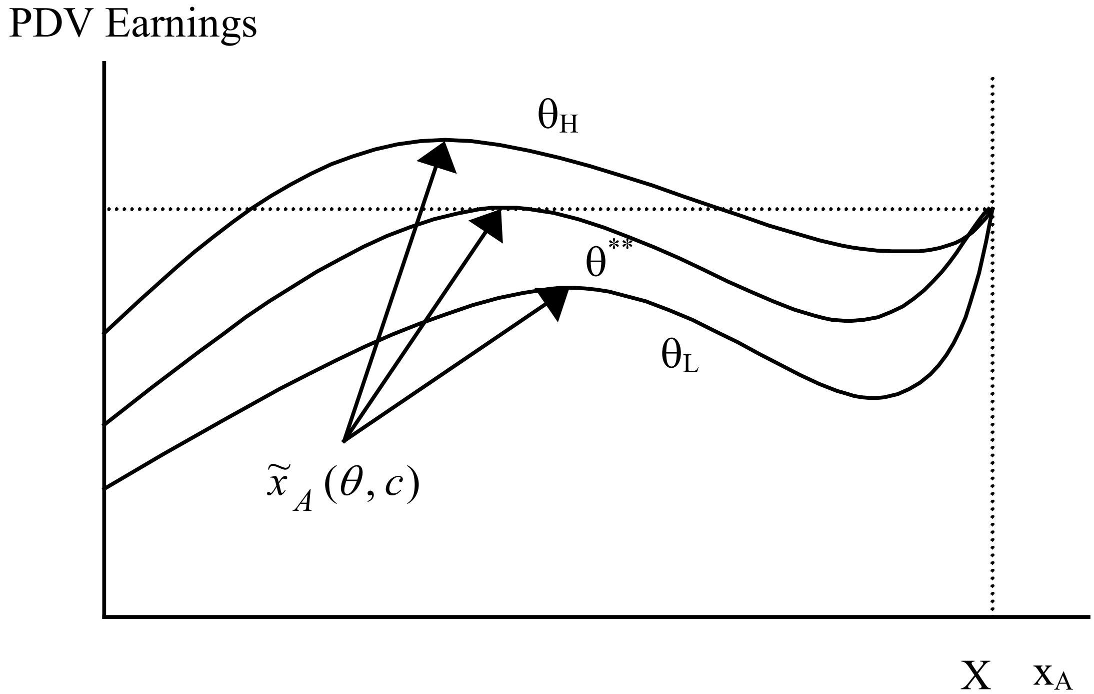

Note. Experience on x-axis, year on y-axis, and log wages on z-axis. Plotted values are derivatives of the predicted values with respect to each parameter.

Figure 7. Pseudo-regressors for college graduate men.
B. Wage equation.




Note. Experience on x-axis, year on y-axis, and log wages on z-axis. Plotted values are derivatives of the predicted values with respect to each parameter.

Appendix Figure 1. Present discounted value of lifetime earnings as a function of the adoption time and $\theta$.




Note. Curves give PDV of lifetime earnings from the time of labor market entry for a given cohort, with $\theta_H > \theta^{**} > \theta_L$.