The Price of Experience

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Abstract

We assess the role of the evolution of supply, driven by the demographic changes of the workforce, in accounting for the large changes in the return to labor market experience over time. We find that the large movements of the return to experience over the last four decades are almost perfectly explained by demographic changes alone, with no role attributable to demand shifts. Moreover, these demographic changes account for the differential dynamics of the age premium across education groups emphasized by Katz and Murphy (1992), and for the differential movements of the college premium across age groups emphasized by Card and Lemieux (2001). Thus, our analysis attributes a key role to demographic change in shaping several empirical regularities that are a focus of active research in macro and labor economics.

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1 Introduction

We assess the role of supply, driven by the demographic changes of the workforce, in accounting for the large changes in the returns to labor market experience over time. The fact that the changing returns to experience are at least as important as the rising returns to education in accounting for the dramatic changes in wage dispersion in the U.S. over the past several decades, suggests that it is important to understand the driving forces of these changes. We find that the movement of the return to experience over the 1968-2007 period is nearly perfectly explained by demographic changes alone, with no role attributable to demand shifts. Moreover, these demographic changes account for the differential dynamics of the age premium across schooling groups emphasized by Katz and Murphy (1992), and account for the differential movements of the college premium across age groups emphasized by Card and Lemieux (2001). Thus, our analysis attributes a key role to demographic change in shaping several empirical regularities that are a focus of active research in macro and labor economics.

Our modeling approach is based on the seminal analysis of the role of supply and demand factors in driving the experience premium in Katz and Murphy (1992). These authors assumed that workers supply two distinct productive inputs to the aggregate production. In particular, they assume that young workers (1-5 years of potential experience) supply exclusively one of these skills, which we will refer to as “pure labor,” or just “labor.” Old workers (25-35 years of potential experience) are assumed to supply exclusively the other skill, which we will refer to as the “pure experience skill,” or simply “experience.” Other workers are assumed to supply a bundle of labor and experience skills. The amount of labor and experience skill supplied by the workers of a particular age is determined by projecting their wages on wages of workers from the two age groups supplying “pure” skills. The correlation between the relative wages of the age groups supplying “pure” skills and the relative aggregate supplies of experience and labor then identifies the elasticity of substitution between these two factors in the aggregate technology.

We adopt a different empirical strategy for measuring the effective supplies of labor and
experience and find that it yields qualitatively different implications in assessing the role of supply and demand factors from Katz and Murphy (1992). We measure the effective amount of labor and experience supplied by each worker by decomposing individual wages using a version of the classic Mincerian wage equation. The individual wage equations are consistent with the aggregate production function and aggregate to determine the total supplies of effective labor and experience. The specification of the wage equation is designed to obtain a good fit to individual wages. It places no restriction whatsoever on whether the dynamics of the price of experience relative to labor – the experience premium – is driven by the relative supply of experience or the relative demand for experience. Nevertheless, our empirical approach reveals a correlation between the experience premium and aggregate relative supply of experience of $-0.95$ over our forty year sample period. We find no role for the demand shifts in accounting for the dynamics of the experience premium.\footnote{The analysis based on Katz and Murphy’s sample and methodology delivers a correlation between the relative wage and relative supplies of 0.6 to 0.8, which leaves considerable room for other demand based explanations for the return to experience as they discuss. Using their data, including a linear demand trend makes the effect of changes in relative supply on relative wages economically and statistically insignificant. Weinberg (2005) also emphasizes the role of demand effects.}

Our use of the panel data drawn from the Panel Study of Income Dynamics (PSID) allows us to separately identify the extent to which the life-cycle earnings profile is determined by the curvature of the technology governing the accumulation of experience versus changing utilization of the stocks of labor and experience with age. This allows us to make a distinction between the experience premium and the age premium (the relative wage of young and old workers). For any demographic subgroup, the wage response to a change in the aggregate price of experience is determined by the share of wages sourced from experience. Thus, when the renumeration for experience accounts for a larger share of wages of older workers, the age premium responds positively to the experience premium. However, the strength of this response can vary across demographic groups depending on how much their effective stock of experience relative to labor changes with age. We show that this insight quantitatively reconciles an economy-wide movement in the experience premium with the differential movements in the age premium across schooling groups.
The distinction between age and experience premia is relevant for assessing the role of supply and demand factors because the age premium rose much more in the 1970s and 80s for non-college than for college educated workers. The approach in Katz and Murphy (1992) cannot rationalize the differential movement in age premia across demographic groups in response to the change in the aggregate supply of experience because their empirical strategy is based on the assumption that the age premium coincides with the experience premium as the old and the young exclusively supply experience and labor, respectively. This led them and the subsequent literature to interpret this evidence as representing a shift in demand against young uneducated men. In contrast, we find no role for such demand effects in favor of non-college workers.

There is an important corollary to this finding. In an influential article, Card and Lemieux (2001) show that the college premium rose sharply after 1973 for young workers while it remained more or less constant for old workers. Thus, the relative college premium fell for old workers. Since the ratio of the age premium between college and non-college workers is mathematically equivalent to the ratio of the college premium between old and young workers, this finding is a dual of the finding in Katz and Murphy (1992) that the relative age premium fell for college workers. Thus, the fact that we match the evolution of the age premium across schooling groups implies that we also quantitatively account for the differential movement of the college premium across age groups.\(^2\) Thus, we identify the changing supply of experience, induced largely by the entry of the baby boom cohorts and women into the labor force, as the common source of changes in the aggregate experience premium, in the age premium across demographic groups, and the cohort effects in the college premium which have previously been studied separately from each other.

In addition to not imposing that certain subgroups exclusively supply either labor or experience, our empirical approach also provides a natural way to control for exogenous changes to the returns of other productive attributes (schooling, gender, race etc.) when measuring

\(^2\)As in Card and Lemieux (2001), we do not attempt to explain the changes in the economy-wide college premium which are treated as exogenous, and are the subject of debate. Krusell, Ohanian, Ríos-Rull, and Violante (2000) show that an aggregate production function featuring complementarity between capital and college educated workers can account for these movements.
the experience premium and the supplies of experience and labor. In contrast, this presents a challenge to the demographic cell-based correction for composition that represents the current standard in the literature. In particular applications, these advantages should be weighted against the possible selection biases affecting Mincerian wage decompositions.

The paper offers several additional contributions. On a methodological level, we show that it is possible to identify parameters of the aggregate production function from individual data by maintaining consistency between individual earnings equations and the aggregate production function. These estimates allow us to conduct the counterfactual analysis and to provide the structural interpretation to additional components of individual wages. For example, we find that the model accounts for much of the decline in the entry wages in the 1970s and 80s and their subsequent increase in response to the changing supply of labor and experience. Moreover, we show that estimation of the technology parameters using the micro data can identify the size and direction of the residual technical change.

As we mentioned above, most of the existing literature proxies actual work experience by the age-based potential experience (equal to age minus years of education minus six). In contrast, we directly measure actual work experience, which enables us to separately identify the effects of age and work experience on wages. We find that the hump shape in the return to experience over the life-cycle is not driven by the decreasing returns in accumulating experience. Instead, it is driven by a less efficient utilization of accumulated experience with age. This appears to be a robust empirical finding that will hopefully stimulate further research on its theoretical underpinnings and implications.

Our paper contributes to the large body of literature devoted to measuring and understanding the substantial change in the return to skill in the U.S. labor market. Skill is typically

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3 For example, Katz and Murphy (1992) construct wages for a potential experience group by adding up the wages of all demographic subgroups belonging to it using the fixed weights given by the average employment shares of the subgroups. This procedure controls for changes in composition of other attributes, e.g., education and gender, however, it cannot filter out the effects of changing returns to other attributes. For instance, changes in the college premium will differentially affect the wages of pure young and pure old workers, and this will bias the estimates of the experience premium. Similarly, the labor and experience supplies are aggregated using fixed efficiency weights, whereas changes in the college premium etc. should be reflected in the measurement of effective supplies.
defined according to its two observable dimensions: education and labor market experience. Katz and Autor (1999) note that this definition of skill follows naturally from the classic models that link higher earnings for more educated workers and upward sloping age-earnings profiles to acquisition of human capital through education and on-the-job training. In the influential Ben-Porath (1967) formulation, skills acquired through education and on-the-job training are perfectly substitutable. Thus, much of the literature has focused on accounting for the returns to education implicitly assuming that since work experience provides the same fundamental skill, the same explanation would also apply to the return to experience. Our findings in this paper suggest that skills acquired through schooling and labor market experience may represent distinct forms of human capital priced separately. This follows because the rising returns to education due to, say, skill-biased technical change or capital-skill complementarity did not affect the relationship between the relative supply of experience and its return that we document.

Another branch of the literature has explored the relationship between the size of a cohort and relative earnings of its members. Motivated by the baby boom generation experience, Freeman (1979), Welch (1979) and Berger (1985) provided early empirical evidence that larger cohorts suffer depressed earnings upon entry into the labor market. More recent evidence is summarized in Wasmer (2001b,a) and Triest, Sapozhnikov, and Sass (2006). Kim and Topel (1995) found that a sharp decline in the share of young workers in South Korea was associated with an increase in their relative earnings. Despite this suggestive evidence, Topel (1997) summarizes this literature by saying: “The effects of cohort size on earnings tend to be a sideline in the inequality literature.” Our theory and quantitative results show that demographic change arising from changes in cohort size may be key to understanding the dynamics of the returns to experience and the associated wage inequality across cohorts. In our setting different cohorts do not supply distinct labor inputs, yet cohorts separated more in time will appear to complement each other because of their compositional difference in terms of labor and experience.4

The remainder of the paper is organized as follows. In Section 2 we provide an overview of

4In Appendix A4, we derive the implications for complementarity across cohorts implied by our aggregate technology.
our measurement approach. In Section 3 we provide descriptive analysis that, without imposing the model structure, illustrates the very strong relationship between the relative price and the relative supply of experience. In Section 4, we structurally estimate the model and evaluate the role of supply and demand factors in accounting for the evolution of the experience premium over time. In Section 5, we use the estimated model to study the role of the dynamics of the supply of experience in driving (1) the rates of return to experience in the aggregate and across demographic groups, (2) age premium across education groups, (3) college premium across age cohorts, and (4) the measured total factor productivity. Section 6 concludes.

2 From Individual Earnings to Aggregate Quantities: Overview of the Measurement Approach

2.1 Individual Earnings

Consider an individual $i$ who at date $t$ supplies $\hat{l}_{it}$ units of effective labor input and $\hat{e}_{it}$ units of effective experience input to the labor market. The individual works for $h_{it}$ hours and has idiosyncratic productivity $z_{it}$. If market prices of labor and experience inputs are given by $R_{Lt}$ and $R_{Et}$, individual earnings can be written as

$$y_{it} = \left[ R_{Lt}\hat{l}_{it} + R_{Et}\hat{e}_{it} \right] z_{it} h_{it} \equiv R_{Lt} \left[ \hat{l}_{it} + \Pi_{Et}\hat{e}_{it} \right] z_{it} h_{it},$$

(1)

where $\Pi_{Et} \equiv \frac{R_{Et}}{R_{Lt}}$ denotes the experience premium, i.e. the relative price of experience to labor. This implies the log-wage equation

$$\ln w_{it} = \ln R_{Lt} + \ln \left[ \hat{l}_{it} + \Pi_{Et}\hat{e}_{it} \right] + \ln z_{it},$$

(2)

that, as we show below, can be extended to be suitable for empirical work and estimated to recover the individual stocks of effective labor and experience and the aggregate time series of the experience premium.
2.2 Aggregate Technology

We consider an aggregate production function that maps the aggregate stock of labor $L_t$ and the aggregate stock of experience $E_t$ into aggregate labor earnings $Y_t$ such that

$$Y_t = A_t G(L_t, E_t),$$

(3)

where $G$ is a constant-returns-to-scale function and $A_t$ represents the aggregate productivity of the composite input of experience and labor.\(^5\) We assume $G$ is continuous and differentiable in its arguments, and the Euler theorem implies $Y_t = A_t (G_{L_t} L_t + G_{E_t} E_t)$, where $G_{E_t} = \frac{\partial G}{\partial E_t}$ and $G_{L_t} = \frac{\partial G}{\partial L_t}$ will be referred to as marginal products of experience and labor (net of the productivity $A_t$), respectively.

Competitive firms can bundle workers to maintain the desired experience to labor ratio as in Heckman and Scheinkman (1987). This implies that prices of the two services provided by workers are competitively determined:

$$R_{L_t} = A_t G_{L_t},$$

(4)

$$R_{E_t} = A_t G_{E_t}.$$  

(5)

Then, the experience premium $\Pi_{E_t} = \frac{G_{E_t}}{G_{L_t}}$, is falling in the ratio of aggregate experience to labor $\frac{E_t}{L_t}$, as long as $G_{E_t} L_t > 0$: that is, as long as experience and labor are complements.

2.3 Consistent Aggregation

Summing the individual earnings equation in (1) over individuals $i$ at a given date $t$, we have

$$\sum_i y_{it} = R_{L_t} \sum_i \hat{l}_{it} z_{it} h_{it} + R_{E_t} \sum_i \hat{e}_{it} z_{it} h_{it}$$

$$= A_t G_{L_t} L_t + A_t G_{E_t} E_t$$

$$= Y_t$$

\(^5\)More precisely, let $\tilde{A}$ denote the Hicks-neutral productivity affecting the constant-returns-to-scale aggregate production function for output $\tilde{Y} = \tilde{A} F(K, G)$, that takes the capital stock $K$ and the the composite input of labor and experience $G(L, E)$ as inputs. Then the aggregate labor earnings are given by $Y = \tilde{Y} - \tilde{A} F_K (\frac{K}{L_t}) K = \tilde{A} F_G (\frac{K}{L_t}) G = AG$. Thus, the tfp term affecting aggregate labor earnings is given by $A \equiv \tilde{A} F_G (\frac{K}{L_t})$. 

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where the aggregate inputs $L_t, E_t$ are measured as

$$L_t = \sum_i \hat{l}_{it}z_{it}h_{it},$$ (6)

$$E_t = \sum_i \hat{e}_{it}z_{it}h_{it},$$ (7)

and prices $R_{Lt}, R_{Et}$ are determined by Equations (4) and (5), respectively.

Thus, the individual earnings in equation (1) consistently aggregate to the aggregate earnings as is implied by the aggregate production function in (3). This consistent aggregation holds for any homogeneous of degree one function $G$ as long as the aggregate inputs $L_t$ and $E_t$ are consistently measured as in equations (6) and (7).

### 2.4 Two Approaches to Estimating the Aggregate Production Function Parameters

To conduct quantitative analysis one must choose a specific functional form for $G$. We follow Katz and Murphy (1992) and restrict our attention to the commonly used class of constant elasticity of substitution (CES) production technologies. Specifically,

$$Y_t = A_t \left( \right.$$ 

(where $\mu \leq 1$), and the parameter $\delta > 0$ adjusts the relative scale between $L_t$ and $E_t$. The degree of substitutability between experience and labor is governed by the value $\mu$. If $\mu = 1$, experience and labor are perfect substitutes. In this case, the demographic change affecting the ratio of labor to experience does not affect the experience premium. However, if $\mu < 1$ so that labor and experience are not perfect substitutes, changes in the demographic composition of the workforce will affect the experience premium. This aggregate production function implies that the experience premium is given by

$$\Pi_{Et} = \delta \left( \frac{E_t}{L_t} \right)^{\mu-1}.$$ (9)

To estimate the parameters $\delta$ and $\mu$ we will follow the following two approaches.
1. The estimation of the log wage equation in (2) delivers the time-series for the experience premium $\Pi_{Et}$ and the measure of effective labor and experience at the individual level, which can be added up as in equations (6) and (7) to obtain the aggregate inputs $L_t$ and $E_t$. Taking logs on both sides of equation (9), one immediately verifies that a simple regression of the time-series of log experience premium on a constant and the time-series of the log of relative supplies allows one to estimate the parameters $\delta$ and $\mu$. This procedure does not impose the restrictions implied by the functional form of the production function on the individual earnings equations. Thus, the measurement of the aggregate prices and quantities is independent of the particular form of the aggregate production function. Consequently, this procedure is in no way hardwired to obtain an estimate of $\mu$ that is statistically different from 1. If changes in relative prices are independent from changes in relative supplies, the regression will reveal this. We pursue this approach in Section 3.

2. An alternative approach that imposes full model structure on individual earnings equations and is therefore more efficient is to substitute the explicit expression for the experience premium given by equation (9) into the individual log wage equation (2) and estimate its parameters directly from the micro data (of course, maintaining the consistent aggregation by imposing equations (6) and (7)). This procedure is computationally considerably more demanding but it also places no ex-ante restrictions making it likely to find evidence of complementarity between the two inputs. We pursue this approach in Section 4.

Finally, to assess the role of changes in aggregate demand driving the experience premium, in either of the two approaches $\delta$ can be assumed to be a particular function of time as in Katz and Murphy (1992) and the parameters of this function can be estimated together with $\mu$.

3 Descriptive Analysis

In this Section we (1) extend the specification of the individual earnings equations to make them suitable for the empirical work, (2) estimate the time-series of the aggregate experience
premium and of the aggregate supplies of labor and experience using the PSID data, and (3) obtain preliminary estimates of the aggregate production function parameters. The estimation in this section does not impose the specification of the aggregate production function on the individual earnings equations. Thus, the resulting estimate of the aggregate experience premium is not restricted by the theory and we will be able to assess the performance of the theory by its ability to match this time series.

3.1 Measuring the Aggregate Prices and Quantities of Labor and Experience using Individual Data

Our objective in modeling individual earnings is to develop a specification such that the mapping from the individual characteristics to wages picks up the first order features of wage differentials as documented by the vast existing labor literature. The basis of our empirical specification is the traditional Mincer equation that is a cornerstone of the empirical work in labor economics. This specification has been remarkably successful at empirically describing individual earnings with only a few shortcomings highlighted in recent work (e.g., Heckman, Lochner, and Todd (2006), Lemieux (2006)). A slight but economically interesting “fine-tuning” of the equation allows us to overcome these shortcomings.\(^6\)

Recall that our basic log-wage equation is given by

\[
\ln w_{it} = \ln R_{Lt} + \ln \left[ \hat{le}_{it} + \Pi Et \hat{\epsilon}_{it} \right] + \ln z_{it}.
\]

We follow the traditional Mincerian specification and model the individual productivity variable \(\ln z_{it}\) as determined by the vector \(\chi_{it}\) of the observable characteristics affecting log earnings in an additive manner (i.e. they scale the supply of labor and experience):

\[
\ln z_{it} = \alpha_t \chi_{it},
\]

where the vector \(\chi_{it}\) includes the observable characteristics, such as years of schooling, sex, race and geographic region, and \(\alpha_t\) is the vector of associated coefficients.

\(^6\)There is considerable debate in the literature regarding the interpretation of the Mincerian coefficient on education. While Mincer (1958, 1974) provided two sets of assumptions that allow for a structural interpretation of this coefficient, these assumptions are often questioned in the literature (e.g., Heckman, Lochner, and Todd (2006)). We do not insist on such an interpretation.
The Mincerian specification is typically applied to the cross-sectional data and it consequently treats $\alpha_t$, $R_{Lt}$ and $\Pi_{Et}$ as constants (that may differ across cross-sections separated in time). As we use the panel data, we allow the economy-wide coefficients on these variables to vary over time. The movements of these coefficients (often interpreted as return to years of schooling, gender gap etc.) have been substantial as documented in earlier studies.

Thus, the only difference between our specification and the Mincerian one is that the standard Mincerian specification assumes that there is only one productive input supplied by workers. In contrast, we would like to assess the possibility that workers supply two distinct factors to aggregate production and that their relative supplies affect their relative prices. If individual earnings consist of a sum of payments to two distinct factors of production, the logarithm of earnings is not equal to the sum of logarithms of constituent factors. This implies a different functional form, which, however nests the traditional specification (by setting $\Pi_{Et} \equiv 1$).

Finally, the standard specification models life-cycle curvature as a polynomial function of potential experience (age minus years of schooling minus six). The motivation for using the potential experience is that this is the only measure of experience available in the cross-sectional datasets. If one has access to the panel data, such as ours, where the actual experience and age can be separately observed, this assumption can be relaxed. Doing so is important in our analysis for the following three reasons:

1. The use of potential experience implies that age and experience co-move one-to-one within education groups, and that the age and experience premia are one and the same object. Relaxing this restriction allows us to study them separately.

2. An important critique of the standard Mincerian specification is that it cannot capture the cohort effects, such as the dramatic growth in “returns” to schooling among cohorts born after 1950 (Card and Lemieux (2001)). We will show below that modeling age and experience separately, allows our model to capture these effects.

3. This is potentially important for measuring the individual stocks of experience and labor. There are a number of reasons that wages may evolve over the life-cycle that imply dif-
ferent decompositions of individual earnings into the payments to labor and experience. First, the technology for accumulating experience skills may exhibit curvature. In other words, the mapping from years of experience $e_{it}$ to effective units of experience accumulated maybe given by some function $g(e_{it})$. Second, the stock of the labor endowment may depend on age. Finally, the efficiency with which the experience skill is utilized might depend on age as well. Our strategy is to allow for all these possibilities in the benchmark and study the sensitivity of results to restricted specifications. Fortunately, it is well known that the correlation between age and actual experience is relatively low, even among male workers (Light and Ureta (1995), among others). The same is true in our data and we face no empirical difficulty in separately identifying these sources of life-cycle wage evolution. A number of articles, e.g., Heckman, Lochner, and Todd (2006), have found that the standard Mincerian specification that implies that potential experience — earnings profiles are parallel across demographic groups is at odds with the data. Consequently, we allow the relationship between wages and age and experience to differ across schooling and gender groups.

We model the dependence of the life-cycle profile on age by introducing the age efficiency schedules for labor and experience $\lambda_L(j_{it}, s_{it}, x_{it})$ and $\lambda_E(j_{it}, s_{it}, x_{it})$, where $j$ denotes age measured in years, $s_{it} \in \{HS, C\}$ denotes either a “high school” education group $HS$ with years of schooling less than or equal to 12, or a “college” education group $C$ with years of schooling beyond 12, and $x_{it} \in \{M, F\}$, denotes gender with $M$ being male and $F$ being female. This implies that, aside from individual productivity $z_{it}$, the effective supply of labor of individual $i$ at date $t$, $\hat{l}_{it}$, depends on age, gender, and education, and is given by $\lambda_L(j_{it}, s_{it}, x_{it})$. Similarly, the effective supply of experience, $\hat{e}_{it}$, depends on the actual years of experience, age, gender, and education, and is given by $\lambda_E(j_{it}, s_{it}, x_{it})g(e_{it})$. It is convenient to define the relative efficiency schedule of experience as the ratio of the efficiency schedule of experience to that of labor $\lambda_{E/L}(j_{it}, s_{it}, x_{it}) \equiv \frac{\lambda_E(j_{it}, s_{it}, x_{it})}{\lambda_L(j_{it}, s_{it}, x_{it})}$. 
With these definitions, the log wage equation can be written as

\[
\ln w_{it} = \ln R_{Lt} + \ln \lambda_L (j_{it}, s_{it}, x_{it}) + \ln \left[ 1 + \Pi_{Et} \lambda_{E/L} (j_{it}, s_{it}, x_{it}) g (e_{it}) \right] + \ln z_{it}.
\]  

(11)

For the empirical implementation we need to assume the functional forms for the age efficiency schedules and for the experience skill production technology. As these have not being studied in the existing literature, we choose to adopt the following parsimonious but flexible specifications. We approximate the age efficiency schedules \( \lambda_L (j_{it}, s_{it}, x_{it}) \) and \( \lambda_E (j_{it}, s_{it}, x_{it}) \) by an exponential function of a second-degree polynomial with coefficients that are allowed to vary with gender and education

\[
\lambda_L (j_{it}, s_{it}, x_{it}) = \exp(\lambda_{L,0} (s_{it}, x_{it}) + \lambda_{L,1} (s_{it}, x_{it}) j_{it} + \lambda_{L,2} (s_{it}, x_{it}) j_{it}^2),
\]

(12)

\[
\lambda_E (j_{it}, s_{it}, x_{it}) = \exp(\lambda_{E,0} (s_{it}, x_{it}) + \lambda_{E,1} (s_{it}, x_{it}) j_{it} + \lambda_{E,2} (s_{it}, x_{it}) j_{it}^2).
\]

(13)

This implies that the relative efficiency schedule of experience is given by

\[
\lambda_{E/L} (j_{it}, s_{it}, x_{it}) = \exp(\lambda_{E/L,0} (s_{it}, x_{it}) + \lambda_{E/L,1} (s_{it}, x_{it}) j_{it} + \lambda_{E/L,2} (s_{it}, x_{it}) j_{it}^2),
\]

(14)

where \( \lambda_{E/L,k} (s, x) = \lambda_{E,k} (s, x) - \lambda_{L,k} (s, x) \) for \( k \in \{0, 1, 2\} \). Without loss of generality, we normalize \( \lambda_{L,0} (s, x) = \lambda_{E,0} (s, x) = 0 \) for the low education \((s = HS)\) group.

For the technology mapping years of experience into effective experience input, we assume a flexible quartic specification\(^7\)

\[
g (e_{it}) = e_{it} + \theta_1 e_{it}^2 + \theta_2 e_{it}^3 + \theta_3 e_{it}^4.
\]

(15)

Substituting expressions (10), (12), (14), and (15) into equation (11), and substituting \( \ln R_{Lt} \) by a time dummy \( D_t \) we obtain the log wage equation to be estimated

\[
\ln w_{it} = D_t + (\lambda_{L,0} (s_{it}, x_{it}) + \lambda_{L,1} (s_{it}, x_{it}) j_{it} + \lambda_{L,2} (s_{it}, x_{it}) j_{it}^2)
\]

\[
+ \ln \left[ 1 + \Pi_{Et} \exp \left( \lambda_{E/L,0} (s_{it}, x_{it}) + \lambda_{E/L,1} (s_{it}, x_{it}) j_{it} + \lambda_{E/L,2} (s_{it}, x_{it}) j_{it}^2 \right) \right] + \alpha_t \chi_{it} + \epsilon_{it},
\]

(16)

\(^7\)To facilitate the transparency of some derivations below we do not allow for the differences in parameters of this mapping across schooling and gender groups. We have verified that allowing for such heterogeneity has no substantive impact on any of the results in the paper.
where $\epsilon_{it}$ represents a classical measurement error.

Estimating equation (16), we obtain the estimates of parameters of the efficiency schedules $\hat{\lambda}_L(j, s, x)$, $\hat{\lambda}_E(j, s, x) = \hat{\lambda}_{E/L}(j, s, x)\hat{\lambda}_L(j, s, x)$ and $\hat{g}(e)$, the estimates of the time-varying coefficients ($\hat{\alpha}_t$, $\hat{D}_t$, and experience premium $\hat{\Pi}_{Et}$). These estimates allow us to construct the estimated aggregate labor and experience inputs $\hat{L}_t$ and $\hat{E}_t$ at each date $t$ as

$$\hat{L}_t = \sum_i \hat{\lambda}_L(j_{it}, s_{it}, x_{it})z_{it}h_{it},$$

$$\hat{E}_t = \sum_i \hat{\lambda}_E(j_{it}, s_{it}, x_{it})\hat{g}(e_{it})z_{it}h_{it}. \tag{17}$$

(18)

To investigate the role of supply in determining the returns to experience, we seek to document a relationship between the estimated experience premium $\hat{\Pi}_{Et}$ and the estimated relative supply of experience $\hat{E}_t/\hat{L}_t$ constructed using these equations. We should emphasize that we did not impose any of the model structure on these earnings equations (except for perfect competition and constant returns to scale in aggregate production). Thus, there is no hardwired relationship between $\hat{\Pi}_{Et}$ and $\hat{E}_t/\hat{L}_t$. To the extent that we find a relationship between them, it will be suggestive of a relationship between the relative supply of experience and its relative price.

3.2 Results

We obtain estimates of the parameters applying a nonlinear least-squares method to the log-wage equation (16). The estimates of these coefficients and their standard errors are reported in Appendix Tables A-1 and A-2. In what follows we first discuss the implied aggregate quantities of interest, followed by the discussion of the individual wage determination.

3.2.1 The Relative Supply of Experience and its Relative Price

The estimated series of the experience premium $\hat{\Pi}_{Et}$ and the implied aggregate experience-labor ratio $\hat{E}_t/\hat{L}_t$ are plotted in Figure 1. We refer to these estimates as “unrestricted” as they are independent of the aggregate production function we are ultimately interested in estimating. There is a substantial movement of the experience premium, which increases with an average
growth rate of 5.1% per year between 1968-1988 and falls thereafter back to its level in 1979 by 2007. The estimated experience-labor ratio over the same period displays a clear negative co-movement with the experience premium. The correlation coefficient between the log experience premium and log of the experience-labor ratio is remarkably high at $-0.95$. Thus, the unrestricted data imply a very strong co-movement between the relative price of experience and its relative price. This suggests that the aggregate technology features complementarity between aggregate experience and labor. We obtain preliminary estimates of this technology next.

### 3.2.2 Preliminary Estimation of the Aggregate Production Function Parameters

Taking logs on both sides of equation (9) that determines the experience premium given the CES aggregator of labor and experience, we obtain:

$$\ln \Pi_{E_t} = \ln \delta + (\mu - 1) \ln \left( \frac{E_t}{L_t} \right).$$  \hspace{1cm} (19)

Treating this equation as a regression of the unrestricted experience premium on a constant and the unrestricted relative supply of labor and experience, one can obtain estimates of the parameters $\delta$ and $\mu$. These estimates are summarized in Column (1) of Table 1. The results of this
experiment suggest that the simple aggregate production function that features complementarity between the aggregate supplies of labor and experience can rationalize the movements in the experience premium remarkably well through the changing relative supply of experience.

Table 1: Estimates of Technology Parameters based on Unrestricted Estimated Experience Premium $\hat{\Pi}_{E_t}$ and the Experience to Labor Ratio $\frac{\hat{E}_t}{L_t}$.

<table>
<thead>
<tr>
<th>parameter</th>
<th>Benchmark (1)</th>
<th>Linear Demand Shifts (2)</th>
<th>Quadratic Demand Shifts (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu$</td>
<td>-3.19 (0.158)</td>
<td>-3.35 (0.244)</td>
<td>-3.39 (0.994)</td>
</tr>
<tr>
<td>$\delta$</td>
<td>16.63 (2.912)</td>
<td>20.16 (5.91)</td>
<td>21.20 (27.34)</td>
</tr>
<tr>
<td>$\delta_1$</td>
<td>—</td>
<td>-0.029 (0.042)</td>
<td>-0.049 (0.0509)</td>
</tr>
<tr>
<td>$\delta_2$</td>
<td>—</td>
<td>—</td>
<td>0.0004 (0.0096)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.953</td>
<td>0.998</td>
<td>0.998</td>
</tr>
</tbody>
</table>

Note - Entries for $\mu$, $\delta$ and the goodness-of-fit represent the results of regressing the unrestricted experience premium on a constant and the relative supply of experience. For sample restrictions and variable construction procedures, see Appendix A1.1.

To assess whether the changing demand for experience played a role in determining its relative price, we follow the literature and re-estimate Equation (19) by allowing the intercept to be a linear or a quadratic function of time, i.e., $\delta_t = \delta + \delta_1 t$ or $\delta_t = \delta + \delta_1 t + \delta_2 t^2$. This is the standard approach to assessing the role of demand shifts in the literature. We find that the estimates of $\delta_1$ and $\delta_2$ are statistically insignificant. Moreover, allowing for demand shifts neither affects the estimates of the complementarity parameter $\mu$ nor improves the overall fit of the regression. This is in contrast to the findings based on the empirical approach of Katz and Murphy (1992). Repeating the same experiment in their data one finds that the experience premium is entirely driven by the change in demand with the estimate $\hat{\mu}$ statistically indistinguishable from one.
3.2.3 Sources of Curvature in Life-Cycle Wage Profiles

Since our modeling of life-cycle profile of wages is novel to the literature, we now comment on the key findings. While the key features of the age efficiency schedules are the same for both genders, we focus the discussion on the efficiency schedules of male workers as these are relevant for the results reported below. The estimated age efficiency schedules of experience and labor for male workers from the two schooling groups are presented in Figure 2. The corresponding estimated schedules for female workers can be found in Appendix Figure A-1. The coefficient estimates and their standard errors reported in Appendix Table A-1 imply that the efficiency schedules are estimated very precisely.

Figure 2(a) illustrates that the male efficiency schedules of labor, $\lambda_L(j_{it}, s_{it}, M)$, are hump-shaped, peaking at age 50 for the college group and age 45 for the high school group. The increase in the effective units of labor in the early part of the life-cycle is considerably larger for the college-educated workers than their high-school educated counterparts.

In contrast, the male estimated efficiency schedules for experience $\lambda_E(j_{it}, s_{it}, M)$ are monotonically decreasing and are below unity over the entire age range as shown in Figure 2(b). This suggests a substantial benefit from accumulating experience early in life, and that this benefit is larger for the college-educated workers, since their stock of experience depreciates at a faster rate. These observations imply that the relative male efficiency schedule $\lambda_{E/L}(j_{it}, s_{it})$ is falling.
in age and is uniformly lower for the college schooling group.

Meanwhile, the mapping from years of experience to the stock of experience skill $g(e_{it})$ is close to being linear (although mildly concave), implying that the hump shape in life-cycle wage profile is not driven by the decreasing returns to accumulating experience. Instead, it is driven by a less efficient utilization of accumulated experience skill with age. Note that the effective supply of experience is the product of the efficiency schedule for experience and the stock of experience skill, implying that for a typical worker the effective supply of experience tends to increase with age.

By re-estimating the model on various time subsamples or even on particular cross-sections of the data we found that the shapes and even the magnitudes of the estimated efficiency schedules are very robust. This suggests that they are primarily identified by the heterogeneity of actual experience with age and not by the time variation in the data.

### 3.2.4 Estimation on Male Sample

So far we have measured the relative prices and quantities on the same samples. While it is clear that factor supplies by female workers must be included in aggregate quantities of labor and experience, one may be concerned with the possibility that strong change in female participation patterns over time may induce selection effects that may bias the estimates of the dynamics of the experience premium.

To assess the robustness of our finding to allowing for this possibility we estimate the individual earnings equations on the sample of male workers only. The resulting estimates generate the time series of the experience premium $\hat{\Pi}_{E_{it}}^{M}$ which is plotted in Figure 3. As it is estimated on a substantially smaller sample, the estimated male experience premium is more volatile, but its dynamics is similar to that estimated on the full sample and plotted in Figure 1.

When we compare the resulting male experience premium to the relative aggregate supply of experience (that includes the supply of both men and women) we find that the correlation between the two series remains high at X.XX. The preliminary estimates of technology are also
little affected with the estimated elasticity of substitution between labor and experience declining slightly from 0.24 in the benchmark to 0.13 in this experiment. Allowing for linear or quadratic trends in parameter $\delta$ to capture the potential role of demand shifts continues to yield highly insignificant estimates of the associated parameters. We conclude that the possible selection biases associated with estimating the returns to experience on a panel of female workers have at best a minor impact on our findings.

4 Estimation Imposing Full Model Structure

In this section we conduct a structural estimation of the model by imposing all the properties of the aggregate production function on the individual earnings equations. This is a more efficient approach to estimating the aggregate production function parameters. However, imposing the full model structure may result in changes to the estimates of all the parameters and in the associated fit of the earnings equations. Indeed, the structural model imposes strong additional restrictions and has considerably less flexibility in fitting the data as compared to the unrestricted specification studied above. The extent to which a structural model can rationalize the relationship between variables of interest without sacrificing the fit to the data

Figure 3: The Unrestricted Experience Premium $\widehat{\Pi}_{Et}$ estimated on the male sample and the Predicted Male Experience Premium from the Benchmark Structural Model.
provides a measure of the quality of the model.

4.1 Measuring the Aggregate Prices and Quantities of Labor and Experience using Individual Data

To structurally estimate the model we modify the specification of the earnings equation estimated in Section 3 by substituting the unrestricted experience premium with the expression implied by the aggregate production function.

\[
\ln w_{it} = D_t + (\lambda_{L,0}(s_{it}, x_{it}) + \lambda_{L,1}(s_{it}, x_{it}) j_{it} + \lambda_{L,2}(s_{it}, x_{it}) j_{it}^2) + \ln \left[ 1 + \delta \left( \frac{E_t}{L_t} \right)^{\mu-1} \exp \left( \frac{\lambda_{E/L,0}(s_{it}, x_{it})}{+\lambda_{E/L,1}(s_{it}, x_{it}) j_{it} + \lambda_{E/L,2}(s_{it}, x_{it}) j_{it}^2} \right) \right] + \alpha_t \chi_{it} + \epsilon_{it},
\]

where consistent aggregation requires that the aggregate inputs \( L_t \) and \( E_t \) are measured as in equations (17) and (18) and hence depend on the parameters of efficiency schedules \( \lambda_L(j, s, x) \) and \( \lambda_E(j, s, x) \), and the coefficient vector \( \alpha_t \). That is, for a consistent estimation of the entire model, the aggregate inputs \( L_t \) and \( E_t \) need to be expressed in terms of these life-cycle efficiency and productivity parameters and estimated at the same time. This creates a complicated nonlinearity inside the arguments of the already nonlinear log wage equation.

To estimate the model, we use the following iterative guess-and-verify strategy. Guess the parameters for \( \lambda_L(j, s, x) \), \( \lambda_E(j, s, x) \), \( g(e) \) and \( \alpha_t \) and compute the implied aggregate experience to labor ratio. Using this guessed ratio, estimate all parameters of the log wage equation using a non-linear least squares method. Then, verify if the estimates for the parameters for \( \lambda_L(j, s, x) \), \( \lambda_E(j, s, x) \), \( g(e) \) and \( \alpha_t \) from this estimation coincide with the initial guess. If not, recalculate the experience-labor ratio using the obtained estimates of those parameters, and iterate this procedure until the guessed estimates and the subsequent estimates coincide.

4.2 Identification of the aggregate production function parameters.

The log wage equation in (20) includes all parameters of the model. In particular, given the measurement of aggregate inputs \( E_t \) and \( L_t \), the variation of experience premium \( \Pi_{E_t} \) in relation
to the variation of the experience-labor ratio \( \frac{E_t}{L_t} \) is the source of identification of the technology parameters \( \mu \) and \( \delta \). The correlation between the relative price \( \Pi_{E_t} \) and the relative factor endowment \( \frac{E_t}{L_t} \) over time \( t \) identifies \( \mu \) (which is scale free). The average magnitude of the \( \Pi_{E_t} \) relative to the magnitude of the \( \frac{E_t}{L_t} \) identifies the scale parameter \( \delta \).

Note that the magnitudes of \( \Pi_{E_t} \) and \( \frac{E_t}{L_t} \) depend on the normalization of the life-cycle efficiency schedules, i.e., \( \lambda_E(0, HS) = \lambda_L(0, HS) = 1 \). Thus, the identification of \( \delta \) is subject to this normalization. More precisely, it is the normalization of the relative efficiency of experience of the youngest workers that affects the identification of \( \delta \). That is, renormalizing \( \lambda_E(0, s) = \lambda_L(0, s) = l \) for any arbitrary constant \( l \) such that \( \lambda_{E/L}(0, s) = 1 \) leaves the estimate of \( \delta \) unchanged. However, if we normalize the life-cycle efficiency schedules asymmetrically between experience and labor such that \( \lambda_L(0, s) = a \) and \( \lambda_E(0, s) = b \), hence \( \lambda_{E/L}(0, s) = c = b/a \neq 1 \), the coefficient function in front of experience in the log wage becomes \( \delta \left( \frac{E_t}{L_t} \right)^{\mu-1} c \lambda_{E/L}(j, s) = \tilde{\delta} \left( \frac{E_t}{L_t} \right)^{\mu-1} \lambda_{E/L}(j, s) \), where \( \tilde{\delta} = \delta c^\mu \). Thus, the estimated value of \( \delta \) may change. The normalization of the life-cycle efficiency schedule of labor affects the scale of the aggregate productivity term. Specifically, with \( \lambda_L(0, s) = a \), the aggregate productivity term turns to \( \ln a A_t \). Note, however, that estimates of \( \mu \) as well as the life-cycle efficiency schedules, our key parameters, are not affected by this normalization.

### 4.3 Results

The estimates of the parameters of Equation (20) and their standard errors are reported in Appendix Tables A-3 and A-4. All estimates are very similar to those obtained without imposing the aggregate production function. In fact, the fit of the model remains unchanged. As discussed above, this indicates the appropriateness of our modeling choices.

The structural estimates of the technology parameters are reported in Column (1) of Table 2. These estimates continue to imply fairly strong complementarity between labor and experience in aggregate production. To assess the role of the changes in aggregate relative supply of experience in driving its relative price, in Figure 4 we plot the predicted experience premium based on the structural estimates to the unrestricted experience premium obtained in Section.
Table 2: Structural Estimates of Technology Parameters.

<table>
<thead>
<tr>
<th>parameter</th>
<th>Benchmark (1)</th>
<th>Linear Demand Shifts (2)</th>
<th>Quadratic Demand Shifts (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>µ</td>
<td>-2.96</td>
<td>-3.02</td>
<td>x.xx</td>
</tr>
<tr>
<td></td>
<td>(0.229)</td>
<td>(0.281)</td>
<td>(x.xx)</td>
</tr>
<tr>
<td>δ</td>
<td>13.26</td>
<td>14.57</td>
<td>x.xx</td>
</tr>
<tr>
<td></td>
<td>(3.45)</td>
<td>(4.87)</td>
<td>(x.xx)</td>
</tr>
<tr>
<td>δ₁</td>
<td>—</td>
<td>-0.024</td>
<td>x.xx</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.032)</td>
<td>(x.xx)</td>
</tr>
<tr>
<td>δ₂</td>
<td>—</td>
<td>—</td>
<td>x.xx</td>
</tr>
<tr>
<td>R²</td>
<td>0.924</td>
<td>0.924</td>
<td>x.xx</td>
</tr>
<tr>
<td>RMSE</td>
<td>0.616</td>
<td>0.616</td>
<td>x.xx</td>
</tr>
</tbody>
</table>

Note - Entries for µ, δ and the goodness-of-fit represent the results of structural estimation. For sample restrictions and variable construction procedures, see Appendix A1.1.

3. Despite the parsimonious specification (two parameters µ and δ, and a single state variable $\frac{E}{L}$), the model tracks the actual time-path of the experience premium very closely. The correlation coefficient between the unrestricted experience premium $\hat{\Pi}_E$ and the predicted experience premium based on the structural estimates is 0.97.

4.3.1 The Role of Demand Shifts

The tight prediction of the experience premium generated by the experience-labor ratio in Figure 4 leaves very little room for other, demand based explanations for the dynamics of the experience premium. To investigate the role of demand shifts more formally, we follow the protocol in the existing literature by modeling demand shifts of a linear form with respect to time. We allow for the share parameter δ in the production function (8) to vary over time as $\ln \delta_t = \delta + \delta_1 t$. To explore whether the results are affected by the restrictive linear specification we also estimate a specification with a quadratic trend $\ln \delta_t = \delta + \delta_1 t + \delta_2 t^2$.

The corresponding estimates for the technology parameters are reported in Columns (2) and (3) of Table 2. The fit of the model is the same as in the benchmark specification, and the
predicted experience premium is indistinguishable across the specifications. The estimate of \( \delta_1 \) (and \( \delta_2 \)) are insignificant at any conventional level. Quantitatively, at the point estimate the time trend in \( \delta \) accounts for a tiny amount of variation in the experience premium. The estimate of the complementarity parameter \( \mu \) is virtually the same as in the benchmark specification.

The conclusion we draw from these findings is that the time variation in the experience premium is almost fully accounted for by the variation in the relative supply of experience. Skill biased technical change, while potentially important in determining the returns to education, plays at best a minor role in determining the experience premium.

5 Using the Model to Understand Additional Patterns in the Data

In this Section we use the estimated model to study the role of the dynamics of the supply of experience in driving (1) the rates of return to experience in the aggregate and across demographic groups, (2) age premium across education groups, (3) college premium across age cohorts, and (4) the measured total factor productivity.
5.1 Rate of Return to Experience

The experience premium in our model measures a relative price of experience. It represents an aggregate variable that is common to all workers and independent of their individual characteristics. Over the life-cycle, however, the rate of return to experience of individual workers may vary depending on their demographic characteristics and their experience level (because experience does not enter the log wage equation linearly). Define the rate of return to experience as the marginal wage increment to the addition of one more year of experience:

\[
\frac{d \ln w_{it}}{de_{it}} = \delta \left( \frac{E_t}{L_t} \right)^{\mu-1} \frac{\lambda_{E/L}(j_{it}, s_{it}, x_{it}) g'(e_{it})}{1 + \delta \left( \frac{E_t}{L_t} \right)^{\mu-1} \lambda_{E/L}(j_{it}, s_{it}, x_{it}) g(e_{it})}.
\]

(21)

The individual rate of return to experience is rising in the aggregate experience premium \( \Pi_{E_t} \equiv \delta \left( \frac{E_t}{L_t} \right)^{\mu-1} \), and falling in the individual level of experience \( e_{it} \) (given that \( g(e_{it}) \) is mildly concave). The return is also increasing in the relative efficiency schedule \( \lambda_{E/L}(j_{it}, s_{it}, x_{it}) \). Our estimates of efficiency schedules imply that the relative efficiency is higher for younger workers than older workers and higher for high school workers than college workers. Thus, the rate of return to experience declines with age and education.

5.1.1 Aggregate Rate of Return to Experience

To summarize the evolution of the returns to experience in a single time-series, we must decide on where to evaluate the function in (21). Consider a “representative worker” whose rate of return to experience is given by \( \frac{\Pi_{E_t} \Lambda_t}{1 + \Pi_{E_t} \Xi_t} \) with \( \Lambda_t \) and \( \Xi_t \) measured as follows

\[
\Lambda_t \equiv \frac{\sum_i \lambda_E(j_{it}, s_{it}, x_{it}) z_{ih_{it}} g'(e_{it})}{\sum_i \lambda_L(j_{it}, s_{it}, x_{it}) z_{ih_{it}}},
\]

(22)

\[
\Xi_t \equiv \frac{\sum_i \lambda_E(j_{it}, s_{it}, x_{it}) z_{ih_{it}} g(e_{it})}{\sum_i \lambda_L(j_{it}, s_{it}, x_{it}) z_{ih_{it}}},
\]

(23)

Hence, this worker supplies the aggregate effective labor and aggregate effective experience.\(^8\)

A solid line, labeled “Actual,” in Figure 5, represents the rate of return to experience for the representative worker constructed using unrestricted estimates of \( \widehat{\Pi}_{E_t}, \widehat{\lambda}_L(j, s, x), \widehat{\lambda}_E(j, s, x) \),

\(^8\)By construction, the effective units of experience to labor for this representative worker coincide with the aggregate experience to labor ratio \( \Xi_t = \frac{E_t}{L_t} \). We weight the life-cycle efficiency schedules of experience and labor by \( z_{ih_{it}} \) to obtain the effective units of experience and labor at the aggregate level.
Figure 5: Actual and Predicted Rates of Return to Experience for the Representative Worker and Counterfactual with Constant Experience Premium.

\( \hat{g}(e) \), and \( \hat{\alpha}_t \) obtained in Section 3. The rate of return, measured directly in the data without imposing the model structure, is sizable and changes substantially over time from 2.1\% in 1968 to 4.1\% in 1988, and then back down to 2.3\% in 2007. The dotted line, labeled “Predicted,” is the predicted path of the return to experience implied by the structurally estimated parameters in Section 4, including the technology parameters \( \hat{\mu}, \hat{\delta} \), and the changing relative supply of experience. The fit is clearly very good.\(^9\)

Equation (21) implies that there are two potential sources of change in the return to experience for a worker of given experience \( e_{it} \): first, changes in the aggregate experience premium \( \delta \left( \frac{E_t}{L_t} \right)^{\mu-1} \), and second, changes in the demographic composition of workers affecting the measured \( \Lambda_t \) and \( \Xi_t \) for the representative worker. The first effect is driven by the complementarity between experience and labor and the evolution of the relative supply, and the second is a composition effect that can arise without such complementarity. Our model provides a simple way to isolate the contribution of the composition effect. To do so, we set \( \mu = 1 \) to eliminate the complementarity effect and normalize \( \delta \) to match the level of the experience premium in

\(^9\)We obtain similar results when considering the average rate of return to experience across workers instead of the return to experience of a “representative worker.”
1968.\textsuperscript{10} With these restrictions we generate a counterfactual series of the rate of return to experience that is driven entirely by the composition effect. This series is labeled “Composition Effect” in Figure 5. Clearly, the composition effect alone does not account for much of the observed changes in the aggregate rate of return to experience. Instead, it is the changing relative supply of experience coupled with the complementarity of labor and experience in aggregate production, that drives the changes in the aggregate rate of return to experience.

5.1.2 Rate of Return to Experience for Demographic Subgroups

Despite the fact that the dynamics of our model is driven by one aggregate state variable, the model is consistent with the evidence on the differential response of the returns to experience of various demographic groups. The reason is that in the model, the return to experience is determined not only by the experience premium which is common to all groups, but also by the compositional characteristics that are group specific. These compositional characteristics affect the strength of the response of the return to experience of each demographic group to changes in the aggregate experience premium.

The top two panels of Figure 6 compare the return to experience of college educated versus high school educated workers over the sample period. The return for high school workers responds much more to the change in the experience premium, implying a steeper path over the period. The middle two panels compare the return to experience of males versus females. In this comparison, the return for females responds more to the change in the experience premium, implying a steeper path of their rate of return to experience. The bottom panel compares the paths of the rate of return to experience for whites and blacks. This comparison reveals a level difference which remains stable over the sample period.

In each of the panels of Figure 6, we also plot the predicted path of the return to experience using experience premia implied by the structurally estimated model, and the predicted change imposing $\mu = 1$ to eliminate the effects of the changes in the aggregate supply of experience on the experience premium. As in the case of the aggregate rate of return of experience, the

\textsuperscript{10}This normalization is inconsequential.
(a) By Education.

(b) By Gender.

(c) By Race.

Figure 6: Actual and Predicted Rates of Return to Experience for the Representative Worker from Different Demographic Subgroups and Counterfactuals with Constant Experience Premium.

prediction is accurate for each demographic group, and is driven by changes in the aggregate experience premium.

5.2 Age premium across schooling groups

Katz and Murphy (1992) were among the first to find that the ratio of wages of old and young male workers, or age premium, has increased more among high school educated workers than among college educated workers in the 1980s. Our PSID data exhibits the same patterns. The solid lines in Figure 7 represent the ratio of wages of “old” male workers aged 41-60 to wages of “young” male workers, aged 18-40 among the college educated and the high school educated workers, respectively.\footnote{\textsuperscript{11}We focus on two broad age categories to define the young and old to encompass the entire sample, and to minimize the small sample issues arising from using the PSID. We note however, that all the results reported below are robust to finer partitions of workers into age groups.}

As discussed in the Introduction, the standard measurement approach

\textsuperscript{11}
pioneered by Katz and Murphy (1992), assumes that the pure old exclusively supply experience and the pure young exclusively supply labor regardless of schooling group. This assumption implies that the wage ratio \( w_{\text{old}}^s / w_{\text{young}}^s \) has an elasticity with respect to experience premium of one regardless of schooling group \( s \in \{ HS, C \} \). This led the literature to emphasize the role of demand shifts against young high school educated males.

In contrast, our model of individual earnings implies that age and experience premia are related but different objects and allows for them to exhibit different trends over time. Specifically, the age premium, \( r_t^s \), among workers with schooling level \( s \) is given at date \( t \) by\(^{12}\)

\[
    r_t^s \equiv \ln \left[ \frac{w_t^s (\text{old})}{w_t^s (\text{young})} \right] = \ln \left[ \frac{\lambda_L (\text{old}, s)}{\lambda_L (\text{young}, s)} \right] + \ln \left[ \frac{1 + \delta \left( \frac{E_t}{L_t} \right)^{\mu-1} \lambda_{E/L} (\text{old}, s) g (e_t^s (\text{old}))}{1 + \delta \left( \frac{E_t}{L_t} \right)^{\mu-1} \lambda_{E/L} (\text{young}, s) g (e_t^s (\text{young}))} \right] + \alpha_t \left[ \chi_t^s (\text{old}) - \chi_t^s (\text{young}) \right].
\]

Thus, the level of the age premium is determined by the differences in the stocks of effective labor and experience supplied by the young and old workers and by the difference in the vector of their demographic characteristics \( \chi \). Over time, the age premium changes due to the evolution of

\(^{12}\)For notational clarity we suppress the dependence of all equations in this and the next section on gender.
the experience premium $\Pi_{Et} \equiv \delta \left( \frac{E_t}{L_t} \right)^{\mu - 1}$ as well as the change in the demographic composition of young and old groups and changes in the “returns,” $\alpha_t$, to their characteristics.

Equation (24) implies that, among workers with schooling level $s$, the elasticity of the age premium with respect to the aggregate experience premium is given by

$$
\epsilon_{\Pi_{Et}} = \frac{\epsilon_{w_t^{s,*},\Pi_{Et}}(old) - \epsilon_{w_t^{s,*},\Pi_{Et}}(young)}{r_t^s},
$$

where

$$\epsilon_{w_t^{s,*},\Pi_{Et}}(j) = \frac{\delta \left( \frac{E_t}{L_t} \right)^{\mu - 1} \lambda_{E/L}(j,s) g_e(j)}{1 + \delta \left( \frac{E_t}{L_t} \right)^{\mu - 1} \lambda_{E/L}(j,s) g_e(j)}$$

is the elasticity of wages of age $j$ workers with respect to the aggregate experience premium.

These equations are insightful. First note that the elasticity of wages with respect to the experience premium, $\epsilon_{w_t^{s,*},\Pi_{Et}}$, is equal to the share of wages that represents the renumeration to experience. Quite naturally, wages of workers with higher relative effective supply of experience, $\lambda_{E/L}(j,s) g_e(j)$, respond more to changes in the price of experience. As our estimates imply that old workers generally have higher relative effective supply of experience, their wage rise more in response to an increase in the relative price of experience then wages of the young workers whose earnings represent mostly the renumeration for labor. This implies that the age premium tends to co-move with the experience premium.

However, the strength of the response of age premium to changes in the experience premium across, say, schooling groups depends on how fast the share of wages sourced from experience rises with age among workers belonging to those groups. Our estimates imply that this share rises faster with age among high school educated than among college educated workers. Consequently, the age premium is more responsive to changes in the aggregate experience premium among high school educated workers then among their more educated counterparts.

Quantitatively we find that our model does a very good job at matching the evolution of the age premium across education groups. The lines labeled “Predicted” in Figure 7 plot the age premium for the two schooling groups implied by the structurally estimated parameters, including the technology parameters $\hat{\mu}$, $\hat{\delta}$, and the changing relative supply of experience. The
lines labeled “Counterfactual” eliminate the effect of the evolution of the aggregate supply of experience by setting $\mu = 1$. Thus, these lines isolate the impact on the age premium of changes in composition of workers within age and schooling groups and changing “returns” to their characteristics (the $\alpha_t [\chi_s^\text{old} - \chi_s^\text{young}]$ term in Equation 24).

We observe that the changing relative supply of experience is the primary determinant of the dynamics of age premium among high school educated workers through its effect on the experience premium. The age premium is highly responsive to changes in the relative price of experience among these workers. Changes in composition play an important role in the early 1970s but have virtually no impact on the subsequent evolution of age premium in this group of workers. In contrast, as the share of wages sourced from experience is relatively constant in our samples of young and old college educated workers, changes in the relative price of experience have little impact on age premium in this schooling group. Instead, it is the changing composition of workers that is responsible for much of the change in the age premium.

Thus, we conclude that our measurement approach that separates the effects of age and experience on wages can quantitatively rationalize the differential impact of the aggregate experience premium on age premium across schooling groups. It interprets this difference not as evidence of demand shifts against particular groups of workers but through the different importance of the experience skill in wages of various schooling groups. This result depends, of course, on the estimated shape on the life-cycle efficiency schedules for labor and experience. In our benchmark estimation the variation in age premium across schooling groups was part of the variation used to identify the parameters of these schedules. This raises the question whether the success of the model in accounting for these facts is a mechanical outcome of targeting this variation. Even if it were, we find it remarkable that a simple and fairly parsimonious model that separates age and experience effects is consistent with so many features of the data. As we mentioned above, however, the estimates of the life-cycle efficiency schedules are very robust to estimating them on different time subsamples of our data, or even in various cross-sections. This suggests that the dynamics of age premium across schooling groups plays a minor role in identifying the parameters of the efficiency schedules. Given this, the ability of the model to
match these patterns in the data presents strong evidence in support of the model.

### 5.2.1 Ratio of age premia

Mathematically, the ratio of the age premium between college and high school educated workers is equivalent to the ratio of the college premium between old and young groups:

$$\frac{w_{C_{old}}}{w_{HS_{old}}} / \frac{w_{C_{young}}}{w_{HS_{young}}} \equiv \frac{w_{C_{old}}/w_{HS_{old}}}{w_{C_{young}}/w_{HS_{young}}}.$$ 

Thus, the fact that the model matches the evolution of the age premia across schooling groups implies that it can also quantitatively account for the differential movement of the college premia across age groups. In the following section, we use this insight to show that the change in the relative supply of experience that drives the movement of the experience premium over time, can also account for the differential changes in the levels of the returns to schooling among young and old workers.

### 5.3 College premium across age groups

In an influential paper, Card and Lemieux (2001) have highlighted the fact that changes in the male college premium have been very different across age groups: the college premium rose sharply after the early 1970s among young workers while it remained more or less constant among old workers. The solid lines in Figure 8 show that the same pattern holds in the PSID data.

In our model, the college premium, \( r^j_t \), among workers in age group \( j \) is given at date \( t \) by

$$r^j_t \equiv \ln \left[ \frac{w^C_t (j)}{w^{HS}_t (j)} \right] = \ln \left[ \frac{\lambda_L (j, C)}{\lambda_L (j, HS)} \right]$$

\begin{align*}
+ & \ln \left[ \frac{1 + \delta \left( \frac{E_t}{L_t} \right)^{1-\rho} \lambda_{E/L} (j, C) \ g (e^C_t (j))}{1 + \delta \left( \frac{E_t}{L_t} \right)^{1-\rho} \lambda_{E/L} (j, HS) \ g (e^{HS}_t (j))} \right] \\
+ & \alpha_{YS,t} \left[ y^C_{t} (j) - y^{HS}_{t} (j) \right] + \alpha_{-YS,t} \left[ \chi^C_{-YS,t} (j) - \chi^{HS}_{-YS,t} (j) \right].
\end{align*}

In the bottom row of Equation (27) we split the vector of productive characteristics into the difference in years of schooling of college and high school workers in a given age group.
\[ ys_t^C (j) - ys_t^{HS} (j) \] multiplied by the aggregate “returns” to schooling \( \alpha_{ys,t} \) and the vector of differences in other productive characteristics \( [\chi_{-ys,t}^C (j) - \chi_{-ys,t}^{HS} (j)] \) with the associated vector of coefficients \( \alpha_{-ys,t} \). This emphasizes the fact that the increase in the aggregate “returns” to schooling, \( \alpha_{ys,t} \), symmetrically increases the college premium in all age groups. However, this effect is modulated by changes in the experience premium \( \Pi_{Et} \equiv \delta^E \left( \frac{E_t}{L_t} \right)^{\mu - 1} \). In particular, the elasticity of the college premium with respect to the aggregate experience premium among age \( j \) workers is given by

\[
\epsilon_{r_t^j, \Pi_{Et}} = \frac{\epsilon_{w_t^j, \Pi_{Et}} (C) - \epsilon_{w_t^j, \Pi_{Et}} (HS)}{r_t^j},
\]

(28)

where, as in Equation (26),

\[
\epsilon_{w_t^j, \Pi_{Et}} (s) = \frac{\delta \left( \frac{E_t}{L_t} \right)^{\mu - 1} \lambda_{E/L} (j, s) g (e_t^s (j))}{1 + \delta \left( \frac{E_t}{L_t} \right)^{\mu - 1} \lambda_{E/L} (j, s) g (e_t^s (j))}
\]

(29)

is the elasticity of wages of age \( j \) workers in schooling group \( s \) with respect to the aggregate experience premium.

As we discussed in Section 5.2, at almost all ages high school educated workers derive a higher share of wages as payments to their supply of the experience skill. Moreover, the share of wages sourced from experience increases faster over the life-cycle among high school
educated compared to college educated workers. These observations imply that (1) an increase in the experience premium lowers the college premium in every age group, and (2) this effect is stronger among older workers. In other words, the college premium among old workers falls relative to young workers when the experience premium rises.

These results explain the success of our model in capturing the dynamics of college premium across age groups. The lines labeled “Predicted” in Figure 8 plot the college premium for the two age groups implied by the structurally estimated parameters. The fit to the raw data series in solid lines is quite close. Comparing to the “Counterfactual” predictions that eliminate the effect of the aggregate relative supply of experience on the experience premium by setting $\mu = 1$, we conclude that it was the rise in the experience premium that almost fully counteracted the effect of the rise in the “returns” to college among old workers, yielding an essentially constant college premium among the old. As there is only a small difference in the share of wages due to experience among college and high school educated young workers, the effect of the rise in the relative price of experience played only a minor role in shaping their college premium, and was not sufficiently strong to counteract the effect of the rising “returns” to education. These results demonstrate that the changing relative supply of experience can simultaneously account for the dynamics of the relative price of experience and for the differential movements of the college premium across age groups. While the literature has treated these developments as being unrelated, our analysis establishes a very tight link between them.

5.4 Aggregate Productivity

Given the estimates of $\hat{\mu}$ and $\hat{\delta}$, we can uncover the marginal product of labor $G_{Lt}$ implied by the specification of the aggregate production function in (8):

$$\hat{G}_{Lt} = \left(1 + \hat{\delta} \left( \frac{\hat{E}_t}{\hat{L}_t} \right)^{\frac{1}{\hat{\mu}} - 1} \right).$$  \hspace{1cm} (30)

Combining $\hat{G}_{Lt}$ and the estimates of the time-varying intercept terms $\hat{D}_t$, the log of the aggregate productivity term $\hat{A}_t$ can be identified by

$$\ln \hat{A}_t = \hat{D}_t - \ln \hat{G}_{Lt}. \hspace{1cm} (31)$$
Thus, we can decompose the changes in $D_t$ into a component due to changes in the experience-labor ratio $\frac{E_t}{L_t}$ and a component due to changes in aggregate productivity level $A_t$.

As shown in Figure 9, $\hat{D}_t$ displays no trend until 1974 and then decreases until 1994 before rising again. The figure also presents the decomposition of this term into log of marginal product of labor $\ln \hat{G}_t$ and log of aggregate productivity $\ln \hat{A}_t$, according to (31). To facilitate comparisons of the movements among these three variables, we normalize values in 1968 to zero (by subtracting a constant). The log of marginal product of labor $\ln \hat{G}_t$ has decreased over the sample period accounting for most of the slowdown in the growth of $D_t$ and its eventual decline. This translates into a substantial 26% fall in the level of the marginal product of labor between 1968 and 1996. Thus, the model not only accounts for the dynamics of the return to experience but also endogenously generates a substantial decline in the intercept of the wage equation. It is not a priori clear that these two features of the data might be related, but the model provides a tight link between them. When the experience to labor ratio declines, the marginal product of labor declines as well. This is exactly what the intercept of the wage equation captures.
6 Conclusion

In this paper we evaluated the role of the changing supply of experience, driven largely by the progression of the baby boom cohorts through the labor market and by the increase in female labor force participation, in accounting for some of the key labor market trends over the last forty years. The main tool of our investigation is the aggregate production function that allows for complementarity between labor and experience - the two productive factors supplied by the workers to the labor market. We found that the evolution of the supply of experience accounts nearly perfectly for the large changes in the relative price of experience over the last forty years. It also accounts well for the changes in age premia across education groups and changes in college premium across age groups. While these developments were studied in separate strands of the literature, we find that the changing supply of experience provides a powerful unifying explanation.

Methodologically, the key innovation of our analysis is in using individual-level data to construct aggregate labor market quantities and prices. Consistent aggregation of individual earnings equations ensures that these quantities correspond to the objects implied by the aggregate production function. Measuring aggregate supplies of labor and experience based on decompositions of individual earnings also allows us to relax some of the assumptions underlying the existing measurement approaches. In particular, we do not need to assume that some demographic groups exclusively supply “pure” labor or experience skills. Instead, all workers can be supplying a bundle of these skills and we can measure the individual components of such bundles. Moreover, our approach provides a way to filter out the effects of changes in, e.g., college or gender premium, when studying the evolution of the experience premium. This is not possible given the existing approaches. We find that the additional flexibility afforded by our approach is important as it helps overturn some of the conclusions in the literature. In particular, while the existing literature ascribes a prominent role to changes in relative demand in shaping the empirical patterns we study, we assign a virtually exclusive role to changes in relative supply in accounting for them. This is not a forgone conclusion in our approach as it
is not designed to favor either demand or supply based explanations.

At a more micro level, we find that separating the effects of age and experience in individual earnings provides a simple way to introduce cohort effects into traditional Mincerian wage equations. The associated findings seem interesting in their own right. In particular, we find that the hump shape in the return to experience over the life-cycle is not driven by the decreasing returns in accumulating experience. Instead, it is driven by a less efficient utilization of accumulated experience with age. This insight is not only important for model building but has a clear relevance for the design of labor market policies. Moreover, we find that the effective units of labor are also hump shaped over the life-cycle. Taken together, these findings imply that the concavity of the age-wage profile or the experience-wage profile (where experience is measured by age-based potential experience) in typical Mincerian regressions is due to age effects rather than decreasing returns in experience skill production.

Finally, our findings contribute to the literature that attempts to isolate age, time, and cohort effects in the earnings equation (e.g., Heathcote, Storesletten, and Violante (2005)). By construction, only two of these effects can be simultaneously identified, when the time effect is identified with the calendar date. We model the time and age effects, where the changes in demographic composition, summarized by the experience-labor ratio, determines a time effect via the experience premium and the age effect is captured by the life-cycle efficiency profiles. As entering cohorts vary in size, distribution of age as well as the experience-labor ratio in the labor market and hence relative wages will change. Thus, we indirectly capture cohort size effects through the structure of the model.
References


Freeman, R. B. (1979): “The Effect of Demographic Factors on Age-Earnings Profiles,” 


APPENDICES

A1 Data Appendix

A1.1 PSID Data

Sample. We use the Panel Study of Income Dynamics (PSID) data from the U.S. for the period 1968-2007. The PSID consists of two main subsamples: the SEO (Survey of Economic Opportunity) sample and the SRC (Survey Research Center) sample. We use both samples and restrict ourselves to the core members with positive sampling weights (not the newly added family members through marriage) to maintain the consistent representativeness of the sample over time.\(^\text{13}\) The sample is restricted to individuals between 18 and 65 years of age.

Actual Labor Market Experience. The procedure we use to construct measures of actual work experience since age 18 is as follows. Questions regarding overall labor market experience (“How many years have you worked for money since you were 18?” and “How many of these years did you work full time for most or all of the year?”) were asked of every household’s head and wife in 1974, 1975, 1976 and 1985.\(^\text{14}\) These questions are also asked for every person in the year when that person first becomes a household head or wife.\(^\text{15}\) Since there are some inconsistencies between the answers, we first adjust 1974 overall experience to be consistent with 1975 and 1976 values where possible. Next, we use 1974 as the base year; i.e., we assume that whatever is recorded in 1974 for the existing heads is true. For the entrants into the sample we assume that the experience they report in their first year in the sample is true. If reported experience implies that an individual started working before the age of 18, we redefine it to be the number of years since age 18 for that individual. If the reported experience in 1974 is smaller than that implied by the reports of hours between the individual entry into the sample (or 1968) and 1974, we replace the 1974 report with that implied by the accumulated reports of hours. We repeat this procedure for 1985 and the reports of the new heads and wives. Finally, using the values of experience in 1974, 1985, and the reports of the new heads and wives, we increment experience variables forward and backward as follows: increment the full-time experience measure by one if individual works at least 1500 hours in a given year.\(^\text{16}\) If

\(^{13}\)We use only the nonimmigrant sample. In 1990 the PSID added a new sample of 2000 Latino households, consisting of families originally from Mexico, Puerto Rico, and Cuba. Because this sample missed immigrants from other countries, Asians in particular, and because of a lack of funding, this Latino sample was dropped after 1995. Another sample of 441 immigrant families was added in 1997. Because of the inconsistencies in these samples, we restrict ourselves to the core SEO and SRC samples throughout the 1968-2007 period.

\(^{14}\)By default, the head of household is the (male) husband if he is present or a female if she is single. In very few cases the head is a female, even when the male husband is present (but is, say, severely disabled).

\(^{15}\)The PSID mistakenly did not ask some people in 1985 and fixed this mistake by asking them in 1987.

\(^{16}\)We experimented with using cutoff values other than 1500 hours of work or using directly the sum of
we observe an individual in the sample since age 18, we ignore his or her reports of experience and instead directly use his or her reports of hours in each year using the cutoff above. If we do not observe an individual in the sample since age 18, we attempt to construct tenure based on the earliest report of his or her overall experience.\footnote{The PSID switched from annual to bi-annual interviewing after 1997. Some data for the non-interview years is available but appears very noisy and with large numbers of missing observations. This led us to use only the data from years when interviews took place. The only exception is hours worked in years between interviews which are needed to construct the actual experience measures. We imputed those hours as the maximum between the reported hours (if available) and the average hours in the two adjacent survey years.}

Other Variables. Our hourly wage measure is equal to the total earnings last year divided by total hours worked last year. To get real wage, we adjust the nominal wage using last year’s CPI (equal to 100 in 1984).\footnote{There is an alternative hourly wage measure in the PSID which reports the current hourly wage at the time of the interview. Unfortunately, this measure is only available for the household heads throughout the period. For wives it is available only in 1976 and after 1979 and it is not available at all for the other family members.}

We define the economically active population as the group of people who worked at least 700 hours last year.\footnote{As in the case of earnings, there is also an employment status variable at the time of the interview. We do not use this variable because (1) the reference period (current year) is different from that of earnings measure (last year), and (2) this variable is available for the heads for all years but not for the wives before 1979 except in 1976 and is not available for the dependents.}

Education is measured by years of final educational attainment.\footnote{Education is reported in the PSID in 1968, 1975, and 1985 for existing heads of households, and every year for the people becoming household heads or wives. It is kept constant between the years in which it is updated. As a result, there would be a bias toward a lower educational level. For example, if education is 10 years in 1975 and 16 in 1985, it would be reported 10 between 1975 and 1985. If the individual, however, had 16 years of education already in 1980, then for five years he would be counted as less educated than he actually is. To minimize this bias, the education variable used in the estimation is fixed to be equal to its mode value among all the reports available. To make the education variable comparable across time we top code it at 16 years.}

We found that the broad region variable provided by the PSID appears to be error-ridden. For example, for some but not all Texas residents region is defined as West. Thus, we reconstructed the broad region variable directly from the state of residence.\footnote{We define the economically active population as the group of people who worked at least 700 hours last year.\footnote{Education is reported in the PSID in 1968, 1975, and 1985 for existing heads of households, and every year for the people becoming household heads or wives. It is kept constant between the years in which it is updated. As a result, there would be a bias toward a lower educational level. For example, if education is 10 years in 1975 and 16 in 1985, it would be reported 10 between 1975 and 1985. If the individual, however, had 16 years of education already in 1980, then for five years he would be counted as less educated than he actually is. To minimize this bias, the education variable used in the estimation is fixed to be equal to its mode value among all the reports available. To make the education variable comparable across time we top code it at 16 years.}}
## A2 Descriptive Analysis, Additional Results

### A2.1 Descriptive Analysis, Benchmark Coefficient Estimates

Table A-1: Descriptive Analysis, Estimates of Time-Invariant Parameters.

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Note - The entries represent the results of the first-stage estimation of time-invariant parameters of the benchmark specification from the PSID. For sample restrictions and variable construction procedures, see Appendix A1.1. See Section 3 for details of the estimation procedure.
Table A-2: Descriptive Analysis, Estimates of Time-Varying Parameters.

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<tr>
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<td>.111(.004)</td>
<td>.07(.018)</td>
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<td>-.26(.07)</td>
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<tr>
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<td>.04(.018)</td>
<td>-.11(.026)</td>
<td>-.29(.07)</td>
</tr>
<tr>
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<td>.04(.018)</td>
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<tr>
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<td>.03(.018)</td>
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<td>.04(.018)</td>
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<td>-.27(.07)</td>
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<td>.07(.017)</td>
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<td>.07(.016)</td>
<td>-.17(.023)</td>
<td>-.12(.07)</td>
</tr>
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</table>

Note - The entries represent the results of the first-stage estimation of time-varying parameters of the benchmark specification from the PSID. Standard errors are in parenthesis. For sample restrictions and variable construction procedures, see Appendix A1.1. See Section 3 for details of the estimation procedure.
Figure A-1: Estimated Age-Efficiency Schedules for Female Workers by Education.
### A3 Structural Estimation, Additional Results

#### A3.1 Structural Estimation, Benchmark Coefficient Estimates

Table A-3: Structural Estimation, Estimates of Time-Invariant Parameters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>Standard error</th>
<th>t-statistic</th>
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<tbody>
<tr>
<td>$\lambda_{L,1} (HS,M)$</td>
<td>0.0239</td>
<td>0.00335</td>
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<td>$\lambda_{L,2} (HS,M)$</td>
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</tr>
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<td>$\lambda_{L,0} (C,M)$</td>
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<td>-8.73</td>
</tr>
<tr>
<td>$\lambda_{L,1} (C,M)$</td>
<td>0.0679</td>
<td>0.00366</td>
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<tr>
<td>$\lambda_{L,2} (C,M)$</td>
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<td>0.0000857</td>
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<td>$\lambda_{E/L,1} (HS,M)$</td>
<td>-0.0773</td>
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</tr>
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<td>$\lambda_{E/L,2} (HS,M)$</td>
<td>0.00107</td>
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</tr>
<tr>
<td>$\lambda_{E/L,0} (C,M)$</td>
<td>0.321</td>
<td>0.122</td>
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<tr>
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<tr>
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<tr>
<td>$\lambda_{L,1} (C,F)$</td>
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<td>0.0269</td>
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</tr>
<tr>
<td>$\lambda_{L,2} (C,F)$</td>
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<td>0.000622</td>
<td>-9.23</td>
</tr>
<tr>
<td>$\lambda_{E/L,1} (HS,F)$</td>
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<td>0.00661</td>
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</tr>
<tr>
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<tr>
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<td>$\theta_1$</td>
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<td>$\theta_3$</td>
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<td>-6.29</td>
</tr>
</tbody>
</table>

Note - The entries represent the results of the first-stage estimation of time-invariant parameters of the benchmark specification from the PSID. For sample restrictions and variable construction procedures, see Appendix A1.1. See Section 4 for details of the estimation procedure.
Table A-4: Structural Estimation, Estimates of Time-Varying Parameters.

<table>
<thead>
<tr>
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<th>Schooling</th>
<th>Male</th>
<th>Black</th>
<th>Intercept</th>
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<tr>
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<tr>
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<tr>
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<td>.068(.004)</td>
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<td>.16(.024)</td>
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<td>-.18(.052)</td>
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</table>

Note - The entries represent the results of the first-stage estimation of time-varying parameters of the benchmark specification from the PSID. Standard errors are in parenthesis. For sample restrictions and variable construction procedures, see Appendix A1.1. See Section 4 for details of the estimation procedure.
A4 The Effect of Cohort Size on Earnings

Given the aggregate technology (3), note that from the Euler theorem

\[ G_{EE} = -\frac{L_t}{E_t} G_{EL}, \]

\[ G_{LL} = -\frac{E_t}{L_t} G_{EL}. \]

The aggregate stocks of labor and experience can be constructed as the sum of effective supplies across cohorts \( j \)

\[ L_t = \sum_j \lambda_L(j) N_{j,t}, \]

\[ E_t = \sum_j \lambda_E(j) e_t(j) N_{j,t}. \]

Here we drop the productive characteristics \( z_{jt} \) and hours \( h_{jt} \) for simplicity. The complementarity between cohorts is given by the condition \( \frac{d^2 Y_t}{d N_{j,t} d N_{k,t}} > 0 \). This cross derivative is given by

\[ \frac{d^2 Y_t}{d N_{j,t} d N_{k,t}} = \frac{L_t}{E_t} \sum_j \left[ \lambda_E(j) e_t(j) \lambda_L(k) + G_{EL} \lambda_E(j) e_t(j) \lambda_L(k) \right] \]

\[ = \frac{L_t}{E_t} \lambda_L(j) \lambda_L(k) \left[ \frac{E_t}{L_t} - \frac{\lambda_E(j) e_t(j)}{\lambda_L(j)} \right] \left[ \frac{\lambda_E(k) e_t(k)}{\lambda_L(k)} - \frac{E_t}{L_t} \right], \]

using the implications of the Euler theorem above.

Since aggregate experience-labor complementarity implies \( G_{EL} > 0 \), cohorts are complements when the cohort specific experience-labor ratios \( \frac{\lambda_E(j) e_t(j)}{\lambda_L(j)} \) are respectively lower and higher than the aggregate experience-labor ratio \( \frac{E_t}{L_t} \). This is because cohorts complement each other through their effect on the aggregate experience-labor ratio. When both cohorts supply cohort specific experience-labor ratios either lower or higher than the aggregate ratio they are substitutes \( \frac{d^2 Y_t}{d N_{j,t} d N_{k,t}} < 0 \). Complementarity or substitutability is stronger the more distant the cohort specific experience-labor ratios from the aggregate ratio. For a cohort where the experience-labor ratio coincides with the aggregate ratio \( \frac{\lambda_E(j) e_t(j)}{\lambda_L(j)} = \frac{E_t}{L_t} \), the marginal product is not affected by changes in the population of other cohorts (at the margin). For the same reason, the effect of own cohort size \( \frac{d^2 Y_t}{d N_{j,t}} \) in reducing the marginal product is rising in the absolute distance of the cohort specific experience-labor ratio from the aggregate ratio \( \frac{\lambda_E(k) e_t(k)}{\lambda_L(k)} - \frac{E_t}{L_t} \).