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**MATCHING, HUMAN CAPITAL, AND THE
COVARIANCE STRUCTURE OF EARNINGS**

Daniel PARENT¹

¹ Département de sciences économiques and Centre de recherche et développement en économique (C.R.D.E.), Université de Montréal.

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C.P. 6128, succursale Centre-ville
Montréal (Québec) H3C 3J7

Télécopieur (FAX) : (514) 343-5831
Courrier électronique (E-Mail) : econo@tornade.ERE.Umontreal.CA

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RÉSUMÉ

Par le biais de la méthode des moments [Chamberlain (1984), Gallant et Jorgenson (1979)] et avec des données non balancées du NLSY, cette étude cherche à tester les prédictions engendrées par la théorie du matching ainsi que par la théorie du capital humain quant à la structure de covariance des résidus d'une équation de salaire typique à la Mincer. Le processus de sélection qu'implique le matching fait en sorte que l'on devrait observer une diminution de la contribution du terme reflétant la variance dans la qualité du match lorsque l'on suit les travailleurs à mesure qu'ils acquièrent de l'ancienneté dans leur emploi. Les résultats corroborent cette prédiction surtout pour les travailleurs plus scolarisés. Par contre, dans la version «pure experience good» de la théorie, la prédiction à l'effet que la variance devrait s'accroître au tout début de la relation d'emploi s'avère non validée par les résultats, sauf peut-être pour les travailleurs moins scolarisés. Par ailleurs, la théorie du capital humain prédit que l'on devrait observer une corrélation négative entre la pente (le rendement lié à l'ancienneté) et l'ordonnée (ou salaire) à l'origine dans un emploi puisque les travailleurs sont supposés payer pour la formation. Ce résultat aussi est corroboré, surtout pour les travailleurs ayant au moins un diplôme d'école secondaire.

Mots clés: appariement, capital humain, structure de covariance des résidus, méthode des moments, modèle à coefficients aléatoires.

ABSTRACT

Using method of moments techniques [Chamberlain (1984), Gallant and Jorgenson (1979)], this paper's objective is to test the predictions of the theory of job-matching and the theory of human capital pertaining to the covariance structure of residuals from a typical Mincer log earnings equation. The selection process implicit to job matching is such that we should observe a decrease in the contribution of the variance of the job-match component when we follow the workers as they acquire tenure in their job. Results are generally in agreement with these predicted patterns, especially in the case of more educated workers. On the other hand, if jobs are considered as pure experience goods, the predicted increase in the variance at the start of the employment relationship is not supported by the data, except perhaps for less educated workers. Turning next to human capital theory, the predicted trade-off between the job-specific intercept and slope parameters is strongly supported by the data, especially in the case of workers having at least a High School diploma.

Key words: matching, human capital, covariance structure of residuals, method of moments, random coefficient model.



I. INTRODUCTION

Two competing explanations for the existence of a positive return to tenure are human capital and matching. In short, both theories yield the prediction that the conditional mean of wages should rise with tenure. In this paper, I intend to compare and distinguish these two theories empirically by focusing on the implications in terms of the covariance structure. To do so, I use the residuals from a log-earnings equation using data from the National Longitudinal Survey of Youth (NLSY) for the period spanning the years 1979-1991. This data set contains detailed employment histories for young people who were aged 14 to 21 at the end of 1978 and who are making their transition to the labor market. Results are presented for the entire sample as well as for subsamples representing different schooling groups. The econometric methodology to be used is borrowed and adapted to unbalanced data from the method of moments estimator of Gallant and Jorgenson (1979).

Flinn (1986) provides a statistical test of the restrictions imposed by the theory on the covariance structure of the log of earnings. To account for the presence of unobserved job-match heterogeneity, Flinn assumes that the residual from the log-earnings function contains a match-specific component, fixed within a job but different across all possible matches. Although the restrictions cannot be rejected by the data, it should be noted that his sample is very small (the sample is made of 248 individuals and is further divided into four distinct subsamples, the smallest of which has 36 workers) and short (three years). Therefore, as a first step in the analysis, it seems appropriate to assess the validity of the covariance structure as implied (in its simplest form) by the matching theory with a longer and larger sample. Next, I study the evolution of the variance of the job-match component across jobs and within jobs. Depending upon the nature of the matching process that one has in mind, we get different predictions concerning the evolution of that component. More particularly, it makes a difference whether jobs are considered as pure experience goods or pure inspection goods. In the former case, nothing can be learned about the characteristics of the job without actually gaining some experience in it. Consequently,

we should first observe an increase in the variance of the job-match component as all worker-firm matches start with the same prior information and workers are paid the same wage. Hence, in theory, the variance at the start should be zero. With each new pieces of information, both parties get a clearer idea as to the quality of their match and the variance increases up to the point where the selection process makes ill matched workers leave their job, thereby truncating the bottom part of the distribution. Then, assuming that the distribution is unbounded, we should see a decline in the variance of the match quality distribution followed by an increase as we reach the right-hand tail. On the other hand, if jobs are pure inspection goods, then everything can be learned merely by contacting a potential employer, in which case we find ourselves with a typical search model (e.g. Burdett (1978)). Both the variance across jobs and within jobs should decline from the start up to the point where, again, the upper tail of the match quality distribution is reached, in which case the variance starts increasing.

Since the predictions of the matching model are derived under the assumption of no acquisition of human capital, which means that workers are assumed to be sampling from a stable wage offer distribution, the results I get suggest that this assumption is likely to be violated. More precisely, it is difficult to find evidence of the patterns predicted by the theory, except for the evolution within jobs. The next step, then, is to focus our attention on the predictions of human capital theory, with the idea of trying to isolate a prediction that is not shared by the theory of job matching. With this goal in mind, I extend Hause's (1980) approach by introducing the concept of job into his framework. Under certain specifications, Hause was able to find evidence for a U-shape pattern of the time profile of variances of the log of earnings for a sample of young Swedes.¹ According to the theory of human capital, this pattern emerges because of a negative covariance between the individual-specific intercept and slope parameters. Those with a lower intercept invest relatively more in human capital by accepting a lower starting salary. Eventually, though, their earnings overtake those of workers who chose

¹ See Mincer (1974), especially as it pertains to the overtaking concept.

not to invest as much. Subsequent work on the theory of matching by Jovanovic (1984) led to the prediction of a U-shape pattern as well when we are studying the wage-experience profile of individuals. The basic reason stems from the fact that individuals would be prepared to leave a job in which pretty much all learning has been done for another which initially pays less but which offers the possibility of growth. Therefore to have a chance of potentially discriminating between the two theories, we need a framework which allows us to circumvent this identification problem.

By introducing jobs into the analysis, it is possible to isolate the key prediction from human capital theory that there should be a tradeoff between the job-specific intercept and the tenure slope. All things being equal, those who start out with a lower salary invest more in human capital and consequently should have a steeper slope. In contrast, the pure theory of matching does not predict such a tradeoff within jobs. In fact, in his work on the complementarity between the quality of a match and firm-specific investment, Jovanovic (1979b) shows that a better match should, *ceteris paribus*, involve more investment. Therefore, the only way that the theory of matching can account for the tradeoff between the job-specific slope and the intercept is through human capital considerations.

All this is not to say that matching is not an important phenomenon. On the contrary, it is shown that even the simplest form of covariance structure implied by the theory of matching fits the data quite well. I would rather want to emphasize the complementarity between matching and human capital. This complementarity makes difficult the isolation of predictions specific to the theory of matching. But, when some control for the acquisition of human capital through on-the-job training is provided, predictions stemming from search/matching considerations are more easily highlighted.

The paper is organized as follows. Section II sketches the main results from the theory of matching with an emphasis on the predictions pertaining to the variance of the

job-match component. Section III follows with a discussion on the theory of human capital and the covariance structure of earnings. Section IV focuses on the empirical implementation of the models discussed in sections II and III, including discussions on the data and on the econometric methodology. Section V presents the results, and at the end of the section, the predictions stemming from matching/search considerations are reexamined in a context where some control is provided for the accumulation of human capital. Section VI concludes the paper.

II. THE THEORY OF MATCHING AND ITS EMPIRICAL IMPLICATIONS

Originating with Stigler's model of search, economists have developed tools for analyzing the way in which individual units such as firms or workers gather and process information. For example, McCall (1970) pioneered the development of the theory of sequential job search in which individuals draw (at a cost) from a wage distribution F and then decide to either accept the offer in hand or to reject it and sample once again. By applying the principle of optimality, each individual will have a decision rule which is characterized by a reservation offer, say w^* , such that any wage offer above this threshold will be accepted and, conversely, all offers below w^* will be rejected.

As emphasized by Rothschild (1973), one problem with this model is the existence of the wage distribution itself in equilibrium. If we assume that the population of workers is homogeneous, then no wages less than w^* would be observed and profit maximizing firms would see no point in offering wages above w^* . Therefore, the wage distribution would collapse to a trivial one where all the probability mass is concentrated at w^* .

The theory of matching offers an answer to this problem by allowing, in an equilibrium context, the existence of both a non-trivial wage distribution and an optimal search strategy by individuals. The classic references on the theory of matching are Jovanovic (1979a, 1979b, 1984). The model described below is a discrete-time version

of the one contained in Jovanovic's 1984 contribution. Note that I will focus mainly on the information processing part of the model as the predictions we are interested in stem from this learning mechanism.

II.1 The Theory in a Nutshell

Let's assume that θ , the quality of a match between a worker and a firm, can be characterized as having been drawn from some known normal distribution. The worker and the firm come from homogeneous populations. The match parameter θ can be seen as representing the marginal productivity of the worker in the firm. The main theme recurring in the analysis is that both the firm and the worker will gain information on the "true" quality of the match first by merely contacting a potential employer and also by observing the evolution of the worker's output over time. Both sources of information are noise ridden and each party is assumed to use Bayes' law to update its beliefs on θ . To be more specific, the assumptions can be summarized as follows:

Assumptions:

- (i) The prior distribution of θ is $N(\gamma, 1/\tau_\theta)$, where τ_θ represents the precision of the distribution. This distribution is stable over time. All workers and firms share this prior distribution.
- (ii) The outcome of the initial screen is denoted as $m_0 = \theta + \epsilon_0$, with ϵ_0 being normally distributed with mean 0 and precision τ_m . When $\tau_m \rightarrow \infty$, all information about the quality of a potential match can be learned merely by contacting an employer. In other words, jobs are pure search or inspection goods. When $\tau_m \rightarrow 0$, nothing can be learned from the match without gaining some experience in it. In that case, jobs are pure experience goods.
- (iii) The output at each period is $x_t = \theta + \epsilon_t$, with $\epsilon_t \sim N(0, 1)$ and $E(\epsilon_t \epsilon_s) = 0$, for all $t \neq s$.

s. At each period t , both parties observe the worker's output and both are equally well informed about the quality of the match. They are assumed to use Bayes' law to update their beliefs on the perceived quality of the match.

(iv) At each period, each worker receives an offer with probability λ .

(v) All draws from the prior distribution are independent from one another. The quality of the present match provides no information on the quality of potential matches. There is no recall (or if recalls are allowed, the quality of the new match is independent of the old one).

(vi) Firms are assumed to pay workers their expected marginal product. This is the equilibrium contract of Jovanovic (1979a) derived under the assumption that firms bid for workers by offering them lifetime contracts which they are assumed to honor ex post.

(vii) Embedded in (vi) is the assumption that workers maximize the expected present value of their lifetime earnings.

(viii) Workers accept the first offer they receive.

The time sequence of events is thus the following: (i) a firm and a worker make contact; (ii) upon contact, they both observe a noisy signal m_0 which provides information on the true value of the match; (iii) the firm makes an offer to the worker on the basis of that information, and the worker accepts; (iv) at each subsequent period t , both parties update their belief on the quality of the match by making use (through Bayes' Law) of the information provided by the output x_t ; (v) the worker makes a stay/quit decision and draws another match parameter, after which the same sequence resumes. Given the assumptions above, we can summarize their implications in the following proposition:

PROPOSITION 1

a) The wage paid at period t , conditional on the outcome of the screen and on the sequence of outputs is equal to:

$$E(\theta | m_0, x_1, x_2, \dots, x_t) = \frac{\bar{x}_t \tau_m m_0 \tau_\theta \gamma}{t \tau_m \tau_\theta} = w(t) \quad (1)$$

with conditional variance given by:

$$V(\theta | m_0, x_1, x_2, \dots, x_t) = \frac{1}{t \tau_m \tau_\theta} = S(t) \quad (2)$$

b) The current wage conditional on the previous wage is:

$$E(w(t) | w(t-1) = w) = w; \quad V(w(t) | w(t-1) = w) = S(t)S(t-1). \quad (3)$$

c) The initial wage (w_0) offer distribution is characterized by:

$$w_0 \sim N\left(\gamma, \frac{\tau_m}{\tau_\theta (\tau_\theta \tau_m)}\right) \quad (4)$$

d) The unconditional distribution of $w(t)$ is normal with moments equal to:

$$E(w(t)) = \gamma; \quad V(w(t)) = \frac{1}{\tau_m \tau_\theta} - \frac{1}{t \tau_m \tau_\theta} \quad (5)$$

PROOF

a) Let $f(\cdot)$ be the posterior distribution, $g(\cdot)$ the likelihood function, and $h(\cdot)$ the prior distribution of θ . From Bayes' Law we know that:

$$f(\theta | m_0, x_1, x_2, \dots, x_t) \propto g(m_0, x_1, x_2, \dots, x_t | \theta) h(\theta); \quad (6)$$

$$\text{with } g(m_0, x_1, x_2, \dots, x_t | \theta) \propto \exp\left(-\frac{1}{2} \sum_{i=1}^t (x_i - \theta)^2 - \frac{\tau_m}{2} (m_0 - \theta)^2\right); \quad (7)$$

$$h(\theta) \propto \exp\left(-\frac{\tau_\theta (\theta - \gamma)^2}{2}\right) \quad (8)$$

If we develop equation (6) given that we know $g(\cdot)$ and $h(\cdot)$, then we obtain after some algebra:

$$f(\theta | m_0, x_1, x_2, \dots, x_t) \propto \exp\left(-\frac{t \tau_m \tau_\theta}{2} \left(\theta - \frac{\bar{x} t \tau_m m_0 + \tau_\theta \gamma}{t \tau_m \tau_\theta}\right)^2\right) \quad (9)$$

$$\bar{x} = \left(\sum_{i=1}^t x_i\right) / t$$

which is the kernel of a normal distribution with conditional expectation given by

$$w(t) = E(\theta | m_0, x_1, x_2, \dots, x_t) = \frac{\bar{x} t \tau_m m_0 + \tau_\theta \gamma}{t \tau_m \tau_\theta} \quad (10)$$

with conditional variance equal to

$$S(t) = V(\theta | m_0, x_1, x_2, \dots, x_t) = \frac{1}{t \tau_m \tau_\theta} \quad (11)$$

b) Rearranging equation (10), we can express $w(t)$ as:

$$w(t) = [S(t)/S(t-1)]w(t-1) + [1 - S(t)/S(t-1)](\theta + \varepsilon_t) \quad (12)$$

Hence,

$$\begin{aligned} E(w(t) | w(t-1) = w) &= [S(t)/S(t-1)]w + [1 - S(t)/S(t-1)]E(\theta + \varepsilon_t | w(t-1) = w) \\ &= [S(t)/S(t-1)]w + [1 - S(t)/S(t-1)]w = w \end{aligned} \quad (13)$$

For the conditional variance, we have:

$$\begin{aligned}
 E((w(t)-w)^2 | w(t-1)=w) &= E((S(t)/S(t-1)-1)w - [1-S(t)/S(t-1)](\theta \epsilon_t))^2 | w(t-1)=w) \\
 &= (1-S(t)/S(t-1))^2 (S(t-1)+1) \\
 &= S(t)^2 \frac{\tau_m \tau_\theta}{(t-1) \tau_m \tau_\theta} = S(t)S(t-1)
 \end{aligned} \tag{14}$$

c) From a) and from the fact that $m_0 - \gamma$ is normally distributed with mean 0 and variance $1/\tau_\theta + 1/\tau_m$, we have:

$$\begin{aligned}
 w(0) &= \gamma - \frac{\tau_m}{\tau_m \tau_\theta} (m_0 - \gamma) \\
 E(w(0)) &= \gamma; \quad V(w(0)) = E\left(\frac{\tau_m}{\tau_m \tau_\theta} (m_0 - \gamma)^2\right) = \frac{\tau_m}{\tau_\theta (\tau_m \tau_\theta)}
 \end{aligned} \tag{15}$$

d) Taking the unconditional expectation of $w(t)$ gives:

$$\begin{aligned}
 E(w(t)) &= \frac{E(\bar{x}) t \tau_m E(m_0) \tau_\theta \gamma}{t \tau_m \tau_\theta} = \gamma \\
 V(w(t)) &= E\left(\frac{\bar{x} t \tau_m m_0 \tau_\theta \gamma}{t \tau_m \tau_\theta} - \gamma\right)^2 = E\left(\frac{t(\bar{x} - \gamma) \tau_m (m_0 - \gamma)}{t \tau_m \tau_\theta}\right)^2 \\
 &= \frac{1}{\tau_m \tau_\theta} - \frac{1}{t \tau_m \tau_\theta}
 \end{aligned} \tag{16}$$

To derive the predictions pertaining to the evolution of the variance, two extreme cases are considered. The first case is when jobs are pure search goods and the second one when they are pure experience goods.

A. Jobs as pure search goods ($\tau_m \rightarrow \infty$).

In this environment, the decision rule for each worker at time t is to accept an outside offer w_t whenever $w_t > w_{t-1}$, where w_{t-1} is assumed to be the wage paid in the current match. Otherwise, the worker stays with the same employer. Note that we are assuming no accumulation of human capital. Therefore, the wage paid on a job is a constant throughout the employment relationship. Under these assumptions, the threshold above which workers quit their match rises at each period t . Hence, the wage distribution of job

changers gradually moves over time toward the right-hand tail.

PROPOSITION 2

For each successive t , the moments of the truncated distribution are then given by:

$$E(w_t | w_t > w_{t-1}) = \gamma + \left(\frac{1}{\tau_\theta}\right)^5 \frac{\varphi((w_{t-1} - \gamma)\tau_\theta^5)}{1 - \Phi((w_{t-1} - \gamma)\tau_\theta^5)} = \gamma + M_1 \quad (17)$$

$$V(w_t | w_t > w_{t-1}) = \frac{1}{\tau_\theta^5} - M_1(M_1 - (w_{t-1} - \gamma))$$

where $\Phi(\)$ is the standard normal distribution function and $\varphi(\)$ is the corresponding density.

PROOF

From c) above, the initial ($t=0$) distribution of wages in the population coincides with the prior distribution. Thus w_0 is normal with mean γ and variance $1/\tau_\theta$. At each period t , the wage w_t has the same distribution as the initial wage only if w_t is greater w_{t-1} i.e. the distribution is truncated. Defining $w_0 = \gamma + 1/\tau_\theta \varepsilon$, where ε is a standard normal variate, the following set of results are obtained:

a)

$$P(w_t > w_{t-1}) = P(w_0 > w_{t-1}) = P\left(\gamma + \frac{1}{\tau_\theta^5} \varepsilon > w_{t-1}\right) = P(\varepsilon > (w_{t-1} - \gamma)\tau_\theta^5) \quad (18)$$

$$= 1 - \Phi((w_{t-1} - \gamma)\tau_\theta^5)$$

b)

$$\begin{aligned}
 E(w_i) &= E(w_0 | w_0 > w_{i-1}) \\
 &= E\left(\gamma + \frac{1}{\tau_\theta} \varepsilon \mid \varepsilon > (\gamma - \tau_\theta) \tau_\theta \delta\right) \\
 &= \gamma (1 - \Phi((\gamma - \tau_\theta) \tau_\theta \delta)) + \frac{1}{\tau_\theta} \varphi((\gamma - \tau_\theta) \tau_\theta \delta)
 \end{aligned} \tag{19}$$

c)

$$\begin{aligned}
 E(w_i | w_i > w_{i-1}) &= \frac{E(w_0 | w_0 > w_{i-1})}{P(w_0 > w_{i-1})} \\
 &= \gamma + \left(\frac{1}{\tau_\theta}\right) \frac{\varphi((\gamma - \tau_\theta) \tau_\theta \delta)}{1 - \Phi((\gamma - \tau_\theta) \tau_\theta \delta)}
 \end{aligned} \tag{20}$$

d)

$$\begin{aligned}
 E(w_i^2) &= E(w_0^2 | w_0 > w_{i-1}) = E\left(\gamma + \frac{1}{\tau_\theta} \varepsilon\right)^2 \mid \varepsilon > (\gamma - \tau_\theta) \tau_\theta \delta \\
 &= \gamma^2 (1 - \Phi((\gamma - \tau_\theta) \tau_\theta \delta)) + (\gamma - \tau_\theta) \frac{1}{\tau_\theta} \varphi((\gamma - \tau_\theta) \tau_\theta \delta) \\
 &\quad + \frac{1}{\tau_\theta^2} (1 - \Phi((\gamma - \tau_\theta) \tau_\theta \delta))
 \end{aligned} \tag{21}$$

e)

$$\begin{aligned}
 V(w_i | w_i > w_{i-1}) &= E(w_i^2 | w_i > w_{i-1}) - (E(w_i | w_i > w_{i-1}))^2 \\
 &= \frac{E(w_0^2 | w_0 > w_{i-1})}{P(w_0 > w_{i-1})} - (E(w_i | w_i > w_{i-1}))^2 \\
 &= \frac{1}{\tau_\theta^2} - (\gamma - \tau_\theta) \frac{1}{\tau_\theta} \frac{\varphi(\cdot)}{1 - \Phi(\cdot)} - \frac{1}{\tau_\theta} \left(\frac{\varphi(\cdot)}{1 - \Phi(\cdot)}\right)^2 \\
 &= V(w_i | w_i > w_{i-1}) = \frac{1}{\tau_\theta} - M_1(M_1 - (w_{i-1} - \gamma))
 \end{aligned} \tag{22}$$

Taking the derivative of $V(\cdot)$ with respect to w_{i-1} gives:

$$\frac{dV(w_t | w_t > w_{t-1})}{dw_{t-1}} = -2M_1 \frac{dM_1}{dw_{t-1}} + M_1 + (w_{t-1} - \gamma) \frac{dM_1}{dw_{t-1}} \quad (23)$$

This expression can be negative or positive. First note that dM_1/dw_{t-1} is strictly positive.² Moreover, there exists a critical value w^* such that for all w_{t-1} below this threshold, $dM_1/dw_{t-1} < 1/2$ and for all values of w_{t-1} at least as large as w^* , then $dM_1/dw_{t-1} \geq 1/2$.³ By substituting $1/2$ for dM_1/dw_{t-1} , $dV(\cdot)/dw_{t-1} < (w_{t-1} - \gamma)$ for all $w_{t-1} < w^*$. Thus, if $w_{t-1} \leq \gamma$, we know for sure that equation(23) is negative. Conversely, for all $w_{t-1} > w^*$, $dV(\cdot)/dw_{t-1} > (w_{t-1} - \gamma)$. With $w_{t-1} \geq \gamma$, then $dV(\cdot)/dw_{t-1} > 0$. Consequently, we should first observe a decline in the variance from job to job followed by an increase as we move towards the right-hand tail.

The same result holds for the evolution within jobs. In a search context, individuals stay with the same employer only if the wage they receive at the start of the employment relationship (and which stays the same throughout the duration of the match) is at least as great as any offer they receive over time. Thus, as $t \rightarrow \infty$, the only people still with the same employer must have drawn from the upper portion of the distribution, where the variance is larger.

B. Jobs as pure experience goods ($\tau_m \rightarrow 0$).

Here the decision to quit an employer depends on the information that can be extracted from the sequence of outputs. Of course, workers know that they can obtain a starting wage equal to γ for any draw made from the prior distribution. But, contrary to

² $dM_1/dw_{t-1} = \varphi(w_{t-1} - \gamma) / (1 - \Phi(w_{t-1} - \gamma)) [\varphi(w_{t-1} - \gamma) / (1 - \Phi(w_{t-1} - \gamma)) - (w_{t-1} - \gamma)]$, which is strictly positive.

³ dM_1/dw_{t-1} is a continuous function of w_{t-1} . It can be shown that the limit of dM_1/dw_{t-1} is zero for $w_{t-1} \rightarrow -\infty$ while it tends to infinity with $w_{t-1} \rightarrow \infty$. Thus, there exists a threshold w^* with $dM_1/dw_{t-1} = 1/2$.

the search model, this is the only offer they will receive over time from the outside as nothing is revealed about the quality of the match short of working in it. Therefore, in this environment, the expected present value from leaving, say V , is a constant and the decision to quit hinges on the belief workers form about the quality of the match. From d) above, we know the unconditional distribution of the wage received by a sample of workers. This would be the eventual distribution of wages across these workers if all of them were to stay with the same employer for their entire career. Over time, however, some workers will quit as the information they get from the sequence of output indicates with more and more precision that it is preferable to accept a wage equal to γ in a new job which offers an expected present value of V . It can be shown that the optimal decision rule for the individual is to stay with the same employer if w_t given by equation (1) is above a critical value w_t^* which rises over time and to quit otherwise.⁴ Consequently, the moments of the truncated distribution are given by:

$$\begin{aligned}
 E(w_t | w_t > w_t^*) &= \gamma + \sigma_t \frac{\phi((w_t^* - \gamma)/\sigma_t)}{1 - \Phi((w_t^* - \gamma)/\sigma_t)} = \gamma + M_1 \\
 V(w_t | w_t > w_t^*) &= \sigma_t^2 - M_1(M_1 - (w_t^* - \gamma))
 \end{aligned}
 \tag{24}$$

where σ_t^2 is the unconditional variance given in equation (5).⁵ As in the case where jobs are pure search goods, the derivative of $V(\)$ could be calculated to get the evolution of the variance within jobs. However, the presence of σ_t^2 greatly complicates the task of determining the sign of that derivative. The reason is that σ_t^2 is not constant and thus additional terms appear in the analog of equation (23). The only solid conjectures that can be advanced are the following: (i) from $t=0$ to $t=1$, there is an increase in the variance (the variance is zero at $t=0$). After that, it may increase or decrease depending upon the

⁴ See Sargent (1985) for a proof in a finite lifetime context.

⁵ Note that the conditional mean indicates that if we were to estimate an earnings equation with ordinary least-squares, we would find a positive return to tenure simply because those that happen to have better matches are still with the same employer, even though their wage does not necessarily rise with tenure.

speed at which the learning process evolves. If all learning is done rapidly, then it is as though the unconditional distribution given by d above stabilizes (the variance stops increasing). Thus, a selection process identical to the one in case A above would impart a decreasing-increasing pattern to the variance within jobs.

The evolution of the variance across jobs is simple: with a totally uninformative screen, all jobs are *ex ante* identical (draws are independent) and thus the variance should be stable from job to job.

To recapitulate, if jobs are pure search or inspection goods, the variance within jobs and across jobs will first decline and eventually will increase as we reach the right-hand tail with $t \rightarrow \infty$. If jobs are pure experience goods, the variance across jobs should be similar while the evolution within jobs is characterized by an increase from $t=0$ to $t=1$. For $t > 1$, the evolution is undetermined. If the learning process is completed fairly rapidly, then we would expect the selection process to impart a decreasing/increasing pattern like in the case where jobs are pure search goods.

III. THE THEORY OF HUMAN CAPITAL AND THE COVARIANCE STRUCTURE.

The question of examining the empirical implications of the theory of human capital is, of course, not new. The human capital earnings function has been used extensively since its development by Mincer (1974). However, the implications in terms of the covariance structure have rarely been looked upon. Hause (1980) is a notable exception. This section will first summarize these implications before turning to the empirical section.

Mincer's overtaking concept is at the heart of the analysis in terms of the covariance structure of earnings. Assuming that two individuals have identical attributes (total labor

market experience, schooling, etc.), then, according to human capital theory, their earnings profiles should differ only if their rates of post-schooling investment are not the same.⁶ The worker who invests more should have lower initial earnings than the other worker. However, as she accumulates human capital, her earnings should increase at a faster rate and eventually surpass the other worker's earnings. Generalizing to a sample of relatively homogeneous workers followed over time, we should then observe a declining profile of the variance of the log of earnings in the years leading to the overtaking point, followed by an increase in variance afterwards. Therefore, we should have a negative correlation between the slope of the earnings profile and its intercept.

Note however that the observed time profile of variances might not necessarily be U-shaped were individuals to differ in some unobserved dimension which is correlated with the rate of investment, as Mincer points out in his analysis of residuals.⁷ More precisely, assuming that individuals who are intrinsically more able also invest more in on-the-job training, then we might have a positive correlation between the slope and the intercept of the earnings profile if the correlation between unobserved "ability" and the rate of investment is sufficiently strong.

These empirical implications of the theory of human capital have been tested by Hause (1980) with a six-year sample of young Swedish white collars who were born the same year and had similar levels of schooling. He allows each individual to have his own level and slope (i.e. experience slope) parameters. In other words, his residual structure of earnings is of the form:⁸

⁶ Of course, we also assume away the presence of uncertainty or informational asymmetries.

⁷ For the full derivation of these assertions, see Mincer (1974), chapter 6.

⁸ Actually, Hause directly fitted the wage observations instead of using the residuals from a fully specified earnings function.

$$w_{it} = \alpha_{1i} + \alpha_{2i} \text{Experience}_{it} + u_{it} \quad (25)$$

The slope and intercept parameters are assumed to be independent of the residual term u_{it} and also independently distributed across individuals. Consequently, taking the expectation over individuals of the cross product of w_{it} and w_{is} gives us:

$$\begin{aligned} E(w_{it}w_{is}) &= \varphi_{11} + \varphi_{22} \text{Exp}_{it} \text{Exp}_{is} + \varphi_{12} (\text{Exp}_{it} + \text{Exp}_{is}) \sigma_u^2 \\ \varphi_{11} &= \text{var}(\alpha_1); \varphi_{22} = \text{var}(\alpha_2); \varphi_{12} = \text{cov}(\alpha_1, \alpha_2) \end{aligned} \quad (26)$$

Relating equation(26) to the discussion above, the overtaking year should be associated with the year at which we observe the minimum variance. Thus, minimizing equation(36) with respect to the level of experience t_0 (i.e. time of overtaking) gives us $t_0 = -\varphi_{12}/\varphi_{22}$. Because of unobserved ability, t_0 will represent a lower bound of the true overtaking year. With six years of data, the empirical covariance matrix contains 21 distinct elements which Hause then fits with the structure implied by human capital theory. He does find a negative correlation between the slope and intercept parameters but whether this correlation is significant or not depends on the residual error structure that he imposes. Under the specification that produces a statistically significant result, he estimates t_0 to be in the neighborhood of five years.⁹ Note that unless he imposes a very loose structure on the u_{it} ¹⁰ term, the model is rejected by the data and there is no significant tradeoff between the slope and the intercept.

To conclude on Hause's paper, it should be mentioned that the time profile of the variances of the log of earnings which he tries to fit is not U-shaped. Instead, the variances shows a monotonic decrease from year one to year six. But this is one pattern which learning theories like the theory of matching predict, especially in the formulation where all learning about the job characteristics is done rapidly. Therefore, to discriminate

⁹ Hause estimated the parameters of his model with quasi-maximum likelihood methods.

¹⁰ Six distinct residual (uit's) variance parameters each following a distinct AR(1) process, which produces 11 parameters (in addition to the other three) for the 21 elements to be fitted.

between the two theories, it is not sufficient to look at the residual earnings structure by focusing only on the variance of the experience profiles of workers. What is done in the next section is to extend Hause's approach to the tenure profiles.

IV. EMPIRICAL IMPLEMENTATION

IV.1 The data

The predictions derived above are examined using unbalanced data from the National Longitudinal Survey of Youth (NLSY) for the period spanning the years 1979-1991. This data set contains the full employment history of young Americans from the moment they make their (full time) transition from the school to the labor market. The workers who were considered as having entered the labor market on a full-time basis were (i) those whose primary activity was either working full-time, on a temporary lay-off or looking actively for a job, (ii) those who did not return to school on a full-time basis within six years and (iii) those who had worked at least half the year since the last interview and who were working at least 20 hours per week. Individuals excluded from the sample are those younger than 18, those that had been in the military at any time, the self-employed, the ones whose jobs were part of a government program and the ones working without pay, those who were in the farming business and also all public sector employees. These restrictions leave us with a sample consisting of 29,020 observations (5,649 workers). Summary statistics are reported in table 1.

IV.2 Log-Earnings Equation

Let the wage of person i at time t be determined according to the following equation:

$$w_{ijt} = E(w_{ijt} | \text{observables}) + \varepsilon_{ijt} \quad (27)$$

where w_{ijt} is the log of the real hourly wage of worker i in job j . The first step is then to estimate equation (27) with ordinary least-squares to obtain the residuals. After that, the models that I estimate are models for the expectation of the cross-products of the residuals, $E(\varepsilon_{ijt}\varepsilon_{iks})$.¹¹ I try to determine to what extent the predictions from the two theories are supported by the data. It is worth reiterating that my primary interest is to examine the implications of the selection process by which workers are sorted into jobs. Therefore, in estimating equation (27), I make no attempt at trying to correct for selection biases.

IV.3 Econometric Models of Matching

As a first step, a test of the matching model in its simplest form is presented. More precisely, I test whether the covariance structure of the error term of a standard human capital earnings equation satisfies the restrictions imposed by the job matching theory. The simplest way to account for the process of matching is to include an error component θ_{ij} as part of the total error term ε_{ijt} . It represents the unobserved (to the econometrician) quality of the match which affects the wage of individual i . This component is assumed to be fixed within matches although there is a whole distribution of match productivities. Assuming that the error term also contains an individual-specific component to reflect time-invariant unobserved individual characteristics, then it can be written as:

¹¹ The matrix of observables includes total experience, total experience squared, tenure, tenure squared, experience in the industry, experience in the industry squared, industry and occupation dummies, year dummies, race, sex, marital status, union membership, SMSA, urban/rural, health, unemployment rate in corresponding region, an intercept, four region and three education dummies. The vector of estimated residuals is then expressed in deviations from annual means.

$$\epsilon_{ijt} = \alpha_i + \theta_{ij} + \eta_{ijt} \quad (28)$$

where η_{ijt} is a white noise error term. Note that the three terms are assumed to be independently distributed. Taking the expectation of the cross-products gives:

MODEL 1

$$\begin{aligned} E(\epsilon_{it}^2) &= \sigma_\alpha^2 + \sigma_\theta^2 + \sigma_\eta^2 \\ E(\epsilon_{it}\epsilon_{is} | I_t) &= \sigma_\alpha^2 + I_t \sigma_\theta^2 \end{aligned} \quad (29)$$

where I_t is an indicator variable equal to 1 if worker i holds the same job at periods t and s . To test the predictions of the theory of matching pertaining to the evolution of the variance of the job-match component across jobs, model 1 is expanded by allowing a different job-match component for each job held by the worker up to job five and over. Let job_{ik} be an indicator variable equal to 1 if worker i is in job k ($k=1, \dots, 5+$) and equal to 0 otherwise, then the model to be estimated is the following:

MODEL 2

$$\begin{aligned} E(\epsilon_{it}^2 | job_{ik}) &= \sigma_\alpha^2 + \sum_{k=1}^{5+} (job_{ik} \sigma_{\theta_k}^2) + \sigma_\eta^2 \\ E(\epsilon_{it}\epsilon_{is} | I_t, job_{ik}) &= \sigma_\alpha^2 + I_t \sum_{k=1}^{5+} (job_{ik} \sigma_{\theta_k}^2) \end{aligned} \quad (30)$$

In the same spirit, to study the evolution of the variance of the match component within jobs, model 1 is generalized with the use of dummy variables for different levels of tenure. More precisely, let $dumten_{is}$ be equal to 1 if the tenure level of worker i is included in the interval corresponding to s and equal to 0 otherwise, where $s=(1$ if $tenure < 1$ month, 2 if $1 \text{ month} \leq tenure < 4$ months, 3 if $4 \text{ months} \leq tenure < 1$ year, 4 if $1 \text{ year} \leq tenure < 2$ years, 5 if $2 \text{ years} \leq tenure < 3$ years, ..., 15 if $tenure \leq 12$ years). By including dummies for low levels of tenure, the hope is to be able to capture any increase (if there is any) in the variance of the job-match component, which is the prediction of the

matching model where at least some learning about the job occurs in the course of the employment relationship. If it is impossible to isolate an increasing pattern with this specification, then it may be that most of the on-the-job learning process is completed very quickly. Or, it may also be the case that some other factor such as the accumulation of human capital is playing a role. The model for the within-job evolution is then:

MODEL 3

$$E(\epsilon_{it}^2 | dumten_{it}) = \sigma_\alpha^2 + \sum_{s=1}^{15} (dumten_{it} \sigma_{\theta_s}^2) + \sigma_\eta^2 \quad (31)$$

$$E(\epsilon_{it} \epsilon_{is} | I_{it}, dumten_{it}) = \sigma_\alpha^2 + I_{it} \sum_{s=1}^{15} (dumten_{it} \sigma_{\theta_s}^2)$$

IV.4 Econometric Model of Human Capital

Generalizing Hausess's model to the tenure profile, let the error term be specified as:

$$\epsilon_{ijt} = \alpha_i \psi_{i1} Experience_{it} + \theta_{ij} \psi_{i2} Tenure_{ijt} + u_{ijt} \quad (32)$$

Now remember that I am using the residuals produced by estimating equation (27). That equation already contains quadratic functions of both tenure and experience. Therefore, how can the presence of these two explanatory variables in the error structure be justified? It turns out that assuming a random coefficient model is perfectly in tune with the spirit of Mincer's derivation of the human capital function.¹² In deriving the earnings function, Mincer first includes a subscript *i* representing each individual with the idea that the rate of investment as well as the return on that investment are individual-specific parameters.¹³

¹² See Mincer (1974), chapter 5, section 5.2.

¹³ "If information were available on all variables and parameters for each individual *i*, the [earnings] equation would represent a complete accounting (...) of the human capital characteristics entering into the formation of earnings." Mincer (1974), page 90.

Since these parameters are not directly observable, their corresponding i subscript is then eliminated and we are left with estimating average rates of returns. By focusing on the second moments, it is possible to take into account the randomness of the tenure and experience slope parameters. Also, given that training occurs within jobs, it seems more natural to model it as such. In view of the foregoing, the model to be estimated has the following basic structure:

MODEL 4

$$\begin{aligned}
 w_{it} &= \beta_1 X_{it} + \beta_2 T_{ijt} + \varepsilon_{it} \\
 \varepsilon_{it} &= \alpha_i + b_{1i} X_{it} + \theta_{ij} + b_{i2} T_{ijt} + \eta_{ijt} \\
 E(\varepsilon_{it} | X_{it}, T_{ijt}) &= E(\alpha_i) = E(b_{1i}) = E(\theta_{ij}) = E(b_{i2}) = E(\eta_{ijt}) = 0 \\
 E(\varepsilon_{it}^2 | X_{it}, T_{ijt}) &= \sigma_\alpha^2 + \sigma_{b_1}^2 X_{it}^2 + \sigma(b_1, \alpha) 2X_{it} + \sigma_\theta^2 + \sigma_{b_2}^2 T_{ijt}^2 \\
 &\quad + \sigma(b_2, \theta) 2T_{ijt} + \sigma_\eta^2 \\
 E(\varepsilon_{it} \varepsilon_{is} | X_{it}, X_{is}, T_{ijt}, T_{iks}, I_i) &= \sigma_\alpha^2 + \sigma_{b_1}^2 X_{it} X_{is} + \sigma(b_1, \alpha) (X_{it} + X_{is}) \\
 &\quad + \sigma_\theta^2 + \sigma_{b_2}^2 (T_{ijt} T_{iks}) + \sigma(b_2, \theta) (T_{ijt} + T_{iks})
 \end{aligned} \tag{33}$$

where T and X are respectively the tenure and experience levels and I_i is the same indicator variable as in the previous section. Note the following implicit assumptions: a) α , θ and η are independent from one another, as previously, b) b_1 and b_2 are also independently distributed, and c) experience and tenure are not correlated with the random parameters. Therefore, I am assuming away any selection effects that would occur were tenure to be positively correlated with the random coefficient b_2 . This orthogonality assumption is likely to be a strong one as we would expect workers with a high b_2 to stay longer on their job. Also, I am assuming that the observable individual characteristics used in estimating equation (33) are independent of the unobservables.

The same type of tradeoff than the one analyzed by Hause is applicable to the tenure profile. Namely, according to human capital theory, we should observe a negative

correlation between job-specific slope and intercept parameters. In other words, workers who have relatively more on-the-job training should pay for it through lower initial earnings.¹⁴ The same sort of counter-effect which made Hause's estimate of Mincer's overtaking point a lower bound is present here. More precisely, Jovanovic (1979b) has shown that the quality of the match and the level of investment in firm-specific capital are complementary. Consequently, according to this line of thought, other things being equal, we should observe a positive correlation between the job-specific slope and intercept parameters. Thus, the U-shape pattern of the variance of the log of earnings within jobs is not a prediction that is shared by the two theories.

Another prediction that is implied by human capital theory is that training should occur early in one's career (e.g. Ben-Porath (1967)). Therefore, the U-shape pattern should be more evident in the first few jobs than later on. On the other hand, the quality of the match should improve as one moves from one job to another. Hence, it is likely that a worker entering the labor market and a firm who find themselves in a bad match would be reluctant to invest in firm-specific skills. It is even conceivable that the worker would be less willing to invest in general human capital. It takes time to complete training and the fact that she is more likely to leave before completing the program than in a job where she would be better matched could provide a rationale for delaying investments in general skills. If these job-matching considerations are at play, then the correlation between the job-specific intercept and slope parameters should tend to be weaker in the first job than in the second. To verify these predictions, equation (33) is expanded by fitting five different quadratic functions to allow examination of the evolution of the parameters from job to job.

¹⁴ Note that we are not making any statement about the degree of firm-specificity of the human capital acquired in the course of OJT.

IV.5 Estimation Methodology

To estimate and test the restrictions imposed by the models, I make use of the methodology proposed by Gallant and Jorgenson (1979) in the context of a system of nonlinear implicit equations. The basic idea is to compare the weighted sum of squares of an unrestricted model with that of the (restrictive) model I wish to estimate. This methodology is closely related to the minimum distance method proposed by Chamberlain (1982, 1984) and adapted by Abowd and Card (1989) to study the covariance structure of earnings (see the appendix for further details). The conditional moments equations are stacked up into a system of equations which, as an example, would be of the following form for model 1:

$$E(m_i | I_i) = f(\beta, I_i)$$

$$m_i = [\epsilon_{i1}^2, \epsilon_{i1}\epsilon_{i2}, \dots, \epsilon_{i1}\epsilon_{iT_i}, \epsilon_{i2}^2, \epsilon_{i2}\epsilon_{i3}, \dots, \epsilon_{iT_i}^2]$$
(34)

where T_i is last period in which worker i is in the sample. β is the vector of parameters to estimate and $f(\cdot)$ is the mapping representing the model. Were all 5 649 individuals present in the sample from 1979 to 1991, each model above would represent a system of 91 equations (13 second moments and 78 cross-products), for a grand total of 514 059 observations. The sample being unbalanced, I end up with 116 715 observations. The objective is then to minimize the following function:

$$S(\beta) = \sum_{i=1}^N (m_i - f(\beta, I_i))' V^{-1} (m_i - f(\beta, I_i))$$
(35)

Where V^{-1} is computed with the cross-products of the residuals from the following unrestricted model:

$$\begin{aligned}
 E(\epsilon_{it}^2) &= cov1_{it} \\
 E(\epsilon_{it}\epsilon_{is} | I_{it}) &= cov1_{is} + I_{it}cov2_{is}
 \end{aligned}
 \tag{36}$$

This unrestricted model contains 91 different cov1 parameters and 78 distinct cov2 parameters. Note that if only the cov1's were estimated, each of these models would be equal to the corresponding sample moment. But for the matching models that I want to estimate to be nested in a more general model which depends on each individual-specific I_{it} , the cov2's have to be estimated as well. Let $S(\beta)_1$ be the value of the objective function for the unrestricted model and $S(\beta)_2$ be defined likewise for the restricted version of equation (34). For more general (i.e. non-linear) models, Gallant and Jorgenson (1979) show that $T_0 = S(\beta)_2 - S(\beta)_1$ is asymptotically distributed as a chi-square with $r-s$ degrees of freedom where $r-s$ is equal to the difference in the number of parameters in the two models.

V. RESULTS

V.1 Matching Models

Results for the entire sample are reported in tables 2, 3 and 4. To get an idea of the impact of including a job-match component in the error structure, columns 1 and 2 of table 2 show the results from estimating model 1 without the match component ("model 0"). The first conclusion to be drawn is the absence of statistical support for the model which provides control for individual heterogeneity only and in which η_{it} is i.i.d. (column 1). The distance statistic of 266 is a surprising value coming from a χ^2 (167). When the job-match component is added (column 2), the fit is substantially improved. In fact, as in Flinn (1986), the structure cannot be rejected. It might seem surprising that the data cannot reject such a simple structure, especially given some recent attempts (e.g. Abowd

and Card (1989), Farber and Gibbons (1994)) at trying to fit parsimonious structures to the error term. However, it should be remembered that the estimated log-wage equation from which the residuals are extracted contains all the explanatory variables which typically appear in such an equation. Consequently, all observable time-varying individual or job-match characteristics are controlled for, which makes it considerably easier to fit a restrictive structure on the error term. On the other hand, Abowd and Card to take an example, control only for potential experience in the labor market.¹⁵

To examine the evolution of the variance of the job-match component from job to job, I need to account in some way for the presence of aggregate effects to avoid as much as possible these effects being picked up by the coefficients. The simplest way to provide such a control is by assuming that the residual error term η is independently but not identically distributed from period to period. Therefore, I estimate 13 period specific variances of η . The results for the whole sample are reported in table 3, column 1. We can see that no clear pattern emerges although the overall tendency would be positive were it not for the component attached to job 4. Remember that in the version of the theory of matching where jobs are pure experience goods, successive and independent sampling from the job-match distribution implied that the variance of that distribution should be stable from job to job, whereas if the jobs were pure inspection goods, then the variance should be declining as we follow a cohort of workers over time and across different jobs. The overall pattern here is non-trivial. One of the reason stems no doubt from using the entire sample which consists of workers who are heterogenous in terms of schooling and also in terms of time of entry into the labor market. Also, because workers with more schooling enter the sample later, they are less likely to be represented in jobs 4 and 5. Consequently, to alleviate to a certain extent these sample composition problems, I present the results by levels of schooling in columns 2, 3 and 4. Here again, we can see that no clear pattern emerges. The fact that the variance increases is not

¹⁵ If I try to fit the same structure controlling only for the experience level, then the model is rejected by the data.

consistent with the matching theory, whether jobs are considered as search goods or as pure experience goods.

Turning now to the within-job evolution of the variance of the job-match component (model 3), we want to see if the contribution of that component is monotonically declining, which would suggest that the screening process reveals a lot of information, or if it is first increasing and then decreasing, a pattern which is indicative of an imperfect screen and of some learning taking place early while gaining experience in the job. Note that if all learning takes place quite early in the employment relationship (say less than one month after the start of the job), then it will be impossible to pick up any increase in the contribution of the variance of the job-match component. We will only be able to see the impact of the selection process by which this contribution decreases with tenure.¹⁶ The results are reported in table 4, column 1 for the whole sample and in columns 2, 3 and 4 for the schooling groups. The estimated coefficients, even for the whole sample, are indicative of a declining pattern. This is particularly true for the more educated workers in the sample. Thus, it seems that the matching process which best corresponds to these results is the one where jobs are better characterized as inspection goods rather than as experience goods. Note however that for workers with less than a high school diploma, the variance at 4 months of tenure is slightly larger than at 1 month, which is quite different than for the other workers. In fact, it does not decrease in the first three years of the employment relationship.

V.2 Human Capital Model.

The model implied by equation (33) is estimated in the same fashion as the "pure" matching model of section II. More precisely, all moment conditions are stacked up into

¹⁶ Results obtained by Farber (1994) with the NLSY on the shape of the hazard function seem to indicate that job attributes are known quite early after the beginning of the employment relationship.

a system and estimated with generalized least-squares where the weighting matrix is computed from the residuals of an unrestricted model. The results are shown in tables 5 and 6 for the whole sample. For comparison purposes with Hause (1980), I have also estimated the structure with only a linear trend in the experience variable (see equation 25), both with and without the term representing the variance of the job-match component (columns 1 and 2). The predicted tradeoff between the experience slope and the individual intercept comes out quite strongly when σ^2_{θ} is absent from the equation. However, once we include it, results are much less convincing in favor of human capital. This illustrates the point made earlier about the need to devise an estimating framework which allows us to isolate the key prediction of the theory of human capital as it pertains to the overtaking concept. Turning now to the estimation of model 4, note the negative covariance between the tenure slope and the job-specific intercept. Depending on the specification, the average overtaking point within jobs is between three years and a little over four years. The estimated variance of the tenure slope imply a standard error of close to 3 percent in the return to tenure. This finding provides strong suggestion that there is no such thing as a return to tenure, but that there is a range of returns.¹⁷ Table 6 shows the results if the model is fitted with five different quadratic functions, one for each job. We can see that the lower bound estimate of the overtaking point reaches a peak in job two with about 7.5 years. The variance of the tenure profile also increases from job 1 to job 2. Note that with the number of degrees of freedom afforded by the size of the unrestricted model, all models tested here cannot be rejected.

The same caveats as those mentioned in section II apply here regarding the lack of homogeneity of the overall sample and the sample composition problems as we move into jobs 4 and 5. Nevertheless, the robustness of the fitted U-shape pattern to different specifications suggests a substantial role for on-the-job investment in human capital.

Tables 7 and 8 show the results by education category. An interesting result is the

¹⁷ See Abowd, Kramarz and Margolis (1994) for similar conclusions with different data.

absence of a U-shape pattern for workers with less than high school education (column 1). Previous studies (e.g. Lynch (1992)) linking the probability of receiving formal training programs to various socio-economic background variables found a positive relationship between having a high school diploma and the occurrence of training. The results here go in the same direction (table 8, column 1). Also, the process described above which tends to make the tradeoff stronger on the second job than in the first job seems to be absent here. The results suggest that for workers with less than high school education, search activity does not lead them to higher quality jobs which entail some on-the-job-training. They seem to move from jobs which do not require a lot of training to other similar jobs. Another result from table 8, column 1 that supports this conclusion is the absence of any statistically significant variance in the tenure slopes for these less educated individuals, which is not the case for the other subsamples.

V.3 Matching with Control for Human Capital Accumulation

Coming back to the results of section II on matching, it was hypothesized that the relative difficulty of getting results that were consistent with the theory might be due to human capital considerations. A direct way of verifying that hypothesis is to enrich models 2 and 3 by including the linear trend in experience in the specifications. Assuming that this linear trend captures all factor reflecting the accumulation of human capital over the course of one's career, it should then be easier to isolate the predictions of the theory of matching. Results are reported in table 9 and 10.

Although the behavior of the variance across jobs does not change markedly, the declining pattern of the within job evolution of the job-match component variance is still further highlighted when the linear experience trend is added to the specification (see figures 1, 2, 3 and 4). For workers with less than a high school diploma, note that the variance in the first job is significantly larger than in jobs 5+, although the behavior of the variance from job 2 to job 4 is erratic according to the theory.

VI. Conclusion.

In extending Hause's original approach by making use of the concept of jobs, I was able to obtain results favoring the theory of human capital. In addition, the estimated U-shape pattern of variances within jobs is a prediction that is exclusive to human capital theory. In other words, there is no identification problem here as far as competing theories are concerned.

Regarding the predictions of the theory of matching, it is likely that better control for aggregate effects would have helped in finding stronger evidence of the patterns predicted by the theory, especially regarding the evolution across jobs of the variance of the job-match component. A more complex modeling allowing for autocorrelation of the residual term (which is considered here as being independently distributed across periods) could have captured some noise which, under the models adopted, may find its way into the coefficients. Also, it may be that testing these predicted patterns requires a balanced panel where a single cohort making its entry into the labor market is followed for many years. Unfortunately, a large random sample of young workers making their transition to the labor market and where no attrition is observed over a fifteen-year (say) period is something labor economists have grown used to dream about. Nevertheless, the results for the within-job evolution are quite consistent with the theory, especially for more educated workers. We should realize, though, that these results are also consistent with workers undergoing training programs early in the employment relationship. For workers with less than a high school diploma, the results are indicative of perhaps some learning taking place in the first few years. It might also be the case the predicted declining pattern is not observed at the beginning of the employment relationship simply because these less educated workers are not being trained by their employers.

The most sensible conclusion from the study is that, while matching plays an important role in explaining the covariance structure of earnings, it is apparent that

randomness in the tenure coefficient stemming from differential amounts of on-the-job training is also a major contributor.

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Appendix

A.1 The Minimum Distance Procedure.

The following is a straightforward adaptation of Chamberlain (1982,1984) and especially Abowd and Card (1989). Let $\hat{\epsilon}_i$ ($i=1,\dots,N$) represent the $T \times 1$ vector of the residuals of individual i estimated in equation (27). It is assumed that $\hat{\epsilon}_i$ is independently and identically distributed across individuals. Therefore it follows that $\hat{\epsilon}_i \hat{\epsilon}_i'$, which represents individual i 's cross-product matrix of dimension $T \times T$ is also i.i.d. Let M be the estimated covariance matrix and m the $T(T+1)/2$ column vector formed with the distinct elements of M . Fourth-moments are assumed to be finite. A typical element of m , $[m_t]$, represents the average of the individual contributions to this sample covariance over all workers at periods t and s , i.e.

$$m = \frac{1}{N} \sum_{i=1}^N m_i \quad (37)$$

$$m_i = \text{vec}(\hat{\epsilon}_i \hat{\epsilon}_i')$$

We wish to impose restrictions on m , i.e. we want m to depend on a lower-dimensional vector $f(\beta)$. More rigorously, let R^p be the p -dimensional Euclidean space and E be a compact subset of R^p that contains the true parameter vector β^0 where $p \leq T(T+1)/2$. Then f is a continuous, one-to-one mapping of E into R^q with a continuous inverse where $q = T(T+1)/2$. Also, f has continuous second partial derivatives in E , the rank of the matrix $[\partial f(\beta)/\partial \beta']$ is p for $\beta^0 \in E$, and the covariance matrix M estimated with β is non-singular for $\beta \in E$.

Under these regularity conditions, the assumption that the m_i 's are i.i.d. allow us to invoke the Central Limit Theorem (Lindeberg-Lévy version) which insures that the sample mean of m_i converges asymptotically to a normal distribution:

$$\begin{aligned}\sqrt{N}(m - \mu) &\rightarrow N(0, \Omega) \\ \mu &= E(m_i) \\ \Omega &= E(m_i m_i') - E(m_i)E(m_i')\end{aligned}\quad (38)$$

Now to test restrictions on m , Chamberlain shows that the following estimator is optimal:

$$\begin{aligned}\hat{\beta} &= \underset{\beta \in \mathcal{E}}{\operatorname{argmin}} \{(m - f(\beta))' V^{-1} (m - f(\beta))\} \\ V &= \frac{1}{N} \sum_{i=1}^N m_i m_i' - m m'\end{aligned}\quad (39)$$

Where V is the sample analog of Ω . In the case where f is linear in β (e.g. $f(\beta) = X\beta$)

$$\hat{\beta} = (X' V^{-1} X)^{-1} X' V^{-1} m \quad (40)$$

Under the hypothesis of a correct specification, the statistic

$$N(m - f(\hat{\beta}))' V^{-1} (m - f(\hat{\beta})) \quad (41)$$

has an asymptotic χ^2 distribution with $q-p$ degrees of freedom. Then, of course, the closer to zero is this statistic, the better is the fit of the underlying model. To summarize the procedure, we compute the empirical covariance matrix M using the residuals estimated with equation (27). Then we form a column vector m with the $T(T+1)/2$ distinct elements of M which we try to fit with a parsimonious representation suggested by the model we want to test. We then compute the generalized least squares estimator $\hat{\beta}$ using the covariance matrix of m as the weighting matrix. Finally, from this estimator we calculate the statistic given by equation (41), which is known to converge in distribution to a $\chi^2(q-p)$. Given the level of the test that we choose, we can then determine whether the restrictions imposed by the underlying model are acceptable or not. Note, however, that the choice of the weighting matrix is of some importance in small samples. On that subject, see Altonji and Segal (1994).

A.2 Gallant and Jorgenson's Procedure

Instead of directly fitting sample moments as done in the previous paragraph, we fit each individual contributions to the corresponding sample second moments. Just to make things clear, in the previous paragraph we computed the sample average of the m_1 , giving us m which we then try to fit with a lower-dimensional parameter vector through the f mapping. Here we stack all m_1 into a $NT(T+1)/2$ column vector M and we fit M in the same manner, except that the f function can now be individual-specific if the model warrants it. Let's suppose, for comparison purposes, that the f mapping is not individual-specific. The objective is then to minimize the following function:

$$S(\beta) = \sum_{i=1}^N (m_i - f(\beta))' V^{-1} (m_i - f(\beta)) \quad (42)$$

Where V^{-1} is computed with the cross-products of the residuals from the following unrestricted model:

$$\begin{aligned} E(\epsilon_{it}^2) &= m_{it} \\ E(\epsilon_{it}\epsilon_{is}) &= m_{is} \end{aligned} \quad (43)$$

Consequently, we can see that the V matrix is the same as in the optimal minimum distance estimator. Let $S(\beta)_1$ be the value of the objective function for the unrestricted model and $S(\beta)_2$ be defined likewise for the restricted version of, say, model 1 (equation (29)). For more general (i.e. non-linear) models, Gallant and Jorgenson (1979) show that $T_0 = S(\beta)_2 - S(\beta)_1$ is asymptotically distributed as a chi-square with $r-s$ degrees of freedom where $r-s$ is equal to the difference in the number of parameters in the two models.

Thus, it is clear that there is a close connection between the two estimation procedures. Namely, if the sample is balanced and the X matrix (the design matrix) is common to all individual, which is the case when we wish to test time series representations of the error process, then the vector of estimated parameters is identical and the Chi-Square statistic is the same. Let β_{OMD} be the minimum distance estimator,

β_{GJ} the Gallant & Jorgenson estimator and $f(\beta)=X\beta$. Then,

$$\begin{aligned}\beta_{OMD} &= (X'V^{-1}X)^{-1}X'V^{-1}m \\ &= (X'V^{-1}X)^{-1}X'V^{-1}N^{-1}\left(\sum_{i=1}^N m_i\right)\end{aligned}\quad (44)$$

whereas the formula for the estimator that makes direct use of each individual contributions is

$$\begin{aligned}\beta_{GJ} &= \left(\sum_{i=1}^N X_i'V^{-1}X_i\right)^{-1}\left(\sum_{i=1}^N X_i'V^{-1}m_i\right) \\ &= (NX'V^{-1}X)^{-1}(X'V^{-1}\sum_{i=1}^N m_i) \\ &= \beta_{OMD}\end{aligned}\quad (45)$$

However, the numerical equivalence of the two estimators does not hold in the case of unbalanced data. There will be a discrepancy between the two and this can be shown with a simple example. Let's assume that we have a sample of four individuals who are present in the data for a maximum of three periods. Without loss of generality, let V be the identity matrix. We wish to test the restriction that only a white noise error term can fit the covariance structure. Therefore, only the empirical variances at periods one, two and three are used in the computation of the coefficient. Let each m_i be given by $m_1=(s_{11}, s_{22}, s_{33})$, $m_2=(s_{22}, s_{33})$, $m_3=(s_{11}, s_{33})$ and $m_4=(s_{33})$. Then,

$$\begin{aligned}\beta_{OMD} &= (X'X)^{-1}X'm \\ &= \frac{1}{3}\left(\frac{s_{11}^1 \oplus s_{11}^3}{2} + \frac{s_{22}^1 \oplus s_{22}^2}{2} + \frac{s_{33}^1 \oplus s_{33}^2 \oplus s_{33}^3 \oplus s_{33}^4}{4}\right) \\ \beta_{GJ} &= \left(\sum_{i=1}^4 X_i'X_i\right)^{-1}\left(\sum_{i=1}^4 X_i'm_i\right) \\ &= \left(\frac{s_{11}^1 \oplus s_{11}^3}{8} + \frac{s_{22}^1 \oplus s_{22}^2}{8} + \frac{s_{33}^1 \oplus s_{33}^2 \oplus s_{33}^3 \oplus s_{33}^4}{8}\right)\end{aligned}\quad (46)$$

The estimator that makes direct use of the individual contributions to the sample moments is less susceptible to sampling error in that it gives relatively more weight to the covariance elements which are computed over a greater number of individuals. On the other hand, the minimum distance estimator places an equal weight on each sample moment; it does not matter whether some of them were computed over 3 individuals or 3000 individuals. In fact, even if the f function is not individual-specific, the design matrix X becomes individual-specific simply because all individuals are not present in the data at the same time. Furthermore, the Chi-Square statistic computed with the optimal minimum distance estimator fails to adjust for the true degrees of freedom which is not the case for the Gallant and Jorgenson procedure which directly accounts for the fact that the sample is unbalanced. Naturally, if the f mapping is individual-specific, which is the case for the models in this paper, then the optimal minimum distance estimator is not applicable.

Table 1. Mean Sample Characteristics (Weighted)-NLSY

Real Hourly Wage (\$1979)	5.75
Hours Worked	41.7
Tenure	2.44
Experience	5.82
Years in School	12.44
Percentage Nonwhite	12.6
Percentage Married	44.7
Percentage Female	45.4
Age	25.1
Number of Observations	29,020
Number of Individuals	5,649
Number of Jobs	13,590

Table 2. Estimation of Covariance Structure Implied
by the Theory of Matching
(Standard Errors in Parentheses)

Parameter	Model 0	Model 1
Variance of unmeasured fixed worker ability σ^2_{α}	0.0446 (0.0010)	0.0315 (0.0017)
Variance of unmeasured fixed job-match quality σ^2_{θ}		0.0284 (0.0013)
Variance of residual white noise error term σ^2_{η}	0.0658 (0.0019)	0.0534 (0.0020)
χ^2 statistic (degrees of freedom)	262 (167)	138 (166)
Number of workers	5 649	5 649
Number of observations	116 715	116 715

Table 3. Evolution of the Variance of the Job-Match Component
from Job 1 to Job 5 and Beyond
(Standard Errors in Parentheses)

Parameter	Total Sample	Less than H.S. Education	High School Education	Above H.S. Education
Variance of unmeasured <u>fixed worker ability</u> σ_a^2	0.0317 (0.0012)	0.0234 (0.0028)	0.0236 (0.0014)	0.0396 (0.0024)
Variance of unmeasured <u>fixed job-match quality</u> $\sigma_\theta^2(\text{job 1})$	0.0255 (0.0022)	0.0245 (0.0043)	0.0221 (0.0021)	0.0296 (0.0035)
$\sigma_\theta^2(\text{job 2})$	0.0299 (0.0021)	0.0226 (0.0049)	0.0223 (0.0025)	0.0393 (0.0041)
$\sigma_\theta^2(\text{job 3})$	0.0303 (0.0031)	0.0270 (0.0068)	0.0359 (0.0038)	0.0198 (0.0059)
$\sigma_\theta^2(\text{job 4})$	0.0256 (0.0049)	0.0444 (0.0097)	0.0282 (0.0063)	0.0302 (0.0103)
$\sigma_\theta^2(\text{job 5+})$	0.0408 (0.0070)	0.0186 (0.014)	0.0523 (0.0097)	0.0429 (0.0129)
Residual term i.d. (13 terms)	Yes	Yes	Yes	Yes
χ^2 statistic (degrees of freedom)	82 (150)	41 (150)	69 (150)	66 (150)
Number of workers	5 649	1 515	3 010	1 702
Number of observations	116 715	20 910	58 539	32 204

Table 4. Evolution of the Variance of the Job-Match Component within Jobs

Parameter	Total Sample	Less than H.S. Education	High School Education	Above H.S. Education
Variance of unmeasured fixed worker ability	0.0316	0.0230	0.0232	0.0404
Variance of unmeasured fixed job-match quality				
Tenure < 1 month	0.0440	0.0221	0.0489	0.0807
1 mo. <= Tenure < 4 mo.	0.0354	0.0249	0.0234	0.0429
4 mo. <= Tenure < 1 yr.	0.0301	0.0257	0.0305	0.0298
1 yr. <= Tenure < 2 yrs.	0.0292	0.0280	0.0267	0.0326
2 yrs. <= Tenure < 3 yrs.	0.0312	0.0310	0.0250	0.0377
3 yrs. <= Tenure < 4 yrs.	0.0258	0.0107*	0.0255	0.0266
4 yrs. <= Tenure < 5 yrs.	0.0258	0.0307	0.0211	0.0340
5 yrs. <= Tenure < 6 yrs.	0.0254	0.0268	0.0206	0.0402
6 yrs. <= Tenure < 7 yrs.	0.0220	0.0321	0.0264	0.0110
7 yrs. <= Tenure < 8 yrs.	0.0227	0.0146*	0.0237	0.0301
8 yrs. <= Tenure < 9 yrs.	0.0251	0.0197*	0.0285	0.0270
9 yrs. <= Tenure < 10 yrs.	0.0360	0.0165*	0.0267	0.0256
10 yrs. <= Tenure < 11 yrs.	0.0193	0.0067*	0.0101*	0.0194*
11 yrs. <= Tenure < 12 yrs.	0.0396	0.1227	0.0228*	0.0139*
12 yrs. <= Tenure	0.0285	-0.0262*	0.0210*	-0.0040*
Residual term i.d. (13 terms)	yes	yes	yes	yes
χ^2 statistic (degrees of freedom)	80 (140)	38 (140)	71 (140)	63 (140)
Number of workers	5 649	1 515	3 010	1 702
Number of observations	116 715	20 910	58 539	32 204

Note- * Not significant at the 5% level.

Table 5. Covariance Structure of Residuals as Function of Tenure, Experience, and Unobserved Components (Entire Sample) (Standard Errors in Parentheses)

Parameter	Hause's model without match component	Hause's model with match component	Model 4
Variance of unmeasured fixed worker ability- σ^2_{α}	0.0494 (0.0027)	0.0289 (0.0029)	0.0235 (0.0031)
Variance of experience slope σ^2_{b1}	0.0008 (0.0001)	0.0004 (0.0001)	0.0003 (0.0001)
Covariance of experience slope and worker-specific intercept- $\sigma(b1, \alpha)$	-0.0026 (0.0004)	-0.0009 (0.0004)	-0.0001 (0.0005)
Variance of unobserved match quality (job-specific intercept) σ^2_{θ}	-	0.0258 (0.0014)	0.0372 (0.0025)
Variance of tenure slope σ^2_{b2}	-	-	0.0005 (0.0001)
Covariance of tenure slope and job-specific intercept $\sigma(b2, \theta)$	-	-	-0.0029 (0.0005)
Residual term i.d. (13 terms)	Yes	Yes	Yes
χ^2 statistic (degrees of freedom)	204 (257)	108 (334)	142 (514)
Number of workers	5 649	5 649	5 649
Number of observations	116 715	116 715	116 715

Table 6. Evolution of Parameters of Quadratic Functions
from Job to Job (Entire Sample)

Parameters	Model 4 Expanded
<u>Job 1</u> σ^2_{θ} σ^2_{b2} $\sigma(b2, \theta)$	0.0322* 0.0007 -0.0024*
<u>Job 2</u> σ^2_{θ} σ^2_{b2} $\sigma(b2, \theta)$	0.0431* 0.0009* -0.0042*
<u>Job 3</u> σ^2_{θ} σ^2_{b2} $\sigma(b2, \theta)$	0.0350* 0.0015* -0.0030
<u>Job 4</u> σ^2_{θ} σ^2_{b2} $\sigma(b2, \theta)$	0.0287* 0.0017 -0.0027
<u>Job 5+</u> σ^2_{θ} σ^2_{b2} $\sigma(b2, \theta)$	0.0500* 0.0033 -0.0058
Residual term i.d. (13 terms)	Yes
χ^2 statistic (degrees of freedom)	133 (502)
Number of workers	5 649
Number of observations	116 715

Note. * Significant at the 5% level. Other parameters not shown are very similar to those estimated in Table 5.

Table 7. Covariance Structure of Residuals as Function of Tenure, Experience, and Unobserved Components (by Education Level)
(Standard Errors in Parentheses)

Parameter	Less than H.S. Education	High School Education	Above H.S. Education
Variance of unmeasured fixed worker ability- σ^2_{α}	0.0263 (0.0070)	0.0159 (0.0036)	0.0436 (0.0075)
Variance of experience slope- σ^2_{b1}	0.0008 (0.0002)	0.0003 (0.0001)	0.0004 (0.0001)
Covariance of experience slope and worker-specific intercept- $\sigma(b1, \alpha)$	-0.0020 (0.0011)	0.0001 (0.0005)	-0.0015 (0.0010)
Variance of unobserved match quality (job-specific intercept)- σ^2_{θ}	0.0244 (0.0054)	0.0330 (0.0029)	0.0414 (0.0048)
Variance of tenure slope σ^2_{b2}	-0.0003 (0.0003)	0.0006 (0.0002)	0.0004 (0.0002)
Covariance of tenure slope and job-specific intercept $\sigma(b2, \theta)$	0.0001 (0.0013)	-0.0027 (0.0006)	-0.0029 (0.0010)
Residual term i.d. (13 terms)	Yes	Yes	Yes
χ^2 statistic (degrees of freedom)	121 (514)	166 (514)	153 (514)
Number of workers	1 515	3 010	1 702
Number of observations	20 910	58 539	32 204

Table 8. Evolution of Parameters of Quadratic Functions from Job to Job (by Education Level)

Parameters	Less than H.S. Education	High School Education	Above H.S. Education
<u>Job 1</u> σ^2_{θ} σ^2_{b2} $\sigma(b2, \theta)$	0.0205* -0.0002 0.0003	0.0257* 0.0007* -0.0019*	0.0457* 0.0007* -0.0039*
<u>Job 2</u> σ^2_{θ} σ^2_{b2} $\sigma(b2, \theta)$	0.0083 -0.0013 0.0041	0.0330* 0.0010* -0.0039*	0.0580* 0.0008 -0.0050*
<u>Job 3</u> σ^2_{θ} σ^2_{b2} $\sigma(b2, \theta)$	0.0254* -0.0008 -0.0008	0.0348* 0.0009 -0.0005*	0.0147* 0.0014 -0.0008
<u>Job 4</u> σ^2_{θ} σ^2_{b2} $\sigma(b2, \theta)$	0.0437* -0.0011 -0.0015	0.0340* 0.0031* -0.0005*	0.0255* 0.0004 0.0018
<u>Job 5+</u> σ^2_{θ} σ^2_{b2} $\sigma(b2, \theta)$	-0.0028 0.0023 0.0043	0.1242* 0.0123* -0.0338*	0.0371 -0.0001 0.0001
Residual term i.d. (13 terms)	Yes	Yes	Yes
χ^2 statistic (degrees of freedom)	113 (502)	160 (502)	148 (502)
Number of workers	1 702	3 010	1 702
Number of observations	20 910	58 539	32 204

Note. * Significant at 5% level.

Table 9. Evolution of the Variance of the Job-Match Component from Job 1 to Job 5 and Beyond with Quadratic Function in Experience (Standard Errors in Parentheses)

Parameter	Total Sample	Less than H.S. Education	High School Education	Above H.S. Education
Variance of unmeasured fixed job-match quality				
$\sigma^2_{\theta}(\text{job 1})$	0.0260 (0.0018)	0.0238 (0.0045)	0.0222 (0.0021)	0.0281 (0.0036)
$\sigma^2_{\theta}(\text{job 2})$	0.0270 (0.0022)	0.0198 (0.0050)	0.0203 (0.0025)	0.0366 (0.0042)
$\sigma^2_{\theta}(\text{job 3})$	0.0249 (0.0032)	0.0220 (0.0069)	0.0324 (0.0038)	0.0159 (0.0060)
$\sigma^2_{\theta}(\text{job 4})$	0.0177 (0.0050)	0.0371 (0.0098)	0.0222 (0.0064)	0.0254 (0.0104)
$\sigma^2_{\theta}(\text{job 5+})$	0.0306 (0.0072)	0.0088 (0.0141)	0.0452 (0.0098)	0.0361 (0.0130)
Residual term i.d. (13 terms)	Yes	Yes	Yes	Yes
χ^2 statistic (degrees of freedom)	107 (332)	121 (332)	104 (332)	111 (332)
Number of workers	5 649	1 515	3 010	1 702
Number of observations	116 715	20 910	58 539	32 204

Note. Parameters not shown include variance of worker ability, variance of experience slope, and covariance of worker-specific intercept and experience slope.

Table 10. Evolution of the Variance of the Job-Match Component within Jobs with Quadratic Function in Experience (Standard Errors in Parentheses)

Parameter	Total Sample	Less than H.S. Education	High School Education	Above H.S. Education
Variance of unmeasured fixed job-match quality				
Tenure < 1 month	0.0434	0.0204	0.0486	0.0792
1 mo. <= Tenure < 4 mo.	0.0346	0.0230	0.0234	0.0419
4 mo. <= Tenure < 1 yr.	0.0292	0.0240	0.0306	0.0281
1 yr. <= Tenure < 2 yrs.	0.0289	0.0261	0.0270	0.0305
2 yrs. <= Tenure < 3 yrs.	0.0309	0.0289	0.0251	0.0354
3 yrs. <= Tenure < 4 yrs.	0.0252	0.0087*	0.0253	0.0249
4 yrs. <= Tenure < 5 yrs.	0.0241	0.0277	0.0198	0.0318
5 yrs. <= Tenure < 6 yrs.	0.0225	0.0227	0.0182	0.0375
6 yrs. <= Tenure < 7 yrs.	0.0180	0.0284	0.0228	0.0081*
7 yrs. <= Tenure < 8 yrs.	0.0167	0.0084*	0.0184	0.0263
8 yrs. <= Tenure < 9 yrs.	0.0163	0.0121*	0.0215	0.0227
9 yrs. <= Tenure < 10 yrs.	0.0261	0.0093*	0.0186	0.0200*
10 yrs. <= Tenure < 11 yrs.	0.0084	0.0036*	0.0008*	0.0129*
11 yrs. <= Tenure < 12 yrs.	0.0263	0.1035	0.0129*	0.0057*
12 yrs. <= Tenure	0.0095*	-0.0511*	0.0070*	-0.0223*
Residual term i.d. (13 terms)	yes	yes	yes	yes
χ^2 statistic (degrees of freedom)	102 (320)	72 (320)	103 (320)	106 (320)
Number of workers	5 649	1 515	3 010	1 702
Number of observations	116 715	20 910	58 539	32 204

Notes. *Not significant at 5% level. Parameters not shown include variance of worker ability, variance of experience slope, and covariance of worker-specific intercept and experience slope.

Figure 1. Within-Job Evolution of Variance
Total Sample-NL.SY

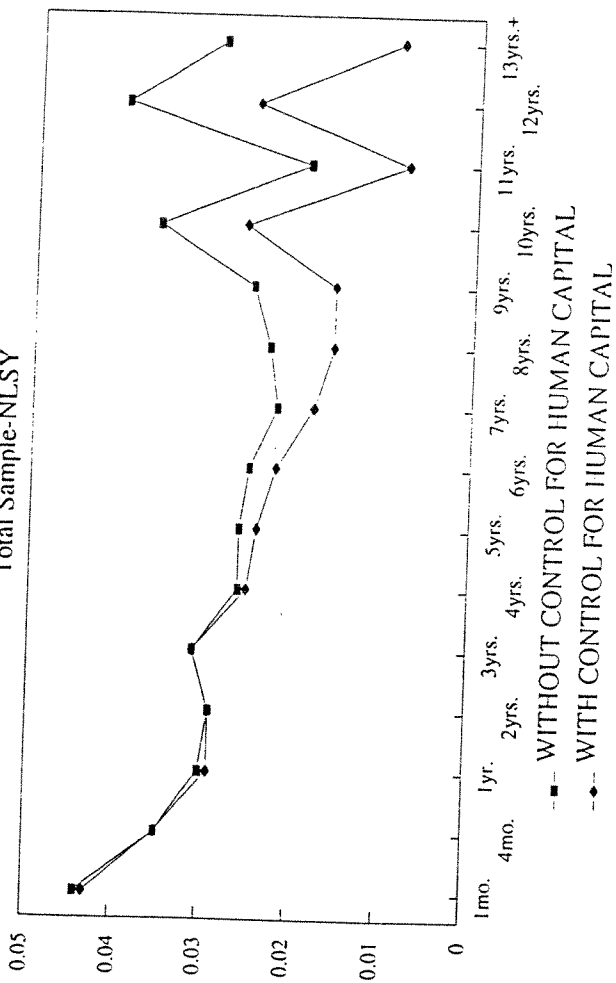


Figure 2. Within-Job Evolution of Variance
 Workers with Less than a High School Diploma

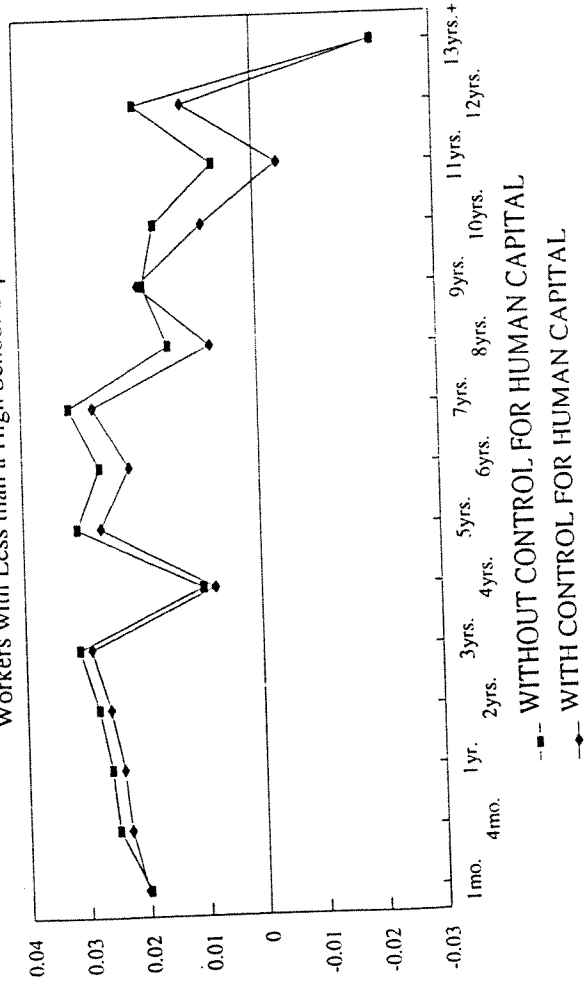


Figure 3. Within-Job Evolution of Variance
 Workers with a High School Diploma

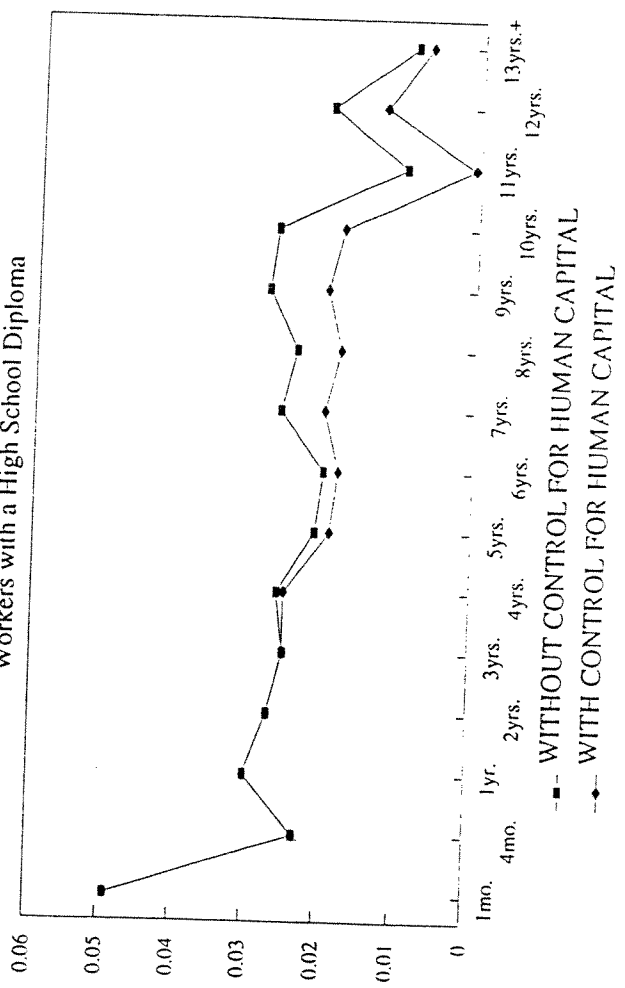
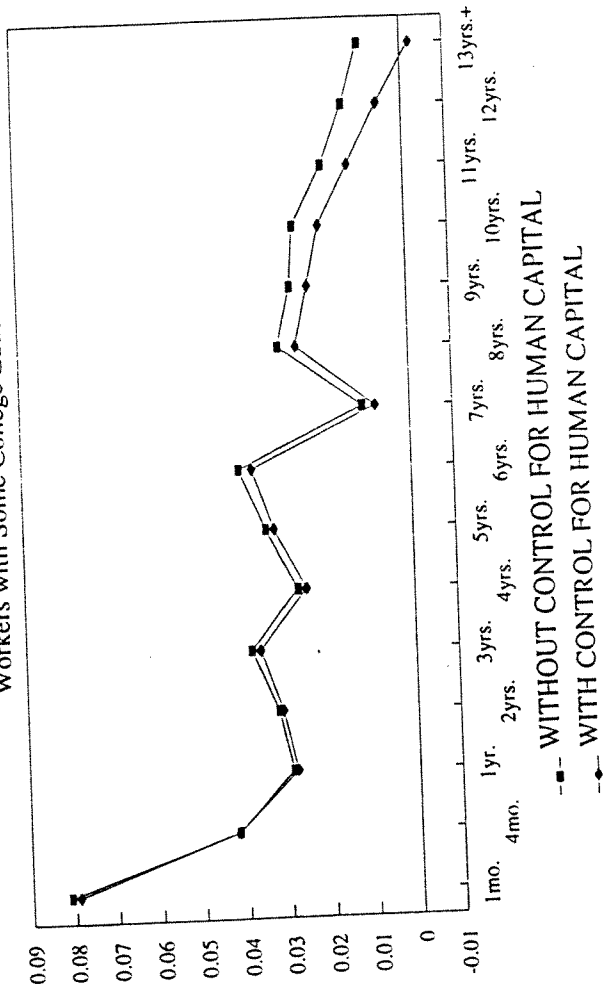


Figure 4. Within-Job Evolution of Variance
Workers with Some College Education



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