THE EVOLUTION OF WAGES OVER THE LIFECYCLE:
INSIGHTS FROM INTERGENERATIONAL CONNECTIONS

ADALBERT MAYER*
Texas A&M University
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Abstract

This paper uses intergenerational information to improve our understanding of lifecycle wage dynamics. I present a simple statistical model that relates the wages of workers at different points in their lifecycle to the earnings of their parents. I decompose cross-sectional variance of wages into a permanent component related to parental background, a permanent component unrelated to parental background, and a transitory component. Data from the Panel Study of Income Dynamics suggests that intergenerational relationships are stronger when measured later in the lifecycle of the son. This implies that the permanent parent-related component is increasingly important for wage determination as workers grow older. This is not consistent with wage evolution through persistent random shocks. Rather, it is consistent with human capital models and learning models of wage evolution.
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* Mayer: Department of Economics, Texas A&M University, College Station, TX 77843 (email:amayer@econmail.tamu.edu)
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1. Introduction

Understanding the process of earnings evolution helps us to design labor market policies (Carneiro and Heckman, 2003, and Pries and Rogerson, 2005) and to study issues like the upward trend in earnings inequality (Haider, 2001, or Baker and Solon, 2003). Furthermore, it improves our understanding of the income risk individuals face. As pointed out by Guvenen (2007), income risk has consequences for wealth inequality (Aiyagari, 1994), the effectiveness of self-insurance (Deaton, 1991), the welfare cost of business cycles (Lucas, 2003), and the determination of asset prices (Constantinides and Duffie, 1996).[1]

The labor literature offers different processes to describe wage or earnings dynamics over the lifecycle. Models with earnings evolution due to persistent random shocks have received a lot of attention in the empirical literature (MaCurdy, 1982). However, Guevenen (2007) and Baker (1997) present evidence against random wage evolution and in favor of models with heterogeneous income growth rates. All of these studies rely on panel data.[2] In this paper, I use both panel data and intergenerational information to study lifecycle wage dynamics.

I present a simple statistical model of wage determination that allows me to investigate the connections between parental background and the evolution of wages.[3] Like Haider (2001) and Baker and Solon (2003), I decompose the cross-sectional variance of wages into a permanent component that does not change over the lifecycle and a transitory component.[4] The permanent component reflects inherent characteristics of the worker, while the transitory component captures random shocks. I envision that parents influence the characteristics of their children but do not affect random shocks after the children have entered the labor market. Therefore, I assume that the transitory component is not related to

[1] The importance of precautionary savings in Sweden is quantified in Lyhagen (2001). McGoldrick and Robst (1996) investigate compensating wage differential due to earnings uncertainty. Borghans and Golsteyn (2007) explain that imperfect information can lead to career switching and loss of sector or firm specific human capital.
[2] See also Baker and Solon (2003) and Oreopoulos et. al. (2006)
[3] This insight is related to Haider and Solon (2006) who point out that the correlation between current earnings and lifetime earnings varies over the lifecycle.
[4] While Haider (2001) and Baker and Solon (2003) focus on changes of the importance of these components over time, I consider changes in the contribution of the two components to the variance of wages over the lifecycle.

the parental background of workers. I further decompose the permanent component into a part that is related to parental features and a part that is unrelated to parental features. Characteristics that are related to parental background may include intelligence, health, and work ethics. The source of these intergenerational connections does not matter for the analysis conducted here.[5]

I use data from the Panel Study of Income Dynamics (PSID) to quantify the elements of the model. The correlation between the wages of workers aged 35 and the income of their parents - measured while the child is 14 to 16 years old - is almost twice as high, as the correlation between wages at age 25 and the same parental income variable. This implies that features related to the parental background of workers become more important for the determination of wages as workers grow older. This is not consistent with wage evolution solely due to random shocks.

However, models with systematic wage evolution are consistent with the increasing intergenerational persistence over the lifecycle. Learning models postulate that employers learn over time about the workers' true productivity (Farber and Gibbons, 1996). The true abilities of workers, which are parent-related, become more important over time and are increasingly reflected in the wage.[6] Individual specific growth rates of wages due to human capital investment (Ben-Porath, 1967) are consistent with an increasing role of the parent related component, as well. Depending on their abilities individuals, choose to forgo part of their earnings to invest in human capital. This reduces the earnings of high ability individuals, from high income backgrounds, while they are young. Later in their career workers are rewarded for their investment, which is reflected in high earnings of high ability individuals.

The learning and human capital models differ in their assumptions about the knowledge of workers. The human capital model assumes knowledge about the return to human capital investments. A learning model allows for workers to be uncertain about their true productivity and future earnings. If

[5] See Solon (1999) for an overview of the literature on intergenerational relationships. Numerous explanations for the intergenerational persistence have been suggested. Bowles and Gintis (2001) differentiate the 'genetic and cultural transmission of traits' and the 'inheritance of income-enhancing group memberships and property'. Piketty (2000) distinguishes transmission of ability, imperfect capital markets, local segregation, and self-fulfilling beliefs. Grawe (2006) shows the importance of lifecycle effects for the measurement of intergenerational relationships.

[6] Farber and Gibbons (1996) confirm the predictions of a learning model using test scores that are unobserved by employers.

workers know more about their parent related permanent abilities than about their non-parent related permanent abilities, it is possible to distinguish the two models empirically. The human capital investment model suggests that known ability differences are increasingly reflected in wages as workers grow older. Ability differences unknown to the worker do not result in human capital investment. The learning model does not differentiate between known and unknown abilities. If workers have no additional knowledge about their parent related abilities, the two models cannot be distinguished by the intergenerational model presented here.

Using both panel data for a single generation and intergenerational information makes it theoretically possible to separately identify changes in relative importance of the parent related permanent component from changes in the importance of the non-parent related permanent component over the lifecycle. However, the sample size of workers who can be linked to their parental background is small, and the wage panel is short. Therefore, joint estimates of the importance of the parent related and the non-parent related permanent components are imprecise.

Besides providing insights about the evolution of wages, the framework presented here also clarifies the role of lifecycle considerations when measuring intergenerational persistence. Comparing intergenerational mobility between different cohorts does not make it possible to distinguish an increase in the importance of permanent parent related component from a strengthening of intergenerational persistence of characteristics. It is necessary to follow different cohorts over time. I find no clear trend for changes in the degree of intergenerational mobility across cohorts. This is consistent with result by Mayer and Lopoo (2005) and Lee and Solon (2006) who find no major changes in intergenerational mobility for cohorts born between 1957 and 1975.

This paper proceeds as follows: Section 2 presents a statistical model that decomposes wages into the effects of permanent personal features and random shocks, and derives their relationship to observable intergenerational connections. Section 3 relates the quantities derived in Section 2 to models of earnings evolution. Sections 4 and 5 present the data and the results. Section 6 concludes.

2. Statistical Model

In this section, I present a simple statistical model of parental influence on wage determination over the lifecycle. The log wage of worker *i*, born in year *b*, and observed in year *t*, is given by Y_{ibt} . The age of the worker in year *t* is given by $a = t - b$. These log wages are determined by observable person-specific characteristics, year effects (both summarized in X) and an individual specific residual,

$$Y_{ibt} = \varphi_{bt} X_{it} + y_{ibt} .$$

The worker specific wage residual, y_{ibt} , is determined by a permanent component, p_i , which does not change over time and a transitory component, u_{it} , so that:

$$y_{ibt} = \lambda_{bt} p_i + \gamma_{bt} u_{it} ,$$

or, expressed in terms of the age of the workers,

$$y_{iba} = \lambda_{ba} p_i + \gamma_{ba} u_{ia} .$$

The variances of the permanent component, p_i , and the transitory component, u_{ia} , are normalized:

$$\operatorname{var}(p_i) = 1 \qquad \text{and} \qquad \operatorname{var}(u_{ia}) = 1 .$$

The contributions of p_i and u_{ia} to the overall earnings variation are given by λ_{ba} and γ_{ba} , and may vary over time. λ_{ba} and γ_{ba} evolve with the age of the worker and between cohorts. I assume that p_i and u_{ia} are distributed independently of one another. The transitory component u_{ia} may be serially correlated.

Now, I add information about the parental background of workers to the model. It is denoted by f_i. In the empirical part of this paper I use parental income. Other measures, like parental education, could be used, as well. For the analysis conducted below it only matters that there is some correlation between characteristics of a worker and parental background. The channel of intergenerational connections does not matter. I assume that the parental background of a person influences the wage residual, y_{iba}, only through the permanent earnings component, p_i. The transitory component of a son's earnings is not affected by his background:[7]

$$\text{cov}(u_{ia}, f_i) = 0 .$$

I decompose the permanent component, p_i, into a part that is related to parental background, m_i, and part that is not related to parental background, r_i. I normalize the variances of m_i and r_i to equal one, $\text{var}(m) = \text{var}(r) = 1$. The contributions of m_i and r_i to the overall earnings variation are given by α_{ba} and β_{ba}. The wage residual is determined by:

$$y_{iba} = \alpha_{ba} m_i + \beta_{ba} r_i + \gamma_{ba} u_{ia} \qquad \text{with } \text{cov}_b(m_i, f_i) \neq 0 \text{ and } \text{cov}(r_i, f_i) = 0 .$$

The covariance between parental background and permanent features is subscripted with the cohort variable *b*, as the intergenerational transmission mechanism responsible for this covariance may change over time.

Observables

A number of observable data features can be expressed in terms of the parameters of this simple statistical model. Intergenerational relationships are implied by:

$$\text{cov}(y_{iba}, f_i) = \lambda_{ba} \text{cov}_b(p_i, f_i) = \alpha_{ba} \text{cov}_b(m_i, f_i). \tag{1}$$

The variance of wages for a given cohort in a given year is determined by:

$$\text{var}(y_{ba}) = \lambda_{ba}^2 + \gamma_{ba}^2 \qquad \text{or by} \qquad \text{var}(y_{ba}) = \alpha_{ba}^2 + \beta_{ba}^2 + \gamma_{ba}^2 . \tag{2}$$

The covariances of earnings over the lifecycle depend on the evolution of α_{ba}, β_{ba} and γ_{ba}, and on the persistence of u_{ba}. Thus, the covariance between wages at age *a* and age *k* is given by:

$$\text{cov}(y_{ba}, y_{bk}) = \alpha_{ba}\alpha_{bk} + \beta_{ba}\beta_{bk} + \gamma_{ba}\gamma_{bk} \text{cov}(u_{ba}, u_{bk}) . \tag{3}$$

[7] The transitory component reflects shocks to earnings that are not related to characteristics of the individual. If parents and sons face the same source of shock (e.g. occupational specific or local shocks) parental income and the transitory earnings component of the son could be correlated. I avoid this complication by using information about parental income before the labor market entry of the son.

To make the model empirically tractable it is necessary to impose some restrictions on $\text{cov}(u_{ba}, u_{bk})$. I assume that the auto-correlation of the transitory component is zero if two periods are at least *q* years apart:[8]

$$\text{cov}(u_{ba}, u_{bk}) = 0 \qquad \text{if} \quad |a-k| > q$$

so

$$\text{cov}(y_{ba}, y_{bk}) = \alpha_{ba}\alpha_{bk} + \beta_{ba}\beta_{bk} \quad \text{if} \quad |a-k| \le q \,. \tag{4}$$

For a given cohort *b*, we observe a panel with *A* different years. Expressions (1) and (2) each provide *A* observable data moments. Expression (4) implies $Aq - (q^2 + q)/2$ additional moments.[9] The model is specified by *3A+3* parameters. Hence, a sufficiently long panel of wages linked to parental income allows identification. One way to infer to the values of α_{ba}, β_{ba}, and γ_{ba} for different ages of workers is to see which parameter values are able to simultaneously match these observable data characteristics. I pursue this route, but I also derive simpler, more transparent implications.

Changes of α_{ba} over the lifecycle and between cohorts

Equation (1) makes it possible to characterize the evolution of α_{ba} through intergenerational relationships. Changes in α_{ba} over the lifecycle can be obtained by comparing the relationship between parental features and sons' wages at two different points in the life of the sons,

$$\frac{\text{cov}(y_{ba}, f)}{\text{cov}(y_{bk}, f)} = \frac{\alpha_{ba}\,\text{cov}_b(m, f)}{\alpha_{bk}\,\text{cov}_b(m, f)} = \frac{\alpha_{ba}}{\alpha_{bk}} \,.$$

If α_{ba} increases over the lifecycle of workers, the magnitude of the observed intergenerational connection increases at the same rate.

A similar expression, holding age constant and comparing different cohorts, makes it possible to infer changes between cohorts,

[8] Another possibility is to impose some structure for the autocorrelation process of *u*. (For example Haider, 2001, or Baker and Solon, 2003).
[9] I assume *A>q*.

$$\frac{\operatorname{cov}(y_{ba}, f)}{\operatorname{cov}(y_{ca}, f)} = \frac{\alpha_{ba}\operatorname{cov}_b(m, f)}{\alpha_{ca}\operatorname{cov}_c(m, f)}.$$

However, it is not possible to simultaneously identify changes in both α_{ba} and $\operatorname{cov}_b(m_i, f_i)$. This is important when interpreting the results of studies that investigate the evolution of intergenerational persistence over time.[10] A weakening of the connection between parental features and the wages of sons could be the result of less wage variation due to the permanent component, i.e. α_{ba} is decreasing between cohorts. Such a shift could be the result of changes in the return to human capital or skill premia. However, it could also be driven by a decrease of the influence of parental background on permanent abilities, $\operatorname{cov}_b(m_i, f_i)$, between cohorts. Changes in child rearing behavior, fertility decisions, or the importance of wealth for access to education could be possible sources for such a change. The model presented here clarifies this fundamental identification problem but does not help to quantify the relative importance of these effects.

Upper and lower bounds

Since $\gamma_{ba} \geq 0$, an upper bound for the value of $\lambda_{ba} = \sqrt{\alpha_{ba}^2 + \beta_{ba}^2}$ is given by the total wage variation:

$$\operatorname{var}(y_{ba}) = \alpha_{ba}^2 + \beta_{ba}^2 + \gamma_{ba}^2,$$

so

$$\lambda_{ba} \leq sd(y_{ba}).$$

Assuming that α_{ba} and β_{ba} change only gradually over time makes it possible to use the persistence of wages over the lifecycle can be used to construct a tighter upper bound for λ_{ba}:[11]

$$\lambda_{ba} = \sqrt{\alpha_{ba}^2 + \beta_{ba}^2} \approx \sqrt{\alpha_{ba}\alpha_{b(a+\Delta)} + \beta_{ba}\beta_{b(a+\Delta)}} \leq \sqrt{sd(y_{ba})\, sd\left(y_{b(a+\Delta)}\right) corr\left(y_{ba}, y_{b(a+\Delta)}\right)},$$

where Δ represents a small change in the age of a worker.

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[10] See Lee and Solon (2006) and Mayer and Lopoo (2005).

[11] Setting the value of γ_{ba} equal to zero yields the weak inequality:

$$corr(y_{ba}, y_{bk}) = \frac{\operatorname{cov}(y_{ba}, y_{bk})}{\sqrt{\operatorname{var}(y_{ba})\operatorname{var}(y_{bk})}} \geq \frac{\alpha_{ba}\alpha_{bk} + \beta_{ba}\beta_{bk}}{\sqrt{\operatorname{var}(y_{ba})\operatorname{var}(y_{bk})}} \quad \text{or} \quad \alpha_{ba}\alpha_{bk} + \beta_{ba}\beta_{bk} \leq sd(y_{ba})\, sd(y_{bk})\, corr(y_{ba}, y_{bk}).$$

An upper bound for α_{ba} is obtained from:[12]

$$\alpha_{ba}{}^2 \approx \alpha_{ba}\alpha_{b(a+\Delta)} \le sd\left(y_{ba}\right)sd\left(y_{b(a+\Delta)}\right)corr\left(y_{bt}, y_{b(a+\Delta)}\right).$$

The intergenerational connections described in equation (1) imply a lower bound for α_{ba}. The weak inequality in the last step is obtained by setting the correlation between α_{ba} and *f* equal to one,

$$corr\left(y_{ba}, f\right) = \frac{\alpha_{ba}\operatorname{cov}_b\left(m, f\right)}{\sqrt{\operatorname{var}\left(y_{ba}\right)\operatorname{var}\left(f\right)}} = \frac{\alpha_{ba}}{\sqrt{\alpha_{ba}{}^2 + \beta_{ba}{}^2}}corr\left(m, f\right) \le \frac{\alpha_{ba}}{\sqrt{\alpha_{ba}{}^2 + \beta_{ba}{}^2}}$$

or

$$\alpha_{ba} \ge corr\left(y_{ba}, f\right)sd\left(y_{ba}\right) \qquad \text{for all } a$$

Combining the two latter restrictions gives an expression that constrains the value of α_{ba} for each cohort at a given point in time. It is:

$$\sqrt{\operatorname{var}\left(y_{ba}\right)}\sqrt{\operatorname{var}\left(y_{b(a+\Delta)}\right)}corr\left(y_{ba}, y_{b(a+\Delta)}\right) \ge \alpha_{ba}\alpha_{b(a+\Delta)} \ge corr\left(y_{ba}, f\right)corr\left(y_{b(a+\Delta)}, f\right)\sqrt{\operatorname{var}\left(y_{ba}\right)}\sqrt{\operatorname{var}\left(y_{b(a+\Delta)}\right)}$$

The values of the all expressions on the left-hand side and the right-hand side of this expression are observable.

3. Theories of earnings evolution

In this section, I present three theories of lifecycle earnings (random shocks, learning, and human capital investment) in a simple, unified framework. I illustrate how knowledge about the lifecycle patterns of λ_α and α_a can be used to distinguish between these theories.

I consider two time periods, $a = 1$ and $a = 2$. Earnings early in the lifecycle are given by y_1, earnings later on are captured by y_2. The importance of workers permanent characteristics is captured by $\operatorname{cov}\left(y_a, p\right)$ and the importance of parent-related characteristics is given by $\operatorname{cov}\left(y_a, m\right)$.

[12] Again, I assume that α_{ba} is changing gradually over time.

Random Shocks

In the simplest model earnings evolve non-systematically as the result of (persistent) random shocks. This can be characterized by:

$$y_2 = y_1 + \omega \ , \qquad \text{where} \ \operatorname{cov}(y_1, \omega) = 0 \ \text{and} \ \operatorname{cov}(p, \omega) = 0 .$$

Consequently, $\operatorname{cov}(y_1, p) = \operatorname{cov}(y_2, p)$, the covariance between earnings and permanent characteristics remains unchanged over the lifecycle. The same is true with respect to parent related abilities.

Learning

An alternative explanation for the evolution of earnings over the lifecycle is offered by learning models (Farber and Gibbons, 1996). In a perfectly competitive labor market without binding contacts, earnings are equal to the expected productivity of workers. The true productivity, *z*, of workers is unknown to employers, but its distribution is known, $z \sim N(0, \sigma_z^2)$. Before the each period, firms observe a signal of *z*. The signal contains a noise component ε_a, drawn from a known distribution: $\varepsilon_a \sim N(0, \sigma_\varepsilon^2)$. I assume that workers' permanent characteristics are reflected in their productivity, $\operatorname{cov}(z, p) > 0$, but are unrelated to the noise component, $\operatorname{cov}(\varepsilon_a, p) = 0$.

The first signal is $s_1 = z + \varepsilon_1$. Thus, the expected productivity in the first period – and hence the wage – is given by:

$$y_1 = E(z|s_1) = E(z|z + \varepsilon_1) = \frac{\sigma_z^2}{\sigma_z^2 + \sigma_\varepsilon^2}(z + \varepsilon_1) .$$

Before the period 2 firms obtain another noisy signal, $s_2 = z + \varepsilon_2$. The expected productivity is now:

$$y_2 = E(z|s_1, s_2) = E\left(z \middle| z + \frac{\varepsilon_1 + \varepsilon_2}{2}\right) = \frac{\sigma_z^2}{\sigma_z^2 + \frac{1}{2}\sigma_\varepsilon^2}(z + \varepsilon_1 + \varepsilon_2) .$$

The covariance between the true ability and earnings is increasing as more information becomes available, $\operatorname{cov}(y_1, z) < \operatorname{cov}(y_2, z)$. The covariance between permanent characteristics and earnings is increasing, as well:

$$\operatorname{cov}(y_1, p) = \operatorname{cov}(y_1, z)\operatorname{cov}(z, p) < \operatorname{cov}(y_2, z)\operatorname{cov}(z, p) = \operatorname{cov}(y_2, p).$$

The gradual learning of firms about the true productivity of workers implies an increase in $\operatorname{cov}(y_a, p)$ over the lifecycle.

The learning model does not differentiate between known and unknown abilities, workers decisions are not based on their knowledge about their true productivity. Even if workers know more about their parent related permanent abilities than about their non-parent related permanent abilities the importance of the two increases at the same rate:

$$\frac{\alpha_2}{\alpha_1} = \frac{\operatorname{cov}(y_2, m)}{\operatorname{cov}(y_1, m)} = \frac{\operatorname{cov}(y_2, p)}{\operatorname{cov}(y_1, p)} = \frac{\lambda_2}{\lambda_1}.$$

Human Capital Investment

Models like Ben-Porath (1967) explain the evolution of earnings over the lifecycle through investment in human capital. Workers maximize the sum of their discounted earnings: $\max(y_1 + \beta y_2)$.

The earnings capacity of a worker is given by his human capital. In period 1 all workers start out with a human capital level of K_1.[13] They split their time between working for income and investing in human capital.[14] The fraction of time used to build additional human capital is given by *s*. The income in period 1 is given by: $y_1 = (1-s)K_1$. Human capital in the second period, $K_2 = \mathrm{H}(k, s)$, depends on the

[13] The purpose of the simple model here is to illustrate the effect of human capital investment on lifecycle earnings and intergenerational connections. A more general model allows for variation in K_1. If K_1 and *k* are correlated the magnitudes of the effects of human capital investment generated by the simplified version presented here are reduced.

[14] This can be achieved through formal schooling or by choosing a career with lower initial wages but better long term career opportunities.

time investment, s, and the ability to profit from this investment, k. The function H describes the effects of k and s on human capital formation. It is non-decreasing in k and increasing in s at a decreasing rate:

$$\frac{\partial \mathrm{H}(k,s)}{\partial k} \geq 0, \qquad \frac{\partial \mathrm{H}(k,s)}{\partial s} > 0, \qquad \text{and} \qquad \frac{\partial^2 \mathrm{H}(k,s)}{\partial s^2} < 0.$$

More talented workers have a higher return to human capital investment:

$$\frac{\partial^2 \mathrm{H}(k,s)}{\partial s \partial k} > 0. \tag{5}$$

The optimization problem of the worker can be expressed as:

$$\max_s (1-s)K_1 + \beta \mathrm{H}(k,s).$$

The tradeoff between income in period 1 and human capital investment to increase earnings in period 2 is captured by the first order condition of the above maximization problem:

$$K_1 = \beta \frac{\partial \mathrm{H}(k,s^*)}{\partial s},$$

where s^* is the solution to the maximization problem. The left hand side reflects the forgone earnings in period one. The right hand side gives the discounted return to human capital investment. Given assumption (5), s^* is increasing in k:

$$\frac{ds^*}{dk} > 0. \tag{6}$$

This implies that k is negatively related to earnings in the first period and positively related to earnings in the second period:

$$\frac{dy_1}{dk} = -K_1 \frac{ds^*}{dk} < 0 \tag{7}$$

and

$$\frac{dy_2}{dk} = \underbrace{\frac{\partial H(k,s^*)}{\partial s^*}\frac{ds^*}{dk}}_{\substack{\text{due to known}\\ \text{ability differences}}} + \underbrace{\frac{\partial H(k,s^*)}{\partial k}}_{\substack{\text{due to known and}\\ \text{unknow ability differences}}} > 0. \tag{8}$$

The connection between *k* and permanent characteristics of workers and is captured by $\operatorname{cov}(k, p)$. If permanent characteristics are related to the ability to benefit from human capital investment, $\operatorname{cov}(k, p) > 0$. Expressions (6), (7), and (8) imply that:

$$\operatorname{cov}(y_1, p) = \operatorname{cov}((1-s)K_1, p) < 0$$

and

$$\operatorname{cov}(y_2, p) = \operatorname{cov}(\beta \mathrm{H}(k,s), p) > 0 .$$

Hence, human capital investment provides a mechanism that leads to an increasing importance of the permanent characteristics over the lifecycle.

This is the same prediction as generated by the learning model. However, differences in human capital investment, s^*, are based on known ability differences. Ability differences unknown to the workers do not result in human capital investment and are reflected in wages to a lesser degree. They affect earnings in period 2 only through *k* (the second part of the expression in equation (8)) and not through s^* (the first part of the expression in equation (8)). If workers know more about their parent related permanent abilities than about their non-parent related permanent abilities, this implies:

$$\frac{\alpha_2}{\alpha_1} = \frac{\operatorname{cov}(y_2, m)}{\operatorname{cov}(y_1, m)} > \frac{\operatorname{cov}(y_2, p)}{\operatorname{cov}(y_1, p)} = \frac{\lambda_2}{\lambda_1} .$$

4. Data

I use data from the Panel Study of Income Dynamics (PSID) conducted by the Survey Research Center, Institute for Social Research at the University of Michigan. The PSID is a longitudinal study that started in 1968 with about 5000 families and includes information about various economic and demographic variables. I use the core sample of 3000 families that was selected to be representative of the U.S. population. All members of the original families and their offspring are interviewed annually. If an individual establishes or joins a new household, the members of this household are interviewed as well. I construct a sample of 1128 males who are sons of heads of households in the original 1968 PSID families.[15] Their own wages can be observed in some of the years from 1975 to 2000 and we have information about their parents' income while growing up.[16] These sons can be matched to 572 different fathers and mothers. The sons were born between 1951 and 1976; their fathers and mothers were born between 1905 and 1953.

I construct yearly wage residuals for the sons from a regression of the log-wages of all males (not just the sons) on year dummies, region and race. I do not include marital status and other variables that may be endogenous choices related to parental background. The residuals (y_{ia} in the notation of Section 2), sorted by age, are presented in Table 1. The sample size is larger for younger ages, as the later cohorts are only observed at the beginning of their professional life. The wages of younger workers are below the average wages of all workers in a given year. As the workers grow older their wages rise relative to the overall average. The variation of wages increases, as well, as workers age.

Previous research relied on panel data of wages or earnings to understand their evolution over the lifecycle. The persistence of wages over the lifecycle can be seen in Tables 2 and 3. Table 2 displays the autocorrelation of the residual log wages, y_{ia}, as the workers age. Table 3 shows the variances (on the diagonal) and autocovariances of the wages. We observe an increasing variation in wages, from about .25 at age 25 to .4 above age 40. Both tables document a strong and increasing persistence of wages over the lifecycle. As workers age their wages tend to fluctuate less than the wages of younger workers.[17] While there is a relatively strong initial drop in the autocovariances and autocorrelations, this decline slows as the age differences increase. One explanation for this pattern could be measurement error (Baker, 1997, or Haider, 2001).

[15] I restrict my males to avoid arising from complications labor force participation decisions of females. Siclian and Grossberg (2001) study gender differences in human capital investment.
[16] The sample includes individuals with observed wage rates in at least 2 years in which they where working more than 100 hours. I varied the sample by including only individuals with at least 5 or 10 years of observed wages. This did not affect the basic data patterns (See appendix).
[17] Tables 2 and 3 resemble similar matrices shown by Baker (1997) or Haider (2001). The difference is that, here individuals are grouped by age and not by the year of the observation. While Baker and Haider find that the autocorrelation is relatively constant over time, Tables 2 and 3 suggest that it increases as workers get older. Haider and Solon (2004) use a panel covering the entire career of workers and also focus on variation over the lifecycle. They find an increasing persistence in earnings as workers age.

5. Results

In this section, I first report the basic relationships between wages, experience and parental background over the lifecycle and cohorts. Then, I abstract from cohort specific effects and focus only on the changes over the lifecycle.

Lifecycle and Cohort Effects

Table 4 describes the evolution of the relationships between wages, experience, education and parental income. To make my results comparable to studies that do not use intergenerational connections, I first report the relationship between wages, experience, and education. Column one shows the results of a regression of log wage on years of education, years of work experience, experience squared, and dummies for year, region, and race. The results are in line with many other studies. Column two includes interaction terms between education, calendar year and potential experience. Consistent with an increase in the return to education over time the coefficient for the interaction between education and year is clearly positive. I find no systematic relationship between years of experience and the return to education. In columns three and four I add parental income (averaged for ages 14 to 16 of the son and controlled for year and region effects)[18] and its interaction with experience and year.

The implications of the model derived in Section 2 are tested in column three. The coefficient for the interaction term between parental income, *f*, and calendar year is negative.[19] This suggests that the relationship between parental income and wages is weakening over time, i.e. $\alpha_{ba} \operatorname{cov}_b(m_i, f_i)$ is decreasing in *b*. The coefficient for the interaction between parental background and experience is positive. Features related to parental background become more important for the determination of wages as workers grow older. This suggests that the variation due to the permanent earnings component, α_{ba},

[18] Mayer (2006) discusses the role of the age of the child at which the parental component of intergenerational connections is measured.
[19] Wage inequality increases over the time period considered. This means that some of the components responsible for wage variation have increased. Haider(2001) decomposes this increase into effects of permanent and transitory components.

increases over the lifecycle. This is consistent with the human capital and learning models. It is not consistent with wage evolution due to persistent random shocks.

As a robustness check, I include education and its interaction with experience and education in column four. The basic results are unchanged. The increasing importance of parental background over the lifecycle is slightly more pronounced when controlling for education. The decreasing importance of parent-related wage determinants between cohorts is partially offset by the increasing importance of parental background through the determination of educational attainment. This is consistent with an increasing return to human capital[20] and increasing importance of credit constraints.[21]

The regressions in Table 4 impose linear trends over time and the lifecycle. To relax this restriction, I present a simple summary of the strength of intergenerational relationships.[22] Table 5 shows the covariance between parental earnings and the wage of the son for different ages and cohorts. In general, we observe an increase with age. This is true when looking at a cross-section (a row in Table 5) or at a cohort over time (a diagonal in Table 5). There is some evidence that this increase slows down, or is even reversed, after a certain age. The changes over cohorts holding age constant are less obvious (comparing numbers within a column in Table 5). In line with the regression results in Table 4, we see evidence of a decrease of intergenerational persistence over time, but the picture not consistent across all cohorts. This is consistent with the findings of Mayer and Lopoo (2005) and Lee and Solon (2006).

Lifecycle effects

Motivated by the small sample size, I now focus on lifecycle effects and disregard changes between cohorts. I drop the subscript for the cohort; the remaining subscript *a* refers to age of the worker. As seen above, relative changes in intergenerational relationships equal the relative changes of α_a:

$$\frac{\operatorname{cov}(y_a, f)}{\operatorname{cov}(y_k, f)} = \frac{\alpha_a \operatorname{cov}(m, f)}{\alpha_k \operatorname{cov}(m, f)} = \frac{\alpha_a}{\alpha_k}. \tag{9}$$

[20] This data pattern is documented in Katz and Autor (1999).
[21] Belley and Lochner (forthcoming)
[22] This strategy also addresses concerns about co-movement of regressors in Table 4.

Table 6 and Figure 1 show the covariance between a son's wages, measured at different ages and levels of potential experience, and the income of his parents, measured when he was 14 to 16 years old. I observe a clear upward trend in the covariance. According to equation (9), the variation in wages due to the permanent, parent related, component increases over the lifecycle in the same ratio. This implies that α_a doubles between the ages of 25 and 45.

In Section 2, I show that the magnitude of intergenerational relationships implies a lower bound for the value of α_a, given by:

$$\alpha_a \geq corr\left(y_a, y^f\right) sd\left(y_a\right).$$

The wage autocovariances provide an upper bound for the value of α_a. Assuming that the value of α_a changes only gradually implies:

$$\alpha_a^{\;2} \approx \alpha_a \alpha_{(a+\Delta)} \leq sd\left(y_a\right) sd\left(y_{(a+\Delta)}\right) corr\left(y_a, y_{(a+\Delta)}\right).$$

Table 7 shows the variation in wages, the persistence of wages, intergenerational relationships, and the implied upper and lower bounds for α_a, by age. The bounds are visualized in Figure 2. As mentioned earlier, the wage variation increases over the lifecycle. The wage persistence and the magnitude of intergenerational connections rise as well, which leads to an increase in both the upper and lower bound for the share of the wage variation attributed to permanent features. The minimum share of the permanent component rises from 2 - 5 percent of total earnings variation at ages 25 - 30, to 7 - 14 percent at ages 40 - 45. The maximum share rises from around 45 percent to a peak of around 70 percent in the mid 30s and drops to approximately 60 percent once the mid 40s are reached.

Complete Statistical Model

Now, I simultaneously estimate the parameters that characterize the statistical model introduced in Section 2. This makes it possible to distinguish between α_a and β_a, and therefore between the learning and human capital models. The parameters are determined by observable data moments according to equations (1) to (4). I use the variance covariance matrix of wages for ages 25 to 40 and intergenerational covariance for each age level to estimate the parameters. This provides me with one variance for each of the 16 age categories. I also observe 16 covarinces between wages and parental income, as well as 15 one year wage autocovariances, $\operatorname{cov}\left(y_{ba}, y_{b(a+1)}\right)$. I assume that the transitory component does not contribute to wage autocovariances for wages that are more than 9 years apart. I observe 6 autocovariances of wages that a 10 years apart, 5 autocovariances for a 11 year difference and 4 for a 12 year difference. This results in a total of $16+16+15+6+5+4=62$ data moments. The estimates for the model parameters, $\hat{\theta}$, are chosen to minimize the difference between observed moments, C, and their theoretical counterparts $f\left(\hat{\theta}\right)$. I employ a minimum distance procedure that minimizes the function:

$$D=\left[C-f\left(\hat{\theta}\right)\right]' W\left[C-f\left(\hat{\theta}\right)\right].$$

Following the standard procedure in the literature (see Haider, 2001 or Baker and Solon, 2003), the moments are weighted using the identity matrix, i.e. *W=I*. The reason for this choice are the small sample properties of Generalized Method of Moments (GMM) estimators (see Altonji and Segal, 1996). Using a non-optimal weighting matrix provides consistent, but not necessarily efficient, results.

I estimated the complete model, with 16 different values for each of the variables α_a, β_a, and γ_a, and one parameter $\operatorname{cov}\left(u_a, u_{(a+1)}\right)$ and $\operatorname{cov}_b\left(m_i, f_i\right)$. This model is theoretically identified. However, the limited data availability and the interdependence of the parameters lead to very high standard errors. Therefore, I estimate a restricted model where I impose a second order polynomial to characterize the evolution of α_a, β_a, and γ_a over the lifecycle.

$$\alpha_a = \mathrm{A}_0 + \mathrm{A}_1 a + \mathrm{A}_2 a^2$$

$$\beta_t = \mathrm{B}_0 + \mathrm{B}_1 a + \mathrm{B}_2 a^2$$

$$\gamma_a = \mathrm{H}_0 + \mathrm{H}_1 a + \mathrm{H}_2 a^2$$

The resulting estimates are presented in Table 8. The results are still very imprecise. It is especially hard to separately identify α_a and β_a.[23] It is possible to see that the contribution of the transitory component is relatively constant over the lifecycle. The point estimates suggest that both α_a and β_a are increasing over the lifecycle. The point estimate for the increase in β_a is higher, than the estimate for the increase in α_a, the non-parent related permanent component grows in importance at a faster rate than the parent related permanent component. This is some – admittedly weak – evidence favoring of a learning model over a model with conscious human capital investment.

6. Conclusion

I develop a statistical framework that makes it possible to use intergenerational information to study lifecycle wage dynamics. I decompose wage variation into a permanent parent-related component, a permanent component that is unrelated to parental background, and a transitory component. The features related to the parental background of workers become more important for the determination of wages, as workers grow older. This increasing contribution of the permanent parent related component to wage variation contradicts models with wage evolution solely due to random shocks. It is consistent with models of systematic wage evolution, like learning or human capital models. It is theoretically possible to distinguish between these two models by comparing the increasing importance of parent-related characteristics and parent-unrelated permanent characteristics. I find some evidence favoring learning models over models model of human capital investment. However, data limitations lead to imprecise estimates.

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[23] The available data makes it hard to distinguish between two possible data patterns. First, the strong intergenerational influence on *m* together with low values of α_a. Second, a weak intergenerational influence on *m* together with high values of α_a. This becomes apparent when assuming the value for $\text{cov}_b(m_i, f_i)$ as given. The resulting standard errors are displayed in column 4 of Table 8.

Appendix: Attrition

If the individuals who are observed at older ages differ systematically from those observed at younger ages, the comparison of the differences in intergenerational relationships over the lifecycle may reflect these differences and not actual changes over the lifecycle. In other words attrition might bias the results.

Even though there are some years with missing observations for most workers, for the majority of the workers at least some wage observations are available during all phases of their career. Table A1 displays the patterns of wage observations over the lifecycle for sons born before 1960. The wages of 478 individuals are observed at least once while 25 to 31 years old. For 459 of these workers wages are observed at least once while 32 to 38 years old. The wages of 412 workers are observed when they are older than 38. At least one wage observation in each age category is available for 402 workers.

The evolution of intergenerational relationships over the lifecycle for the workers who are observed over their entire career does not differ visibly from picture for the overall population. Figure A1 displays the evolution of the covariance between parental income and the wages of sons over the lifecycle of sons. The observations a categorized by age and the ability to observe wages at different points in the lifecycle. The categories, captured by the 4 different lines, are:

- All sons (the same line as in Figure 1),
- Sons born before 1960,
- Sons born before 1960 with wages observed at least once between the ages of 25 and 31, at least once between the ages 32 and 38 and at least once at an age older than 38.
- Sons born before 1960 with at most two missing wage observations in each of the wage intervals 25 to 31, 32 to 38 and above 38.

The evolution of the intergenerational connections over the lifecycle for all these categorizations is very similar. A clear upward trend is always visible.

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Table 1 **Deviation from average yearly wage by age.**
Residuals of regressions of log wages on year, region, and race dummies.

Age	Number of Observations	Mean	Standard Deviation
25	793	-0.21	0.51
26	805	-0.16	0.51
27	809	-0.12	0.51
28	804	-0.10	0.53
29	796	-0.06	0.59
30	763	-0.04	0.54
31	742	-0.01	0.58
32	703	0.01	0.59
33	686	0.04	0.57
34	619	0.04	0.60
35	579	0.08	0.58
36	529	0.08	0.63
37	487	0.14	0.59
38	433	0.12	0.63
39	380	0.13	0.60
40	360	0.13	0.64
41	301	0.17	0.63
42	258	0.14	0.62
43	212	0.20	0.62
44	173	0.08	0.65
45	146	0.23	0.59

Table 2 Autocorrelation of log wage residual, by age.

Age	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45
25	1.000																				
26	0.663	1.000																			
27	0.579	0.659	1.000																		
28	0.525	0.641	0.691	1.000																	
29	0.400	0.532	0.601	0.678	1.000																
30	0.431	0.524	0.584	0.675	0.784	1.000															
31	0.431	0.493	0.522	0.586	0.685	0.729	1.000														
32	0.391	0.447	0.498	0.576	0.563	0.642	0.736	1.000													
33	0.348	0.456	0.460	0.562	0.604	0.663	0.711	0.803	1.000												
34	0.324	0.459	0.454	0.550	0.556	0.605	0.641	0.741	0.785	1.000											
35	0.293	0.411	0.383	0.493	0.545	0.576	0.635	0.718	0.737	0.855	1.000										
36	0.216	0.376	0.432	0.440	0.551	0.526	0.583	0.680	0.681	0.780	0.833	1.000									
37	0.267	0.305	0.377	0.495	0.544	0.583	0.637	0.706	0.694	0.724	0.783	0.847	1.000								
38	0.260	0.336	0.361	0.375	0.529	0.496	0.561	0.648	0.677	0.745	0.791	0.771	0.839	1.000							
39	0.247	0.289	0.313	0.375	0.442	0.491	0.478	0.591	0.603	0.660	0.651	0.704	0.718	0.829	1.000						
40	0.262	0.263	0.324	0.358	0.472	0.464	0.551	0.600	0.624	0.727	0.722	0.736	0.780	0.772	0.797	1.000					
41	0.239	0.264	0.340	0.363	0.381	0.407	0.448	0.566	0.484	0.617	0.638	0.665	0.690	0.724	0.797	0.776	1.000				
42	0.271	0.321	0.416	0.445	0.454	0.496	0.534	0.621	0.642	0.643	0.661	0.652	0.677	0.714	0.704	0.704	0.802	1.000			
43	0.188	0.204	0.284	0.315	0.365	0.339	0.343	0.445	0.507	0.553	0.576	0.570	0.636	0.680	0.779	0.679	0.757	0.762	1.000		
44	0.301	0.276	0.300	0.324	0.387	0.476	0.493	0.561	0.598	0.591	0.604	0.648	0.650	0.636	0.622	0.763	0.678	0.664	0.818	1.000	
45	0.358	0.256	0.384	0.297	0.361	0.279	0.406	0.569	0.601	0.634	0.678	0.682	0.725	0.696	0.717	0.765	0.773	0.780	0.818	0.759	1.000

Note: Wage residuals from regression on Year, Race and Region Dummies

Table 3 Part a) Autocovarinaces of wage residuals, by age. Standard errors in small print.

Age	25	26	27	28	29	30	31	32	33	34	35
25	0.255										
	0.0171										
26	0.159	0.264									
	0.0132	0.0177									
27	0.141	0.163	0.256								
	0.0112	0.0124	0.0146								
28	0.134	0.168	0.173	0.283							
	0.0121	0.0141	0.0133	0.0184							
29	0.116	0.148	0.166	0.200	0.350						
	0.0153	0.0140	0.0121	0.0134	0.0277						
30	0.116	0.141	0.157	0.188	0.227	0.286					
	0.0107	0.0124	0.0130	0.0123	0.0152	0.0171					
31	0.116	0.135	0.149	0.163	0.213	0.206	0.328				
	0.0131	0.0122	0.0133	0.0133	0.0172	0.0146	0.0216				
32	0.111	0.129	0.143	0.165	0.176	0.190	0.237	0.353			
	0.0130	0.0156	0.0136	0.0141	0.0160	0.0167	0.0200	0.0258			
33	0.090	0.122	0.120	0.160	0.187	0.180	0.217	0.253	0.320		
	0.0119	0.0143	0.0126	0.0130	0.0164	0.0145	0.0179	0.0220	0.0216		
34	0.088	0.126	0.136	0.158	0.174	0.191	0.213	0.258	0.237	0.366	
	0.0140	0.0143	0.0148	0.0137	0.0151	0.0158	0.0186	0.0205	0.0193	0.0249	
35	0.077	0.107	0.108	0.144	0.164	0.166	0.189	0.228	0.220	0.277	0.332
	0.0130	0.0135	0.0142	0.0145	0.0155	0.0141	0.0180	0.0207	0.0185	0.0215	0.0237

Table 3 Part b) Autocovarinaces of wage residuals, by age. Standard errors in small print.

Age	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45
36	0.063	0.108	0.139	0.134	0.181	0.163	0.198	0.246	0.228	0.291	0.285	0.396									
	0.0155	0.0155	0.0183	0.0154	0.0186	0.0172	0.0205	0.0234	0.0211	0.0238	0.0252	0.0303									
37	0.075	0.081	0.109	0.136	0.159	0.167	0.194	0.215	0.208	0.238	0.255	0.300	0.350								
	0.0155	0.0148	0.0158	0.0142	0.0174	0.0158	0.0193	0.0202	0.0208	0.0249	0.0243	0.0291	0.0301								
38	0.075	0.100	0.111	0.119	0.170	0.152	0.182	0.225	0.236	0.263	0.269	0.291	0.272	0.400							
	0.0170	0.0179	0.0164	0.0177	0.0199	0.0187	0.0206	0.0256	0.0240	0.0248	0.0265	0.0266	0.0290	0.0350							
39	0.070	0.078	0.093	0.108	0.129	0.144	0.153	0.185	0.177	0.214	0.207	0.229	0.231	0.263	0.373						
	0.0194	0.0172	0.0185	0.0173	0.0179	0.0199	0.0252	0.0235	0.0191	0.0247	0.0271	0.0307	0.0293	0.0320	0.0396						
40	0.081	0.082	0.109	0.116	0.159	0.154	0.184	0.203	0.211	0.261	0.260	0.283	0.283	0.295	0.302	0.429					
	0.0219	0.0208	0.0222	0.0203	0.0241	0.0235	0.0251	0.0278	0.0252	0.0318	0.0287	0.0294	0.0383	0.0298	0.0391	0.0413					
41	0.066	0.069	0.108	0.106	0.116	0.131	0.136	0.188	0.144	0.209	0.200	0.223	0.226	0.241	0.315	0.277	0.404				
	0.0189	0.0159	0.0218	0.0223	0.0231	0.0265	0.0265	0.0295	0.0241	0.0311	0.0317	0.0317	0.0342	0.0420	0.0480	0.0445	0.0482				
42	0.084	0.099	0.125	0.140	0.149	0.158	0.179	0.215	0.218	0.208	0.224	0.232	0.236	0.254	0.242	0.282	0.271	0.382			
	0.0196	0.0238	0.0252	0.0269	0.0292	0.0275	0.0307	0.0358	0.0367	0.0322	0.0328	0.0379	0.0370	0.0388	0.0414	0.0376	0.0519	0.0521			
43	0.054	0.054	0.077	0.083	0.116	0.105	0.104	0.136	0.149	0.170	0.186	0.180	0.204	0.230	0.246	0.221	0.273	0.269	0.378		
	0.0250	0.0254	0.0246	0.0248	0.0336	0.0296	0.0310	0.0355	0.0357	0.0311	0.0425	0.0340	0.0438	0.0432	0.0380	0.0414	0.0435	0.0680	0.0504		
44	0.088	0.083	0.096	0.104	0.136	0.149	0.171	0.198	0.207	0.203	0.199	0.263	0.242	0.208	0.228	0.294	0.265	0.263	0.283	0.429	
	0.0229	0.0269	0.0296	0.0267	0.0358	0.0308	0.0355	0.0405	0.0395	0.0307	0.0401	0.0530	0.0473	0.0449	0.0336	0.0570	0.0567	0.0599	0.0709	0.0693	
45	0.084	0.064	0.101	0.075	0.107	0.084	0.115	0.168	0.166	0.177	0.226	0.228	0.226	0.240	0.232	0.228	0.270	0.311	0.288	0.284	0.350
	0.0235	0.0287	0.0271	0.0307	0.0382	0.0332	0.0424	0.0499	0.0472	0.0299	0.0460	0.0445	0.0593	0.0496	0.0444	0.0379	0.0576	0.0879	0.0580	0.0923	0.0567

Note: Wage residuals from regression on Year, Race and Region Dummies

Table 4: Regression of log wages on education, experience and parental income

Dependent Variable:	Log Wages			
	1	**2**	**3**	**4**
Education	0.1192	0.0604		0.0343
	0.0029	0.0095		0.0098
Experience	0.0558	0.0645	0.0103	0.0654
	0.0014	0.0067	0.0009	0.0066
Experience squared	-0.0009	-0.0012	0.0001	-0.0012
	0.0000	0.0001	0.0000	0.0001
Education * Experience		0.0000		-0.0002
		0.0002		0.0002
Education * (Year - 74)		0.0029		0.0034
		0.0004		0.0004
Parental Income			0.2311	0.2365
			0.0365	0.0364
(Parental Income) * (Year -74)			-0.0053	-0.0088
			0.0022	0.0021
(Parental Income) * Experience			0.0141	0.0102
			0.0021	0.0019
region and race dummies	yes	yes	yes	yes
year fixed effect	yes	yes	yes	yes
R2	0.357	0.360	0.302	0.380

Note: Parental income is average parental income while 14-17 years old.
Controlled for year and region effects.
Huber/White Standard errors in small print.
11536 Observations.

Table 5: Covariance between residual log wage and parental income, by age and year

Year	Age 25-29	30-34	35-39	40-44	45-50
75-79	0.060				
	0.012				
80-84	0.060	0.092			
	0.009	0.017			
85-89	0.052	0.081	0.093		
	0.009	0.009	0.016		
90-94	0.047	0.071	0.092	0.077	
	0.010	0.010	0.009	0.016	
95-01	0.053	0.068	0.066	0.088	0.081
	0.022	0.011	0.012	0.013	0.022

Note: Parental income is average parental income while 14-17 years old.
Controlled for year and region effects.
Wage residuals from regression on Year, Race and Region Dummies
Standard errors in small print.

Table 6: Covariance between log wage residuals and parental income

Age	cov (y_a, f)	standard error
25	0.057	0.011
26	0.042	0.011
27	0.054	0.010
28	0.046	0.011
29	0.063	0.015
30	0.071	0.011
31	0.077	0.014
32	0.079	0.013
33	0.067	0.012
34	0.083	0.013
35	0.084	0.013
36	0.089	0.014
37	0.088	0.015
38	0.075	0.017
39	0.073	0.017
40	0.081	0.019
41	0.092	0.022
42	0.087	0.020
43	0.080	0.026
44	0.094	0.024
45	0.106	0.031

Note: Parental income is average parental income while 14-17 years old.
Controlled for year and region effects.
Wage residuals from regression on Year, Race and Region Dummies

Table 7: Maximum and minimum values for alpha, implied by the restrictions of the model.

Age	corr (y_a, f)	sd (y_a)	corr (y_a, y_{a+1})	Minumum α corr (y_a, f)*sd (ya)	Maximum α corr (y_a, y_{a+1})*sd (ya)
25	0.209	0.505	0.663	0.106	0.335
26	0.162	0.513	0.659	0.083	0.338
27	0.192	0.506	0.691	0.097	0.350
28	0.163	0.532	0.678	0.087	0.361
29	0.211	0.592	0.784	0.125	0.464
30	0.253	0.535	0.729	0.135	0.389
31	0.241	0.573	0.736	0.138	0.422
32	0.262	0.594	0.803	0.155	0.477
33	0.253	0.566	0.786	0.143	0.444
34	0.265	0.605	0.856	0.160	0.518
35	0.290	0.577	0.833	0.167	0.480
36	0.301	0.629	0.847	0.189	0.533
37	0.302	0.592	0.840	0.179	0.497
38	0.231	0.632	0.829	0.146	0.524
39	0.247	0.611	0.797	0.151	0.487
40	0.290	0.655	0.777	0.190	0.509
41	0.276	0.636	0.802	0.175	0.510
42	0.328	0.618	0.762	0.202	0.471
43	0.273	0.615	0.818	0.168	0.503
44	0.306	0.655	0.759	0.200	0.497
45	0.377	0.592		0.223	

Note: Parental income, f, is average parental income while 14-17 years old.
Controlled for year and region effects.
Wage residuals, y, from regression on Year, Race and Region Dummies

Table 8: Minimum distance estimation of Model

Parameter	Estimate	Standard error	$\text{cov}_b(m_i, f_i)$ fixed Standard error	Restriction: $A_1 = B_1$; $A_2 = B_2$ Estimate	Standard error
A_0	0.147	1.106	0.030	0.136	0.068
A_1	0.015	0.110	0.008	0.018	0.009
A_2	-0.001	0.004	0.001	-0.001	0.001
B_0	0.118	1.173	0.047	0.140	0.083
B_1	0.030	0.033	0.018	0.018	0.009
B_2	-0.001	0.002	0.001	-0.001	0.001
H_0	0.445	0.050	0.028	0.453	0.027
H_1	-0.002	0.010	0.011	-0.002	0.009
H_2	0.000	0.001	0.001	0.000	0.001
$\text{cov}_b(m_i, f_i)$	0.347	2.618	-	0.332	0.105
$\text{cov}(u_a, u_{(a+1)})$	0.509	0.059	0.035	0.518	0.032

$$\alpha_a = A_0 + A_1 a + A_2 a^2$$

$$\beta_t = B_0 + B_1 a + B_2 a^2$$

$$\gamma_a = H_0 + H_1 a + H_2 a^2$$

Note: In the calculation of standard errors a numerical derivative is used to calculate the gradient. The covariance matrix of the data moment is bootstraped to deal with the unbalanced panel.

Table A1 - Observable wages by age of sons born prior to 1960, with at least one wage observation between age 25 and 31

Observable Wages		***Age>38***		
		Not observed	***Observed***	***Total***
Age 32-38	***Not observed***	9	10	19
	observed	57	402	459
	Total	66	412	478

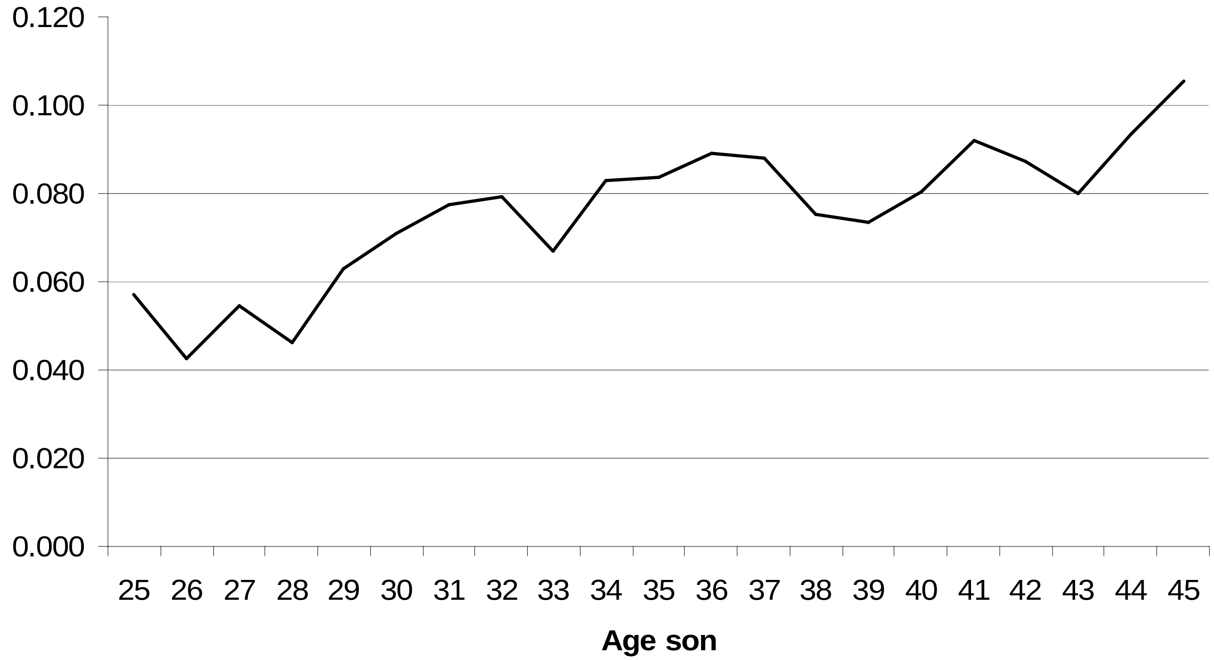

Figure 1: Intergenerational Covariance between parents' income while son 14 to 16 years old and wages of the son measured at different ages

Figure 2: Share of permanent ability in wage variation by age
minimum and maximum values implied by model restrictions

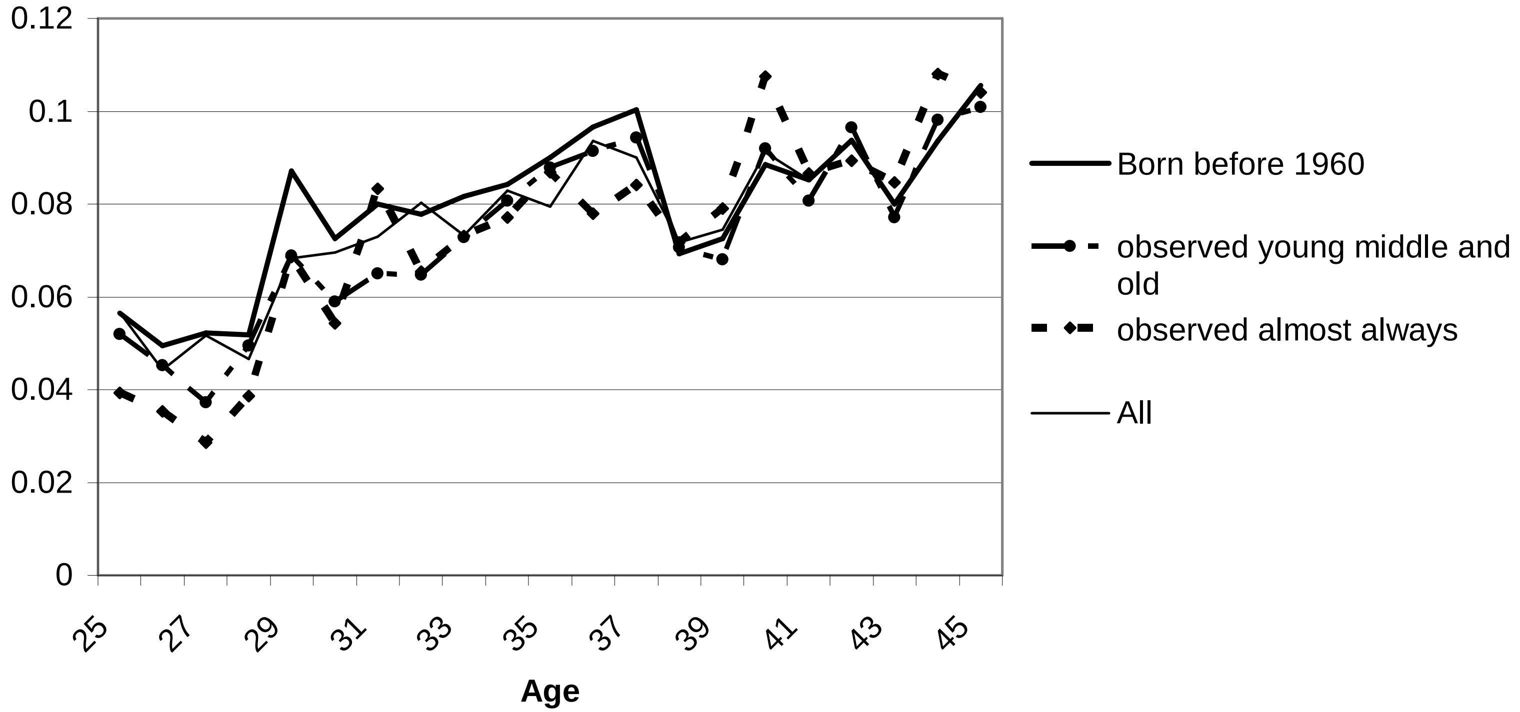

Figure A1: Intergenerational covariance and attrition