Understanding Wage Growth: Estimating and Testing Learning-by-Doing*

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Abstract

I adapt the basic insight from the literature that tests the permanent income theory to test the Learning-by-Doing (LBD) model of human capital accumulation. I propose three measures of workers' incentives to accumulate skills. These incentives correlate with wage growth conditional on hours worked and past wages, implying that significant components of wage growth are not accounted for by the LBD model. This suggests that wage growth is costly and that workers face a trade-off between current and future earnings. This trade-off has ramifications for wage subsidy policies and for understanding women's decisions about children and career.

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1 Introduction

In this paper I propose a framework to test whether there is a trade-off between wage growth and current earnings. This trade-off results from a direct or indirect cost of wage growth. It implies that workers with the same observables (e.g. age, education, current wage, hours of work, occupation) may trade current earnings for future earnings to different extents if there are variations in the benefits and costs of increasing future wages.[1] If wage growth is costly, the difficulty of measuring the extent of this cost is a special case of missing variables, but it has important implications. Labor market policies, such as wage subsidies for low-income workers, that augment current earnings may hamper future earnings by increasing the cost of wage growth. The cost of wage growth could also depend on the taste for labor versus non-labor market activities, suggesting that the trade-off between current and future earnings may be important to understanding the relationship between labor supply, wage growth, and fertility decisions for women. Finally, if wage growth involves mainly indirect costs, then earnings become biased measures of worker productivity. Heckman, Lochner and Taber (1998) suggest that this wedge between wages and productivity can be crucial in understanding the evolution of the college earning premium and wage inequality.

The test I propose works by examining whether wage growth, conditional on other observable determinants of wage growth, is affected by variation in the returns to foregone current earnings. Finding an effect suggests that wage growth is costly. I use this framework to test a specific model of costless wage growth: Learning-By-Doing (LBD) (Weiss [1971,1972]).[2] In its most common form (to which I will refer to as the "LBD model" or the "pure LBD model"), learning is a by-product of productive work, so there is no trade-off between current and future earnings. Workers complete the tasks they are remunerated for and accumulate human capital at the same time. My results are inconsistent with the model's prediction that (conditional on current wage, ability, and age) only hours of work determine wage growth. It is not surprising that the pure LBD model is rejected as it is meant to be a convenient simplification of reality. However, my results also suggest that modeling wage growth solely on the basis current hours worked and other observables may overlook significant portions of wage growth. For example, the estimates presented in this paper suggest that the wages of future mothers grow by 2 to 3 percentage points less than other women with the same hours worked. To put this in perspective, average annual wage growth for women in my sample is slightly above 6%.

[1] The On-The-Job-Training (Becker [1964], Ben-Porath [1967], Mincer [1974]) is an example of a model where increasing future earnings comes at the cost of lower current earnings.

[2] Olivetti (2006) uses the LBD model in a life-cycle model to show that changing returns to work experience explain the increase in labor supply by married women from the 1970s to the 1990s. Imai and Keane (2004) use it to estimate the intertemporal elasticity of substitution of labor supply. Chang, Gomes and Schorfheide (2002) incorporate LBD in a real-business-cycle (RBC) model and show that skill accumulation allows the RBC model to generate a positive correlation in output growth, which is consistent with U.S. gross domestic product data.

At this point, an example might help understand how the test works. Consider two women aged 21 years old who currently hold a job. In the near future, woman A is planning to have children while woman B is planning to focus entirely on her career. These two women have different incentives to accumulate human capital, which are weaker for woman A who will leave the labor market to take care of her young children. Despite this variation in skill accumulation incentives, the LBD model predicts that these two women should experience the same wage growth from age 21 to age 22 if they work the same number of hours. Conditional on hours worked, ability and current skills, there should be no correlation between wage growth and future fertility decisions, or any other variable that identifies variation in a worker's incentives to invest in human capital.

I therefore test the pure LBD model by examining, conditional on hours worked, how sensitive wage growth is to factors that affect a worker's incentives to accumulate human capital. That these factors should not affect wage growth once hours of work are factored in, is a fundamental prediction of the LBD model. So once the LBD human capital production function is accounted for, "excess sensitivity" of wage growth to variables reflecting variation in human capital accumulation amounts to a rejection of the pure LBD model.[3] To identify variation in the incentives to accumulate human capital, I use three test variables that distinguish workers following different life-cycle profiles of human capital accumulation: expected future hours of work, career expectations, and expected future fertility. I find that male wage growth displays "excessive sensitivity" to future hours of work. Female wage growth is affected by all three variables. These results point to a rejection of the pure LBD model and suggest that another mechanism plays a role in wage determination. The effect of this alternative mechanism on wages can be crudely compared to that of the LBD mechanism by using the elasticity of wages to both hours worked and test variables. These elasticities indicate that both mechanisms have effects of the same magnitude on wages.

The test framework I use does not however formally identify what other wage growth mechanisms lead to this "excessive sensitivity" of wage growth. Rather, it sets up the pure LBD model as the null hypothesis and reports on whether the data deviates from this null hypothesis.[4] I can however use the estimated effects of my test variables on wages to speculate about whether they are consistent with a model of costly wage growth. In doing so I focus on the On-the-Job Training (OJT) model (Becker [1964], Ben-Porath [1967], Mincer [1974]). In the OJT model, workers

[3]This empirical test is adapted from the permanent income hypothesis literature that studies how sensitive changes in consumption are to changes in income. See, for example, Flavin (1981), Attanasio and Weber (1995), or Stephens (2008).

[4]For studies that implement a comparison of two competing wage growth mechanisms in a common structural framework see, for example, Bowlus and Liu (2013) that compares human capital accumulation to search, and Sanders (2016) that compares multi-skill accumulation to reducing uncertainty about these skills. Hansen and İmrohoroğlu (2009) study how endogenous human capital accumulation through either LBD or On-the-Job Training affect the life-cycle profile of average hours worked and their volatility in a calibrated general equilibrium model. Wallenius (2011) compares the impact of using LBD versus On-the-Job Training human capital accumulation on the estimate of the intertemporal elasticity of substitution of labor supply.

allocate their time between productive work and human capital investments. This leads to a trade-off between increasing current earnings through productive work and increasing future earnings through human capital investments. Because investment can vary independently of hours of work, wage growth can differ for two workers who work the same hours. This implies that wage growth should vary with the incentives to invest in human capital, even after conditioning on hours worked. In the previous example, woman A who plans to have children in the near future, has weaker incentives to invest in human capital than woman B, so a negative correlation between expected fertility and wage growth should be observed.

Comparing the LBD and OJT models provides an example of how policy implications may differ if wage growth is costly. Cossa, Heckman and Lochner (2003) show that the Earned Income Tax Credit has different implications for human capital accumulation depending on whether an LBD or OJT framework is assumed. Hansen and İmrohoroğlu (2009) find that both mechanisms lead to different steady state and business cycle properties in a calibrated general equilibrium model. Moreover these two models have different implications about the measurement of workers' marginal productivity. Because OJT investments are unobserved, wages (total income divided by total hours of work) provide a downward biased measure of marginal productivity when individuals invest in human capital. This means that studying observed wages across workers with different levels of investment leads to invalid conclusions about the distribution of productivity or the price of skills. Finally, the costly nature of investment in the OJT model implies that workers who face borrowing constraints might have to make sub-optimal investments in human capital. There is less scope for this in the LBD model where human capital accumulation is costless.

There are other models of wage growth. Rosen (1972) presents a LBD model where workers learn as a by-product of productive work and where firms can offer jobs with differing rates of learning. Offering a higher learning rate is costlier for a firm and, in equilibrium, jobs with more learning content offer higher rates of human capital accumulation but lower current earnings. In the search framework with endogenous search effort (Mortensen [1990], Burdett and Mortensen [1998]), wage growth is generated by workers searching and moving on to jobs with better wage offers. Workers have only partial information about available jobs and those who undertake a costlier search for employment opportunities are more likely to find a better wage offer and experience stronger wage growth. In a model where workers can invest in multiple skills (e.g. Kambourov and Manovskii [2009]), workers contemplating occupational mobility may have to invest in skills that increase their productivity in their future occupation without increasing it in their current occupation. If workers do not observe their own skills, these can be revealed by moving across occupations that are defined by how much earnings they offer and the speed at which they reveal skills (Antonovics and Golan [2012], and James [2012]).

In all these models, wage growth comes at a cost, while hours worked and other observables do not account for how much of this cost a worker bears. Young workers who expect to work more in the future should initially choose jobs with more learning content (and lower wages) to accumulate more human capital, and eventually move on to jobs with less learning content as their career progresses. Young workers who expect to work more in the future should spend more effort searching for better paying employment opportunities. Workers who expect to work more hours in a different occupation should invest in skills specific to that occupation. Workers who expect to work more in the future have a stronger incentive to work in an occupation with lower earnings but speedier skill revelation. In all these cases there should be a positive correlation between current wage growth and expected future hours of work. This correlation should be observed even after controlling for current hours of work, wage and ability, and the test I implement should reject the pure LBD model.

To test the LBD model's prediction that hours of work determine wage growth, I use data on hourly wages and annual hours of work from the 1979 cohort of the National Longitudinal Survey of Youth (NLSY79) to estimate a pure LBD human capital production function. The assumed parametric form of this production function shares features with that of Imai and Keane (2004): human capital is lost through depreciation and gained through learning, learning is more productive for workers with more skills. The production function includes age and a measure of cognitive ability to account for observed heterogeneity. I account for unobserved heterogeneity with a fixed effects approach. I use multi-period lagged values of hours worked, wages, and household characteristics as instruments in a Generalized Method of Moments (GMM) estimator to address the endogeneity of the production function's inputs: hours of work and skills. Identification through these instrumental variables relies on the assumption that workers cannot predict wage shocks a long time ahead, and that present and past labor market decisions are optimal career choices driven by characteristics (ability, preferences, beliefs and finances) that vary across workers. Relative to a structural approach that would estimate a more general model that includes LBD and other competing wage growth mechanisms, the approach I propose has the advantage of foregoing assumptions about preferences and credit markets, while making weaker assumptions about expectations and beliefs. My approach cannot however formally identify the wage growth mechanisms that compete with LBD. The approach also relies on the assumption that I have valid instrumental variables, but these instruments are in line with what has been used previously in the literature (Shaw [1989], Kim and Polachek [1994]).

This paper is structured as follows. Section 2 discusses the methodology I use to test the pure LBD model while section 3 explains the identification strategy. The fourth section describes the data. Results are presented in section 5. Section 6 concludes.

2 Testing the Learning-by-Doing Model

2.1 The Basic LBD Model and its Testable Implication

Consider a life-cycle model of labor supply where individuals choose consumption and leisure in order to maximize lifetime utility. At the beginning of period t, exogenous inputs to the production of human capital $(W_{it}, X_{it}^{\text{ex}})$ are realized and observed by agent i. The current level of human capital is given by W_{it} while vector X_{it}^{ex} contains other state variables, such as ability, age, and education. Each period, an agent has one unit of time that must be allocated either to leisure or work. Let H_{it} denote time allocated to work.

The following earnings and human capital equations capture the essence of the pure LBD model: human capital is accumulated as a by-product of productive work.

$$
\begin{aligned}
E_{it} &= W_{it} H_{it} && (1) \\
W_{it+1} &= f\left(H_{it}, W_{it}, X_{it}^{\text{ex}}, \theta_i, \right) e^{\varepsilon_{it}}, && (2)
\end{aligned}
$$

where E_{it} represents earnings during period t, θ_i is unobserved heterogeneity (which, for expositional purposes in this section, I assume is known and can be accounted for), and ε_{it} is a transitory random shock to the human capital production process. The LBD production function (2) makes it clear that once skill level W_{it}, other exogenous inputs X_{it}^{ex}, and unobserved heterogeneity θ_i are held constant, only observed hours of work H_{it} generate systematic variation in human capital W_{it+1}.

This is not true in the OJT model since hours of work do not measure all the variation in investments. The key to testing the LBD model is finding variables that measure variation in incentives to invest in skills, and test for any systematic association between these variables and skill accumulation once hours of work are held constant.

To illustrate this consider a modified version of a model proposed in Killingsworth (1982) where both OJT and LBD accumulation mechanisms play a role:

$$\ln W_{it+1} = \ln f\left(H_{it}, W_{it}, X_{it}^{\text{ex}}, \theta_i\right) + \ln g\left(I(H_{it}, W_{it}, X_{it}^{\text{ex}}, S_{it}, \theta_i), W_{it}, X_{it}^{\text{ex}}, \theta_i\right) + \varepsilon_{it},$$

where costly OJT investments I_{it} are written as a function of observables, unobserved permanent ability θ_i, and some variables S_{it} that affect the incentive to accumulate skills: $I_{it} = I(H_{it}, W_{it}, X_{it}^{\text{ex}}, S_{it}, \theta_i)$. For example, I use future hours of work as a test variable: individuals who expect to work more in the future have a stronger incentive to accumulate human capital. I describe in details all the variables I use as S_{it} factors in the next section. These S_{it} factors cause workers with identical $(H_{it}, W_{it}, X_{it}^{\text{ex}}, \theta_i)$ to choose different levels of investment. Consider the following estimating equation

$$\ln W_{it+1} = \ln f\left(H_{it}, W_{it}, X_{it}^{\text{ex}}, \theta_i\right) + \delta S_{it} + \tilde{e}_{it}. \tag{3}$$

Intuitively, the LBD framework predicts that $\left(H_{it}, W_{it}, X_{it}^{\text{ex}}, \theta_i\right)$ should account for all systematic variation in human capital W_{it+1}, so $\widehat{\delta} = 0$. In the OJT model, it is expected that $\widehat{\delta} \neq 0$ since the term δS_{it} picks up variation in $\ln g\left(I_{it}, W_{it}, X_{it}^{\text{ex}}, \theta_i\right)$ due to variation in I_{it} conditional on $\left(H_{it}, W_{it}, X_{it}^{\text{ex}}, \theta_i\right)$. Then equation (3) can be estimated and finding estimates of δ that are statistically different from zero is interpreted as a rejection of the pure LBD model.

2.2 Measuring Variations in Incentives to Accumulate Skills

I consider three S_{it} variables that may affect the incentives to accumulate human capital. The first is expected future hours of work which capture variation in a worker's returns to human capital investment. Incentives to invest are greater for those who expect to work more in the future. I use realized future work hours (H_{it+1}) as a proxy for expected hours of work.

To test the LBD model in the sample of women I use expected career path to identify variation in a worker's optimal life-cycle profiles of skill accumulation and labor supply. Workers are asked at ages 17 to 22 which occupation they expect to hold when they are 35 years old. I create three broad occupational categories (non-professional job, professional job, and other non-labor market activities such as homemaking) and assume that each category represents a distinct human capital accumulation path and, therefore, identifies variation in human capital accumulation incentives.

The third and last variable is based on expected future fertility and used only to test the LBD model for women. Women who expect to have more children in the future are likely to take more time off from work in the future. This reduces the returns to human capital accumulation, implying that expected fertility identifies variation in the incentives to invest in human capital. I use realized future fertility interacted with the age of the youngest children as a proxy for expected fertility.

2.3 Avoiding Incorrect Rejections of the LBD Model

When choosing test variables, care must be taken to avoid mistakenly rejecting the LBD model. If an exogenous input of X_{it}^{ex} is incorrectly omitted, then parameter δ provides an estimate of the effect of the missing input on wages, scaled by the (conditional) correlation between the test variable S_{it} and the missing exogenous input. The likelihood of type I errors is therefore weaker if *(i)* missing exogenous inputs have a weak effect on wages, and *(ii)* if missing inputs are weakly correlated with the test variable S_{it}. Since it is harder to achieve the latter with test variables that measure the incentives to accumulate human capital, I strive to achieve the former by including in the production function current skills, age, and observed cognitive ability, all important determinants of wage growth

Even if I account for all of the necessary inputs, the LBD model could still be falsely rejected if the test variable is systematically related to any mis-specification of the human capital production function. To minimize specification errors I use a fairly general parametric model for the LBD human capital production function; the details are provided in section 3.

2.4 Improving Test Power

I now discuss situations where the test procedure would fail to reject the LBD model. Suppose that the true human capital production function is given by:

$$\ln W_{it+1} = \ln g_1\left(H_{it}, X_{it}^{\text{en}}, W_{it}, X_{it}^{\text{ex}}, \theta_i\right) + \varepsilon_{it}.$$

Here human capital still depends on pre-determined inputs $\left(W_{it}, X_{it}^{\text{ex}}, \theta_i\right)$ and on learning H_{it}. But there is now another endogenous input X_{it}^{en} chosen by the worker in period t that affects wage growth. If wage growth has an OJT component to it, then unobserved investments I_{it} would be an element of X_{it}^{en}. But it could also reflect search effort or the chosen learning content of a job.

If I assume the LBD model, which excludes the alternative endogenous input X_{it}^{en} and estimate equation (3) then test variable S_{it} reflects variation in missing endogenous input X_{it}^{en} and parameter δ gives an estimate of $\frac{\partial \ln g_1}{\partial X_{it}^{\text{en}}} \cdot C(S_{it}, X_{it}^{\text{en}} | H_{it}, W_{it}, X_{it}^{\text{ex}}, \theta_i)$.

The likelihood of rejecting the LBD model therefore depends on how strong the test variable S_{it} is correlated with the missing endogenous input, and the importance of this endogenous input to skill accumulation. This correlation between the test variable and the missing endogenous input is likely reduced by ensuring that the estimated LBD production function is general enough to avoid type I errors. That is, once current hours of work, current wage, age, and ability are held constant, variable S_{it}, being an imperfect measure of human capital accumulation incentives, may not provide any additional information about variations in missing endogenous input X_{it}^{en}.

I expect test variables S_{it} to be more powerful when testing the LBD model in the sample of female workers because these variables are related to expected fertility. Female fertility decisions depend on preferences and household conditions and are jointly determined with human capital and labor supply profiles. There might be more variation in female endogenous input X_{it}^{en} even after holding constant age, ability, current levels of human capital, and hours worked.

Finally, I show in Appendix section A.1 that an OJT component to skill accumulation makes wages a biased measure of human capital. I also show that this increases the likelihood of failing to reject the pure LBD model.

3 Identification Strategy

3.1 Unobserved Heterogeneity in Ability

Skill production depends on unobservable ability θ_i. I assume multiplicative separability between the deterministic and unobserved heterogeneity component of the production function:

$$f(H_{it}, W_{it}, X_{it}^{\text{ex}}, \theta_i) = \widetilde{f}(H_{it}, W_{it}, X_{it}^{\text{ex}})\, e^{\theta_i}. \tag{4}$$

This allows unobserved ability to affect the productivity of inputs $(H_{it}, W_{it},\ X_{it}^{\text{ex}})$.[5] Imai and Keane (2004) also assume multiplicative separability between the deterministic and stochastic components of their pure LBD production function.

After taking the log of equation (4) one can first-difference it in order to eliminate unobserved ability θ_i:

$$\triangle \ln W_{it+1} = \ln \widetilde{f}(H_{it}, W_{it}, X_{it}^{\text{ex}}) - \ln \widetilde{f}\left(H_{it-1}, W_{it-1}, X_{it-1}^{\text{ex}}\right) + \triangle \varepsilon_{it} \tag{5}$$

where $\triangle$ denotes the first difference operator (*e.g.* $\triangle \ln W_{it+1} = \ln W_{it+1} - \ln W_{it}$). A test variable S_{it} can be included in (5) to implement the LBD excess sensitivity test

$$\triangle \ln W_{it+1} = \triangle \ln \widetilde{f}(H_{it}, W_{it}, X_{it}^{\text{ex}}) + \delta S_{it} + \triangle \varepsilon_{it}. \tag{6}$$

Assuming that unobserved heterogeneity does not affect log-wage growth is somehow restrictive. To make the specification slightly more flexible I include a measure of cognitive ability in X_{it}^{ex}. Misspecifying unobserved heterogeneity is akin to having an input missing from the production function. As the assumed effect of unobserved heterogeneity on wages deviates further from the true production function, the effect of this "missing" input on wages increases. This implies an increase in the likelihood of type I errors, since test variables S_{it} are likely correlated with the missing unobserved heterogeneity input θ_i. For type II errors, misspecifying unoberved heterogeneity will bias parameter δ to zero if variable S_{it} is associated with higher unobserved ability θ_i, but lower endogenous input X_{it}^{en}.

3.2 Endogeneity of Hours Worked and Current Skills

Individuals may adjust their hours of work to wage shocks that I do not observe. For example, a worker who is ill or has to take care of an ill family member might resort to part-time employment where hours and wages are lower. Or lower prices in an employer's product market might lead to

[5] More able workers (large θ_i) will accumulate human capital at a faster rate since $\frac{\partial^2 W_{it+1}}{\partial H_{it} \partial \theta_i} = \frac{\partial \widetilde{f}}{\partial H_{it}} e^{\theta_i + \varepsilon_{it}}$.

both a lower wage and reduced hours. This implies that hours of work likely correlate with wages through mechanisms other than wage growth.[6]

Formally, I assume that H_{it} and H_{it-1} are correlated with, respectively, ε_{it} and ε_{it-1} which are found in the error term of both equations (5) and (6). Also note that W_{it} is a function of ε_{it-1} and is therefore correlated with $\triangle\varepsilon_{it}$. I assume that the following moment condition holds

$$\mathbb{E}\left[\triangle\varepsilon_{it}|H_{it-2},W_{it-1},X^{\text{ex}}_{it-1}\right]=0. \tag{7}$$

This moment condition is consistent with workers accounting for wage shocks a short time ahead: based on the information available to the worker at the beginning of period $t-1$, the worker expects no difference between today's shock (ε_{it-1}) to wage formation and tomorrow's shock (ε_{it}). This implies that I can use lagged hours of work and lagged wages as instrumental variables. I include $(H_{it-2},W_{it-1},X^{\text{ex}}_{it-1})$ and nonlinear functions of these variables in what I call the "standard" set of instrumental variables. These nonlinear functions of $(H_{it-2},W_{it-1},X^{\text{ex}}_{it-1})$ are crucial to my identification strategy as they insure that I have enough orthogonality conditions to estimate all the parameters of wage functions (5) and (6), but this strategy has been used in previous literature (Shaw [1989], Kim and Polachek [1994]).[7] These instruments are valid under two conditions. First, unobserved wage shocks are transient and workers can only account for them a short time ahead. Second, although transient shocks affect work decisions, these past and present labor market decisions are optimal career choices driven by characteristics (ability, preferences, beliefs and finances) that vary across workers. Under these two conditions lagged hours and lagged wages are good predictors of current hours of work decisions, and they do not correlate with current wage shocks. The combination of these instrumental variables with the first-difference log-wage equations that I use to deal with unobserved ability implies that identification of the impact of hours of work on wages comes from the co-movement between changes in hours worked and changes in wage predicted by past decisions.

The validity of these instrumental variables however relies on shocks being transient and hard to predict long in advance. If the illnesses requiring workers to change their work arrangements tend to last many years, or if their employers face enduring slumps in their product demand, the identification that I propose here breaks down. Theoretically I could get around this issue by using higher order lags of past wages and past hours of work. In practice their correlation with current wages and current hours of work is marginal, making them weak instruments.

[6]Some of the test variables that I describe in section 2.2 are endogenous for similar reasons. I address this issue in section 3.3.

[7]Let $F(H_{it-2},W_{it-1},X^{\text{ex}}_{it-1})$ be a vector of functions of $(H_{it-2},W_{it-1},X^{\text{ex}}_{it-1})$. GMM estimations for the standard set of instrumental variables presented in section 5 are based on the following vector of orthogonality conditions: $\mathbb{E}\left[F(H_{it-2},W_{it-1},X^{\text{ex}}_{it-1})\triangle\varepsilon_{it}\right]=0$. See Appendix section A.3 for a complete list of instrumental variables.

Additionally, if human capital is accumulated through regular involvement in productive work, then skill accumulation depends on the allocation of hours across current and past periods. This suggests that the skill production function should also include the vector of past hours of work, as in Altuğ and Miller (1998). In this case using lagged hours worked as an instrument for the estimation of (6) might lead to falsely rejecting the LBD model because the human capital production function is misspecified. To account for this I also consider what I call the "alternative" set of instruments that excludes lagged hours of work and instead includes lagged household characteristics: number of children in the household, number of children interacted with an indicator variable for whether the youngest child is at least 6 years old, number of children interacted with worker age, family size, and indicator variables for marital status. These variables and hours of work are jointly determined but the household related variables should not appear directly in the production function. Formally, the alternative set of instruments includes lagged household characteristics Z_{it-1} as a replacement for lagged hours of work on the basis that the following moment condition holds[8]

$$\mathbb{E}\left[\triangle\varepsilon_{it}|Z_{it-1},W_{it-1},X^{\text{ex}}_{it-1}\right]=0. \tag{8}$$

Finally it should be noted that identification relies on workers making optimal time-consistent career decisions, making lagged hours, lagged wages, and lagged household characteristics (the instrumental variables) good predictors of current hours and current wages (the endogenous variables). These optimal career decisions most likely depend on unobserved heterogeneity in ability, which suggests a second channel through which my identification strategy hinges on correctly specifying the nature of unobserved ability. If it is misspecified in equation (4) then I expect the parameters of the wage function associated with current hours and current wages would partly pick up the impact of unobserved ability on wages.

Conditional expectations (7) and (8) hold if ε_{it} is serially independent or if it follows a unit root process. The case for labor earnings residuals following a unit root process is supported by previous research (Abowd and Card [1989], Meghir and Pistaferri [2004]).[9]

[8]GMM estimations for the alternative set of instrumental variables presented in section 5 are based on the following vector of orthogonality conditions: $\mathbb{E}\left[F(Z_{it-1},W_{it-1},X^{\text{ex}}_{it-1})\triangle\varepsilon_{it}\right]=0$, where $F(Z_{it-1},W_{it-1},X^{\text{ex}}_{it-1})$ is a vector of functions of $(Z_{it-1},W_{it-1},X^{\text{ex}}_{it-1})$. See Appendix section A.3 for a complete list of instrumental variables.

[9]Altonji, Smith and Vidangos (2013) empirically reject the unit root process in favor of an AR(1) process, which would generate correlation between the instruments and the error term in my specification. But their estimated AR(1) autocorrelation coefficient of 0.908 being close to a unit root combined with the fact that I estimate a log-wage growth equation suggest a relatively small bias. Moreover, it biases coefficients toward zero in the very likely case where the predicted endogenous wage determinant's correlation with ε_{it} has the same sign as its impact on wages through the wage function (see Appendix A.4 for more details). Both hours of work and current wages are expected to have a positive direct impact wage formation, see for example the LBD human capital production function estimates presented in Imai and Keane (2004). By construction the endogenous current wage is positively correlated with the log-wage error term. Hours of work should also be positively correlated with this error term based on the positive estimates of the intertemporal elasticity of substitution of labor supply (Imai and Keane [2004], Wallenius [2011]).

3.3 Endogeneity of Test Variables

I use realized future hours of work and realized future fertility as test variables in equation (6). As I explain in section 2.2 these variables are meant to serve as proxies for unobserved expected future hours and fertility and should capture variation in workers' incentives to invest in human capital. But a positive shock to wages this year increases the incentive to work next year. A negative shock to wages this year decreases the indirect cost of taking time off work to care for children next year. These wage shocks that I do not observe therefore make realized future hours and fertility endogenous in equation (6). As long as these wage shocks cannot be predicted a long time ahead by workers, I can instrument future hours and future fertility with lagged hours, lagged wages, and lagged household characteristics. These instrumental variables are adequate since optimal career decisions by the worker should generate coherency between past and future decisions.[10] Formally, moment conditions (7) and (8) imply that I can use the same two sets of instrumental variables to deal with the endogeneity of realized future hours and fertility.

When estimating equation (6) with realized future hours of work as test variable S_{it}, I use the same sets of instrumental variables that are employed for the estimation of equation (5). Since I instrument both current wage, current hours, and realized future hours with the same set of variables, I reiterate that identification of all the parameters relies on a nonlinear relationship between these instruments and the endogenous variables.[11]

When realized future fertility is used as test variable S_{it}, I add lagged fertility to the standard set of instruments, which normally includes functions of lagged hours and lagged wages. I however use the exact same set of alternative instruments since it already includes lagged fertility.

Finally, when career expectations is used as test variable S_{it} I add career expectations to both sets of instruments. Under the assumption that workers cannot predict wage shocks a long time ahead, career expectations are exogenous.[12] However, career expectations partly reflect workers' unobserved heterogeneity in ability. If this ability is not properly accounted for by the functional form of equation (4) then career expectations would tend to pick up the impact of unobserved ability on wages and lead to an incorrect rejection of the pure LBD model.

[10] Endogeneity may also arise if wage shocks unexpected by the worker generates discrepancies between expected and realized future hours of work and fertility. My identification is robust to this source of endogeneity since these unexpected wage shocks cannot, by definition, be predicted a long time ahead by the worker.

[11] Identification does not rely on the nonlinearity of log-wage function $\ln \widetilde{f}(H_{it}, W_{it}, X_{it}^{\text{ex}})$ in equations (5) and (6). I obtain qualitatively similar results to those presented in section 5 when I use the same instrumental variables with a linear log-wage equation.

[12] In the estimation, I use wages observed at least two years after workers answer the career expectation questions.

3.4 Functional Form of LBD Production Function

With the aim of detecting deviations from the pure LBD model rather than misspecifications of LBD production function I use a fairly general parametric model for the production function $\widetilde{f}(H_{it}, W_{it}, X_{it}^{\text{ex}})$:[13]

$$\widetilde{f}(H_{it}, W_{it}, X_{it}^{\text{ex}}) = B(X_{it}^{\text{ex}}) \cdot W_{it} + A(X_{it}^{\text{ex}}) \cdot H_{it}^{\alpha_1} W_{it}^{\alpha_2} \tag{9}$$

A similar specification has been used by Imai and Keane (2004). It allows for depreciation in skills $(B(X_{it}^{\text{ex}}) \cdot W_{it})$ and for accumulation through learning $(A(X_{it}^{\text{ex}}) \cdot H_{it}^{\alpha_1} W_{it}^{\alpha_2})$. Parameters α_1 and α_2 determine the productivity of hours of work and lagged human capital. Parameters A and B are functions of state variables X_{it}, allowing the human capital production function to differ based on age and observed ability.

Inserting equation (9) into (5) and (6) yields

$$\begin{aligned} \triangle \ln W_{it+1} &= \triangle \ln \left[B(X_{it}^{\text{ex}}) \cdot W_{it} + A(X_{it}^{\text{ex}}) \cdot H_{it}^{\alpha_1} W_{it}^{\alpha_2} \right] + \triangle \varepsilon_{it} && (10) \\ \triangle \ln W_{it+1} &= \triangle \ln \left[B(X_{it}^{\text{ex}}) \cdot W_{it} + A(X_{it}^{\text{ex}}) \cdot H_{it}^{\alpha_1} W_{it}^{\alpha_2} \right] + \delta S_{it} + \triangle \varepsilon_{it}. && (11) \end{aligned}$$

4 NLSY79 Data

The NLSY79 is a random survey of American youth aged 14 to 21 in 1979 which provides extensive panel data on wages and work experience from 1979 to 2006. In this study, I use the cross-sectional sample of whites excluding the poor white supplemental sample, and implement the analysis separately for men and women. The time unit I consider is a year, so I do not use wage and hours data collected after 1994, when the NLSY79 surveys were conducted every two years.

Human capital is not observable, so I use hourly wage which is a valid measure of skills under the assumption of a pure LBD model. The variable of interest in this study, skills next period W_{it+1}, are given by the hourly wage in the current survey. Current skills W_{it} are given by the hourly wage in the previous survey, which I refer to as the lagged wage. Current hours of work H_{it} is the sum of all hours worked at all jobs from the time of the previous survey interview to the current interview.

The NLSY79 data also provides a wealth of information about respondents' household composition. Among these, I use the number of children in the household, the age of the youngest child in the household, family size and the worker's marital status as state variables Z_{it-1} to build the

[13] As explained in Section 2.3, even if I include all the relevant LBD human capital production inputs, I could still erroneously reject the LBD model if I incorrectly specify the parametric form of the LBD human capital production function. One way to get around this problem would be to nonparametrically estimate the LBD production function. However the lack of an instrumental variable that correlates only with the unobserved endogenous non-LBD input to human capital production and test variables S_{it}, but not with the observed inputs of the LBD production function, implies that equation (6) is not identified in a nonparametric setting.

alternative set of instruments discussed in section 3.2.

After applying a number restrictions to the sample described in Appendix section A.2, I obtain 9,566 wage observations for 1,772 men and 7,560 wage observations for 1,580 women.[14] Table 1 contains sample descriptive statistics. Average hourly wage is $17 for men and lower for women at $14. Average wage growth is quite similar across gender at around 6% but its variance is higher for men. Men also work more than women on average. This sample includes relatively young workers aged 28 years old on average. For both men and women, more than 80% of the sample is made up of individuals who have at least graduated from high school.

Figures 1 and 2 present age profiles of wages and hours of work across education levels for men and women. As expected, wage profiles become steeper as education increases. Hours worked profiles are quite similar across education levels. Women's wage and hours profiles are always below that of men.

5 Results

Estimation focuses on a pure LBD production function which incorporates age and observed ability effects on skill production. To do this, I assume both parameters A and B to be linear functions of age a_{it} and the worker's Armed Force Qualification Test (AFQT) score percentile as a measure of cognitive ability:[15]

$$\triangle \ln W_{it+1} = \triangle \ln \left[B(a_{it}, AFQT) \cdot W_{it} + A(a_{it}, AFQT) \cdot H_{it}^{\alpha_1} \cdot W_{it}^{\alpha_2}\right] + \triangle \varepsilon_{it},$$

where $A(a_{it}, AFQT) = A_0 + A_1 \cdot a_{it} + A_2 \cdot AFQT$ and $B(a_{it}, AFQT) = B_0 + B_1 \cdot a_{it} + B_2 \cdot AFQT$. At this point it should be noted that constant parameters A_0 and B_0 cannot be separately identified so I normalize A_0 to 1.[16]

All models are estimated in a GMM framework instrumenting for endogenous variables $(H_{it}, H_{it-1}, W_{it})$. The first set of instruments, which I label the standard instrumental variables set, includes non-linear functions of lagged wage W_{it-1}, second order lagged hours of work H_{it-2}, as well as age, lagged age, and AFQT percentile.[17] These instruments are meant to capture the non-linear effects

[14] The initial random sample of white respondents includes 2,236 men and 2,279 women. My sample therefore represents 80% of the full sample for men and 70% for women. For men (women), 15% (25%) of the sample is lost due to missing wages, outlier wages, exclusion of years preceding the end of formal schooling, and the fact that I use only surveys from 1979 to 1994.

[15] The AFQT score aggregates results for tests on word knowledge, paragraph comprehension, mathematics knowledge, and arithmetic reasoning. The AFQT is a subset of the Armed Services Vocational Aptitude Battery administered to NLSY respondents in 1980. I also estimated models where A and B are quadratic functions of both age and AFQT, but estimates of quadratic terms are not statistically significant.

[16] See Appendix section A.5 for more details.

[17] I treat the AFQT test percentile score as an exogenous state variable. The AFQT test was administered in 1980.

of $(H_{it}, H_{it-1}, W_{it})$ on wage growth implied by the non-linear production function.

As discussed in section 3.2, I use an alternative set of instruments that excludes the second order lag of hours worked H_{it-2}. Instead I include second order lags of variables representing the household composition of the worker: number of children, age of the youngest child, family size and marital status.[18] The household variables will help identify variations in hours of work, especially for the female sample. I find that both sets of instruments are strongly correlated with the endogenous variables based on criterions suggested by Bound, Jaeger and Baker (1995).[19]

Table 2 presents estimates of the benchmark production function with no test variables for men in the first two columns, and women in the last two columns. For each sample, I present on the left results obtained using the standard set of instrumental variables, while I use the alternative set of instruments in the right column. The data seem to support the LBD model as none of these models are rejected by the over-identifying restrictions test proposed by Hansen (1982), as illustrated by its *p-value* in the next to last row of Table 2.[20] As can be seen by comparing estimates across columns 1 and 2 for men, and columns 3 and 4 for women, both sets of instrumental variables lead to similar estimates

Parameter α_1 dictates the marginal return of hours worked to skill formation. This parameter is statistically significant and positive for men, implying that wages increase with hours worked at a decreasing rate. The elasticity of wages W_{it+1} with respect to current hours H_{it} for males implies that a one percent change in hours of work increases wages by roughly 0.04 percent.[21] The fact that the estimates of α_1 are positive and statistically significant is consistent with the pure LBD model. For females, I also find a positive and decreasing marginal product of current hours H_{it}, but these estimates are not statistically significant.

5.1 Testing the Learning-by-Doing Model

5.1.1 Expected Future Hours of Work

Tests of the pure LBD model for men using realized future hours of work are presented in the first two columns of Table 3. The coefficient on future hours of work is positive and statistically signif-

No wage observation from 1980 is used in the estimation while only 2% of the sample of wage observations is from 1981.

[18] See Appendix section A.3 for a complete list of instrumental variables.

[19] For both sets of instruments, the F statistics for tests of the joint significance of the identifying instruments is always larger than 10, while their partial R^2 are always larger than 1%.

[20] The overidentifying restrictions test serves as a test of both the exogeneity of the instruments and the functional form chosen for the production technology. It can be implemented here since the GMM estimation is based on more orthogonality conditions ($r = 17$) than parameters ($q = 7$). The GMM objective function and overidentification test statistic is asymptotically distributed as a χ^2 with $r - q$ degrees of liberty.

[21] To compute the elasticity of wages with respect to hours worked I use the model estimates to compute the average of expression $(\partial \ln W_{it+1}/\partial H_{it})H_{it}$.

icant. Men who work more in the future experience stronger wage growth, which is inconsistent with the pure LBD model.[22] But if men who work more in the next period also consistently work more for the rest of their career, they have more incentives to accumulate human capital, and would make more costly unobserved OJT investments and experience stronger wage growth.

Results for the tests of the pure LBD model, using realized future hours of work, in the sample of women are presented in columns 3 and 4 of Table 3. Inconsistent with the LBD model, future hours of work are found to be positively correlated with wage growth in column 4, where I use the alternative set of instruments. One interpretation of this discrepancy between columns 3 and 4, is that the alternative instruments, which include variables such as the lagged number of children and lagged marital status, are better at identifying variation in future hours worked associated with fluctuations in incentives to make costly unobserved OJT investments. To see how these instruments lead to relevant variation in future hours worked, consider the following example. Take two young women at the beginning of period $t-1$ (the point at which household composition instruments are observed) who are both childless, but only one of them is married. Compared to the single woman, the married woman is more likely to have a child in period $t+1$, work less in period $t+1$, and therefore have weaker incentives to invest in human capital during period $t-1$ and t. These weaker incentives are identified through the dummy variables for marital status and the number of children used as instruments. Note also that I am using hours of work in one specific future period as a proxy for workers' expected hours of work over the rest of their career. This proxy might be more noisy for women since their labor participation is subject to more fluctuations than that of men.

5.1.2 Career Expectations

Columns 1 and 2 of Table 4 present the results when career expectations are used as test variables in the female sample. Two indicator variables are included in the equation. The first equals one if the worker expects to hold a job in a non-professional occupation by age 35. The second equals

[22] It is noteworthy that the LBD model is rejected here but not by Hansen's overidentifying restrictions test in Table 2. These results are not necessarily contradictory. First, the predicted test variables likely correlate with the LBD wage determinants (hours worked, lagged wage, age, observed ability). These LBD wage determinants therefore pick up some of the explanatory power of the test variables when they are excluded from the model, and the model fits the data well enough to pass the overidentifying restrictions test. When test variables are included, they claim their explanatory power and reveal the actual source of variation in wage growth. Second, the overidentifying restrictions test evaluates the correlation between the instruments and the residuals generated by the model. It is in essence reporting that the chosen model offers a good fit to the data and that its error term is weakly correlated with the instrumental variables. At the same time, the t-stat for parameter δ explicitly evaluates the correlation between the test variable S_{it} and wage growth $\triangle \ln W_{it+1}$ predicted by the instrumental variables net of the correlation they predict between S_{it} and the other wage determinants. The overidentifying restrictions test would only pick up that S_{it} is missing if it generates a large portion enough of the variation in log-wage growth, and if most of that variation is not assigned to regressors correlated with S_{it}, so that its omission leads to large residuals.

one for workers who expect to hold a job in a professional occupation, and could be argued to account for individuals who are expected to accumulate more human capital.[23] The benchmark is workers who had non-labor market aspirations (travel, get married, have a family) by age 35. The indicator variables for career aspirations are considered exogenous. The LBD model is rejected, as women who aspire to hold non-professional or professional occupations by age 35 experience stronger wage growth than women who aspire to non-labor market activities. This last group of women seems to be making weaker investments in human capital.[24]

5.1.3 Expected Future Fertility

Columns 3 and 4 of Table 4 present a test of the LBD model based on women's expected future fertility. To proxy for expected fertility, I use the number of children in the respondent's household as reported at the next interview. Furthermore, I interact number of children with a set of dummy variables indicating the age of youngest child at the time of this future survey. I categorize the youngest child's age in the following manner: aged 5 or less, aged 5 to 12, aged 12 or more. I use this interaction to account for the fact that women are more likely to reduce their labor supply when their children are not of schooling age. Columns 3 and 4 show that women who will have children aged less than five years old in the near future also experience weaker wage growth, which is inconsistent with the LBD model. It is consistent with the OJT model if women with very young children expect to spend less time working in the future; having weaker incentives to invest in human capital they experience weaker wage growth.

5.2 Gauging the Magnitude of LBD's Unaccounted Wage Growth

My results suggest that the pure LBD model is rejected. But is LBD missing important portions of wage growth by conditioning only on current hours worked and other observables? Based on the estimates of Table 3, male workers who expect to work an additional thousand hours in the future experience stronger wage growth by roughly 3%. This is of the same magnitude as the 7% to 8% wage growth associated with an additional thousand current hours. This 3% wage growth is also significant compared to the average wage growth of 6%.

Results for the sample of women in Tables 3 and 4 suggest that wages grow by 1% to 5% for

[23]Professional careers include among others: professionals, managers, and officials. Non-professional careers include among others: salesperson, clerical worker, etc. This question was asked in the 1979 and the 1982 surveys. For respondents who answered the question at only one of the survey, I use the available one. For respondents who answered in both surveys, I select one of the survey based on a criteria that reduces the variation in the age at which respondents reported their aspirations. As a result, respondents were aged 14 to 25 when answering the question but most of the female sample was aged 17 to 22 when answering the question.

[24]Consistent with this is the fact that they have more children on average, and have them earlier (their youngest child are on average older), than women who have professional aspirations.

each thousand current hours of work. When future hours of work increase by a thousand, wages grow by almost 4% more. Having labor market related career expectations is associated with a wage growth of 1% to 2%, while expecting to have young infants is associated with weaker wage growth of 2% to 3%.

These figures suggest that modeling wage growth only on the basis of current hours worked and other observables may miss important portions of wage growth for both men and women. These figures also suggest that the impact of the LBD and OJT mechanisms on wage growth are of the same magnitude.

5.3 Results Within Educational Categories

Tables 5 to 8 test the LBD model separately for workers who did not complete high school, workers who graduated from high school, and workers who attended or graduated from college.[25] Tables 5 to 8 have two panels. The left panel shows results based on the standard set of instruments, while the right panel contains results for the alternative set of instruments. Each panel has three columns, one for each education category.

Table 5 shows that the LBD model is rejected for male high school graduates and male college attendees. High school graduates who work more in period $t+1$ experience *weaker* wage growth. It might be that the labor market for high school graduates offers safer jobs with more hours of work or riskier jobs with more wage growth. This implies a tradeoff between current and future earnings, and a rejection of the LBD model.

Table 6 presents results using expected hours of work as a test variable in the female sample. The LBD model is only rejected for high school dropouts in column 1 and high school graduates in column 2.

In Table 7 I add expected fertility variables to the equation. Columns 2 and 5 show that high school graduates who expect to have young children in the future experience weaker wage growth. Column 1 seems to indicate that dropout women who will have teenage children experience stronger wage growth. These could be women who had their children at a young age and expect to focus on labor market activities. College attendees' wage growth is not affected by expected fertility. They may spend less time out of labor market activities because they have fewer children and more resources to pay for substitutes to their maternal care and time. College attendees might also hold jobs that offer better amenities for women to harmonize their work and family responsibilities.

Table 8 reports results for the test of the LBD model using women's career expectation. Here

[25] The attained level of education could be argued to be an input to the production of human capital. However, in results not shown here I find no evidence that education belongs in the production function. When education is included as an input in the production function, parameters associated with it are not statistically significant.

there is little evidence that the LBD model is rejected, although test variables are marginally statistically significant in columns 2 and 3 where I use the standard set of instruments. Women who expect to hold a job by age 35 experience stronger wage growth.

The rejection of the LBD is not as strong when I implement it separately for each educational group. This is not necessarily inconsistent with the results from Tables 3 and 4 since holding constant education likely reduces variation in optimal life-cycle profiles of human capital accumulation, therefore decreasing the test's power.

6 Conclusion

I use the NLSY79 data to estimate and test the LBD model of costless wage growth. I achieve identification through an instrumental variables approach which has the advantage of foregoing assumptions about preferences and credit markets, while making weaker assumptions about expectations and beliefs.

I find that both women and men who expect to work more in the future experience significantly stronger wage growth. For women, I also test the LBD model using future fertility and career expectations as test variables. Women who expect to have very young children suffer from significantly weaker wage growth, while women who expect to have a career in a non-professional or a professional occupation experience stronger wage growth. These test results are inconsistent with the pure LBD framework, suggesting that wage growth may be costly to the worker. The drawback of my instrumental variable approach is that it cannot identify which costly wage growth mechanisms lead to this rejection of the LBD model. Among the many models of costly wage growth, I focus on the OJT model in discussing my results as I find that, for the most part, the estimated impact of the test variables on wage growth are consistent with that model.

Although my results suggest a rejection of the pure LBD model, they should not be interpreted as saying that workers learn nothing from productive work. Indeed, I do find that the pure LBD models I estimate are not rejected by the GMM over-identifying restrictions test, suggesting that it fits the data reasonably well. However, the OJT component is non-negligible, and according to my estimates, may play a role as important as LBD. This implies that modeling wage growth solely on current hours and other observables may lead to overlooking significant portions of wage growth for both men and women. It also implies that observed wages (earnings divided by hours worked) are a biased measure of workers' productivity, and that this bias becomes more important as workers spend more time making unobserved OJT investments. Therefore, any study of workers productivity must correct for this bias, or at least investigate how results are affected by this bias.

It is worth asking whether the OJT model could on its own appropriately fit the NLSY79 data on early career wages that I use in this paper. I expect the OJT model to be successful since it would naturally associate the strong wage growth in the early career with the fact that the reward of investment is large relative to the low forgone early career earnings it entails. But the OJT model would have trouble explaining how workers with different incentives to invest can achieve the same level of wage growth. For example, Belley and Jiao (2015) find evidence in the NLSY79 that women who become mothers after the age of 25 experience wage growth in their early career as strong as that of women who do not become mothers, despite the fact that their labor supply decreases relative to non-mothers after that first birth. Having costless wage growth by adding an LBD component would make the model better able to deal with this type of situation. This might be something worth investigating in future research. Note also that the OJT model on its own would have trouble explaining the negative impact of future hours of work on the wage growth of less educated workers presented in Tables 5 and 6.

The LBD and OJT models are two of many models of wage growth. But the framework I use can be adapted to test other models if their determinants of wage growth are observable, and if appropriate test variables can be found. This is where testing for trade-offs between current earnings and wage growth plays an important role. The extent to which workers make these tradeoffs is a special case of unobserved wage determinants. But it provides theoretical pinnings to design test variables.

An important implication of the LBD model is that wage growth comes "for free" as a by-product of productive work. My results show that wage growth comes at a cost. If workers have to devote time to human capital accumulation, wage subsidy programs for low income workers may hinder human capital investment since the subsidy increases the opportunity cost of investing. Costly human capital accumulation implies that borrowing constraints can also affect workers human capital accumulation even after leaving school. Finally, costly accumulation of human capital implies that women who have children might have to choose between investing resources in their own human capital, or in their children's human capital. Mothers who want to invest more in their children would experience weaker wage growth, partly explaining why mothers have on average lower wages than non-mothers.

A Appendix

A.1 The Effect of Measuring Human Capital with Wages on the Likelihood of Type II Errors

Let W_{it}^{o} represents observed wage: $W_{it}^{o} = \frac{E_{it}}{H_{it}}$. With an OJT component, human capital W_{it} is given by $W_{it} = \frac{E_{it}}{H_{it}-I_{it}}$. Observed wages W_{it}^{o} are therefore a biased measure of a workers' human capital W_{it}: $W_{it}^{o} = W_{it}\frac{(H_{it}-I_{it})}{H_{it}} = W_{it}\widetilde{H}_{it}$, where $\widetilde{H}_{it}$ is the fraction of work hours H_{it} used to complete the tasks the worker is paid for. I estimate the following LBD production function using observed wages:

$$W_{it+1}^{o} = f\left(H_{it}, W_{it}^{o}, X_{it}^{\text{ex}}, \theta_i\right) + e_{it}, \tag{12}$$

whereas the true human capital production function has both a learning and an investment component:

$$W_{it+1} = g_2\left(H_{it}, I_{it}, W_{it}, X_{it}^{\text{ex}}, \theta_i\right) + \varepsilon_{it}. \tag{13}$$

Given this, the error term in (12) can be written as

$$e_{it} = \widetilde{H}_{it+1} \cdot g_2\left(H_{it}, I_{it}, W_{it}, X_{it}^{\text{ex}}, \theta_i\right) - f\left(H_{it}, W_{it}^{o}, X_{it}^{\text{ex}}, \theta_i\right) + \widetilde{H}_{it+1}\varepsilon_{it}.$$

Notice that both current and future unobserved investments are found in this error term: I_{it} is found in $g_2(\cdot)$ and $f(\cdot)$ while I_{it+1} multiplies $g_2(\cdot)$. Since the test variable S_{it} should correlate with both current and future unobserved investments when testing the LBD model with the following equation

$$W_{it+1}^{o} = f\left(H_{it}, W_{it}^{o}, X_{it}^{\text{ex}}, \theta_i\right) + \delta S_{it} + \tilde{e}_{it}, \tag{14}$$

parameter δ should give an estimate of the first order effects of both I_{it} and I_{it+1} on $\widetilde{H}_{it+1}g_2(\cdot)$ and $f(\cdot)$ (through the effect of I_{it} on observed wage W_{it}^{o}) scaled by their correlation with test variable S_{it}, conditional on the other inputs. This yields the following approximation for δ

$$\delta \approx \left(\widetilde{H}_{it+1}\frac{\partial g_2}{\partial I_{it}} + \frac{W_{it}}{H_{it}}\frac{\partial f}{\partial W_{it}^{o}}\right) \cdot C(I_{it}, S_{it}|\Phi_{it}) - g_2 \cdot C(I_{it+1}, S_{it}|\Phi_{it}), \tag{15}$$

where $\Phi_{it} = (H_{it}, W_{it}^{o}, X_{it}^{\text{ex}}, \theta_i)$. The first term on the right side of equation (15) results from the true production function having an OJT component. The second and third terms on the right side result from using observed wages to estimate equation (14). All three terms are most likely positive so if correlations between the test variable S_{it} and both current and future investments have the same sign, the substraction of the third term reduces the estimate of parameter δ and increases the likelihood of failing to reject the LBD model.

One way to reduce the likelihood of a type II error would be to use a test variable S_{it} which correlates positively with current investments and negatively with future investments. This could be achieved if S_{it} is an indicator variable for an economic shock (temporary increase in productivity) or a policy (temporary reduction of labor income taxes) that temporarily raises the benefit of productive work in period $t+1$. During that period the worker has an incentive to increase productive work to take advantage of its temporarily increased return, leading to lower investments in period $t+1$. If the worker anticipates this temporary higher return from productive work, he has an incentive to increase investment in period t (and previous periods) to increase his productivity in preparation for period $t+1$. Such a temporary shock or policy increases the opportunity cost of investments in $t+1$ but increases the returns to investments in previous periods.

The test variables I use to identify different incentives to invest in human capital represent variation in optimal paths of life-cycle investments and labor supply, and not temporary anticipated changes along these optimal life-cycle paths. For example, expected fertility distinguishes female workers with different life-cycle labor supply and investment profiles: those who expect to have children from those who do not. I therefore expect the correlation between my test variables and current unobserved investments to have the same sign as its correlation with future investments. As seen in equation (15) this increases the likelihood of failing to reject the LBD model if there is an OJT component to human capital accumulation. The advantage of using this type of variable is that it allows to test the pure LBD model in a very general population of workers because it does not rely on using specific policy changes or economic shocks that affect a particular segment of the workforce.

A.2 Details of Restrictions to Sample

The variable of interest in this study, skill level next period W_{it+1}, is given by the hourly wage in the current survey. Current skill level W_{it} is given by the hourly wage in the previous survey, which I refer to as the lagged wage. The NLSY79 provides hourly wages for each job held and it is not unusual for an individual to report more than one wage in a particular survey. I first restrict my sample to wages related to jobs held at the time of the survey. If at that time the respondent holds more than one job, I select the job with the highest weekly hours of work. All wages are then adjusted to 2004 dollars using the Bureau of Labor Statistics Consumer Price Index for all urban consumers. To exclude outlier wage values, I restrict the sample to wages greater than \$1.90 and less than \$100.[26] I also exclude wage observations that represent a wage growth below -50% and above 100% from the previous period.

[26]In practice, both male and female estimation samples contain one wage observation below \$2 after applying all the sample selection criteria described in this section.

Hours of work are measured as the sum of all hours worked at all jobs since the date of the last interview. Given the yearly time unit considered in this study, the last interview must have taken place no more than 14 months and no less than 10 months prior to the current interview.[27] To exclude outlier values and to focus the analysis on workers who demonstrate a significant level of participation in the labor market, I further restrict the sample to respondents who worked more than 780 hours (15 hours per week, for 52 weeks) and less than 4368 hours (84 hours per week, for 52 weeks). Moreover, I use the number of weeks worked since the date of the last interview to compute the average number of hours worked per week. This average must be above 15 and below 84 for a wage observation to remain in the sample.

I exclude individuals who have not completed their schooling. To determine when a respondent has completed schooling, I use years of schooling from 1979 to 2004. Based on years of schooling, the respondent is categorized as high school dropout (less than 12 years of schooling), high school graduate (12 years of schooling), at least some college (between 13 to 15 years of schooling), and completed college (at least 16 years of schooling) in each survey year. I then identify the highest education category for each respondent as well as the first survey year in which it is observed. Wage observations preceding this first year are excluded from the sample.[28]

My sample includes individuals aged 18 or older if their highest level of schooling is high school graduate or less. Respondents with at least some college must be at least 21 years old. I compute age in months for each survey year based on the interview date and the respondent's date of birth. After applying the relevant transformation, age in years, net of 18, is used in regressions for more straightforward interpretations.

A.3 Instrumental Variables

For the estimation of the pure LBD model I include the following instruments in the standard instrument set: an intercept, W_{it-1}, W_{it-1}^2, $\ln W_{it-1}$, $(\ln W_{it-1})^2$, H_{it-2}, H_{it-2}^2, $\ln H_{it-2}$, $(\ln H_{it-2})^2$, $W_{it-1} \times H_{it-2}$, $\ln W_{it-1} \times \ln H_{it-2}$, linear and quadratic age, linear and quadratic first order lagged age, and linear and quadratic terms of the AFQT score percentile.

For the estimation of the pure LBD model I include the following instruments in the alternative instrument set: an intercept, second order lagged number of children, second order lagged interaction of number of children with an indicator for whether the youngest child is at least 6 years

[27] Although the NLSY79 survey are conducted every year between 1979 and 1994, interviews do not always take place every 12 months. The time interval between two consecutive interviews also exceeds 12 months for respondents who have been brought back in the NLSY79 after missing one interview or more.

[28] This sample selection implies that some individuals might go back to school and still be included in the sample if they do not achieve a higher level of education. In the male and female estimation sample, respectively 9% and 15% of all wages are observed during years when the worker is enrolled in school or during years preceding a return to school. However, I keep these observations since, for both males and females, they have the same average wage, average wage growth and average hours worked as the sample of wages observed after any enrollment in formal schooling.

old, second order lagged interaction of number of children and age, second order lagged family size, second order lagged dummies for marital status, W_{it-1}, W_{it-1}^2, $\ln W_{it-1}$, $(\ln W_{it-1})^2$, linear and quadratic age, linear and quadratic first order lagged age, and linear and quadratic terms of the AFQT score percentile.

When I test the pure LBD model with future realized hours of work I use both the standard and alternative sets of instrumental variables as they are described above.

When I test the pure LBD model with future realized fertility I use the alternative set of instruments as described above. I add the following variables to the standard set of variables: second order lagged interaction of number of children with an indicator variables for whether the youngest child is less than 5 years old, 5 years old or more but less than 12, or 12 years old or more. I also add second order lagged dummies for marital status.

When I test the pure LBD model with career expectations as the test variable I assume it is exogenous and therefore add to both sets of instruments an indicator variable for workers who expect to hold a job in a non-professional occupation by age 35, and an indicator variable for workers who expect to hold a job in a professional occupation. The benchmark is workers who had non-labor market aspirations (travel, get married, have a family) by age 35.

A.4 Bias if Log-Wage Shocks Follow an AR(1) Process

If the log-wage shocks follow an AR(1) process we have that $\varepsilon_{it} = \rho\varepsilon_{it-1} + u_{it}$ where u_{it} is an i.i.d process such that $\mathbb{E}[u_{it}\varepsilon_{it-s}] = 0$ for $s \geq 1$. This implies that the error term for the fixed-effects wage equation is given by

$$\triangle\varepsilon_{it} = \rho(\rho-1)\varepsilon_{it-2} + (\rho-1)u_{it-1} + u_{it}.$$

This makes it clear that if the log-wage error term follows an AR(1) process, the instrumental variables suggested in Section 3.2 are correlated with $\triangle\varepsilon_{it}$ because $(H_{it-2}, W_{it-1}, X_{it-1}^{\text{ex}}, Z_{it-1})$ should be correlated with ε_{it-2} (but not u_{it} or u_{it-1}). The last equation also reveals how the autocorrelation coefficient ρ scales down the bias by a factor of $\rho(\rho-1)$ that tends to zero as ρ approaches one. This factor is -0.084 if $\rho = 0.908$ as estimated in Altonji, Smith and Vidangos (2013). This factor is also negative, implying that if the correlation with the wage shock has the same sign as the predicted endogenous variable's direct impact on the wage through the human capital production function, this correlation biases the estimates of the associated parameters toward zero.

A.5 Identification of Constant Parameters in Skill Production Function

Constant parameters A_0 and B_0 cannot be separately identified. To illustrate this, consider the estimated model:

$$\begin{aligned}\triangle \ln W_{it+1} &= \triangle \ln \left[\left(B_0 + B_1 a_{it} + B_2 AFQT\right) W_{it} \right. \\ &\quad \left. + \left(A_0 + A_1 a_{it} + A_2 AFQT\right) H_{it}^{\alpha_1} W_{it}^{\alpha_2} \right] + \triangle \varepsilon_{it} \end{aligned} \tag{16}$$

$$\begin{aligned} &= \triangle \ln \left[\frac{B_0 + B_1 a_{it} + B_2 AFQT}{A_0} W_{it} \right. \\ &\quad \left. + \frac{A_0 + A_1 a_{it} + A_2 AFQT}{A_0} H_{it}^{\alpha_1} W_{it}^{\alpha_2} \right] + \triangle \varepsilon_{it} \end{aligned} \tag{17}$$

where equation (17) is obtained by adding and subtracting $\ln A_0$ from equation (16). Equation (17) shows that I can only identify parameters in B and A normalized by the constant term A_0. I can also normalize by constant term B_0, and both normalisations yield equivalent estimates. An exception to this is when either constant term is negative. If for example $A_0 < 0$, I cannot estimate the model where B and A are normalized with respect to A_0, since it is not possible to take the logarithm of a negative number.

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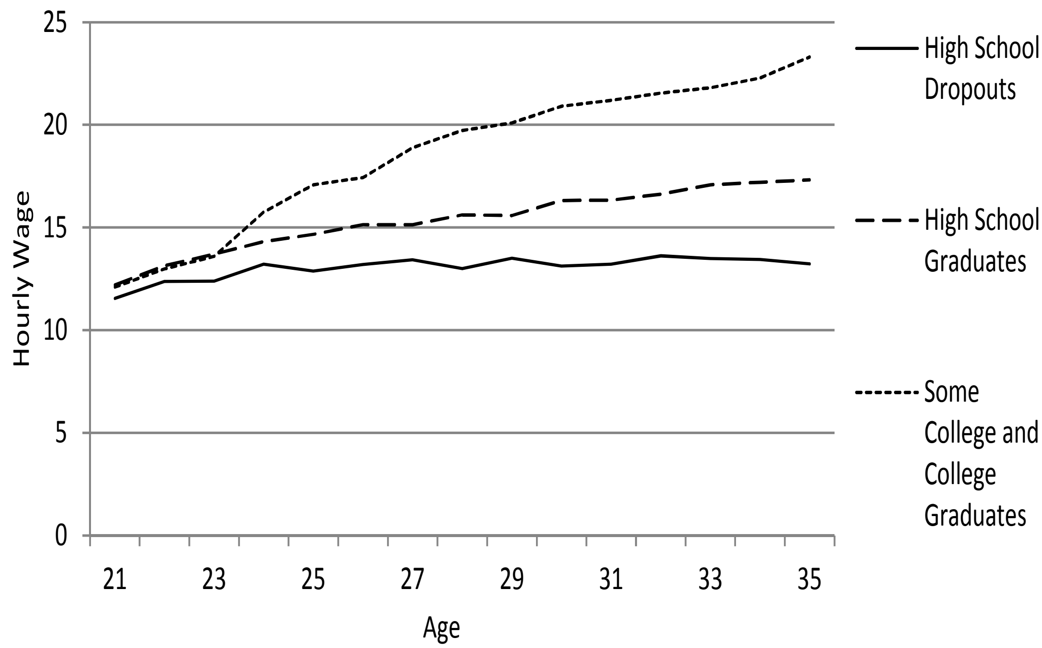
Table 1: Sample Descriptive Statistics

	Men	Women
Hourly Wage	16.79	13.91
	(7.69)	(6.70)
Wage Growth	6.26%	6.32%
	(21.69)	(19.96)
Annual Hours of Work	2348.03	2100.13
	(535.26)	(497.67)
Age	28	28
	(4)	(4)
Number of Children	0.71	0.61
	(1.01)	(0.91)
High School Dropout	14%	7%
High School Graduates	44%	42%
Some College	42%	52%
Sample Size	9,566	7,560

Note.– Standard deviation in parentheses. The men sample includes 1,772 individuals. The women sample includes 1,580 individuals. Both samples include individuals who have completed their formal schooling. Individuals who completed high school or less must be at least 18 years old. Individuals with some college or more must be at least 21 years old. Samples exclude individual with outlier values for hourly wage, hourly wage growth and hours of work.

Figure 1:

Panel A: Age Profiles of Hourly Wage by Education Level for Men



Panel B: Age Profiles of Hours Worked by Education Level for Men

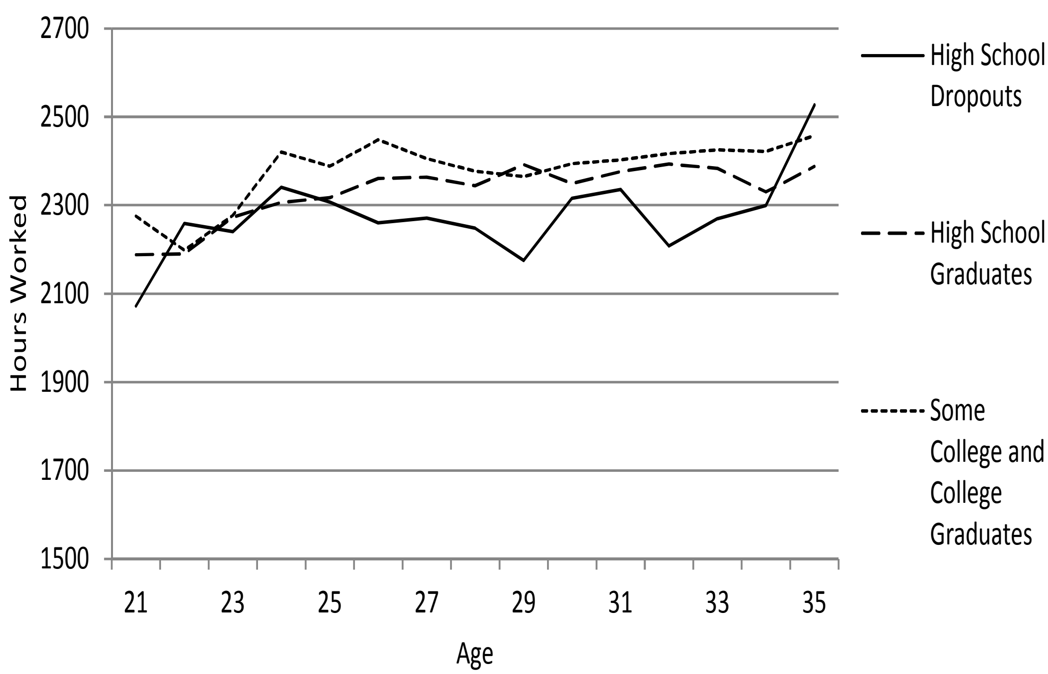
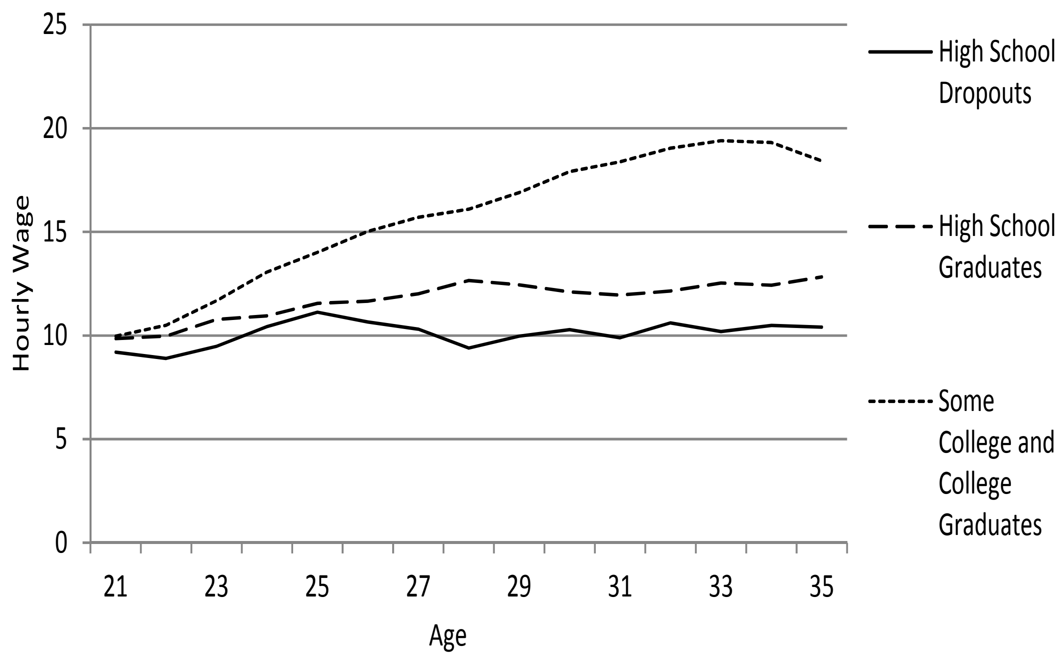


Figure 2:

Panel A: Age Profiles of Hourly Wage by Education Level for Women



Panel B: Age Profiles of Hours Worked by Education Level for Women

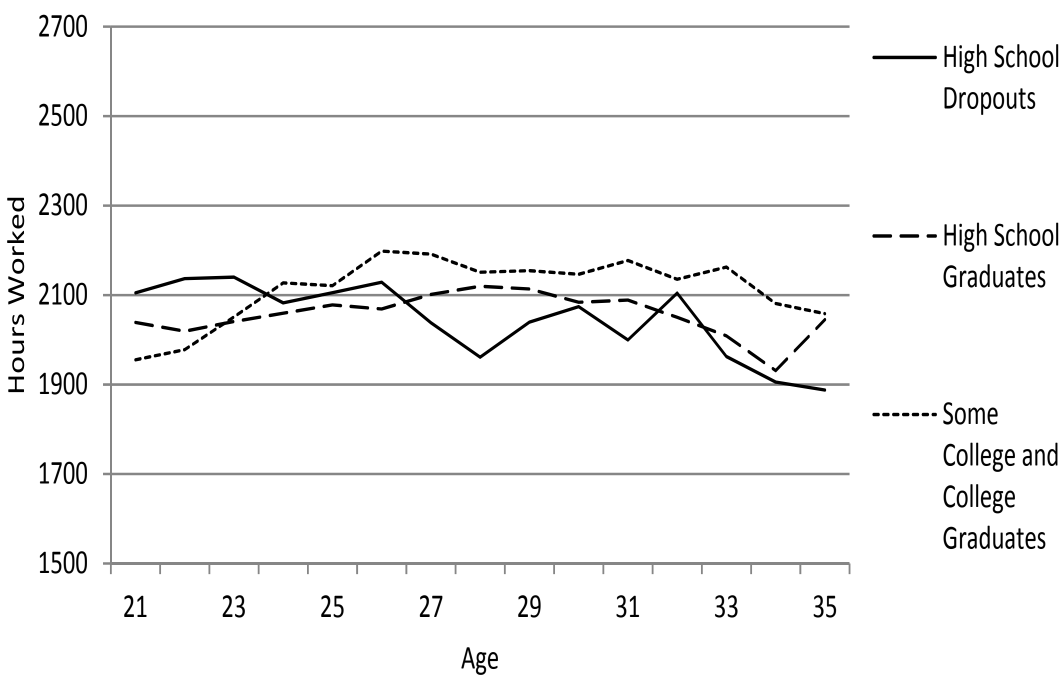


Table 2:
Human Capital Production Function Estimates, White Males and Females

		Males		Females	
		Standard IV	Alternate IV	Standard IV	Alternate IV
Retention Rate	Constant (B_0)	0.0163	0.0405	-0.3674	0.0871
		(0.0359)	(0.0443)	(0.1245)	(0.2416)
	Age (B_1)	-0.0027	-0.0021	-0.0047	-0.0013
		(0.0010)	(0.0010)	(0.0021)	(0.0032)
	AFQT (B_2)	0.0002	-0.0003	0.0047	-0.0009
		(0.0006)	(0.0005)	(0.0011)	(0.0028)
Productivity Factor	Age (A_1)	0.0593	0.0476	0.0248	0.0400
		(0.0142)	(0.0091)	(0.0099)	(0.0111)
	AFQT (A_2)	-0.0101	-0.0103	-0.0078	-0.0088
		(0.0009)	(0.0006)	(0.0009)	(0.0010)
Exponents	Hours Worked (α_1)	0.0359	0.0448	0.0088	0.0275
		(0.0193)	(0.0234)	(0.0100)	(0.0342)
	Lagged Wage (α_2)	0.0756	0.0868	0.6123	0.0887
		(0.1092)	(0.1396)	(0.1208)	(0.5844)
Joint Sig. Age Param.	P-Value	0.8788	0.4043	0.0184	0.2647
Joint Sig. AFQT Param.	P-Value	0.5181	$< .0001$	$< .0001$	$< .0001$
Hansen Over-Identifying Restrictions Test	P-Value	0.7746	0.9663	0.9912	0.9878
Sample Size		9,080	9,132	7,309	7,372

Note.– Standard errors in parentheses. Sample includes white workers who have completed formal schooling. Respondents who did not attend college must be at least 18 years old. Respondents who attended college must be at least 21 years old. Wages below $1.90 and above $100 are excluded. Wage observations with wage growth below -50% and above 100% are excluded. Annual hours of work must range between 780 and 4368. Average hours worked per week of work must be between 15 and 84. Wage observations for which the previous survey interview took place less than 10 months or more than 14 months before the current survey interview are excluded. Standard instruments set includes functions of second order lagged hours of work. Alternative instruments set includes functions of second order lagged number of children, second order lagged family size, and second order lagged marital status. Both sets of instruments include functions of first order lagged wage, as well as linear and quadratic terms of age, lagged age, and AFQT score percentile.

Table 3:
Testing the Learning By Doing Model, Expected Hours of Work,
White Males and Females

		Males		Females	
		Standard IV	Alternate IV	Standard IV	Alternate IV
Retention Rate	Constant (B_0)	0.1969	1.8546	-0.0349	-0.1254
		(0.2721)	(4.7693)	(0.2388)	(0.1082)
	Age (B_1)	-0.0080	-0.0006	-0.0041	0.0002
		(0.0073)	(0.0437)	(0.0057)	(0.0034)
	AFQT (B_2)	0.0004	0.0014	0.0005	0.0008
		(0.0015)	(0.0144)	(0.0027)	(0.0008)
Productivity Factor	Age (A_1)	-0.0409	-0.0452	0.0634	-0.0229
		(0.0143)	(0.0206)	(0.0286)	(0.0087)
	AFQT (A_2)	0.0022	-0.005	-0.0085	-0.0003
		(0.0052)	(0.005)	(0.0019)	(0.0044)
Exponents	Hours Worked (α_1)	0.2359	0.5245	-0.0006	0.0617
		(0.0769)	(0.2407)	(0.0165)	(0.0244)
	Lagged Wage (α_2)	0.1063	-0.0385	0.3235	0.3780
		(0.1316)	(0.2626)	(0.3610)	(0.1505)
Expected Hours of Work	Hours Worked Next Year (δ)	0.0340	0.0273	-0.0057	0.0384
		(0.0027)	(0.0035)	(0.0053)	(0.0037)
Hansen Over-Identifying Restrictions Test	P-Value	0.7914	0.7768	0.6333	0.3677
Sample Size		7,647	7,693	6,134	6,190

Note.– Standard errors in parentheses. Hours worked between the current and the next survey are used as a proxy for expected hours of work and are treated as endogenous. Sample includes white workers who have completed formal schooling. Respondents who did not attend college must be at least 18 years old. Respondents who attended college must be at least 21 years old. Wages below \$1.90 and above \$100 are excluded. Wage observations with wage growth below -50% and above 100% are excluded. Annual hours of work must range between 780 and 4368. Average hours worked per week of work must be between 15 and 84. Wage observations for which the previous survey interview took place less than 10 months or more than 14 months before the current survey interview are excluded. Standard instruments set includes functions of second order lagged hours of work. Alternative instruments set includes functions of second order lagged number of children, second order lagged family size, and second order lagged marital status. Both sets of instruments include functions of first order lagged wage, as well as linear and quadratic terms of age, lagged age, and AFQT score percentile.

Table 4:
Testing the Learning By Doing Model, Career Expectations and Expected Fertility, White Females

		Standard IV	Alternate IV	Standard IV	Alternate IV
Retention Rate	Constant (B_0)	-0.1757	-0.1681	-0.2991	0.1187
		(0.0837)	(0.0700)	(0.1135)	(0.4482)
	Age (B_1)	-0.0060	-0.0074	-0.0050	-0.0007
		(0.0025)	(0.0027)	(0.0020)	(0.0053)
	AFQT (B_2)	0.0034	0.0034	0.0041	-0.0013
		(0.0009)	(0.0008)	(0.0011)	(0.0050)
Productivity Factor	Age (A_1)	0.0522	0.0622	0.0332	0.0662
		(0.0172)	(0.0198)	(0.0114)	(0.0728)
	AFQT (A_2)	-0.0061	-0.0040	-0.0083	-0.0068
		(0.0034)	(0.0036)	(0.0011)	(0.0035)
Exponents	Hours Worked (α_1)	0.0065	0.0055	0.0095	0.0144
		(0.0189)	(0.0185)	(0.0121)	(0.0334)
	Lagged Wage (α_2)	0.3452	0.3361	0.5360	0.0476
		(0.1579)	(0.1324)	(0.1320)	(1.0241)
Career Expectations	Non-Professional	0.0116	0.0174		
		(0.0058)	(0.0062)		
	Professional	0.0156	0.0186		
		(0.0063)	(0.0058)		
Expected Number of Children	Youngest Child Aged 5 or Less			-0.0221	-0.0349
				(0.0124)	(0.0126)
	Youngest Child Aged 5 to 12			0.0023	0.0013
				(0.0177)	(0.0166)
	Youngest Child Aged 12 or More			-0.0109	0.0026
				(0.0404)	(0.0364)
Joint Sig. Test Variables	P-Value	0.0322	0.0026	0.0697	0.0020
Hansen Over-Identifying Restrictions Test	P-Value	0.7155	0.2090	0.9122	0.9885
Sample Size		6,974	7,036	6,409	6,481

Note.– Standard errors in parentheses. Career expectations are two dummy variables indicating whether the respondent expected at ages 17 to 22 to hold a professional or a non-professional occupation by age 35. The base category is individuals who aspired to non-labor market activities by age 35. These dummy variables are treated as exogenous. Expected number of children is proxied by the number of children at the next survey interacted with dummy variables for the age of the youngest child. These test variables are treated as endogenous. Sample includes white women who have completed formal schooling. Respondents who did not attend college must be at least 18 years old. Respondents who attended college must be at least 21 years old. Wages below \$1.90 and above \$100 are excluded. Wage observations with wage growth below -50% and above 100% are excluded. Annual hours of work must range between 780 and 4368. Average hours worked per week of work must be between 15 and 84. Wage observations for which the previous survey interview took place less than 10 months or more than 14 months before the current survey interview are excluded. Standard instruments set includes functions of second order lagged hours of work. When testing the LBD model with expected number of children, I add a second order lagged interaction between the number of children in the household and the age of the youngest child to the standard instrumental variables set. Alternative instruments set includes functions of second order lagged number of children, second order lagged family size, and second order lagged marital status. Both sets of instruments include functions of first order lagged wage, as well as linear and quadratic terms of age, lagged age, and AFQT score percentile. When testing the LBD model with career expectations I add dummy variables for workers who expect to hold a job in a professional and non-professional occupation by age 35 to both sets of instruments.

Table 5:
Testing the Learning By Doing Model Across Educational Levels, Expected Hours of Work, White Males

		Standard Instrument Variables			Alternative Instrument Variables		
		High School Dropouts	High School Graduates	Attended College	High School Dropouts	High School Graduates	Attended College
Expected Hours of Work	δ	0.0178	-0.0093	0.0463	-0.0175	-0.0105	-0.0004
		(0.0100)	(0.0065)	(0.0045)	(0.0123)	(0.0051)	(0.0067)
Hansen Over-Identifying Restrictions Test	P-Value	0.5638	1.0000	0.8095	0.9924	0.9976	0.5580
Sample Size		1,076	3,394	3,177	1,080	3,406	3,207

Note.– Standard errors in parentheses. Estimates for other parameters are not shown here. Hours worked between the current and the next survey are used as a proxy for expected hours of work and are treated as endogenous. Sample includes white men who have completed formal schooling. Respondents who did not attend college must be at least 18 years old. Respondents who attended college must be at least 21 years old. Wages below \$1.90 and above \$100 are excluded. Wage observations with wage growth below -50% and above 100% are excluded. Annual hours of work must range between 780 and 4368. Average hours worked per week of work must be between 15 and 84. Wage observations for which the previous survey interview took place less than 10 months or more than 14 months before the current survey interview are excluded. Standard instruments set includes functions of second order lagged hours of work. Alternative instruments set includes functions of second order lagged number of children, second order lagged family size, and second order lagged marital status. Both sets of instruments include functions of first order lagged wage, as well as linear and quadratic terms of age, lagged age, and AFQT score percentile.

Table 6:
Testing the Learning By Doing Model Across Educational Levels, Expected Hours of Work, White Females

		Standard Instrument Variables			Alternative Instrument Variables		
		High School Dropouts	High School Graduates	Attended College	High School Dropouts	High School Graduates	Attended College
Expected Hours of Work	δ	-0.0222	-0.0191	-0.0072	0.0204	0.0366	-0.0092
		(0.0106)	(0.0050)	(0.0082)	(0.0117)	(0.0060)	(0.0077)
Hansen Over-Identifying Restrictions Test	P-Value	0.8425	0.9666	0.7348	1.0000	0.7668	0.7231
Sample Size		396	2,604	3,134	398	2,620	3,172

Note.– Standard errors in parentheses. Estimates for other parameters are not shown here. Hours worked between the current and the next survey are used as a proxy for expected hours of work and are treated as endogenous. Sample includes white women who have completed formal schooling. Respondents who did not attend college must be at least 18 years old. Respondents who attended college must be at least 21 years old. Wages below \$1.90 and above \$100 are excluded. Wage observations with wage growth below -50% and above 100% are excluded. Annual hours of work must range between 780 and 4368. Average hours worked per week of work must be between 15 and 84. Wage observations for which the previous survey interview took place less than 10 months or more than 14 months before the current survey interview are excluded. Standard instruments set includes functions of second order lagged hours of work. Alternative instruments set includes functions of second order lagged number of children, second order lagged family size, and second order lagged marital status. Both sets of instruments include functions of first order lagged wage, as well as linear and quadratic terms of age, lagged age, and AFQT score percentile.

Table 7:
Testing the Learning By Doing Model Across Educational Levels, Expected Number of Children, White Females

		Standard Instrument Variables			Alternative Instrument Variables		
		High School Dropouts	High School Graduates	Attended College	High School Dropouts	High School Graduates	Attended College
Expected Number of Children	Youngest Child Aged 5 or Less	0.0788	-0.0672	-0.0099	-0.0895	-0.0937	-0.0181
		(0.0442)	(0.0253)	(0.0151)	(0.0126)	(0.0345)	(0.0143)
	Youngest Child Aged 5 to 12	0.1071	0.0457	-0.0175	0.0130	0.0382	-0.0089
		(0.0777)	(0.0245)	(0.0352)	(0.0503)	(0.0295)	(0.0291)
	Youngest Child Aged 12 or More	0.1865	-0.1005	-0.0459	0.0200	-0.0686	0.0503
		(0.0915)	(0.0529)	(0.1137)	(0.0663)	(0.0580)	(0.0967)
Joint Sig. Test Variables	P-Value	0.0210	0.0496	0.4515	0.02286	0.0355	0.3016
Hansen Over-Identifying Restrictions Test	P-Value	0.9803	0.9195	0.9948	0.9524	0.7745	1.0000
Sample Size		420	2,699	3,290	424	2,722	3,335

Note.– Standard errors in parentheses. Estimates for other parameters are not shown here. Expected number of children is proxied by the number of children at the next survey interacted with dummy variables for the age of the youngest child. These test variables are treated as endogenous. Sample includes white women who have completed formal schooling. Respondents who did not attend college must be at least 18 years old. Respondents who attended college must be at least 21 years old. Wages below \$1.90 and above \$100 are excluded. Wage observations with wage growth below -50% and above 100% are excluded. Annual hours of work must range between 780 and 4368. Average hours worked per week of work must be between 15 and 84. Wage observations for which the previous survey interview took place less than 10 months or more than 14 months before the current survey interview are excluded. Standard instruments set includes functions of second order lagged hours of work, and second order lagged interaction between the number of children in the household and the age of the youngest child. Alternative instruments set includes functions of second order lagged number of children, second order lagged family size, and second order lagged marital status. Both sets of instruments include functions of first order lagged wage, as well as linear and quadratic terms of age, lagged age, and AFQT score percentile.

Table 8:
Testing the Learning By Doing Model Across Educational Levels, Career Expectations, White Females

		Standard Instrument Variables			Alternative Instrument Variables		
		High School Dropouts	High School Graduates	Attended College	High School Dropouts	High School Graduates	Attended College
Career Expectations	Non-Professional	-0.0035	0.0060	0.0157	0.0000	0.0058	0.0129
		(0.0169)	(0.0066)	(0.0084)	(0.0182)	(0.0073)	(0.0096)
	Professional	-0.0257	0.0113	0.0116	-0.0142	0.0070	0.0052
		(0.0313)	(0.0068)	(0.0078)	(0.0295)	(0.0117)	(0.0057)
Joint Sig. Test Variables	P-Value	0.7022	0.2230	0.1523	0.8657	0.7024	0.3769
Hansen Over-Identifying Restrictions Test	P-Value	0.9772	0.9688	0.2590	0.9615	0.9940	1.0000
Sample Size		446	2,784	3,744	450	2,798	3,788

Note.– Standard errors in parentheses. Estimates for other parameters are not shown here. Career expectations are two dummy variables indicating whether the respondent expected at ages 17 to 22 to hold a professional or a non-professional occupation by age 35. The base category is individuals who aspired to non-labor market activities by age 35. These dummy variables are treated as exogenous. Sample includes white women who have completed formal schooling. Respondents who did not attend college must be at least 18 years old. Respondents who attended college must be at least 21 years old. Wages below \$1.90 and above \$100 are excluded. Wage observations with wage growth below -50% and above 100% are excluded. Annual hours of work must range between 780 and 4368. Average hours worked per week of work must be between 15 and 84. Wage observations for which the previous survey interview took place less than 10 months or more than 14 months before the current survey interview are excluded. Standard instruments set includes functions of second order lagged hours of work. Alternative instruments set includes functions of second order lagged number of children, second order lagged family size, and second order lagged marital status. Both sets of instruments include functions of first order lagged wage, as well as linear and quadratic terms of age, lagged age, and AFQT score percentile, and indicator variables for workers who expect to hold a job in a professional and non-professional occupation by age 35.