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Training and Business Cycles

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Abstract

This paper examines the behavior of skill acquisition through training at business cycles frequencies. A time series of training is first constructed using individual data from the NLSY79 database. We document the cyclical properties of the series, and find that training is weakly countercyclical, leads the cycle, and has a standard deviation of more than ten times that of output. We show that a model where employment, but not hours per week, is costly to adjust, is able to account for most of the documented regularities.

1 Introduction

This paper studies the behavior of skill acquisition through training at business cycles frequencies. Beginning with Mincer [1974] and Porath [1967], human capital accumulation has been extensively studied as one of the main determinants of productivity growth along a worker's life cycle. Human capital investment also plays an important role in accounting for cross country differences in growth rates in the empirical literature spanned by Barro [1991] and Mankiw et al. [1992]. In an influential paper, Lucas [1988] suggests that human capital investment is the main force driving long run growth. While the literature on human capital accumulation on both the life cycle and aggregate growth dimensions is vast, we still have a limited understanding of

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the mechanics of skill acquisition over the cycle. This paper contributes to bridging this gap.

Understanding the behavior of skill acquisition during the cycle has potentially important implications. From a policy perspective, firms implement training programs -and workers engage in them- after deciding that future benefits in terms of higher productivity offset current opportunity costs. If training turns out to have a strong cyclical component, then the rate of return on the large number of government-sponsored training programs might be affected by the time at which they are implemented. Moreover, the cyclical behavior of training may help explain both the phenomenon of procyclical productivity, and the empirical finding that recessions tend to be followed by periods of higher than average productivity growth (see Bean [1990] and Saint-Paul [1996]). In both cases, it has been conjectured that training occurs in downturns and the economy starts a new cycle with higher levels of human capital. Finally, we will argue that the behavior of skill acquisition is strongly linked with the ease with which firms can adjust their factors of production, so that the analysis in this paper will shed light on the cyclical behavior of employment, hours, and labor productivity.

Our empirical knowledge of human capital investments during the cycle is limited to Dellas and Sakellaris [1996], who study skill acquisition activities through formal schooling. In that paper, a database of college enrollments is constructed and the cyclical properties of the series examined. The authors report that college enrollments are countercyclical, and strongly tied to local labor market conditions.

The theoretical implications of skill acquisition activities are explored in a limited number of papers. DeJong and Ingram [2001] estimate a real business cycle (RBC) model with human capital production, investment goods and final goods sectors, and a rich stochastic specification. In their paper, the authors note that there is a lack of usable data on skill acquisition at high frequencies, and address this issue by using their model to infer what the behavior of skill acquisition should be given the realization of the remaining variables. Using a maximum likelihood procedure, they find that a countercyclical and highly volatile behavior of skill acquisition time provides the best fit of their model to existing data.

Einarsson and Marquis [1998] show that adding human capital accumulation can improve the capacity of a model to match the low observed correlation between hours and productivity. A second paper, by Perli and Sakellaris [1998], shows that the countercyclical allocation of resources from a goods producing sector to a sector producing human capital adds a strong propagation mechanism to the standard model. While these results are important, we believe that the ability to assess their empirical relevance is hampered by lack of reliable data [1].

This paper is closer in scope to DeJong and Ingram [2001] in that we are interested in the cyclical behavior of the types of skill acquisition that occur after workers leave formal schooling. In so doing, our study complements the work by Dellas and Sakellaris [1996], who focus on skill acquisition through formal schooling. This paper contributes to the literature in two ways. One, it is the first paper to construct a time series of training activities, and to document its cyclical properties. Two, it highlights the role of labor adjustment costs in explaining the cyclical behavior of skill acquisition.

Our results show that training, both on and off-the-job, is weakly countercyclical, leads the cycle, and has a standard deviation of more than ten times that of output. We show that a standard RBC model with human capital accumulation is unable to reproduce this volatility, but a model with empirically plausible adjustment costs of employment can.

The rest of the paper is organized as follows. Section 2 describes the data used and documents the regularities to be explained by a business cycle model. Section 3 presents the model. Section 4 calibrates the model, and section 5 presents the results. The last section concludes.

2 Data

2.1 Data description

In this study we use the National Longitudinal Survey of Youth 1979 (NLSY79) as the source of training data. The NLSY79 is a longitudinal survey of 12686 individuals who are interviewed every year from 1979 to 1994, and every two

[1] The data on human capital used in Einarsson and Marquis [1998] and Perli and Sakellaris [1998] is a series constructed by Jorgenson et al. [1987]. To construct this series, at every period classes of workers are aggregated using both their wage levels (which are intended to measure the level of human capital) and relative weights in the workforce. While wages are at best weakly procyclical, it is well known that low wage workers drop out of the workforce in higher proportions during recessions, and return during booms. The resulting index shows a clear countercyclical pattern, but this is influenced by the effects of the cycle on the composition of the workforce, and it is unclear to what extent it measures skill acquisition activities.

years since until 1998. The same respondents are followed every interview year without replacement, so that the age distribution of the sample ranges from 14 to 22 years in 1979 and from 34 to 44 in 1998.

With this dataset we first construct a quarterly panel from 1978Q1 to 1998Q4, using questions on the incidence and time spent in training, the type of training provider, working status (working/not working), industry code, and education level (less than high school, high school and some college, college graduate). The questions on training, however, are not consistent across time. From 1979 to 1986, the survey registers information on up to three training programs in which the respondent enrolled for more than one month since the date of last interview, and up to two programs in which the respondent was enrolled at the time of the last interview. In 1987 no training questions were fielded, and in 1988 no information is recorded about training programs in which the respondent was enrolled at the time of last interview. From 1988, information is recorded on up to four training programs started since the date of last interview, regardless of the duration of the program [2].

The questions on the type of training provider are used to separate training into On-The-Job (OJT) and Off-The-Job (OFFJT) training, a distinction that intends to separate firm-specific skill acquisition (OJT) from investments in general skills (OFFJT). The assignment of training programs to either OJT or OFFJT is done according to whether the program took place at the workplace or not. Table 2 details how the different NLSY training categories are aggregated in On-The-Job and Off-The-Job training.

Once the panel is constructed, there are 12,686 individuals, with each being observed for up to 84 quarters, or 1,065,624 observations in total. The NLSY79 oversamples the military population, and this subsample is dropped (107,520 observations). Further, all observations prior to the respondent last being enrolled in school, and posterior to the respondent's last interview are also dropped (414,976 observations) [3]. Finally, we divide the sample into two subperiods to address the problem of data inconsistency, as explained below.

A total of 543,128 observations remain, and are matched with business cycle indicators: GDP and Investment from the Bureau of Economic Analysis,

[2] To construct this panel, we consider a respondent to be in a training program in any quarter if he was enrolled in training for more than one of the three months. For consistency between time periods, we use a maximum of three training programs per year for each respondent, which has negligible effects on the resulting series.

[3] There is also an oversampling of the economically disadvantaged groups, and this subsample is kept, but weighted accordingly in the calculations of means, etc

and industrial production by 2-digit industry from the Board of Governors of the Federal Reserve System, for respondents who report working in manufacturing industries (SIC 20-39).[4] Table 3 shows descriptive statistics for this data, and Table 4 describes the nomenclature. This panel is then used to produce time series at different levels of aggregation: by education groups, working status, etc.

The NLSY79 data has the natural advantages of a panel dataset over aggregated data, and for the purpose of this study it contains extremely detailed information on training at the individual level. There are also two potential problems associated with it when used to construct an aggregate time series. The first problem, as explained above, is that the data collection criteria for training questions previous to 1986 and posterior to 1988 are not entirely consistent. The second potentially important problem is that we observe the same individuals at every time period, so we must be careful to filter out life cycle effects. We discuss these questions in turn.

To address the question of data consistency, we choose to divide our sample in two subperiods, and report our results separately for both. Additionally, we choose to keep in our time series only the periods with more than 3500 observations. Since about 3 to 4 percent of the respondents are enrolled in a training program in each period, this procedure mitigates sampling errors to be amplified in the time series. With these adjustments, we have two periods of valid data, one from 1979Q2 to 1985Q4 (Period 1), and 1989Q1 to 1997Q1 (Period 2).

For the life cycle problem, we begin by noting that at any period a 9 year window of the age distribution is observed, and this cross sectional variation can be exploited in order to separate life cycle effects from business cycle effects. To do this we run a pooled regression of training variables (incidence and hours) on time dummies, that capture business cycle effects, and *age* and *age squared*, that capture life cycle effects. While we find, using an F test, significant coefficients for OFFJT that suggest declining investments in general human capital, we find no such effects for OJT programs. With these results in hand, we choose to use the time series data without applying any transformation, other than logging the hours variables, and we will report the results for both types of training programs.

[4]GDP and Investment downloaded from www.Economagic.com on November 10,2001. Two-digit industrial production downloaded from the Board of Governors of the Federal Reserve System's web site (www.federalreserve.gov) on October 25,2001.

2.2 Stylized facts

We now document the cyclical properties of the variables. The correlations with output (Table 5) of hours in production, investment and productivity display well known regularities: all variables are strongly procyclical, with the exception of labor productivity in period 2. The correlations between the training series and other business cycle variables are shown in Table 6. The results are consistent for both time periods, and suggest that both OJT and OFFJT are countercyclical. Table 6b, computed using pooled data, shows that these correlations are statistically significant when estimated taking advantage of individual variation in the data. [5]

A disaggregated analysis (not reported) reveals that this pattern is broadly consistent across education groups, with hours in training of higher educated workers showing stronger (larger in absolute value) negative correlations with output and investment. Only hours in off-the-job training (*hoff*) in period 2 shows a weakly procyclical pattern. These results suggest that skill acquisition activities that would tend to make hours in on-the-job training (*hojt*) procyclical, such as those associated with the acquisition of new capital goods, are unimportant in the aggregate and are small compared to training activities driven by opportunity cost considerations.

Cross correlations of output with investment, hours and productivity (Table 7), and training variables (Table 8) are discussed now. In our sample, hours are not a leading indicator, but show the strongest correlation with contemporaneous output. This is also true for investment and productivity, with the noted exception of output per hour (*prodh*) in period 2. Table 8 indicates that, while training incidence does not show a clear pattern (it lags output by 2 quarters in period 1, and seems to lead in period 2), the response of hours in training clearly leads output by as much as 3 quarters ($HOJT$, period 1).

Finally, table 9 shows the volatility of aggregated variables. The standard deviation of the (log) hours in training variables is extremely high, as much as 17 times that of output and hours (see figures 3 and 4) . Note that this is not an artifact of training having a growth or life cycle trend. When detrended using a Hodrick-Prescott filter, the volatility of $HAGG$ decreases to .137 and .174 for periods 1 and 2 respectively, and a regression of $HAGG$ on *year* and

[5] Note that the results from tables 6a and 6b are not comparable: table 6a uses log aggregate hours in training at time t as the training variable, while table 6b uses hours in training at time t for each individual.

year squared show insignificant (at 5%) coefficients for both subperiods.

At any quarter, note that only about 4% of workers are enrolled in training programs, and in average about 1.58% of aggregate hours are spent in training, so the proportionally large cyclical variations observed in training hours and incidence need to be weighted by these scaling factors. But even with this caveat, the high volatility of training hours makes training a margin with an importance of the same order of magnitude as employment in adjusting aggregate hours.

3 Model

In section 2 we presented a description of the high frequency regularities of the training series. Some of these regularities, such as the high volatility and moderate correlation with the main cycle indicators, are stark and defy obvious explanations, hence providing a test of high power that can be used to discriminate among competing models.

A natural place to start is the model by Lucas [1988], where human capital accumulation is the driving force of long-run growth. A close examination of this model, or a RBC version of it (see Appendix A), shows that it fails along important dimensions. In particular, it cannot reproduce the high volatility of skill acquisition hours, it tends to produce too high degrees of countercyclicality, and fails to match the observation that training leads the cycle.

The standard RBC model with human capital fails to reproduce these facts because, we believe, it does not incorporate the frictions that make some dimensions of labor input, such as employment or weeks worked, much costlier to adjust than others, such as hours per week. In this vein, we will explore the hypothesis that this high volatility of the training variables is driven by the difficulty in adjusting employment at business cycles frequencies due, for instance, to the existence of hiring and firing costs. This difficulty creates a labor hoarding effect, so that the marginal product of labor is adjusted partially on the extensive margin -employment or weeks worked- but mainly on the intensive margin of hours devoted to work/skill acquisition.

To examine this hypothesis, we construct a model where it is costly to adjust the number of weeks worked every year, while marginal adjustments in hours per week can be done at the prevailing wage. We do this in the spirit of Bils and Cho [1994], who examine the behavior of employment, hours and effort over the cycle. In this model, firms produce a single good using a Cobb-Douglas production function

$$Y_t = A_t K_t^{\alpha} (l_t N_t H_t)^{1-\alpha}. \tag{1}$$

Here Y is output, K is capital, N is weeks worked per quarter, l is hours per week devoted to work, and H is human capital. $\ln A$, a measure of total factor productivity, is a random variable that follows an $AR(1)$ process:

$$\ln A_{t+1} = \rho \ln A_t + \epsilon_t \qquad \epsilon_t \sim N(0, \sigma_\epsilon^2). \tag{2}$$

To produce, firms hire capital and efficiency units of labor lNH, and pay the costs of adjusting weeks. These costs take the quadratic form:

$$C(\Delta N_t) = B \frac{[N_t - N_{t-1}]^2}{2}. \tag{3}$$

The existence of adjustment costs implies that the firm faces a dynamic problem when it chooses employment, and it may incur negative profits at time t. While this cost structure is standard in studies of aggregate employment dynamics (see Hamermesh and Pfann [1996] for a survey), there is strong evidence that it is a poor approximation of the structure of labor adjustment costs at the firm level. At least two features of such a structure are absent in (3): *(a)* a fixed cost of adjusting, that drives a pattern of lumpy adjustment at the firm level [6], and *(b)* asymmetric costs of positive (net hirings) versus negative (net layoffs) changes.

The lumpiness in adjusting employment, however, disappears once data is aggregated over firms (see Hamermesh [1989]). Since we do not have a panel of firms that would allow for modeling the firm's decisions when facing fixed costs of adjustment, and then aggregating over firms, the approach in this paper is to use "reduced form"-equation 3- to interpret aggregate labor market observations. We believe that this approach is useful, in that the main mechanism that drive our results, namely the relative difficulty of adjusting employment versus hours, is explicitly modeled.

[6] This first point is most clearly made in Hamermesh [1989]. In a study of seven large plants, employment was found to adjust only after deviations of actual output from expected output reached 60%. Using a flexible parametric specification, the author reports significant fixed and marginal costs of adjusting employment. The same qualitative results were found in a study of airline technicians (Hamermesh [1992]).

The second feature of the firm-level structure of adjustment costs that is missing in our framework is the asymmetric nature of these costs. The evidence surveyed by Hamermesh and Pfann [1996] suggests that firing costs are larger than hiring costs, and that this asymmetry might still be present in aggregate data. We believe that, although the question is important, it goes beyond the scope of this paper, given that our dataset does not allow for observing firm-level data.

If we let r_t be the interest rate net of depreciation, and using the conventions $r_0 = 0$ and $R_t = r_t + \delta$, the firm's problem can be stated as:

$$\max_{\{K_t, H_t, l_t, N_t\}_{t=0}^{\infty}} E_0 \sum_{t=0}^{\infty} \left(\prod_{\tau=0}^{t} \frac{1}{1+r_\tau}\right) \quad \Big(A_t K_t^{\alpha} (l_t N_t H_t)^{1-\alpha} - w_t l_t N_t H_t \qquad [P1]$$
$$-R_t K_t - B\tfrac{[N_t - N_{t-1}]^2}{2}\Big).$$

Households have preferences defined over consumption $\{c_t\}_{t=1}^{\infty}$, weeks worked $\{N_t\}_{t=1}^{\infty}$, and hours per week devoted to on the job activities: work plus skill acquisition activities $\{l_t + n_t\}_{t=1}^{\infty}$. The distinction between weeks and hours per week allow for the study of two margins of labor input with different cost structures. From the perspective of individual preferences, casual observation indicates that most workers choose an internal solution to their problem of allocating time resources on both margins. Moreover, data on the behavior of weeks and hours per week are available to restrict these preferences. The utility function is similar to that proposed by Bils and Cho:

$$U = E_0 \sum_{t=1}^{\infty} \beta^t \left(\log c_t + m N_t \frac{(n_t + l_t)^{1+\varphi}}{1+\varphi} + f \frac{{N_t}^{1+\phi}}{1+\phi}\right). \tag{4}$$

Equation 5 shows the law of motion for human capital. Human capital depreciates at a rate δ_H, and is accumulated by devoting time to learning activities. The technology for producing it is in the spirit of Lucas [1988], although human capital is not used to produce more human capital, and the specification in 5 does not allow for unbounded growth. Given our focus on business cycles, these simplifications are sensible. Allowing for the level of human capital to influence the efficiency of training hours ($N_t n_t$) would only tend to increase volatility, via a feedback effect from human capital to training.

$$H_{t+1} = H_t(1 - \delta_H) + e\frac{(n_t N_t)^{1+\theta}}{1+\theta}. \tag{5}$$

The description of this economy is completed by making explicit the law of motion for capital:

$$K_{t+1} = (1-\delta)K_t + i_t - B\frac{[N_t - N_{t-1}]^2}{2}. \tag{6}$$

The household problem is then to maximize 4 subject to 5 and the budget constraint (equation 7below):

$$\begin{aligned} \max_{\{c_t,N_t,l_t,n_t,K_{t+1},H_{t+1}\}_{t=0}^{\infty}} \quad \textstyle\sum_{t=0}^{\infty} & \quad \beta^t(\log c_t + mN_t\frac{(n_t+l_t)^{1+\varphi}}{1+\varphi} + f\frac{N_t^{1+\phi}}{1+\phi}) & [P2] \\ s.t. \quad 0 = & \quad -H_{t+1} + H_t(1-\delta_H) + e\frac{(n_tN_t)^{1+\theta}}{1+\theta} & \\ 0 = & \quad w_tH_tN_tl_t + (1+r_t)K_t - c_t - K_{t+1}. & (7) \end{aligned}$$

Equations 1- 6 provide a complete description of this economy. We are now ready to define an equilibrium.

Definition 1 *An equilibrium for this economy is a collection of sequences for allocations* $\{N_t, c_t, K_t, H_t, n_t, l_t\}_{t=1}^{\infty}$, *prices* $\{R_t, r_t, w_t\}_{t=1}^{\infty}$, *and shocks* $\{A_t\}_{t=1}^{\infty}$ *such that:*

1. *Given sequences for prices and shocks, the sequence for* $\{N_t, c_t, K_t, H_t, n_t, l_t\}_{t=1}^{\infty}$ *solve the household problem [P2].*

2. *The allocation for* $\{N_t, K_t, H_t, l_t\}_{t=1}^{\infty}$*solve the firm problem [P1], given sequences for prices and shocks.*

3. *Labor, capital, and goods markets clear. In particular, in the goods market:*
$$C_t + I_t + B\frac{[N_t - N_{t-1}]^2}{2} = A_tK_t^{\alpha}(l_tN_tH_t)^{1-\alpha}.$$

Since this is an economy without distortions, the second welfare theorem holds. The above arrangement is then one in a class of alternatives that would yield the same equilibrium allocation. We could, for instance, have the firm hire $l_t + n_t$ and decide how much to invest in human capital accumulation. The resulting wage rate would then reflect a lower marginal product of labor of the aggregated training and working hours. This motivates the interpretation of the equilibrium allocation as the solution to the social planner's problem. This problem is:

$$\max_{\{c_t,N_t,l_t,n_t,K_{t+1},H_{t+1}\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \beta^t(\log c_t + mN_t\frac{(n_t+l_t)^{1+\varphi}}{1+\varphi} + f\frac{N_t^{1+\phi}}{1+\phi}) \qquad [P3]$$

$$\begin{aligned} s.t. \quad 0 = & -H_{t+1} + H_t(1-\delta_H) + e\frac{(n_tN_t)^{1+\theta}}{1+\theta} \quad (a) \\ 0 = & A_tK_t^{\alpha}(l_tN_tH_t)^{1-\alpha} + (1-\delta)K_t - K_{t+1} \quad (b) \\ & -c_t - B\frac{[N_t - N_{t-1}]^2}{2} \end{aligned}$$

Let λ and μ be the Langrange multipliers for restrictions (b) and (a) respectively. Then the first order conditions are:

$$(c_t) \quad 0 = \frac{1}{c_t} - \lambda_t \tag{8}$$

$$\begin{aligned}(N_t) \quad 0 = & -fN_t^{\phi} - m\frac{(n_t+l_t)^{1+\varphi}}{1+\varphi} + \lambda_t(1-\alpha)\frac{A_tK_t^{\alpha}(l_tN_tH_t)^{1-\alpha}}{N_t} \\ & -\lambda_tB[N_t-N_{t-1}] + E_t\lambda_{t+1}B[N_{t+1}-N_t] + \mu_teN_t^{\theta}n_t^{1+\theta}\end{aligned} \tag{9}$$

$$(l_t) \quad 0 = -mN_t(l_t+n_t)^{\varphi} + \lambda_t(1-\alpha)\frac{A_tK_t^{\alpha}(l_tN_tH_t)^{1-\alpha}}{l_t} \tag{10}$$

$$(n_t) \quad 0 = -mN_t(l_t+n_t)^{\varphi} + \mu_teN_t^{\theta+1}n_t^{\theta} \tag{11}$$

$$(K_{t+1}) \quad 0 = -\lambda_t + \beta E_t\lambda_{t+1}\{\alpha\frac{A_{t+1}K_{t+1}^{\alpha}(l_{t+1}N_{t+1}H_{t+1})^{1-\alpha}}{K_{t+1}} + (1-\delta)\} \tag{12}$$

$$\begin{aligned}(H_{t+1}) \quad 0 = & -\mu_t + \beta(1-\delta_H)E_t\mu_{t+1} \\ & +\beta E_t\lambda_{t+1}(1-\alpha)\frac{A_{t+1}K_{t+1}^{\alpha}(l_{t+1}N_{t+1}H_{t+1})^{1-\alpha}}{H_{t+1}}\end{aligned} \tag{13}$$

$$\begin{aligned}(\lambda_t) \quad 0 = & A_tK_t^{\alpha}(l_tN_tH_t)^{1-\alpha} + (1-\delta)K_t - K_{t+1} - c_t \\ & -B\frac{[N_t-N_{t-1}]^2}{2}\end{aligned} \tag{14}$$

$$(\mu_t) \quad 0 = -H_{t+1} + H_t(1-\delta_H) + e\frac{(n_tN_t)^{1+\theta}}{1+\theta} \tag{15}$$

Equations 8- 15, along with standard transversality conditions for physical and human capital, define the equilibrium allocation.

4 Calibration

In this section we restrict this model quantitatively by choosing values for the four types of parameters:

- Preferences $\{\phi, \varphi, \beta\}$.
- Final good technology $\{\delta, \alpha, B\}$.
- Human capital technology $\{\delta_H, \theta\}$.
- Stochastic process for A $\{\rho, \sigma_\epsilon^2\}$.

These choices are summarized in table 10 [7].

We start with the preference parameters. In steady state, given a quarterly interest rate of 1% (see Kotlikoff and Summers [1981]), the discount factor β equals .99. In choosing values for the parameters $\{\varphi, \phi\}$ that govern the labor supply elasticities, we follow the discussion in Bils and Cho [1994]. In our model, the responses of labor input to changes in the wage rate have two components: changes in weeks worked and changes in hours per week. From the optimality condition on l in the household problem (see appendix B), the Frisch elasticity of hours per week is $1/\varphi$. Evidence from studies using microdata, reviewed by Pencavel [1986], indicates that this elasticity is no higher than .5, which gives a value of 2 for φ. The optimality condition on weeks N in the household problem provides an expression for the elasticity of weeks with respect to hours per week worked. Using Canadian data, Reilly [1994], calculates this elasticity at .6, so we set ϕ accordingly.

For the technology parameters (α, δ), we follow the literature in choosing $\alpha = .36$, equal to the share of capital in aggregate income, and $\delta = .018$, which together with a quarterly interest rate of 1% is consistent with a yearly capital-output ratio equal to 3 (Prescott [1986]). To determine a value for the parameter B, we use evidence on the size of labor adjustment costs. Burgess and Dolado [1989] report that, for firms in the UK, these costs amount to .25% of the quarterly payroll, which in our model translate to .17% of output. We set the parameter B so that $\frac{EB[N_t - N_{t-1}]^2}{EY_t} = .0017$.

To pick values for the human capital production technology, we can use results from the growing literature on the productivity effects of training.

[7] The parameters $\{m, f, e\}$ are purely normalization parameters, and therefore not considered in the discussion that follows.

A number of papers attempt to identify the effect of different measures of training on labor productivity. While most of these papers use discrete measures of training, such as participation dummies (Bartel [1994], Black and Lynch [1996]), at least two papers use a quantitative right hand side variable: hours in training (Schonewille [2001]), and training days (Barrett and O'Connell [1999]); these results can be more readily interpreted in terms of the parameters of the model.

In our model, the elasticity of human capital with respect to training time (nN) is $\delta_H(1+\theta)$. Since the share of human capital augmented labor (lNH) in income is $(1-\alpha)$, a 1% increase in training time translates into a $(1-\alpha)\delta_H(1+\theta)$ percent increase in labor productivity (Y/lN). since α has been picked, we need to choose values for δ_H and θ. Using British data (UK Labor Force Survey), Schonewille [2001] reports significant estimates of .04 for $\delta_H(1+\theta)$ with a measure of *hours in training* as the right hand side variable. Barrett and O'Connell [1999], using data on a nationally representative sample of 1000 Irish firms, find a point estimate of .014 for the elasticity of labor productivity with respect to the variable *training days/total employment* (table 2 in their paper). With $\alpha = .36$, this implies that $\delta_H(1+\theta) = .021$. These estimates are clearly an upper bound for the value of $\delta_H(1+\theta)$, since most estimates are not different from zero. We choose a small value of .0005 for $\delta_H(1+\theta)$, which implies $\delta_H = 0.0005$ and $\theta = -0.0095$. In the next section we will discuss how sensitive the results are to this choice.

It is unfortunate that we have no useful results that rely on US data. A survey of the evidence based on US data highlights the difficulty of estimating precisely the training parameters. Bartel [1994] finds that implementing a new training program increases firms productivity by as much as 41% over a 3 year span, but old training programs seem to have no effect. Bishop [1994] reports that new workers enrolled in formal OJT programs at their previous jobs were more productive by an amount equivalent to 9.5% of their wage, and that this effect disappears after six months. Black and Lynch [1996] are unable to find significant effects of their main training variables on firm sales.

We interpret the evidence as indicating that the elasticity of human capital with respect to training $\xi_{HC,training} = \delta_H(1+\theta)$ lies between zero and the estimate by Schonewille [2001], 0.04. Besides ensuring that $\{\delta_H, \theta\}$ satisfy this elasticity, we need to impose that these parameters are consistent with the steady state condition $\delta_H = \frac{\frac{n}{l}(1-\beta)}{\beta((1+\theta)-\frac{n}{l}}$. We will choose two values for $\xi_{HC,training}$: $\{0.0002, 0.01\}$ and discuss the importance of choosing $\xi_{HC,training}$

accurately in the next section.

Finally, we set $\rho = .95$ and $\sigma_\epsilon^2 = .007$, borrowing these values from Bils and Cho [1994].

5 Results

We solve the model by linearizing the optimality conditions 8- 15 around the deterministic steady state, and solving for the recursive law of motion. We begin by describing the main mechanisms at work in the model, using the beginning of a boom as the starting point. As the economy takes off, driven by positive TFP shocks, the marginal product of labor increases, and firms adjust largely by increasing hours and only gradually adjusting weeks, a process that entails direct costs to firms. Moreover, given that the marginal disutility of working activities $(n_t + l_t)$ has increased, households choose to devote less time to acquiring human capital. The response of n_t is large because the increase in hours of work l_t had to be large enough to compensate the slow adjustment of weeks (we may think employment). Since preferences are convex in hours-per-week of leisure $(1 - l_t - n_t)$, the large increase in n_t implied a sharp increase in the marginal utility of this dimension of leisure. Figure 1, with impulse responses to a shock in A_t for weeks N_t, hours at work l_t and in training n_t, illustrates this process. Training has a large negative response to a TFP shock, and hours-at-work show a larger response to shocks than weeks, even though the elasticity of labor supply for hours-at-work (.5) is smaller than that for weeks (.6).

In the goods market, a positive shock increases output, consumption and investment (figure 2). As the effects of the shock on TFP die out, and capital is accumulated above its steady state level, the interest rate increases, reducing the incentives to invest and fostering the consumption of the now large capital stock.

The model cross correlations with output are shown in table 11. It is clear that, although the signs are all correct, this model fails to reproduce both the weak level of countercyclicality of training, and its leading indicator characteristics.

Table 12 shows the volatility of selected variables. With the calibration of table 10, the model successfully reproduces the extremely high levels of volatility of time in training, and its relative volatility with respect to output and investment, but not hours.

We now study the sensitivity of our results to changes in the parameter values. Table 13 shows the effects of changing one by one the parameter values of table 10, and guides us as to which are the important calibration choices in this model. We see that the model fails both in reproducing the correlation between training and gdp, and in leading gdp. We thus concentrate on the volatility of training.

Row 2 of table 13 show the effects of increasing $\xi_{HC,training}$ from the (arbitrary) baseline level of .00016. Calibrating this elasticity to values reported by Schonewille [2001] and Barrett and O'Connell [1999] (.04 and .02 respectively) would imply a depreciation factor δ_H higher than 1, but even with $\xi_{HC,training} = .01$ consistency with the steady state requires the factor $(1+\theta)$ to drop to .016 from .977 in the baseline. In this case, the standard deviation of training is lower than that of output, and training displays a *positive* correlation with output. Figure 5 shows the pairs $\{\theta, \xi_{HC,training}\}$ consistent with the steady state in a neighborhood of the baseline; it shows that θ, and therefore $\sigma_{training}$, is extremely sensitive to very small changes in $\xi_{HC,training}$ around the baseline: decreasing $\xi_{HC,training}$ to .00016 increases $\sigma_{training}$ to 177 (!), while increasing it to .0003 brings $\sigma_{training}$ down to .43.

It is clear that the choice of $\{\delta_H, \theta\}$, that determines how efficiently training time is converted into new human capital, is crucial for our results. To understand this point, it is useful to decompose $\xi_{HC,training}$ into $(1+\theta)$ and δ_H. While the first term indicates that a 1% change in the time spent in training translates into a $(1+\theta)$% change in human capital *investment*, δ_H is a scale factor that indicates how large is human capital investment with respect to the stock of human capital[8]. Even if a high $(1+\theta)$ can drive human capital investment to display large fluctuations with respect to its level, as it does in our simulations, this level is so small with respect to the stock of human capital that the ultimate effect of training on human capital and labor productivity is barely distinguishable from zero[9].

Changing the size of adjustment costs has predictable effects on the second moments of training (rows 3 and 4): increasing these costs to one percent

[8]Investment in human capital is $e\frac{(n_tN_t)^{1+\theta}}{1+\theta}$, and in steady state we have $\delta_H H = e\frac{(nN)^{1+\theta}}{1+\theta}$.

[9]A stochastic depreciation factor δ_H is a possible avenue to improve on the results of this model, as noted by Einarsson and Marquis [1998]. However, as we know of no procedure to directly estimate the series $\{\delta_H\}$, we believe that examining this possibility is of limited use at this point

of *gdp* increases the standard deviation of training by 22%, while bringing B to zero has a small negative impact on σ^2_{nN}.

While formal training programs of the type considered in this paper are an important source of human capital accumulation, learning by doing and other informal means to acquire skills are also available but difficult to measure. We examine in row 5 whether increasing the time devoted to skill acquisition has significant effects on the results, and find that increasing the share of time devoted to skill acquisition from .0158 to .02 increases the volatility of training time by 12%.

Varying the size of the labor elasticities (rows 6 and 7) has also quantitatively minor effects on σ^2_{nN}. While increasing $\xi_{N,wage}$ makes it less costly to adjust weeks than hours per week, increasing $\xi_{(n+l),wage}$ has the opposite effect. As explained in section 3, σ^2_{nN} increases in this model when weeks become costly to adjust with respect to hours per week.

6 Conclusion

In this paper we have first characterized the behavior of training at business cycles frequencies, and proposed a model to reproduce this behavior. We find that training has a clear countercyclical behavior, leads the cycle, and is extremely volatile, making it an important margin in allocating time at the frequencies considered. We also found that our model shows the potential to reproduce the volatility of training, but does not fare as well in reproducing the remaining stylized facts. Moreover, our calibration exercise has identified the elasticity of human capital with respect to training as the key parameter to reproduce this volatility. We now believe that studying the technology used to convert training into new human capital is of great importance in understanding human capital accumulation, and plan to work on this issue in the future.

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A Standard RBC Model with Human Capital

Model
Utility

$$U = E_t \sum_{t=0}^{\infty} \beta^t (\log c_t - m \frac{(1 - l_t - n_t)^{1-\theta}}{1-\theta})$$

Resource constraint

$$0 = A_t K_t^{\alpha} (H_t l_t)^{1-\alpha} - c_t - K_{t+1} + (1-\delta) K_t$$

Law of motion for human capital

$$0 = -H_{t+1} + H_t (1 - \delta_H) + e \frac{(n_t)^{\gamma}}{\gamma}$$

Stochastic process for A

$$\ln A_{t+1} = \rho \ln A_t + \epsilon_t \qquad \epsilon_t \sim N(0, \sigma_\epsilon^2).$$

Table 1: Variable description

H	Human Capital
K	Capital
β	Discount factor
c	Consumption
l	Hours at work
n	Hours in skill acquisition
A	TFP shock
δ	Rate of depreciation of K
δ_H	Rate of depreciation of H

B First Order Conditions in the Household Problem [P2]

Problem:

$$\max_{\{c_t,N_t,l_t,n_t,K_{t+1},H_{t+1}\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \beta^t(\log c_t + mN_t\frac{(n_t+l_t)^{1+\varphi}}{1+\varphi} + f\frac{N_t^{1+\phi}}{1+\phi}) \qquad [P2]$$

$$\begin{aligned} s.t. \quad 0 = &\; -H_{t+1} + H_t(1-\delta_H) + e\frac{(n_tN_t)^{1+\theta}}{1+\theta} \\ 0 = &\; w_tH_tN_tl_t + (1+r_t)K_t - c_t - K_{t+1}. \end{aligned}$$

Lagrangian:

$$\begin{aligned} \mathcal{L} = \quad E_t \sum_{t=0}^{\infty} \beta^t\{ \quad & \log c_t + mN_t\frac{(n_t+l_t)^{1+\varphi}}{1+\varphi} + f\frac{N_t^{1+\phi}}{1+\phi} \\ & +\mu_t[H_{t+1} - H_t(1-\delta_H) - e\frac{(n_tN_t)^{1+\theta}}{1+\theta}] \\ & +\lambda_t[w_tH_tN_tl_t + (1+r_t)K_t - c_t - K_{t+1}]\} \end{aligned}$$

First Order Conditions:

$$\begin{aligned} (c_t) \quad 0 = &\; \frac{1}{c_t} - \lambda_t \\ (N_t) \quad 0 = &\; -fN_t^{\phi} - m\frac{(n_t+l_t)^{1+\varphi}}{1+\varphi} - \lambda_tw_tH_tl_t + \mu_teN_t^{\theta}n_t^{1+\theta} \\ (l_t) \quad 0 = &\; mN_t(l_t+n_t)^{\varphi} + \lambda_tw_tH_tN_t \\ (n_t) \quad 0 = &\; -mN_t(l_t+n_t)^{\varphi} + \mu_teN_t^{\theta+1}n_t^{\theta} \\ (K_{t+1}) \quad 0 = &\; -\lambda_t + \beta E_t\lambda_{t+1}(1+r_{t+1}) \\ (H_{t+1}) \quad 0 = &\; -\mu_t + \beta(1-\delta_H)E_t\mu_{t+1} - E_t\lambda_{t+1}w_{t+1}N_{t+1}l_{t+1} \\ (\lambda_t) \quad 0 = &\; w_tH_tN_tl_t + (1+r_t)K_t - c_t - K_{t+1} \\ (\mu_t) \quad 0 = &\; -H_{t+1} + H_t(1-\delta_H) + e\frac{(n_tN_t)^{1+\theta}}{1+\theta} \end{aligned}$$

Figure 1: Impulse Responses: Time Allocations.

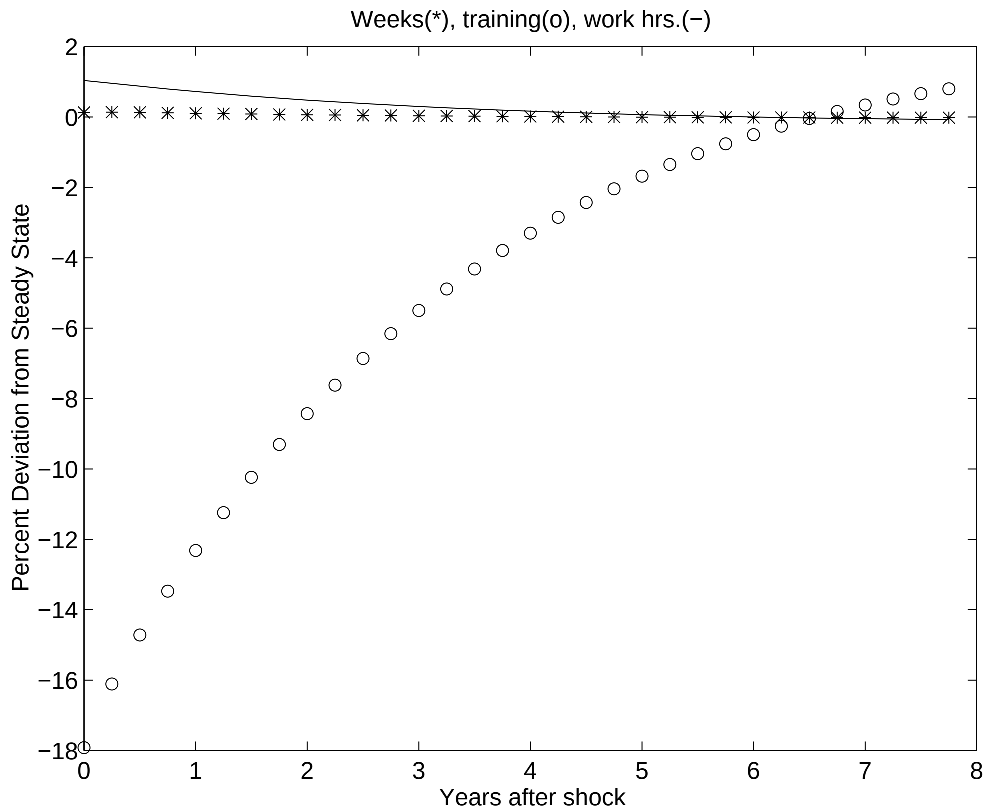

Figure 2: Impulse Responses: GDP, C, I.

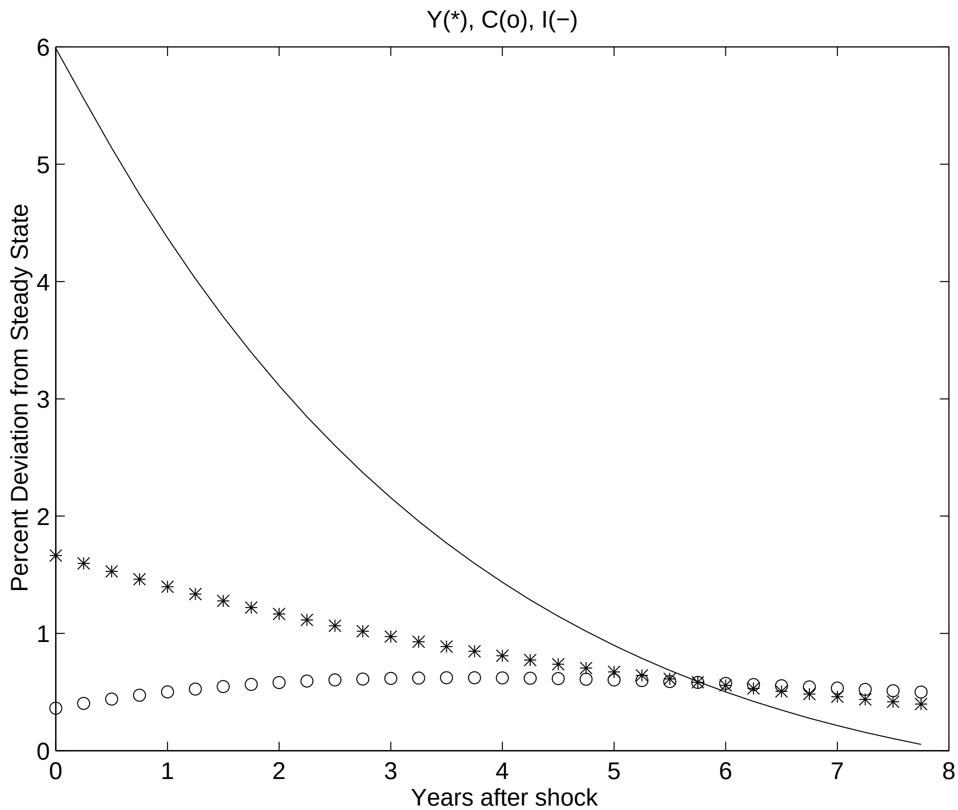

Figure 3: Training and GDP, Period 1.

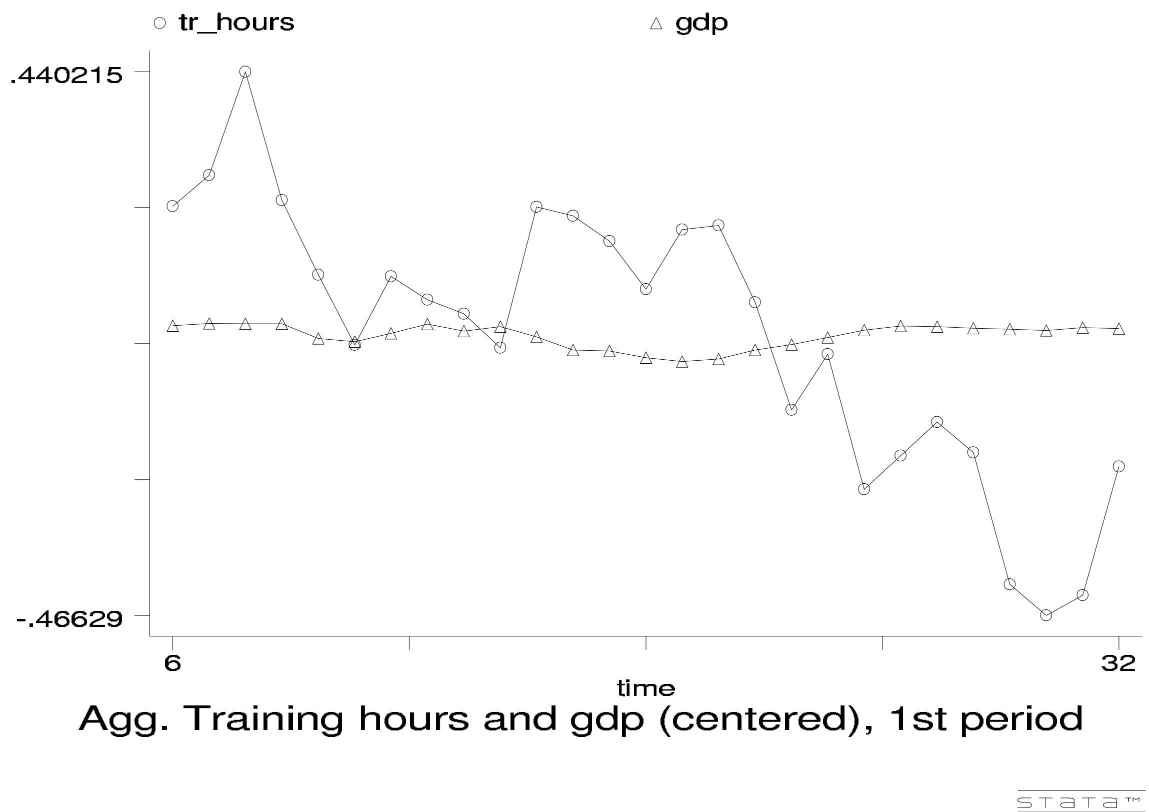

Figure 4: Training and GDP, Period 2.

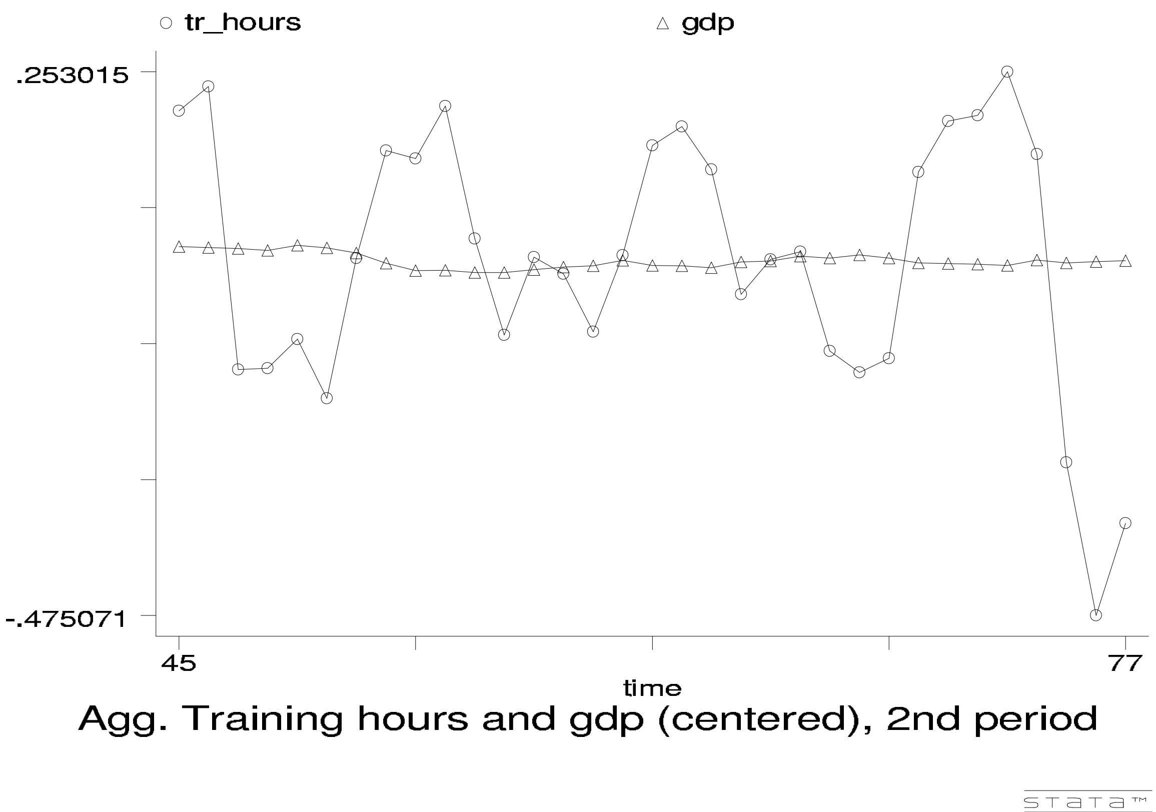

Figure 5: $\{\theta, \xi_{HC,training}\}$ pairs consistent with the steady state

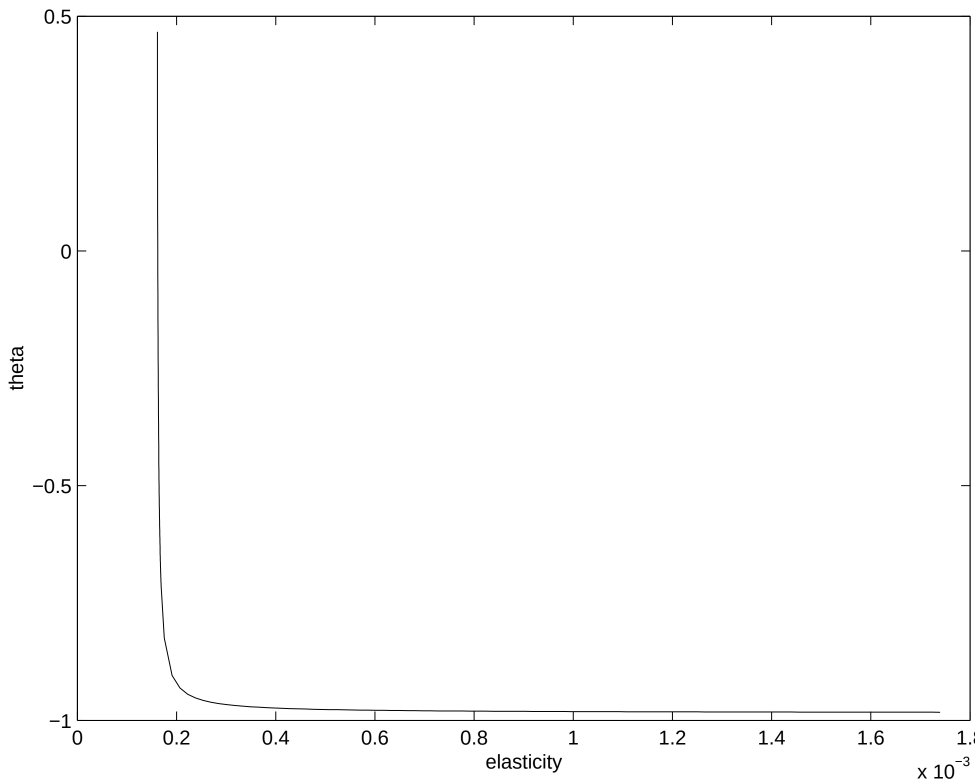

Table 2: Assignment of training Program

	NLSY Classification	
	Years 1978-1986	Years 1988-1998
On The Job Training	Company Training	Formal Company Training run by Employer Seminars at work not run by employer
Off The Job Training	Business College Nurses Program Vocational Technical Institute Barber-Beauty Flight School Correspondence Other	Business School Vocational Technical Institute Correspondence Course Seminar or training program outside of work Vocational Rehabilitation Center Other
Dropped Observations	Apprenticeship	Apprenticeship Program Government Training Program

Table 3: Descriptive statistics

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
age	543128	28.236	5.379	14	41
hoff	542836	3.343	33.210	0	1248
hojt	542778	2.379	30.167	0	2496
job	543128	0.750	0.433	0	1
toff	543128	0.020	0.140	0	1
tojt	543128	0.016	0.126	0	1

Table 4: Description of variables

Variable	Description
age	age, in years
hoff	hours spent in off the job training programs
hojt	hours spent in on the job training programs
hagg	Hours spent in either off or on the job training
toff	Binary training variable, =1 if enrolled in a off the job training program
tojt	Binary training variable, =1 if enrolled in a on the job training program
tagg	Binary training variable, =1 if enrolled in either type of training program
HOJT	Natural log of time t aggregated hojt
HOFF	Natural log of time t aggregated hoff
HAGG	Natural log of time t aggregated hagg
TOJT	Time t mean tojt
TOFF	Time t mean toff
TAGG	Time t mean tagg
H	Index of total hours worked in the business sector, hp filtered
gdp	Log real gdp, hp filtered
I	Log real investment, hp filtered
prodh	Log real gdp per hour, hp filtered
prodp	Log real gdp per person, hp filtered

Table 5: Contemporaneous correlation of I, hours and productivity with GDP-Data

	Period 1	Period 2
I	0.91	0.86
H	0.97	0.87
Prodh	0.77	0.01
Prodp	0.79	0.39

Table 6: Contemporaneous correlations of training with GDP, I-Data

Table a. Correlations using time series

	Period 1		Period 2	
	gdp	I	gdp	I
TOFF	0.0026 (0.9898)	-0.2246 (0.2599)	-0.1307 (0.4684)	-0.0073 (0.9678)
TOJT	-0.3919* (0.0432)	-0.1924 (0.3364)	-0.3564* (0.0417)	-0.1957 (0.2750)
TAGG	-0.1033 (0.6083)	-0.2746 (0.1657)	-0.2622 (0.1405)	-0.1124 (0.5335)
HOFF	-0.2338 (0.2405)	-0.3992* (0.0391)	0.2555 (0.1512)	0.2577 (0.1477)
HOJT	-0.2020 (0.3124)	-0.1104 (0.5837)	-0.3860* (0.0265)	-0.4668* (0.0062)
HAGG	-0.2511 (0.2065)	-0.3912* (0.0436)	-0.2079 (0.2457)	-0.2766 (0.1191)

Table b. Correlations using pooled data

	Period 1		Period 2	
	gdp	I	gdp	I
toff	-0.0027 (0.2772)	-0.0072* (0.0039)	-0.0070* (0.0003)	-0.0011 (0.5871)
tojt	-0.0036 (0.1471)	-0.0022 (0.3713)	-0.0151* (0.0000)	-0.0074* (0.0001)
tagg	-0.0038 (0.1232)	-0.0074* (0.0031)	-0.0157* (0.0000)	-0.0060* (0.0019)
hoff	-0.0063* (0.0113)	-0.0092* (0.0002)	0.0013 (0.5184)	0.0039* (0.0421)
hojt	-0.0018 (0.4766)	-0.0018 (0.4788)	-0.0114* (0.0000)	-0.0110* (0.0000)
hagg	-0.0064* (0.0103)	-0.0089* (0.0003)	-0.0077* (0.0001)	-0.0055* (0.0043)

Table 7: Cross correlations of I, H and productivity with GDP-Data ($corr(x_t, gdp_{t+j})$)

Period 1

Lags	I	H	prodh	prodp
-6	-0.40	-0.18	-0.26	-0.39
-5	-0.34	-0.03	-0.38	-0.44
-4	-0.11	0.19	-0.37	-0.38
-3	0.2	0.46	-0.18	-0.18
-2	0.47	0.69	0.08	0.09
-1	0.76	0.89	0.41	0.45
0	0.91	0.97	0.77	0.79
1	0.74	0.80	0.72	0.78
2	0.49	0.53	0.60	0.68
3	0.27	0.25	0.48	0.53
4	0.02	0.00	0.27	0.34
5	-0.10	-0.14	0.11	0.20
6	-0.10	-0.21	0.04	0.12

Period 2

Lags	I	H	prodh	prodp
-6	-0.47	0.03	-0.46	-0.70
-5	-0.34	0.24	-0.62	-0.75
-4	-0.15	0.46	-0.67	-0.65
-3	0.06	0.64	-0.67	-0.51
-2	0.38	0.78	-0.52	-0.25
-1	0.68	0.86	-0.30	0.04
0	0.86	0.87	0.01	0.39
1	0.77	0.71	0.06	0.42
2	0.64	0.53	0.09	0.42
3	0.44	0.32	0.08	0.32
4	0.29	0.13	0.09	0.25
5	0.10	-0.05	0.07	0.14
6	-0.05	-0.22	0.14	0.11

Table 8: Cross correlations of training with GDP-Data ($corr(x_t, gdp_{t+j})$)

Period1

Lags	TOJT	TOFF	TAGG	HOJT	HOFF	HAGG
-6	-0.04	0.28	0.26	0.24	0.26	0.32
-5	-0.29	0.27	0.19	0.05	0.18	0.19
-4	-0.41	0.22	0.11	-0.09	0.08	0.07
-3	-0.35	0.16	0.06	-0.18	-0.01	-0.03
-2	-0.37	0.11	0.01	-0.23	-0.07	-0.10
-1	-0.36	0.05	-0.05	-0.23	-0.13	-0.16
0	-0.39	0.00	-0.10	-0.20	-0.23	-0.25
1	-0.51	-0.05	-0.18	-0.27	-0.27	-0.32
2	-0.50	-0.14	-0.28	-0.38	-0.30	-0.37
3	-0.40	-0.22	-0.32	-0.45	-0.26	-0.35
4	-0.25	-0.14	-0.21	-0.44	-0.16	-0.25
5	-0.09	-0.06	-0.08	-0.26	-0.04	-0.10
6	0.19	-0.05	0.00	0.00	-0.01	-0.01

Period 2

Lags	TOJT	TOFF	TAGG	HOJT	HOFF	HAGG
-6	-0.23	-0.33	-0.29	0.30	-0.22	0.16
-5	-0.27	-0.24	-0.27	0.28	-0.07	0.19
-4	-0.30	-0.17	-0.25	0.21	0.09	0.19
-3	-0.37	-0.21	-0.31	0.05	0.15	0.09
-2	-0.41	-0.20	-0.32	-0.18	0.16	-0.09
-1	-0.35	-0.16	-0.27	-0.30	0.19	-0.18
0	-0.36	-0.13	-0.26	-0.39	0.26	-0.21
1	-0.33	-0.13	-0.25	-0.42	0.23	-0.24
2	-0.23	-0.08	-0.16	-0.36	0.28	-0.17
3	-0.03	0.04	0.00	-0.19	0.36	0.01
4	0.12	0.14	0.13	-0.07	0.44	0.14
5	0.24	0.21	0.23	0.05	0.39	0.21
6	0.31	0.23	0.29	0.10	0.29	0.19

Table 9: Standard deviations-Data

	Period 1	Period 2
gdp	0.020	0.010
I	0.096	0.048
H	0.019	0.015
prodh	0.009	0.008
prodp	0.014	0.009
TOFF	0.006	0.005
TOJT	0.002	0.006
TAGG	0.006	0.010
HOFF	0.270	0.168
HOJT	0.274	0.257
HAGG	0.230	0.177

Table 10: Baseline parameter values

ϕ	2.46
φ	2
β	.99
δ	.018
α	.36
B	13,450
δ_H	.0002
θ	-.0228
ρ	.95
σ_ϵ^2	.00712

Table 11: Cross correlations with output-Model ($corr(x_t, gdp_{t+j})$)

Lags	I	Hours	Training hrs.	Labor Prod.
-5	-.05	.01	.11	.1
-4	.05	.11	.01	.19
-3	.26	.32	-.2	.38
-2	.43	.49	-.38	.54
-1	.66	.70	-.62	.73
0	.99	.99	-.98	.99
1	.72	.73	-.72	.68
2	.54	.54	-.55	.46
3	.39	.38	-.41	.29
4	.20	.19	-.22	.08
5	.10	.09	-.13	-.01

Table 12: Standard deviations-Model

Var.	σ
Y	.012
I	.043
Hours	.0024
Training hrs.	.159
Labor prod.	.01

Table 13: Sensitivity analysis

Calibration	σ_{nN}	$corr(gdp_t, nN_t)$	$argmax_j\{corr(nN_t, gdp_{t+j})\}$
Baseline	.159	-.98	0
$\xi_{HC,training} = .01$	.0016	1	0
Adjustment costs are 1% of gdp	.194	-.98	0
No adjustment costs	.153	-.99	0
$\frac{n}{l} = .02$	.179	-.99	0
$\xi_{N,wage} = .7$	.137	-.98	0
$\xi_{(n+l),wage} = .6$	.175	-.99	0