CENTRE FOR APPLIED MACROECONOMIC ANALYSIS

The Australian National University

CAMA Working Paper Series **June, 2011**

THE CYCLICALITY OF SKILL ACQUISITION: EVIDENCE FROM PANEL DATA

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CAMA Working Paper 13/2011
http://cama.anu.edu.au

The cyclicality of skill acquisition: evidence from panel data

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June 1, 2011

Abstract

This paper presents new empirical evidence regarding the cyclicality of skill acquisition activities. The paper studies both training and schooling episodes at the individual level using quarterly data from the NLSY79 for a period of 19 years. We find that aggregate schooling is strongly countercyclical, while aggregate training is acyclical. Several training categories however behave procyclically. The results also indicate that firm-financed training is procyclical while training financed through other means is countercyclical; and that the cyclicality of skill acquisition investments depends significantly on the educational level and the employment status of the individual.

1 Introduction

The response of human capital investments to business cycle fluctuations is key to a number of theoretical results in macroeconomics. Among other issues, cyclical fluctuations in skill acquisition activities may help explain the propagation of shocks and the persistence of growth (Perli and Sakellaris (1998), DeJong and Ingram (2001)), the comovement in employment and output across sectors of the economy (Einarsson and Marquis (1996)), the observed asymmetry of cycles (Jovanovic (2006)), the allocation of time along the cycle (Kim and Lee (2007)), and differences in the volatility of wages and employment between the US and Europe (Fukao and Otaki (1993)).

Unfortunately, we know little about the actual fluctuations in skill acquisition activities. There is a small empirical literature discussing the behavior of human capital investments

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both through formal schooling and on-the-job training; but the lessons from this literature are mixed. For the US, previous studies suggest skill acquisition activities are counter-cyclical: Betts and McFarland (1995), Dellas and Koubi (2003), and Dellas and Sakellaris (2003) report attendance and enrollment to be counter-cyclical in U.S. colleges. Sepulveda (2002) finds on-the-job training of American workers to be weakly counter-cyclical. For other countries, the evidence points to a pro-cyclical behavior instead: King and Sweetman (2002) find that Canadian workers quit their job and return to school in a "strongly pro-cyclical manner". Felstead and Green (1996) report training was pro-cyclical in Britain during the 1970's, 80's and 90's.

What is more problematic, however, is that this empirical literature does not differentiate between specific types of human capital investments and, thus, it offers little guidance for theoretical models which are very precise about the type of skill acquisition they examine. Jovanovic (2006), for example, presents a model where firm-financed training is triggered by the introduction of new production technologies, Einarsson and Marquis (1996) and Kim and Lee (2007) model employee-financed human capital investments that are motivated by future expected earnings, Fukao and Otaki (1993) focus on the training associated with learning the skills necessary to begin a new job, etc. Clearly, because contributions aiming to understand specific phenomena assign emphasis to different types of skill accumulation processes (which may not share the same cyclical behavior), a disaggregate analysis is warranted if we are interested in testing the models predictions. The empirical literature available lacks such a level of disaggregation.

In this paper, we take a closer look at the cyclicality of skill acquisition activities. To do so, we use the National Longitudinal Survey of Youth 1979 (NLSY79) and construct a longitudinal dataset of schooling and training episodes at the individual level for a period spanning 19 years. The NLSY79 follows individuals who are 14 to 22 years old in 1979, with annual interviews until 1994 and bi annual interviews from 1996 to 2006. From 1988 onwards, the survey records information on up to 4 new training episodes per wave and up to two episodes that were not completed at the time of the previous interview, making it one of the best sources of information on schooling and training at the individual level. We complement the NLSY with data on time devoted to schooling activities using the American Time Use Survey (ATUS) for the period 2003 to 2009.

The paper makes a contribution to the existing empirical literature in several respects: first, in that our data contains simultaneous records of both schooling and training episodes at the individual level. Thus, in contrast with previous work that examined schooling or training separately, we examine a complete profile of human capital investments. Second, in that this is the first study to use panel data in order to control for unobserved individual characteristics and changes in the cyclical composition of the workforce. We show that failing to account for either of these issues leads to large biases in the coefficients of interest. And third, in that this is the first study to follow individuals as they come in and out of unemployment without missing any information on their skill acquisition activities. We document that the unemployed undergo substantial training and schooling. Moreover, we show that the cyclical behavior of training, but not schooling, is in general qualitatively different for employed and unemployed individuals.

The paper also makes a contribution to the broader macroeconomic literature by narrowing the gap between the evidence available and the information required for making theoretical assumptions about the cyclicality of specific job-training investments. In particular, the paper exploits the information contained in the NLSY79 in order to differentiate between employer-financed and self-financed training; between blue-collar and white-collar training activities; and between four different motives for obtaining training: regular training, training required after the adoption of a new technology, training necessary to begin a new job, training necessary to obtain a promotion, and a residual training category. Using this wealth of information, we evaluate some of the specific assumptions used in theoretical models and provide distinct estimates of cyclicality for the different categories that arise.

The results of the paper indicate that, while aggregate schooling exhibits a countercyclical pattern, the case for countercyclical training is weak at the aggregate level. However, when training episodes are decomposed into independent categories, we find that most categories are actually procyclical. Three key distinctions appear throughout the results. First, between firm financed training, which tends to be strongly procyclical, and training financed by the individual, which tends to be countercyclical. Second, between college and non college educated individuals. In most of our results, the cyclical skill acquisition patterns of skilled individuals are different from those of the unskilled, although no clear pattern emerges across categories. Third, between employed and unemployed individuals; training seems much more procyclical for the former than for the latter. As a result, the cyclical behavior of training and schooling in any category depends crucially on the relative prevalence of firm versus self financed programs, skilled versus unskilled individuals, and working versus unemployed individuals.

These results then offer suggestions as to why previous studies have reached seemingly contradictory conclusions. Quite likely, differences in institutional arrangements across countries are at the base of these conflicting findings. The disparity between Sepulveda (2002) and Felstead and Green (1996) with regards to training, for example, may be explained by the prevalence of different types of training programs and government incentives in Britain and the U.S.A. In turn, the disparities between King and Sweetman (2002) and others like Betts and McFarland (1995) or Dellas and Sakellaris (2003) with respect to schooling may be explained by the fact that the former use a particular sample of people who quit their job and return to school with the (presumably) common objective of finding a new job afterwards. In our study, we do not have information regarding why people enroll in school, but when we look exclusively at people who enter new jobs, our results on training coincide with those obtained by King and Sweetman (2002).

The remaining of the paper is organized as follows: Section 2 provides a description of the data set and some basic facts. The empirical methodology and the main results of the paper are described in Section 3. Section 4 concludes.

2 Data

The NLSY79 follows individuals who are 14 to 22 years old in 1979, with annual interviews until 1994, and bi annual interviews from 1996 to 2006. From 1988 on, the survey records information on up to 4 new training episodes per wave, and up to two episodes that were not completed at the time of the previous interview, making it one of the best sources of information on training at the individual level [1]. To construct our dataset, we use waves 1989 to 2006, creating individual histories that span up to 75 quarters, or 19 years, from Q1:1988 to Q3:2006.

We construct a quarterly panel of individual training incidence, school attendance, employment status, as well as variables representing age, race, sex, education, employment status, wealth, and workplace (establishment) size. After dropping observations where the respondent has a gap of at least three years between interviews (46,313), is enrolled in the armed forces (97,280), is younger than 24 years old (875), and has missing information on employment status (47,697), we obtain histories on 9,342 individuals, totalling 519,925 (individual-quarter) observations.

We examine skill acquisition through training and formal schooling. While schooling is generally associated with the acquisition of general purpose skills in trade schools, colleges and universities, training is associated with acquiring specific skills pertaining or related with the tasks performed in one's current occupation. Our schooling variable (*School*) indicates whether the individual is enrolled in school, from primary school to higher education, during the quarter. Our training variable (*Training*) is a dummy equal to one if the respondent reported spending at least one day of the quarter in a formal training program, either sponsored by the firm or not.

Training programs can be further classified into five categories. For each one of these categories we created a dummy variable equal to one if the respondent reported experiencing

[1]From the 1988 wave on, the NLSY drops a 1 month limitation on the length of training programs, effectively registering every single program, subject to the limits mentioned.

such type of training and zero otherwise. The corresponding dummy variables are: *Training for promotions* for programs related to promotion; *Training for technology adoption* for programs required after the adoption of new technologies; *Training for new job* for programs necessary to become proficient in a new job; *Regular training*; and *Other training* for programs not included elsewhere.

The classification is done according to a question fielded from 1991 on for each training episode: [2]

> Primary reason for taking 1st (2nd, 3rd, 4th) vocational/technical program since last interview?
>
> 1. The training was associated with promotion or job advancement opportunity. (*Training for promotions*)
> 2. New methods or processes were introduced – additional training required to do the same job. (*Training for technology adoption*)
> 3. Part of regular program to maintain/upgrade skills. (*Regular training*)
> 4. The training was necessary when I began a job. (*Training for new job*)
> 5. Other (specify). (*Other training*)

Since the classification into the different types of training is done by the individual and not by the firm, there is some scope for misclassification. It could be, for instance, that a firm runs an annual training program to improve "leadership skills". A new employee who takes the program would possibly classify it as *Training for new job*, while an employee with more tenure would classify it as *Regular training*. In other cases, such as when firms hire and provide training with the goal of developing new products, training could belong to more than one category. Even with these qualifications, we see the question above as providing respondents with clear guidelines to classify training programs.

[2]Note that "vocational/tecnical training" encompasses all types of training in the NLSY.

We also construct an indicator variable for being unemployed (*Not working*), equal to zero if the respondent was employed for at least three weeks during the quarter and one otherwise; a variable measuring age (*Age*); a variable indicating having a college degree (*College*); variables that indicate whether the training program was at least partially funded by the employer (*Firm financed*), or by the individual (*Self financed*); and two variables that intend to capture the ability to access capital markets: *Establishment size*, expressed in thousands of workers, in the case of firms, and *Net worth*, a variable capturing household assets minus debts expressed in millions of 1990 dollars, in the case of individuals [3]. To this dataset, we add the quarterly national unemployment rate from the Bureau of Labor Statistics and use it as our cycle indicator (*Unemployment rate*) [4].

We were unable to obtain measures of the time devoted to either schooling or training from the NLSY79. The NLSY79 does not contain any records of the time devoted to schooling, and although it contains information regarding the time devoted to training, this information is missing in over 63% of the observations where training took place. We decided against using this data [5]. We are not aware of any alternative panel data survey that provides a similar account of time devoted to these activities. The American Time Use Surveys (ATUS), however, contain information on time devoted to schooling activities from annual cross sectional samples since 2003. These surveys allow us to study the time devoted to educational activities. Unfortunately, the ATUS surveys do not contain information on time devoted to training. A detailed description of the ATUS data sets and a statistical analysis of the cyclicality of time devoted to schooling can be found in the web-appendix that accompanies this paper.

[3] The variable *Net worth* is only available every two waves in the NLSY79. For the years where it is not available, we use the value from the following wave.

[4] Our unemployment variable is BLS series id LNS14000000Q.

[5] Feng (2009) provides complementary evidence that hours in training from the NLSY contain no substantial information above that included in training incidence, something that is possibly due to the poor quality of this data, as reported here.

2.1 Facts about skill acquisition activities

Skill acquisition activities constitute a significant part of the workforce's time. Table 1 presents summary statistics of our main variables. As shown, 11% of the total quarter-periods in our sample were occupied by some type of training (6.5% of all periods) or schooling (4.9%). In addition, table 2 presents summary statistics of the time devoted to educational activities from the ATUS surveys. As shown in this table, the average working age individual spends approximately 12.4 hours per quarter in school related activities.

The NLSY79 data effectively covers every single training program in the waves we study, so underreporting due to survey design can be ruled out. Barron et al (1997), however, document that training incidence in the NLSY79 is lower than in other nationally representative surveys. Of these, the most closely comparable is the National Longitudinal Survey of the high school class of 1972, where training incidence is 19.7% in 1973. One possible source of underreporting is recall bias: the bias that may appear when individuals underreport the occurrence of distant events. To investigate the extent of underreporting due to such bias, we regressed training incidence on the distance between current quarter and the next interview date (a variable we label *Recall*). Using this estimate, we obtain a level of underreporting of 18.9%, implying an actual incidence of 8% [6]. We control for recall bias in all our results.

Table 3 disaggregates training into the different categories studied and presents additional statistics regarding the fraction of programs financed by the employer, the percentage of individuals that were employed when they took the training, and the percentage of individuals that held a college degree when they took the training. Regular training programs represent the most frequent type of training reported at 33.1% of all training reported, followed by *Other training*, a residual category, with 24.7%, and training related to the adoption of new technologies with 20.1%. Note that both the employed and the college educated are overrepresented among training recipients. The former comprise 81% of the sample, and 88.7% of

[6] To measure the extent of recall bias, we first estimate the model $Training = \beta_0 + \beta_1 Recall + \epsilon$, then the proportion of training programs that is underreported is $\frac{-\beta_1 \overline{Recall}}{\overline{Training} - \beta_1 \overline{Recall}}$, where overlined variables denote averages.

those enrolled in training. The latter comprise 19.8% of the sample, and 31.9% of training recipients. Moreover, note that those who enroll in training programs associated to technology adoption have both the highest educational attainment, and the highest likelihood of being financed by the firm.

A significant amount of training is funded by the employer, except for the category other, which contains training related to job seeking. In our sample, 76% of total training episodes were at least partially funded by the employer. We do not have data on the percentage of schooling episodes that are financed by the employer, but the data suggests it is lower: unemployed individuals attended school during 4.0% of the periods and received training during 3.9%. In contrast, employed individuals spent 5% of the same periods in schooling and 7% in training. Both training and schooling activities are carried out mostly by employed individuals. Of the total quarter periods occupied by schooling activities in our sample, 84% came from employed individuals. This number is 88.7% for training activities [7].

Regarding the behavior of these two types of skill acquisition activities along the life-cycle, our data shows significant variation. Figure 1 uses data from both the NLSY and the ATUS surveys to illustrate the life-cycle of training and schooling. The top panel in this figure shows the proportion of individuals of any given age who report having participated in a training program together with a cubic polynomial on age; the middle panel shows the proportion enrolled in school; and the bottom panel shows the average time devoted to education, as reported by ATUS respondents. While the proportion of people attending school and the time devoted to schooling clearly decline with age, the proportion of individuals that obtain training is steady at about 7.2% until approximately 33 years of age before starting to decrease. Recent anecdotal evidence suggests this turning point might be moving towards older stages in life (see, for example, Carey (2009)).

Finally, a first look at the cyclical behavior of our main series, aggregate training and schooling incidence, as well as the unemployment rate, is presented in Figure 2. Life cycle

[7] For individuals without a job we make no difference between those who are unemployed and those who are out of the labor force. We refer to both groups indistinctly as “unemployed”.

effects have been removed from training and schooling through linear regressions on a cubic polynomial of age. The series are seasonally adjusted using the Census Bureau X-12 ARIMA procedure. Two NBER recessions are present in the data: the first, from July 1990 to March 1991, is accompanied by very high unemployment rates, while the second, from March to November 2001, seems much milder.

As shown in the figure, schooling exhibits a clear countercyclical pattern. The correlation between the incidence of schooling and the unemployment rate is positive (0.54) and significant at the 1% level. Such a correlation corresponds closely with results in the literature based on college enrollment data, discussed in the introduction. With regards to training, in contrast, no obvious pattern emerges: the correlation with unemployment is small (.01) and not significant (p=.89) [8].

3 Methodology and Results

In defining a statistical model that captures the response of skill acquisition to macroeconomic conditions, we allow for the identification of different responses by employed and unemployed individuals. The incentives faced by both groups are in fact quite different. For the unemployed, there is significant uncertainty as to what types of skills will be most useful in their future jobs. For the employed, this uncertainty is greatly reduced and, in addition, the employer may have an interest in financing the acquisition of new skills. In order to deal with these differences, we consider a latent variable model where the effects of macroeconomic conditions on skill acquisition variables may depend on the employment status of the individual. The model can be described as follows:

$$I_{i,t}^{*j} = \beta_0^j + \beta_1^j unemp_t + \epsilon_{i,t}^j \quad (1)$$

[8] We have eliminated from Figure 2 the quarters constructed with less than 1000 observations, on the grounds that variance of these points will be larger and therefore they will be less informative. This eliminated year 1988 and the last 3 quarters of 2006 . The remaining data points are constructed using -except for one quarter - more than 7000 observations each.

$$I^j_{i,t} = 1_{[I^{*j}_{i,t} \geq 0]} \tag{2}$$

Where $I^{*j}_{i,t}$ is the latent variable for individual i at time t, $I^j_{i,t}$ is the incidence of the skill acquisition activity, and $unemp_t$ is the unemployment rate. The index j may take on the values $\{e, u\}$, depending on whether the individual is employed (e) or unemployed (u).

Let *not working* be an indicator for being unemployed. A general model of training that captures the differential effects of unemployment is then $I^*_{i,t} \equiv I^{*u}_{i,t} not\ working + I^{*e}_{i,t}(1 - not\ working)$, together with $I_{i,t} = 1_{[I^*_{i,t} \geq 0]}$. After substituting the expressions for I^{*e} and I^{*u} and rearranging terms, we obtain the following expression:

$$I^*_{i,t} = \beta^e_0 + \beta^e_1 unemp_t + (\beta^u_0 - \beta^e_0) not\ working_{i,t} + (\beta^u_1 - \beta^e_1) unemp_t \times not\ working_{i,t} + \epsilon_{i,t}. \tag{3}$$

Where $\epsilon \equiv \epsilon^e + not\ working(\epsilon^u - \epsilon^e)$. To this equation we add a vector X of control variables, and obtain our main econometric specification:

$$\begin{aligned} I^*_{i,t} &= \gamma_0 + \gamma_1 unemp_t + \gamma_2 not\ working_{i,t} + \gamma_3 unemp_t \times not\ working_{i,t} + \gamma_4' X_{i,t} + z_{i,t} \quad (4) \\ I_{i,t} &= 1_{[I^*_{i,t} \geq 0]} \end{aligned}$$

In the empirical implementation of this model, $I_{i,t}$ represents either the training status of individual i during quarter t (1 if in training and 0 otherwise) or her schooling status (1 if enrolled in school and 0 otherwise), and $X_{i,t}$ represents a vector of control variables that consists of a cubic expansion in age, seasonal dummies, and a variable measuring distance to the next interview date [9].

[9] The cubic polynomial in age is included to capture age effects. It is well known that separate age, time, and cohort effects cannot be statistically identified (see, e.g, the discussion in Hall *et al* (2007)). We have chosen to assume no cohort effects in the models without fixed effects. At the same time such effects vanish naturally in the FE models. Our models with quadratic age and time-varying covariates is then identified. The question that remains is whether the variation in age versus time is sufficient to allow for estimating precisely the effects. The problem we face is that the age variation is smaller than the time variation, so there is no single age category observed in every year. This constrains us to assume stationarity on aggregate training and schooling, the variables that are age-detrended. In simulations carried out to better understand this issue (not reported), we found that even though an age detrending procedure like ours tends to produce biased age estimates in the presence of a time trend, the coefficient on the variable of interest, in this case

We propose the following structure for the error term $z_{i,t}$, which should be general enough to discuss the main problems attached to identifying the parameters in (4):

$$z_{i,t} = v_i + q_t + \epsilon_{i,t} \tag{5}$$

This structure contains both an individual, time invariant effect (v_i), and a variable q_t that captures seasonal effects. Seasonal effects are dealt with by including quarterly dummies in all regressions. We also make the assumption that $\epsilon_{i,t}$ is i.i.d.

If the independence assumption on $\epsilon_{i,t}$ holds, we still have to consider the case that the individual effect v_i may be correlated with some of the regressors, and cause the coefficient on unemployment rate to be inconsistent. A classical example, that is relevant to our case, is that of unmeasured ability being correlated with the probability of being employed. In this case, we can identify the parameters of (4) by using the Conditional Maximum Likelihood (CML) Logit model. CML Logit has the advantage that it does not restrict the form of the correlation between the individual effect and the covariates. This advantage comes at the cost of intercepts, and therefore average marginal effects, being unidentified.

The case where the conditional independence assumption does not hold, including the case of serial correlation in $\epsilon_{i,t}$, has only recently been examined. Kwak and Wooldridge (2009) provide Monte Carlo evidence suggesting the CML Logit model is inconsistent in this case. An alternative is to impose a functional form for the dependence of v_i on the covariates, which leads to Correlated Random Effects models. We discuss the robustness of our main findings to using the CRE Probit model, and place the results in an appendix.

Let $P(I = 1|\mathbf{x}) = G(\gamma'\mathbf{x}) \equiv p(\mathbf{x})$ be the response probability associated with model 4, where $\mathbf{x}$ is the entire set of explanatory variables, and define $g(x) = \frac{dG(x)}{dx}$. Three effects are of particular interest. The first is the response of the skill acquisition variable to changes in

unemployment, was very precisely estimated.

the unemployment rate for the employed. This effect is

$$\frac{\partial p(\mathbf{x})}{\partial unemp}|_{not\ working=0} = g(\gamma^{'}\mathbf{x}|not\ working = 0)\gamma_1, \quad (6)$$

where $\gamma_1 = \beta_1^e$. The second is the equivalent effect for the unemployed, measured by

$$\frac{\partial p(\mathbf{x})}{\partial unemp}|_{not\ working=1} = g(\gamma^{'}\mathbf{x}|not\ working = 1)(\gamma_1 + \gamma_3). \quad (7)$$

Where $\gamma_1 + \gamma_3 = \beta_1^u$. Finally, to obtain the aggregate effect of unemployment on $p(\mathbf{x})$, while keeping the composition of the labor force constant, we take the derivative of $p(\mathbf{x})$ with respect to unemployment, and take the expectation with respect to *not working*:

$$E_{not\ working}\frac{\partial p(\mathbf{x})}{\partial unemp} = E_{not\ working}g(\gamma^{'}\mathbf{x}|not\ working)(\gamma_1 + \gamma_3 not\ working). \quad (8)$$

A discussion of the role that composition bias might play in our estimations is in order. Our discussion is based on Solon *et al* (1994), who examine composition bias in the measurement of the cyclicality of wages. We are interested in isolating the incentives to acquire skills along the cycle faced by employed and unemployed individuals, from changes in the composition of the labor force between these two groups. Let us return to the response probability associated to model (1). To simplify the exposition, we substitute in $p(\mathbf{x})$ the variable *not working* by its expected value conditional on the remaining covariates, θ. If we estimate the model $I^* = \eta_0 + \eta_1 unemp + error$, together with (2), the reduced form effect captured by the marginal effect $p(\mathbf{x})\eta_1$ would represent [10]:

$$\begin{aligned} E_{not\ working}\frac{\partial p(\mathbf{x})}{\partial unemp} &\simeq g(\gamma^{'}\mathbf{x}|\theta)(\beta_1^e + (\beta_1^u - \beta_1^e)\theta) \\ &+ g(\gamma^{'}\mathbf{x}|\theta)((((\beta_0^u - \beta_0^e) + (\beta_1^u - \beta_1^e)unemp)\frac{\partial \theta}{\partial unemp}) \end{aligned} \quad (9)$$

[10]This approximation allows for the use of calculus instead of finite differences deriving equation 9.

Where $g(\gamma'\mathbf{x}|\theta)$ is equal to $g(\gamma'\mathbf{x}) = p'(\mathbf{x})$ with *not working* substituted by θ.

We want to know the response of our measure of skill acquisition once we hold participation shares constant, but we must deal with the shares themselves having a defined cyclical behavior. The first term, equivalent to the expression in (8), is the statistic of interest. The last term represents the changes in skill acquisition that result from the changing composition of the labor force. Note that, if we disregard movements in and out of the labor force, we have $\frac{\partial\theta}{\partial unemp} = 1$. The sign of this term is that of the difference in the indexes $(\beta_0^u + \beta_1^u unemp) - (\beta_0^e + \beta_1^e unemp)$. In the data, this difference is negative in the case of training, so failing to control for differential responses of employed and unemployed individuals' training to macroeconomic conditions results in a procyclical bias.

The solution, then, is to keep the sample composition constant by following the same individuals as they go in and out of employment, and to allow for differential effects of the unemployment rate on the employed and the unemployed. It is worth noting that we must also use a complete sample (employed plus unemployed) when examining those types of training, such as training associated to obtaining a promotion, where the likelihood of obtaining training is in principle zero for the unemployed.

In what follows we show the results of estimating model (4) when using different types of skill acquisition as the dependent variable. We use a separate table to display the results for schooling, aggregate training, and each one of the training categories examined. For all regressions, we display the estimates of γ_1 to γ_3. We also include, at the bottom of each column, estimates of the marginal effect of the unemployment rate on the employed (expression 6); on the unemployed (expression 7); and the aggregate effect while holding constant the composition of the labor force (expression 8). In the Logit model, an expression for the marginal effect of x_i on the probability of success is $p(\overline{\mathbf{x}})(1 - p(\overline{\mathbf{x}}))\beta_i$, where $p(\overline{\mathbf{x}})$ is the response probability evaluated at the expected value of the covariates. Since CML Logit does not estimate the intercepts, we cannot use the sample counterpart $G(\hat{\gamma}'\hat{\overline{\mathbf{x}}})$, where hats denote sample moments, in the calculations. Instead, we replace $p(\overline{\mathbf{x}})$ by the sample average of the dependent variable, which in our case is always a proportion. Standard errors are computed using the delta method, and p values are reported below each marginal effect [11].

All tables have a similar structure. In the first column, we use the Logit model to establish the stylized facts at the aggregate level, while in the remaining columns we use Conditional Logit on different specifications of model (4) to identify the effects of interest.

We are interested in examining the roles of educational attainment, and of the source of financing -the firm versus the individual- in shaping the cyclicality of skill acquisition. In the case of educational attainment, adding *College* plus an interaction with unemployment would not be appropriate in the CML Logit regressions. Here, the effect of having a college degree would be identified from the same individual being observed first while going through college, and then after graduation. The time and resources devoted to attending school would then act as a confounding effect in this case. We then choose to present separate estimates for the two education groups. We follow a similar strategy to identify the cyclical behavior of firm versus self financed training programs [12].

3.1 Aggregate training and schooling

Table 4 shows the results of estimating equation (4) with aggregate training (*Training*) as the dependent variable. The aggregate series is acyclical for both the Logit and FE Logit-based marginal effects in columns 1 and 2. In both cases, training appears countercyclical for the unemployed, but acyclical for employed workers. For the unemployed, a one percentage point increase in unemployment increases probability of being in a training program by .3 percentage points in the pooled estimates, and .4 points in the FE estimates [13]. As expected,

[11]The marginal effect "at the mean" computed here is different from the average marginal effect,$E_j p(x_j)(1-p(x_j))\beta_i$, where j indexes individual observations.

[12]To see why it is not appropriate to add indicators for self financed and firm financed training -along with interactions with unemployment- to the right hand side of an equation, note that either *Firm financed* and *Self financed* predict training incidence perfectly. In a Conditional Logit framework, the coefficient associated to, say *Firm financed*, would capture the likelihood that a program is financed by the firm relative to the likelihood it is financed by other sources, but we are interested in this likelihood relative to the program not being financed by the firm.

[13]A Hausman test indeed rejects the null of no fixed effects against the alternative of random effects

both working and having a college degree are positively associated to a higher likelihood of training.

In columns 3 and 4, we estimate the model for employer financed programs (column 3), and self financed programs (column 4) separately. Employer financed programs are procyclical in the aggregate, driven by procyclical training by the employed. In contrast,self financed programs are countercyclical regardless of employment status. We next divide the sample between unskilled individuals without a college degree (column 5) and college educated individuals (column 6). The aggregate series for the unskilled, in column 5, is acyclical. In this educational category, training is countercyclical for the unemployed, but acyclical for the employed. For college educated individuals the series is procyclical, which is driven by the behavior of the employed.

The corresponding results for schooling are shown in table 5. The dependent variable is general schooling, including higher education (*School*). The Logit results, in column 1, show that schooling is countercyclical, and the response is common across employment status groups. These results are similar to those reported by Dellas and Sakellaris (2003), Dellas and Koubi (2003) and Betts and McFarland (1995), all of whom used pooled cross sectional data on school enrollments. Column 2 shows results for the FE estimation with unemployment, and column 3 adds *Not working* and its interaction with unemployment, but neither variable is significant. In the FE estimates of column 3, a 1 percentage point increase in the unemployment rate increases the odds of being in formal schooling by .6 percentage points.

Columns 4 and 5 restrict the sample to unskilled and skilled individuals respectively. In column 4, schooling again appears countercyclical. A one percentage point increase in aggregate unemployment increases the odds of being in formal education by .9 percentage points. In column 5, schooling appears acyclical.

Note that controlling for individual fixed effects (FE) increases the estimated effect of *Not working* in both tables, which is consistent with individual heterogeneity in a variable representing good job market traits, such as work ethics, ability, or effort. These traits are likely to be negatively correlated with being unemployed, and thus would bias downwards the coefficient on *Not working*. Even though the unemployment rate is exogenous to each individual, the correlation just described also has the effect of creating a countercyclical bias in the estimates on *Unemployment rate* (see, e.g., columns 1 vs. 2 in table 4). For this reason, in what follows we emphasize the results of the FE model.

As previously mentioned, we supplemented the results presented in Table 5 with an analysis of the cyclicality of time devoted to schooling, using data from the ATUS surveys. These surveys are a repeated cross section rather than a panel data, but they contain exact measures of the time spent in educational activities as well as other measures of demographic and educational characteristics. We conducted OLS and Tobit estimations using time devoted to educational activities as the dependent variable and the monthly unemployment rate as the main explanatory variable. The results obtained indicate that time devoted to schooling is countercyclical and that there are significant differences between the reactions of skilled and unskilled individuals. The analysis of the ATUS data then confirms the results presented in Table 5; they are presented in detail in the web appendix.

Finally, we test the robustness of these results under two scenarios. First, since the unemployment statistics do not take into consideration discouraged workers who stop actively looking for a job, it is possible that these estimates overstate the effects of unemployment on skill acquisition activities. We tested for the presence of a discouraged worker effect by reproducing tables 4 and 5, using the rate of those not working over the population aged 19 to 65 instead of the unemployment rate as our cycle indicator. The second scenario is the violation of the independence assumption for the errors, including the possibility of serial correlation. As a test of robustness in this case we reproduce the results in this section using the correlated random effects probit model. The results obtained in both cases are quite similar to those presented in tables 4 and 5, and can be consulted in a web appendix that accompanies this paper.

The results so far show a marked countercyclical pattern for schooling, while the case for countercyclical training is more qualified. As discussed in the introduction, however, aggregating training masks important differences in the behavior of training programs. While for some types of training the only relevant cost is the alternative use of time, other types of training are complements to activities that have a defined cyclical pattern, such as job creation or technology adoption. We expect this complementarity to affect the optimal timing of investment in the relevant skills.

3.2 A decomposition of training programs

In what follows we present a disaggregate analysis of training by dividing it into five types, as discussed above: training related to promotions, training related to technology adoption, regular training programs, training needed as workers begin a new job, and a residual category (*Other training*).

3.2.1 Training related to promotions

We begin by examining the behavior of training programs related to promotions and job advancement. A number of contributions, including Prendergast (1993) and Gibbons and Waldman (2004), link certain types of skill acquisition to promotions within a firm, but we are unaware that any has definite implications for the cyclical behavior of this type of training. There is evidence that promotions are procyclical (Devereux (2002)); but it might be optimal for individuals and firms to engage in such training activities in recessions, in anticipation of future promotion opportunities.

In particular, we should expect that firms and individuals take decisions on this type of training by weighting the (procyclical) opportunity costs in terms of foregone wages versus its (also procyclical) expected returns. To quantify these returns, we would need to understand the nature of promotions within firms. In one scenario, training provides a signal of the workers' unobserved ability, and having the relevant type of training increases workers' chances of being promoted. In this case, even though promotions are procyclical, there is large scope for intertemporal substitution in training by workers. In a second scenario, ability can be observed, and promotions are awarded to high ability individuals, who then acquire the necessary new skills through training. Here, training should follow promotions closely.

Table 6 displays the results for training related to promotions. The first two columns show evidence on unconditional and conditional Logit estimates. In column 1, training is found to be acyclical both for the aggregate sample and employed workers. For the unemployed, training is found to be countercyclical. About 9% of individuals receiving this type of training are unemployed. We speculate that a number of unemployed trainees anticipate obtaining a promotion once they get a job, and therefore include themselves in this category. In column 2, the FE estimates provide evidence that the aggregate series is procyclical, driven by the behavior of employed workers.

When running separate estimations for firm financed and self financed programs, in columns 3 and 4, we obtain clear results: this type of training is procyclical in the aggregate in employer-financed programs; and countercyclical for programs that are self financed. In both cases, the results are driven by the behavior of the employed. When we separate the sample by education groups in columns 5 and 6, we find that for unskilled individuals the aggregate series is acyclical. For skilled individuals, however, the series is strongly procyclical. This behavior is, once again, driven by procyclical skill acquisition of the employed.

Our evidence then points to training by the employed, who comprise 91% of trainees, as being clearly procyclical, following the cyclical behavior of promotions. A notable exception is that of self financed training programs, which are countercyclical. In our sample, however, employer-financed programs constitute the bulk of promotions-related training: 81% and 88% of promotions-related training taken by low and high skilled employees respectively are employer-financed, while only 13% and 14% respectively are self financed.

3.2.2 Training related to Technology adoption

We next turn to training programs related to technology adoption by firms. As in the previous case, it is not clear what the cyclical behavior of this type of training should be. Authors like Jovanovic (2006), and Helpman and Rangel (1999), associate the incidence of training programs with the adoption of new productive technologies by the firm. In Jovanovic's model, if the new technology adopted constitutes a good fit for the worker's existing skills, the firm decides not to invest in any further training. In a similar manner, if the new technology adopted constitutes a poor fit for the worker's existing skills, the firm decides to invest in training. Since technologies that are well suited for workers are more productive, training is countercyclical in his model. In turn, Helpman and Rangel (1999) make a distinction between technological improvements that require new training investments and technological improvements that substitute human capital and tend to diminish the need for training. In their model, training can be procyclical or countercyclical, depending on the type of technological shock experienced.

With regards to the timing of technological innovations itself, Comin (2009) documents the rates of adoption in a sample of 22 technologies and finds that these rates increase with output growth. Thus, as long as training is triggered by technological innovation, Comin's results suggest that training should be procyclical.

The results regarding training linked to technology adoption are shown in table 7. Columns 1 and 2 show the results when estimating unconditional and conditional Logit models, respectively. The aggregate series appears acyclical in the unconditional model of column 1, but it is countercyclical for the unemployed. About 6% of those enrolled in this type of training are unemployed. We again speculate that some unemployed individuals report enrolling into training in response to what they perceive as generalized technical change in the economy. In the FE model of column 2, training appears procyclical, and the effect is driven by employed workers.

In columns 3 and 4 we present the results for employer financed training and self financed training, respectively. As with the FE estimates of column 2, firm financed training is procyclical in the aggregate and for the employed (column 3). Self financed training, by contrast, is acyclical, as none of the marginal effects is significantly different from zero. When we restrict the sample to low skilled individuals, in column 5, we obtain again a pattern similar to that with the unrestricted sample (column 2): the aggregate series is strongly procyclical, driven by procyclical training by the employed. In contrast, the results for college graduates, in column 5, show no defined cyclical pattern.

We thus obtain evidence that workers engage in procyclical training in response to technical change, and that most of this response is driven by employer-financed programs directed to employed, unskilled individuals. These findings are compatible with the strong evidence on procyclical technology adoption presented in Comin (2009), and with the theoretical arguments in Helpman and Rangel (1999) for the case of technological investments that require workers to be trained. At the same time, our findings are difficult to reconcile with Schumpeterian models where technology adoption and the training related to it are associated with economic downturns [14].

One remaining question is why skill acquisition seems acyclical for skilled individuals, who are possibly the ones who have benefited the most from technical change in the period examined. We believe that the distinction between embodied and disembodied technology might provide a solution to this apparent conflict: the evidence in Comin (2009) refers to technologies embodied in capital goods, but technical progress occurs also through the adoption of disembodied, or "soft" technologies, such as new human resource practices, just in time practices, and so on, that are intensive in skilled labor. We are however unaware of any evidence regarding the cyclicality of disembodied technology adoption.

[14] Admittedly, our analysis does not consider the possibility that firms develop multi year plans for technology adoption, in which case the timing of adoption decisions and training may not coincide.

3.2.3 Regular training programs

We continue with the analysis of regular training programs. The description given to regular training in the survey question requires that it serves to "maintain" or "upgrade" skills. In order to learn more about the types of training that fall into this category, we used a complementary classification of training available in some waves of the NLSY79; which provides information regarding the way in which training was delivered. According to this classification, 76% of regular training programs were delivered through classroom instruction (the largest of any training category). We interpret this admittedly incomplete description as an indication that regular training programs are deliver the type of skills that could also be delivered, for instance, in a two year college.

If the interpretation is correct, we would then expect regular training to be countercyclical; since the opportunity cost of time is lower in recessions. Models in which the opportunity cost of time leads to countercyclical training include DeJong and Ingram (2001), who derive its equilibrium behavior by treating the observations on skill acquisition hours as parameters to be estimated. This result also appears in Kim and Lee (2007), who explore the bias in the estimation of the elasticity of intertemporal substitution that arises from omitting training hours in a standard Real Business Cycle (RBC) model; and in Perli and Sakellaris (2007), who show that including general training as a separate production sector in an RBC model improves its propagation properties.

The results are shown in table 8. We obtain a consistent pattern of procyclical training incidence for employed individuals, and acyclical incidence for the unemployed. The aggregate series is procyclical in all regressions with the only exception of self financed programs in column 4, where training appears acyclical.

3.2.4 Training related to a new job

We now examine the behavior of training programs that are needed as workers begin a new job. Most individuals enrolled in such programs are employed (85%), but a significant proportion are unemployed, and in transition to a new job. This is the type of investment studied by Fukao and Otaki (1993). In their paper, they show that differences in the in the costs of hiring, given in particular by training costs, can explain differences in the volatility of hours, wages, and employment between the U.S., Japan, and the U.K. For their argument to hold, this type of training must also be procyclical. In our data, job creation is weakly procyclical, with a correlation between the occurrence of beginning a new job and the unemployment rate of -.01 ($p = .00$). Thus, we expect a similar (procyclical) behavior for training related to job creation.

Table 9 shows the results regarding the cyclicality of this type of training. As expected, the Logit estimates in column 1, as well as the conditional Logit estimates in column 2 point to *Training for new job* being procyclical, and the effect is driven by procyclical training by the employed. A one percentage point increase in the unemployment rate decreases the odds of participating in training by .02 and .2 percentage points in the Logit and conditional Logit estimates, respectively. The estimates for firm financed training, in column 3, display a similar pattern -but here the effect is common across employment groups- as do those for unskilled individuals, in column 5. Both training programs that are self financed (column 4), and training for skilled individuals (column 6), are acyclical.

Our results then mostly validate the assumption of Fukao and Otaki (1993) regarding the cyclicality of training related to job creation. They are also in accordance to the empirical findings of King and Sweetman (2002). While King and Sweetman (2002) focus on workers who leave their jobs in order to return to school, we focus on workers who obtain the training necessary to begin a new job. Both phenomena are procyclical.

3.2.5 Other training programs

Finally, we comment on the results of our residual category, Other training. From 1994 to 2006, this category branched out. Even though we maintained the aggregation pre-1994, this branching out gives us clues as to the type of training programs in this category. The new categories are “The training was necessary for a license or a certificate” (55% of training programs formerly under “Other”), “The training was associated with looking for a new job” (19%) and “Other” (27%).

Despite the heterogeneous composition of the category, the results are not unfamiliar. Columns 1 and 2 show a common pattern of procyclical aggregate incidence, but (marginally) acyclical incidence for the unemployed. When we estimate the model using employer financed training, in column 3, we find that this type of training is procyclical for the employed only. Self financed programs, by contrast, show no defined cyclical behavior. This result is found again in column 5 for unskilled individuals. Finally, column 6 show the results for college graduates. Training is procyclical in this case, again driven by the behavior of the employed.

3.3 The role of credit constraints

We now turn to the analysis of the role that credit constraints may play in shaping the cyclicality of training. Credit constraints are important in this context because, while it could be optimal for many individuals to engage in countercyclical skill acquisition, the inability to obtain financing in recessions may distort this decision towards acquiring skills procyclically. This argument was first developed and explored empirically by Sakellaris and Spilimbergo (2000), using flows of international students to US colleges.

In our case, note that a downturn would affect the ability of both the firm and the individual to finance training and schooling. To examine the role that credit constraints plays in shaping the cyclicality of skill acquisition, we use two variables that represent ability to finance for firms and individuals respectively. The first, *Establishment size*, reflects the ability of larger employers to access capital markets in recessions. The second, *Net worth*, intends to capture the ability of individuals to do the same.

Table 11 shows the results of adding these two variables, and their interactions with unemployment, to the baseline results in table 4. Note that none of the financing variables are significant in the first two columns, with Logit and CML Logit using *Training* as the dependent variable. When we use firm financed and self financed training, in columns 3 an 4, the interaction of *Net worth* with *Unemployment rate* is significant and has the predicted sign: wealthier individuals, who presumably do not face credit constraints, show a stronger countercyclical behavior of skill acquisition. Even for individuals in the highest decile of the wealth distribution, however, the effect of ability to finance is not large enough to make firm financed training countercyclical (the coefficient is negative with a p value of .02).

Finally, in columns 6 and 7 we divide the sample between Skilled (col 5) and Unskilled individuals (col 6). Here, it is establishment size, as opposed to net worth, that shows explanatory power. In the case of skilled individuals, the interaction of this variable with unemployment has the expected sign. For the unskilled, however, working in larger establishments seem to make it less likely that they will engage in training in recessions, but the effect is, again, small. For employed individuals in the highest decile of establishment sizes, the response of training to unemployment is still not different from zero (p=.64).

The results for schooling, which are omitted, show very limited evidence that firm size has an effect on the cyclical properties of this variable, and no evidence that net worth has any effect. We find, in summary, clear effects of financing constraints on the cyclical properties of training alone. These effects, however are small in magnitude and do not modify the qualitative results found in previous sections.

4 Conclusion

We provide novel evidence regarding the cyclicality of skill acquisition activities via both formal schooling and on-the-job training. Our results indicate that both the incidence of schooling and the time devoted to schooling are strongly countercyclical. These results coincide with the previous literature that studied the cyclicality of school enrollment and attendance in the USA.

Our results also indicate that while aggregate training seems acyclical, most training categories are procyclical instead.Three recurrent findings cut across the analysis of different types of skill acquisition activities: first, that employer-financed programs tend to be procyclical, while programs not financed by the employer tend to be countercyclical. Second, that investments by skilled individuals and unskilled individuals differ across training categories, although no clear pattern emerges. And third, that training is more procyclical for the employed than for the unemployed. Finally, we identify a quantitatively limited role for credit constraints in shaping the cyclical properties of training alone. By providing a disaggregate analysis of human capital acquisition along the cycle, the paper provides previously unavailable guidelines for theoretical applications.

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Table 1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Training	0.065	0.247	0	1	567622
Training for promotion	0.009	0.096	0	1	475390
Training required to adopt new methods	0.012	0.11	0	1	475390
Regular training	0.02	0.14	0	1	475390
Training for new job	0.004	0.064	0	1	475390
Other training	0.015	0.122	0	1	475390
Unemployment rate	5.556	0.950	3.9	7.600	567622
College	0.198	0.398	0	1	567622
School	0.049	0.217	0	1	567622
Firm financed	0.046	0.21	0	1	567601
Self financed	0.01	0.098	0	1	567572
Age	34.944	5.528	24	49	567622
Not working	0.191	0.393	0	1	519925
Net worth	0.082	0.208	-1.06	1.778	515710
Establishment size	0.376	2.013	0	99	507100

Table 2: Quarterly hours in schooling activities

	Age group						
	19 to 24	**25 to 29**	**30 to 34**	**35 to 39**	**40 to 44**	**45 to 49**	**Total**
Education							
Less than college	66.7	23.7	13.9	8.7	9.3	7.5	19.6
College	74.8	35.4	21.5	11.4	9.8	9.2	17.3
Total	67.5	27.3	16.7	9.8	9.5	8.1	18.8
Gender							
Male	65.8	25.8	14.6	6.4	6.3	5.8	16.1
Female	68.9	28.4	18.2	12.5	12.2	10.0	21.0
Total	67.5	27.3	16.7	9.8	9.5	8.1	18.8

Source: ATUS

Table 3: Types of training

Reason	**Proportion financed by employer**	**Proportion with college degree**	**Proportion employed**	**Proportion of total training**
Training for promotions	.821	.242	.916	.154
Training for technology adoption	.92	.393	.941	.201
Regular training	.917	.363	.927	.331
Training for new job	.818	.284	.848	.067
Other training	.379	.258	.783	.247
Training	.763	.319	.887	1

Table 4: Aggregate training incidence

	Pooled	Pooled-FE	Firm-FE	Self-FE	Unsk-FE	Skilled-FE
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment rate	-.002	-.01	-.02	.06	-.001	-.03
	(.007)	(.008)	(.009)***	(.02)***	(.01)	(.01)**
Not working	-.99	-.39	-.19	-.45	-.33	-.45
	(.10)***	(.11)***	(.16)	(.25)*	(.12)***	(.28)
Not working× Unemployment rate	.08	.07	.05	.07	.06	.09
	(.02)***	(.02)***	(.03)	(.04)	(.02)***	(.05)*
College	.59					
	(.01)***					
Observations	519925	327600	260721	81871	243946	79865
Marginal effect of unemployment						
Employed	-.0001	-.001	-.002	.004	-.000092	-.004
	[.75]	[.15]	[.00]	[.02]	[.91]	[.00]
Unemployed	.003	.004	.001	.007	.004	.005
	[.00]	[.00]	[.44]	[.00]	[.00]	[.23]
Aggregate	.0005	-.0002	-.002	.004	.0006	-.003
	[.26]	[.75]	[.01]	[.00]	[.43]	[.03]

Dependent variable: *Training* (cols. 1,2,5,6), *Firm financed* (col. 3), *Self financed* (col. 4)
Vars. not shown: age, age sq, age cb, Recall, quarter dummies
Standard errors in parentheses; p-values in square brackets
*** significant at 1%,** significant at 5%,* significant at 10%

Table 5: Schooling incidence

	Pooled	Pooled-FE	Pooled-FE2	Unsk-FE	Skilled-FE
	(1)	(2)	(3)	(4)	(5)
Unemployment rate	.05	.05	.05	.07	-.01
	(.008)***	(.009)***	(.01)***	(.01)***	(.02)
Not working	-.11		-.09	-.24	-.40
	(.10)		(.12)	(.14)*	(.28)
Not working×	-.002		.003	.03	.07
Unemployment rate	(.02)		(.02)	(.02)	(.05)
College	.76				
	(.01)***				
Observations	519925	190293	174247	119607	50068
Marginal effect					
of unemployment					
Employed	.002		.006	.008	-.002
	[.00]		[.00]	[.00]	[.38]
Unemployed	.002		.006	.01	.008
	[.02]		[.01]	[.00]	[.27]
Aggregate	.002	.007	.006	.009	-.001
	[.00]	[.00]	[.00]	[.00]	[.63]

Dependent variable: *School*
Vars. not shown: age, age sq, age cb, Recall, quarter dummies
Standard errors in parentheses; p-values in square brackets
*** significant at 1%,** significant at 5%,* significant at 10%

Table 6: Training related to promotions

	Pooled	Pooled-FE	Firm-FE	Self-FE	Unsk-FE	Skilled-FE
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment rate	-.001	-.06	-.11	.31	-.04	-.15
	(.02)	(.03)**	(.03)***	(.07)***	(.03)	(.05)***
Not working	-1.76	-.69	-.62	-.46	-.15	-3.90
	(.32)***	(.34)**	(.41)	(.90)	(.36)	(1.11)***
Not working×	.15	.11	.12	.05	.02	.65
Unemployment rate	(.05)***	(.06)*	(.07)*	(.15)	(.06)	(.18)***
College	.18					
	(.04)***					
Observations	442380	66470	57531	8159	50510	14563
Marginal effect						
of unemployment						
Employed	-.0000126	-.003	-.006	.02	-.002	-.009
	[.95]	[.00]	[.00]	[.09]	[.09]	[.00]
Unemployed	.0005	.003	.0003	.02	-.001	.03
	[.03]	[.4]	[.94]	[.12]	[.75]	[.04]
Aggregate	.0000924	-.003	-.006	.02	-.002	-.008
	[.62]	[.00]	[.00]	[.08]	[.11]	[.00]

Dependent variable: *Training for promotions* (cols. 1,2,5,6), *Training for promotions*×*Firm financed* (col. 3), *Training for promotions*×*Self financed* (col. 4).
Vars. not shown: age, age sq, age cb, Recall, quarter dummies
Standard errors in parentheses; p-values in square brackets
*** significant at 1%,** significant at 5%,* significant at 10%

Table 7: Training related to technology adoption

	Pooled	Pooled-FE	Firm-FE	Self-FE	Unsk-FE	Skilled-FE
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment rate	.01	-.05	-.06	.04	-.08	.02
	(.02)	(.02)**	(.02)***	(.08)	(.03)***	(.03)
Not working	-1.83	-.35	-.23	-1.57	-.19	-.85
	(.32)***	(.34)	(.37)	(.99)	(.40)	(.66)
Not working×	.11	.07	.05	.30	.04	.15
Unemployment rate	(.06)**	(.06)	(.06)	(.16)*	(.07)	(.11)
College	.87					
	(.03)***					
Observations	442380	95202	88672	8690	59924	33319
Marginal effect						
of unemployment						
Employed	.0001	-.003	-.003	.002	-.004	.001
	[.55]	[.00]	[.00]	[.67]	[.00]	[.62]
Unemployed	.0005	.0008	-.0006	.02	-.002	.008
	[.05]	[.78]	[.82]	[.18]	[.57]	[.18]
Aggregate	.0002	-.003	-.003	.003	-.004	.001
	[.34]	[.00]	[.00]	[.49]	[.00]	[.51]

Dependent variable: *Training for technology adoption* (cols. 1,2,5,6), *Training for technology adoption*× *Firm financed* (col. 3), *Training for technology adoption*×*Self financed* (col. 4).
Vars. not shown: age, age sq, age cb, Recall, quarter dummies
Standard errors in parentheses; p-values in square brackets
*** significant at 1%,** significant at 5%,* significant at 10%

Table 8: Regular training programs

	Pooled	Pooled-FE	Firm-FE	Self-FE	Unsk-FE	Skilled-FE
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment rate	-.03	-.10	-.10	-.07	-.10	-.12
	(.01)**	(.02)***	(.02)***	(.06)	(.02)***	(.03)***
Not working	-1.42	-.30	.007	-.64	-.51	.04
	(.22)***	(.24)	(.28)	(.76)	(.28)*	(.48)
Not working×	.07	.06	-.002	.14	.08	.02
Unemployment rate	(.04)*	(.04)	(.05)	(.13)	(.05)*	(.08)
College	.77					
	(.02)***					
Observations	442380	126811	116770	10590	82843	41740
Marginal effect						
of unemployment						
Employed	-.0006	-.007	-.007	-.004	-.006	-.008
	[.01]	[.00]	[.00]	[.06]	[.00]	[.00]
Unemployed	.0003	-.002	-.005	.004	-.0007	-.007
	[.28]	[.27]	[.02]	[.63]	[.8]	[.22]
Aggregate	-.0004	-.006	-.007	-.003	-.006	-.008
	[.05]	[.00]	[.00]	[.19]	[.00]	[.00]

Dependent variables: *Regular training* (cols. 1,2,5,6), *Regular training*×*Firm financed* (col. 3), *Regular training*×*Self financed* (col. 4).
Vars. not shown: age, age sq, age cb, Recall, quarter dummies
Standard errors in parentheses; p-values in square brackets
*** significant at 1%,** significant at 5%,* significant at 10%

Table 9: Training related to beginning a new job

	Pooled	Pooled-FE	Firm-FE	Self-FE	Unsk-FE	Skilled-FE
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment rate	-.05	-.07	-.11	-.01	-.08	-.005
	(.03)*	(.04)*	(.04)***	(.11)	(.04)*	(.07)
Not working	-.63	-.19	.16	-2.62	-.34	.15
	(.36)*	(.38)	(.44)	(1.13)**	(.43)	(.84)
Not working×	.07	.04	-.007	.39	.06	.02
Unemployment rate	(.06)	(.06)	(.07)	(.18)**	(.07)	(.14)
College	.45					
	(.05)***					
Observations	442380	44686	38638	5241	32519	11184
Marginal effect						
of unemployment						
Employed	-.0002	-.003	-.004	-.0005	-.003	-.0002
	[.02]	[.00]	[.00]	[.91]	[.00]	[.95]
Unemployed	.0000641	-.001	-.004	.02	-.001	.0006
	[.74]	[.62]	[.08]	[.27]	[.68]	[.93]
Aggregate	-.0002	-.002	-.004	.003	-.003	-.0001
	[.08]	[.01]	[.00]	[.63]	[.00]	[.97]

Dependent variable: *Training for new job* (cols. 1,2,5,6), *Training for new job×Firm financed* (col. 3), *Training for new job×Self financed* (col. 4).
Vars. not shown: age, age sq, age cb, Recall, quarter dummies
Standard errors in parentheses; p-values in square brackets
*** significant at 1%,** significant at 5%,* significant at 10%

Table 10: Other training programs

	Pooled	Pooled-FE	Firm-FE	Self-FE	Unsk-FE	Skilled-FE
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment rate	-.07	-.06	-.10	.05	-.02	-.17
	(.02)***	(.02)***	(.03)***	(.03)	(.02)	(.04)***
Not working	-.42	-.61	-.12	-.43	-.35	-.48
	(.16)**	(.18)***	(.44)	(.35)	(.20)*	(.53)
Not working× Unemployment rate	.12	.12	.06	.06	.07	.09
	(.03)***	(.03)***	(.08)	(.06)	(.03)**	(.10)
College	.35					
	(.03)***					
Observations	442380	103284	47815	36176	76790	24583
Marginal effect of unemployment						
Employed	-.0009	-.004	-.005	.003	-.001	-.01
	[.00]	[.00]	[.00]	[.23]	[.33]	[.00]
Unemployed	.0008	.004	-.002	.006	.003	-.005
	[.1]	[.1]	[.63]	[.13]	[.17]	[.38]
Aggregate	-.0006	-.002	-.005	.003	-.0001	-.01
	[.00]	[.02]	[.00]	[.15]	[.91]	[.00]

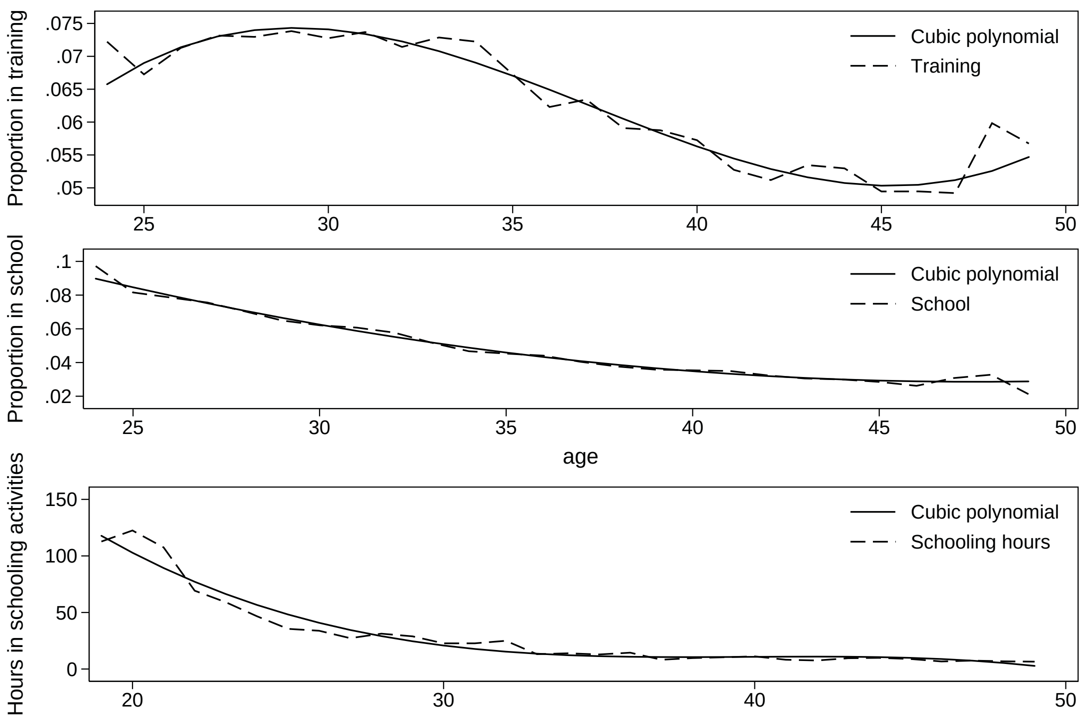
Dependent variable: *Other training* (cols. 1,2,5,6), *Other training*×*Firm financed* (col. 3), *Other training*×*Self financed* (col. 4).
Vars. not shown: age, age sq, age cb, Recall, quarter dummies
Standard errors in parentheses; p-values in square brackets
*** significant at 1%,** significant at 5%,* significant at 10%

Table 11: The role of credit constraints: Aggregate training

	Pooled	Pooled-FE	Firm-FE	Self-FE	Unsk-FE	Skilled-FE
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment rate	.002	-.01	-.04	.07	.009	-.07
	(.009)	(.01)	(.01)***	(.03)***	(.01)	(.02)***
Not working	-.97	-.39	-.12	-.52	-.30	-.53
	(.11)***	(.12)***	(.17)	(.27)*	(.13)**	(.29)*
Not working×	.08	.07	.04	.07	.05	.11
Unemployment rate	(.02)***	(.02)***	(.03)	(.05)	(.02)**	(.05)**
Establishment size	.01	-.009	-.03	-.03	.04	-.08
	(.01)	(.02)	(.02)	(.05)	(.02)*	(.03)***
Unemployment rate×	.001	.001	.004	.007	-.009	.02
Establishment size	(.002)	(.003)	(.003)	(.008)	(.004)**	(.005)***
Net worth	.02	-.18	-.75	-1.09	-.32	-.37
	(.16)	(.20)	(.23)***	(.52)**	(.33)	(.26)
Unemployment rate×	.02	.02	.11	.16	.05	.05
Net worth	(.03)	(.04)	(.04)**	(.10)*	(.06)	(.05)
College	.56					
	(.01)***					
Obs.	417761	251540	197279	56981	187404	61158

Dependent variable: *Training* (cols. 1,2,5,6), *Firm financed* (col. 3), *Self financed* (col. 4)
Vars. not shown: age, age sq, age cb, Recall, quarter dummies
Standard errors in parentheses
*** significant at 1%,** significant at 5%,* significant at 10%

Figure 1: Life cycle effects in training and schooling



Sources: NLSY79 (top and middle panels), ATUS (bottom panel)

Figure 2: Age detrended training and unemployment: 1988-2006