Destruction of Cognitive and Noncognitive Skills in Adulthood

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Abstract

The formation of cognitive and noncognitive skills in adulthood has been scarcely studied in the economic and psychological literature. The lack of studies addressing this production process is explained in part by past results pointing to the stabilization of skills at the last years of adolescence. However, recent evidence supports the malleability of skills during adulthood. Following the latter strand of the literature, we identify events associated with the destruction of skills during this age. Furthermore, we evaluate the effects of the skills dynamics on labor market outcomes such as wages and employability. We extend the model of formation of skills (Cunha and others , 2010) and estimate it in its reduced form using the 1970 British Cohort Study. Results show that three or more months of unemployment are related to a decrease of 0.15 SD of skills level.

1 Introduction

The study of human capital and its relation to aggregate and individual productivity has been fundamental on the policy making process focused on the development of society (see, for example, Heckman, 2000). It is also known that the main investments on human capital are numbered by a set of different educational inputs. Departing from childhood, individuals are influenced by their familiar and social background, in addition to the educational institution they attend. Later, they continue their skills formation process through tertiary education or vocational training. Those who finally enter to the labor market are constantly enrolled in continuous training processes, some more job-specific than others.

Although every individual has received a minimum level of education (in any of its forms), the quantity and quality of this input may be heterogeneous. The degree of this heterogeneity can be explained, from the supply side, by the limitations on some educational markets due to asymmetric information, liquidity constraints, transportation costs, among others. From the demand side, the analysis may seem more complex since is necessary to identify the decision-making process in labor and schooling (Ben-Porath, 1967). For instance, a graduate from basic education has to choose to continue his formation through the higher education sector or enter directly to labor market; his decision finally lies on what he considers as more profitable.

This set of decisions is relevant because there is supporting evidence in favor of the determination of wages conditional on education level, a result that follows the theoretical model proposed by Becker (1964). In consequence, the analysis of schooling and skills formation is closely related to the study of wage distribution. Decades ago, Becker and Chiswick (1966) shed light on the importance of this relationship, while Mincer (1958, 1974) established a structural relation among years of schooling, labor experience and wages. The reduced form of this specification has been extensively used in the study of returns to education. An extense and recent revision of this literature was developed by Heckman, Lochner and Todd (2006).

The development of this strand of the literature brought more attention to the decomposition of the causal relation between education inputs and wages. Currently, evidence is not limited to the effect of schooling years on wages. A new approach adopted last decade focused on the effect of cognitive skills on wages (Carneiro and others, 2003; Hansen and others, 2004). However, more recently, Heckman and others (2006) pointed out the relationship between noncognitive skills and wages. Even, researchers analyzed the importance of these skills in a large range of social behaviors (Almlund and others, 2011; Borghans and others, 2008; Heckman and Kautz, 2012).

The skill formation and distribution gained special attention from policymaking actors and academia given its relevance on human capital formation and complex identification based on observable measures. Cunha and Heckman (2007) and Cunha, Heckman and Schennach (2010) have elaborated the more comprehensive analysis of the skill formation technology from childhood through adolescence. Furthermore, they introduced the estimation of optimal levels of investments for each type of skill and the trade-off between them in terms of timing (childhood or adolescence) and type of skill.

Skills dynamics on adulthood is a phenomenon much less studied. This lack of attention may be explained, in part, for its apparent minor relevance for public policy because of the diminishing marginal returns, but still significant, of schooling activities conditional on age (Heckman and others, 2015). On the other hand, it is argued that during adulthood skills experience a stabilization stage, so that they are no more longer malleable reached certain age (Jencks, 1972: Herrnstein and Murray, 1994). However, this theory is obsolete given the findings of new studies demonstrating the malleability of skills in years posterior to adolescence (OECD, 2004; Kautz and others, 2014; Heckman and others, 2015). Furthermore, the development of skills on working age are strongly supported by the seminal human capital models proposed by Becker (1964).

Although some efforts have been made towards the study of skills, especially in young ages, there is a relation that has not been studied by economic literature: skills destruction in adulthood. This paper focuses in the identification of events during adulthood that caused a reduction in the skills level. The relevance of such a study relies on the relationship between the skills decrease and labor market indicators. Behrman and others (2014) tried to identify this effect using a limited longitudinal dataset of Guatemala. They evaluate the effect of unemployment and migration on skills level. However, their analysis is restricted to a specific vocabulary test instead of the level of latent skills. Borghans and others (2008) analyzed the skills evolution during adulthood from a qualitative approach focused mainly on the study of standardized tests. In this study, along with Gottschalk (2005), it was found that skills can change in adulthood, but not in a permanent way. The main reasons for these changes are associated to the environment or socioeconomic background. They conclude that while stability of skills is an analytical convenient assumption it is a result that is not supported empirically.

The document is structured as follows. Section 2 introduces the model of skills formation on adulthood, as an extension to the proposal of Cunha and others (2010). Section 3 describes the data and estimation strategy. Section 5 presents the results and Section 6 concludes.

2   The Model

The model has two periods $t \in \{T+1, T+2\}$ preceded by T childhood periods denoted as $\tau \in \{1, ..., T\}$. The first period of adulthood denote the state where the individual is a youth adult, while the second is when he is mature. The labor market outcomes are Q_{jt} where j index the individuals outcomes variables. Thereby, this indicators depend on the level of the cognitive θ_t^C, and noncognitive skills θ_t^N in period t. Skills are indexed by $k \in \{C, N\}$. Besides, it is assumed the conditioning of control variables X_t. Hence,

$$Q_{jt} = g_j(\theta_t^C, \theta_t^N), \quad j \in \{1, ..., J\}, t \in \{T+1, T+2\} \tag{1}$$

Skills follow an independent production function[1]. During the first years, $\tau \in \{1, ..., T\}$[2], the skills stock, $\theta_\tau = (\theta_\tau^C, \theta_\tau^N)$, is determined by the initial conditions given at birth, $\theta_\tau = (\theta_\tau^C, \theta_\tau^N)$ with $\tau = 1$.

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[1]Cunha and others (2010) used dependent production functions to analyze complementarity and substitution of both type of skills. Our objective is distinct, so we follow the specification developed by Cunha and Heckman (2007).

[2]T denotes the last period of childhood before entering to the two periods of adulthood $t \in \{1, 2\}$.

Furthermore, skills are determined by familiar background and genetic antecedents denoted by $\theta_P = (\theta_P^C, \theta_P^N)$. Finally, they are function of the investment level in each activity, I_τ^k. To sum up, the technology of skill production during childhood can be defined as a function of parents abilities, the initial skill *stock*, the investment in each ability and the *shock* on the skill accumulation in period τ, η_τ^k, so

$$\theta_{\tau+1}^k = f^k(\theta_\tau^k, I_\tau^k, \theta_P^k, \eta_\tau^k)., \quad \tau \in \{1, ..., T\}, k \in \{C, N\} \tag{2}$$

Following the objective, we sum the process of skill accumulation during childhood, recursively, for both periods of adulthood $t \in \{T+1, T+2\}$ as

$$\theta_{t+1}^k = \phi^k(\theta_1^k, I_t^k, \theta_P^k, \eta_t^k), \quad t \in \{T+1, T+2\}, k \in \{C, N\} \tag{3}$$

Therefore, we extend the model proposed by Cunha, Heckman and Schenach (2010) by relaxing the stability assumption beginning adulthood: $\theta_T^k = \theta_s^k \; \forall \; s > T$. On the other hand, we permit $\theta_T^k \neq \theta_{T+1}^k \neq \theta_{T+2}^k$. Borghans and others (2008) present an empirical analysis of skill evolution in periods after childhood[3]. To identify the effect of *shocks* on skill accumulation in adulthood, we decompose it in two parts: an observed, δ_t^k, and an unobserved, ε_t^k, by the econometrician. We take as an assumption that these events affect independently to each of these production functions, ϕ^k, hence,

$$\eta_t^k = \varphi^k(\delta_t^k, \varepsilon_t^k). \tag{4}$$

Joining these terms, we define skill production function in adulthood as

$$\theta_{t+1}^k = \phi^k(\theta_1^k, I_t^k, \theta_P^k, \varphi^k(\delta_t^k, \varepsilon_t^k)), \quad t \in \{T+1, T+2\}, k \in \{C, N\} \tag{5}$$

In that way, the challenge consists in identifying events δ_t^k and the form in which they affect skill level in adulthood θ_t^k. Specifically, we need to find those *shocks* that determine the negative relationship between the skill *stock* and the occurrence of the event, so

$$\frac{\partial \theta_{t+1}^k}{\partial \delta_t^k} = \frac{\partial \theta_{t+1}^k}{\partial \varphi^k} \frac{\partial \varphi^k}{\partial \delta_t^k} < 0. \tag{6}$$

Finally, we propose to link latent skills on labor market outcomes, such as wages and employability. Therefore, we can directly evaluate the effect of skill destruction on market outcomes, Q_{jt}.

3   Data and Estimation Strategy

In this section, we present the information used to estimate the model and the empirical strategy implemented.

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[3]We have to consider that investment level, I_t^k in adulthood periods are determined by individual and not by his parents. It is assumed that this is an observed variable.

3.1 Data

There is limited data available at international sources for the implementation of the model and to achieve the objective. We need longitudinal data including skill measures of adults in labor market. We only know two database commonly used in the literature that accomplish this requirements. The first is the *German Socio Economic Panel Study* (SOEP) and the second one is the *1970 British Cohort Study* (70BCS). Although the first has richer information, there are several access limitations for residents outside the European Union. Finally, we opted for the use of the *70BCS*.

The longitudinal study started with a sample of 17,200 born in England, Scotland and Wales in the same week in April 1970. Until now, there have been eight gatherings information. The last one is from 2012. The gathering information was in charge of the Centre of Longitudinal Studies of *University College of London*. This last round was supervised by *TNS-BMRM UK*.

Some of the rounds had specific objectives and focused on topics like health, employment, cognitive functions, and social behaviors, among others. As individual have grown up, questionnaires have adapted to new topics such as the history of relationships, clinical background, among others.

For this paper, we center in the use of two rounds. The first, completed in 2004, has a sufficient number of skill measures[4] with the background of potential effects associated with skill reduction. 9,665 individuals were asked by questionnaires assisted by computers. Besides, they included a specific module to evaluate the basic skills in adulthood. For instance, there were tests for mathematics, language, vocabulary, attitudes, self-esteem, internal control, external control, among others.

The second round was the one gathered in 2012. This period consisted from May 2012 to April 2013, so some individuals were 43 years old at the moment of the interview. There were 9,841 participants. It contains a section specialized in vocabulary evaluation and one in personality. Both permitted the identification of latent skills in the sample.

Then, Table 1 shows, succinctly, the descriptive statistics of the interviews second round.

3.2 Latent Skills Distribution

Latent skills distribution, θ_t^k, is unobserved for the econometrician. To recover these abilities, we propose an analysis of principal components, following the base of Carneiro and others (2003) implemented in Heckman and others (2006).

For these, we consider a set of measures as additively separable functions of the latent variables, θ_t^k,

$$Z_{m,t}^C = \mu_{m,t}^C + \alpha_{m,t}^C \theta_t^C + \xi_{m,t}^C, \quad t \in \{T+1, T+2\}, m \in \{1, ..., M_t^C\} \tag{7}$$

$$Z_{m,t}^N = \mu_{m,t}^N + \alpha_{m,t}^N \theta_t^N + \xi_{m,t}^N, \quad t \in \{T+1, T+2\}, m \in \{1, ..., M_t^N\} \tag{8}$$

where M_t^k denotes the number of measures for each skill k during period t. It is assumed that each measure, Z_t^k, includes outcomes variables, abilities and attitudes tests scores, among others, that are not

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[4]Even some measures do not correspond to standardized tests in psychological literature, we can implement the model through variables that depend in the underlying skills distribution.

Variables	Statistic	2004 (N = 9665)	2012 (N = 9841)
Age	Mean	33.8	42.6
	Std. Dev.	0.35	0.89
% Women	Mean	0.521	0.52
	Std. Dev.	0.499	0.49
% Own House	Mean	98.5	99.49
	Std. Dev.	0.06	0.07
Birth Country	England	85.5	86.4
	Wales	5.3	5.3
	Scotland	9.3	8.3
Civil status: Married	Mean	0.643	0.604
	Std. Dev.	0.54	0.48

SOURCE: 70BCS

contingent to the state where the individual is located (previous decisions); hence, they are observable for all the individuals in the sample. For instance, a college graduate wage is a contingent variable to the state, because it is only observable for those individuals who decided to conclude their tertiary education.

We consider the following system joining the measures for both type of skills in each $t \in \{T+1, T+2\}$:

$$
\begin{array}{cccccc}
Z_t & = & \Lambda_t & \theta_t & + & \xi_t \\
M_t \times 1 & & M_t \times 2 & 2 \times 1 & & M_t \times 1
\end{array}
\tag{9}
$$

To identify the model, we assume that the error, ξ_t^k, has a zero mean and is not correlated with k nor m, hence

$$
E(\xi_t) = 0
\tag{10}
$$

$$
Var(\xi_t \xi_t') = \begin{bmatrix} \sigma_{\xi_1}^2 & 0 & \dots & 0 \\ 0 & \sigma_{\xi_2}^2 & 0 & \vdots \\ \vdots & 0 & \ddots & \vdots \\ 0 & \dots & 0 & \sigma_{\xi_{M_t}}^2 \end{bmatrix}
$$

$$
E(\theta_t) = 0
\tag{11}
$$

Besides,

$$
Var(Z_t) = \Lambda \Sigma_{\theta_t} \Lambda + \Omega
\tag{12}
$$

where

$$\Sigma_{\theta_t} = \begin{bmatrix} \sigma_C^2 & 0 \\ 0 & \sigma_N^2 \end{bmatrix}.$$

Therefore, $\theta_t^C \perp\!\!\!\perp \theta_t^N$, $t \in \{T+1, T+2\}$. We have to consider two more assumptions. First, that every θ_t^k has an independent measure system and, second, given that the scale of every factor is arbitrary, the unity is normalized to a coefficient for each measure system, $\alpha_{1,t}^k = 1$. Hence,

$$\Lambda_t = \begin{bmatrix} 1 & 0 \\ \alpha_{2,t}^C & 0 \\ \vdots & \vdots \\ \alpha_{M_t^C,t}^C & 0 \\ 0 & 1 \\ 0 & \alpha_{2,t}^N \\ \vdots & \vdots \\ 0 & \alpha_{M_t^N,t}^N \end{bmatrix}.$$

Therefore, the system can be expressed as the following for $t \in \{T+1, T+2\}$:

$$\left.\begin{aligned} Z_{1,t}^C &= \theta_t^C + \xi_{1,t}^C \\ Z_{2,t}^C &= \alpha_{2,t}^C \theta_t^C + \xi_{2,t}^C \\ &\vdots \\ Z_{M_t^C,t}^C &= \alpha_{M_t^C,t}^C \theta_t^C + \xi_{M_t^C,t}^C \end{aligned}\right\} \text{Cognitive Skills}$$

$$\left.\begin{aligned} Z_{1,t}^N &= \theta_t^N + \xi_{1,t}^N \\ Z_{2,t}^N &= \alpha_{2,t}^N \theta_t^N + \xi_{2,t}^N \\ &\vdots \\ Z_{M_t^N,t}^N &= \alpha_{M_t^N,t}^N \theta_t^N + \xi_{M_t^N,t}^N \end{aligned}\right\} \text{Noncognitive Skills}$$

Following these assumptions, it is possible to identify all the coefficients $\alpha_{m,t}^k$ through the ratios of the covariances of the measure variables, $Z_{m,t}^k$. For example, to obtain $\alpha_{2,t}^C$, we have

$$Cov(Z_{1,t}^C, Z_{2,t}^C) = \alpha_{2,t}^C \sigma_C^2,$$

$$Cov(Z_{1,t}^C, Z_{3,t}^C) = \alpha_{3,t}^C \sigma_C^2$$

and

$$Cov(Z_{2,t}^C, Z_{3,t}^C) = \alpha_{2,t}^C \alpha_{3,t}^C \sigma_C^2$$

Therefore, we have

$$\frac{Cov(Z_{2,t}^C, Z_{3,t}^C)}{Cov(Z_{1,t}^C, Z_{2,t}^C)} = \alpha_{3,t}^C$$

$$\frac{Cov(Z_{2,t}^C, Z_{3,t}^C)}{Cov(Z_{1,t}^C, Z_{3,t}^C)} = \alpha_{2,t}^C$$

We can also identify,

$$\sigma_C^2 = \frac{Cov(Z_{1,t}^C, Z_{2,t}^C)}{\alpha_{2,t}^C}$$

Hence, we continue with the next coefficients until we identify completely the model.

3.3 Estimation Strategy: Reduced Form

To estimate the model, we assume lineal functions in the parameters from equation (5). If we consider the reduced form of the equation, we have the specification of the technology of skills production in adulthood for every individual $i \in \{1, ..., N\}$ for both periods in time:

$$\theta_{i,T+1}^k = \beta_0 + \alpha_i + \beta_1 \theta_{i,1}^k + \beta_2 I_{i,T+1}^k + \beta_3 \theta_{i,P}^k + \beta_4 \delta_{i,T+1}^k + \varepsilon_{i,T+1}^k, \quad k \in \{C, N\}\ i \in \{1, ..., N\}$$
$$\theta_{i,T+2}^k = \beta_0 + \alpha_i + \beta_1 \theta_{i,1}^k + \beta_2 I_{i,T+2}^k + \beta_3 \theta_{i,P}^k + \beta_4 \delta_{i,T+2}^k + \varepsilon_{i,T+2}^k, \quad k \in \{C, N\}\ i \in \{1, ..., N\}$$

where α_i is a constant effect in time for every individual i. Under the assumptions of exogeneity of the production function's parameters, $E(\theta_{i,1}^k \varepsilon_{i,t}^k) = E(I_s^k \varepsilon_{i,t}^k) = E(\theta_{i,P}^k \varepsilon_{i,t}^k) = E(\delta_{i,s}^k \varepsilon_{i,t}^k) = 0, k \in \{C, N\}, s, t \in \{T+1, T+2\}$, and the absence of correlation among α_i and the other parameters, we propose a fixed effect estimator. To achieve these, we take the first difference using two observations in time[5]:

$$\Delta \theta_i^k = \beta_2 \Delta I_i^k + \beta_4 \Delta \delta_i^k + \Delta \varepsilon_i^k, \quad k \in \{C, N\}\ i \in \{1, ..., N\} \tag{13}$$

The important coefficient is β_4. Besides, we assume that $\delta_{i,t}^k$ follows the pattern:

$$\delta_{i,t}^k = \begin{cases} 1, & \text{if the event occurs} \\ 0, & \text{if the event does not occur} \end{cases}$$

In that way, we focus in identifying events, $\delta_{i,t}^k$, part of the set $E = \{\delta_{i,t}^k \mid \Delta \delta_i^k = 1\}$. Therefore, those events that were performed in $T+2$ and are not present in $T+1$.

4 Results

First, we present the results derived from the estimation of the latent skills distributions. Then, we show the evidence of skills destruction due to specific events.

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[5]We need to remember that, in the analysis, we maintain the conditioning of control variables, X_{it}.

4.1 Latent Skills Distribution

Table 2 shows the estimated coefficients that relate latent and measure variables, i.e. loading factors, $\alpha_{m,t}^k$. As expected, all the coefficients are positive since each measure can be understood as a signal of the unobserved skill level of the individual and due to the item questionnaires were designed in a positive sense basis. Furthermore, the coefficients were significant at 99% confidence level, a result that was expected too since all the measures were previously validated in the psychometric literature.

Provided these estimates, we are able to recover the latent skills distribution using the system of equations of measurement variables. Figure 1 shows the estimated distribution for cognitive skills in young adulthood and middle adulthood. Distribution of cognitive skills is less variable during the former period in comparison to middle adulthood and is characterized by a certain degree of negative skewness. Thus there is a major presence of extremely low skilled individuals than extremely high skilled individuals. When individuals grow up, the scenario is quite similar which is a fact that is consistent with cognitive development theories regarding stabilization of skills once reached certain age. However there are still some differences that are worth to mention.

First, the distribution is more dense among low levels, a feature that may insinuate the deterioriation of skills acquired during earlier stages of life. Furthermore, this downgrade in skills leads to a multimodal shaped distribution. Secondly, the upper bound of the distribution in young adulthood is surpassed by some individuals during middle adulthood which may hold for those individuals who continued investing in skills formation until later stages of life. Both variations in the skills distribution depict two possible shifts in skills level during adulthood. Overall, these facts can introduce us to a stabilization of skills period but we still need information about skills in late adulthood to validate this hyphotesis.
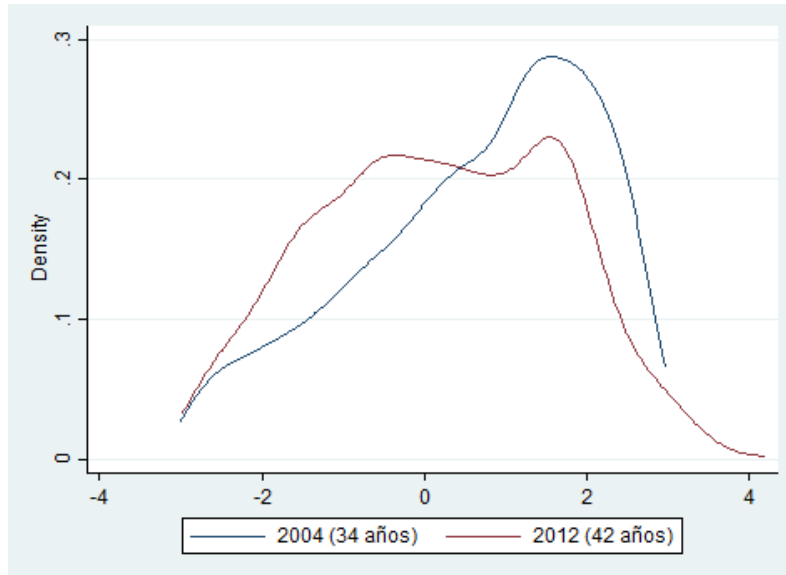
Table 2: Estimated Values for the Principal Components Analysis

Parameter	Estimated Value
$\alpha_{1,T+1}^{C}$	1
$\alpha_{2,T+1}^{C}$	.342***
$\alpha_{3,T+1}^{C}$	.264***
$\alpha_{4,T+1}^{C}$	1.169***
$\alpha_{1,T+2}^{C}$	1
$\alpha_{2,T+2}^{C}$	.167***
$\alpha_{1,T+1}^{N}$	1
$\alpha_{2,T+1}^{N}$	.326***
$\alpha_{3,T+1}^{N}$	1.126***
$\alpha_{4,T+1}^{N}$	.276***
$\alpha_{1,T+2}^{N}$	1
$\alpha_{2,T+2}^{N}$	0.344***
$\alpha_{3,T+2}^{N}$	0.179***

SOURCE: 70BCS
NOTE: ***Significant Coefficient at 99%.

**Figure 1: Cognitive Skills Distribution**

SOURCE: 70BCS

Figure 2 shows the corresponding distributions of noncognitive skills. In general, these are less dispersed than cognitive since even low educated and less favored background individuals are able to develop abilities such as persistence, motivation, failure-tolerance, among others, in harshly conditions. Specif-

ically, during young adulthood, the skills distribution is unimodal and slightly negatively skewed while it is positevely skewed in middle adulthood. This transition may be explained by a similar reason to that mentioned in the cognitive skills case: deterioration. In parallel, the upper bound is surpassed in the second wave as in the cognitive skills case. The hypothesis is the same, investment in continuing education.

Analyzed dynamics shed light on the direction of a heterogeneous technology of skills formation on adulthood. Given this, our main objective is to identify the sources of this variations such as exogenous life events or decisions endogenous to the individual. Provided the underlying distributions of skills, we are able to estimate the model proposed in Section 3.3 in its reduced form.

Figure 2: Noncognitive Skills Distribution
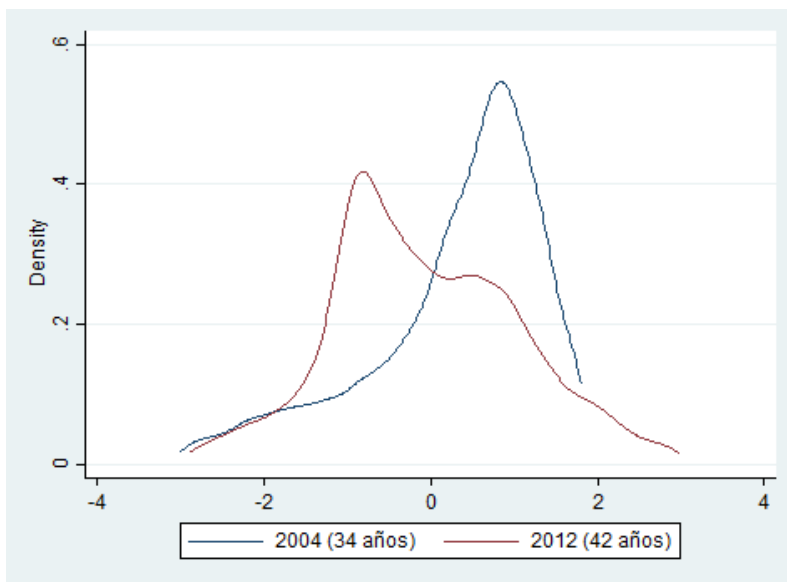
SOURCE: 70BCS

4.2 Skills Destruction Preliminary Evidence

Preliminary evidence presented below draws a picture of the possible explanations to the formation and destruction of skills on adulthood. However, is important to consider the endogeneity degree of some of the events included in the production function of skills. For instance, drug abuse is a decision taken by the individual which may be correlated with his skills stock (Heckman and others, 2006). Given this limitation, we present the results of the reduced form as a tip for the consideration of this topic as a major area of research lacking of solid evidence. Furthermore, the anchoring of this results on labor market outcomes is pending.

Tables XX,XX and XX presents a pair of specifications for each event identified. Each of them considers socioeconomic controls such as nationality, social class, geographic characteristics, among others. As the descriptive statistics anticipated, deterioration of skills is evident as adulthood years go by in average. The older, the less skilled one becomes; however this natural process seems to be counteracted by investment

in skills formation. The return to this educational activities seems to be significant for those who enroll in training programs in comparison to those who not. Thus this evidence supports the theoretical findings of Cunha and others (2010) in the sense of the complementarity of investment on skills among different life stages.

The decease of a child has a minimum effect while significant on cognitive skills level. There is no significant effect identified on noncognitive skills distribution. In the event of the decease of an individual's spouse, there is no significative effect on cognitive as well as on noncognitive distribution. This finding contrasts with Zisook and Schuter (1991) and Niaz and Hassan (2006) results since there is low variability in the ocurrence of the event, so identification is hampered. In third place, a divorce event is associated with a decrease in noncognitive skills. One possible mechanism explaining this relation could be the post-divorce depression period documented by Trivedi et al. (2009). In case of relationship separation, there is no significant effect.

Table XX presents a second group of events analyzed. In first place, we may take a look at the effect of unemployment persistence on skills dynamics. Similar to the findings of Lavado et al. (2016) with Peruvian data, unemployment periods are associated with skills destruction. This may be the major interesting finding given the great incidence of this event among the labor market. However, this coefficient stills lacks of exogeneity validity since the likelihood of being unemployed may be determined by the lack of skills. Notwithstanding, we include initial skills controls as well as we only consider unemployment periods posterior to this initial measurement. For both cognitive and noncognitive skills, large unemployment periods (longer than twelve months) lead to a 0.2 standard deviatons decrease on skills level. This finding supports the common assumption of search models developed by Pissarides (for instance, see Esteben-Pretel (2005)).

Daily smoking is also associated with a lower level of cognitive skills. Despite this result can be biased by reverse causality, the negative correlation between both variables confirms the direction of the relation (Heckman and others, 2006). Table XX shows that the decease of any parent is not related to variations in the level of skills, whilst the diagnosis of chronic disease seems to increase the skills level of the pacient. Clearly, this is not a direct relation, however a possible mechanism could be the discipline process through an individual is involved after being diagnosed.

5 Conclusions

We took an important step in the identification of the skill production theorical model in adulthood. Any study has formalized the skill treatment in this period. One reason might be the reduced skill malleability at maturity, a statement that is partially supported nowadays. Our extension considers the presence of negative *shocks* in the skill formation dynamics or stabilization. We found that different levels of cognitive and noncognitive skills can be reduced when they are affected by any important event during lifetime.

Although we work using some important events during lifetime, it is important to recognize that endogeneity should be treated with a special approach. To solve this disadvantage, we are analyzing

Table 3: Skills destruction from events during labor life

Shocks:	Death of son		Death of couple		Divorce		Separation	
	Cognitive	Noncognitive	Cognitive	Noncognitive	Cognitive	Noncognitive	Cognitive	Noncognitive
Interest Effect	-0.258	-1.732***	0.674	-1.508	-0.447**	-0.447	-0.0932	-0.823***
	(0.277)	(0.489)	(0.636)	(1.158)	(0.201)	(0.362)	(0.107)	(0.194)
Training	0.0111	-0.0201	0.0105	-0.0199	0.0112	-0.0198	0.0106	-0.0212
	(0.0106)	(0.0198)	(0.0106)	(0.0198)	(0.0106)	(0.0198)	(0.0110)	(0.0200)
Age	0.00315	-0.105***	0.00206	-0.108***	0.00406	-0.107***	0.00361	-0.0975***
	(0.00414)	(0.00754)	(0.00412)	(0.00746)	(0.00418)	(0.00756)	(0.00435)	(0.00787)
Constant	-0.0319	3.566***	-0.00600	3.658***	-0.0743	3.624***	-0.0584	3.315***
	(0.156)	(0.283)	(0.155)	(0.280)	(0.157)	(0.283)	(0.163)	(0.294)
Individual Observations	9,610	9,610	9,612	9,612	9,612	9,612	9,612	9,612
R2	0.000	0.028	0.000	0.027	0.001	0.027	0.000	0.029

different instruments to obtain consistent estimators of those events that does not guarantee exogeneity. Besides, we are working in the structural estimation of the model considering that some events are outcomes of the agent decision-making process, such as drug abuse, divorce, alcoholism, among others.

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