FOSTERING TEACHING STAFF'S ENGAGEMENT IN CONTINUOUS ASSESSMENT

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Abstract

Among the factors that affect the convergence towards the European Higher Education Area, university teaching staff's motivation is fundamental, and consequently, it is crucial to empirically know what this motivation depends on. In this context, one of the most relevant changes in the teacher-student relationship is assessment. In fact, the transition from a *static assessment* -focused on only one temporal point (final exam)- to a *dynamic assessment*, will require changes in thought and action, both on the part of teachers and students. In this line, the objective of this paper is to analyze the determinants of teaching staff's predisposition to the continuous assessment method. Specifically, we consider the following explanatory dimensions: teaching method used (which measures their degree of involvement with the ongoing adaptation process), type of subject (core, compulsory and optional), and teacher's personal characteristics (professional status and gender). The empirical application carried out at the University of Alicante uses Logit Models with Random Coefficients to capture heterogeneity, and shows that "cooperative learning" is a clear-cut determinant of "continuous assessment" as well as "continuous assessment plus final examination". Also, a conspicuous result, which in turn becomes a thought-provoking finding, is that professional status is highly relevant as a teacher's engagement is closely related to prospects of stability. Consequently, the most relevant implications from the results revolve around the way academic institutions can propose and implement inducement for their teaching staff.

Keywords - continuous assessment, European Higher Education Area, teaching staff.

1 INTRODUCTION

Universities are expected to afford their current and future students a number of tools, abilities and competences that allow them to successfully deal with the extant challenges in a global society, including a markedly competitive job market. This crucial -and hefty- task involves students, teaching staff, academic authorities and administration. Beyond the application of new information and communication technologies (ICT) and a conceptual shift as to what the teaching-learning process should be, there are other factors that affect the convergence towards the European Space for Higher Education (ESHE). Among them, university teaching staff's motivation is fundamental; ,it is therefore crucial to empirically know what this motivation depends on.

In this context, one of the most relevant changes in the teacher-student relationship is assessment. In fact, the transition from a *static assessment* -focused on only one temporal point (final exam)- to a *dynamic assessment*, will require changes in thought and action, both on the part of teachers and students. Therefore, on the one hand, motivation is a key point as it represents an individual's internal force that drives him or her into action and, on the other hand, knowing the predisposition to that action is critical for establishing stimulating inducements. In the framework of this paper, this *action* is the "continuous assessment". Specifically, we examine teachers' predisposition to a continuous evaluation method in terms of teaching method (which measures their degree of involvement with the ongoing adaptation process), type of subject, and teachers' personal characteristics. To this end, the rest of the paper is organized as follows: the second section shows the literature review on continuous assessment; the third section describes the research design where method of analysis and sample are depicted; the fourth presents the results and the fifth the conclusions and practical implications.

2. THE CONTINUOUS ASSESSMENT METHOD

Students' level of knowledge is valued by their assessment,[1] which originally consisted of comparison between learning outcomes and the objectives previously determined [1]. Afterwards, this model was substituted by a broad, valid, exact assessment based on experimental procedures [2]. As a consequence of the changes promoted by the ESHE, the student is the main figure in the learning process (not the teacher in the teaching process). In this context, assessment goes beyond the mere measurement of knowledge assimilation to evaluate the acquisition of competences defined beforehand by the teaching staff. Traditionally, the final stage of the learning process has been the *final assessment*, closely related to passing an *objective test* in which the student must show the acquisition of knowledge [3]. Therefore, students' learning is subject to the evaluation method proposed by teachers.

According to the guidelines suggested by the ESHE, the valuation function of teachers does not finish with the final assessment, but they have to get involved in controlling students' assimilation of a series of contents as well as the development of competences. In fact, Delgado and Oliver [4] consider that continuous assessment is the optimum procedure to evaluate competences because what has to be assessed is the execution of the competence [5]. In this context, university teachers have to design a series of evaluation proposals throughout the academic year that the students must pass periodically. This way of operating makes it easier for the future graduate to acquire knowledge and competences, as well as for the teachers to continuously assess the progressive evolution of students' work and achievements (for en extensive review of traditional and new assessment techniques, see Dixon and Rawlings [6] for the former, and Isaksson [7] for the latter).

Thus, continuous assessment is a holistic, significant and accumulative evaluation that can bring huge advantages for all the parts that form the teaching-learning process. Students receive information about their learning rate -making it possible to modify methods and habits-, about the way they are assessed in a practical way, re-orienting their learning if necessary, and gradually acquiring certain knowledge and competences. For teachers, applying continuous assessment as a substitute or complement to final evaluation permits the possibility to improve their teaching process over an academic year. This is an advantage as it allows them to raise quality, because follow-up throughout the whole academic year is guaranteed, and it provides them with several indices and value judgments to configure a complete assessment system [8]. However, there is no denying that huge

[1] See Bernad (2000, p. 14-26) for a synthetic review on the learning and assessment relationship.

support is required to carry out this process [10]: the effort university teachers must put in to correctly apply continuous assessment is large, and sometimes it is not in line with their professional and environmental characteristics.

As a consequence, it is crucial to identify the factors that drive the choice of evaluation method. In this paper, we focus on three dimensions: i) the teaching method employed, which captures, to some extent, the degree of involvement with the new dynamics advocated in the ESHE; ii) type of subject (core, compulsory and optional), which permits the analysis of teachers' predisposition to "experiment" contingent upon this taxonomy; and iii) personal characteristics -professional status and gender-, which allow us to detect behavioural patterns.

3 RESEARCH DESIGN

3.1 Method

The method proposed to identify and test the determinant factors that drive university teachers to undertake dynamics related to continuous assessment included in the ESHE is based on Logit Models with Random Coefficients as they can capture non-observed heterogeneity. It is highly unlikely that all teachers in the sample have the same set of parameters (i.e. same attitudes and preferences as to how to adapt the ESHE). This means considering non-observed heterogeneity in parameter estimates. Hence, the utility of alternative *i* for teacher *n* is defined as $U_{in} = X_n \beta_n + \varepsilon_{in}$ where X_n are the teacher's features (teaching method, type of subject, professional status and gender); β_n is the vector of coefficients of these characteristics for each individual *t,* which represent personal tastes (these coefficients β_n vary over decision makers with density $f(\beta)$); and ε_{in} is a random term that is iid extreme value. This specification of the RCL model differs from the traditional Logit model in which β is fixed. In fact, if parameter β_n were observable, the choice probability of alternative *i* conditional on parameter β_n would be given by this expression:

$$P_n(i/\beta_n) = \frac{e^{X_n \beta_n}}{\sum_{j=1}^{J} e^{X_n \beta_n}}$$

which is the standard Logit Model. However, as it is not observable, the non-conditional probability is the integral of $P_n(i/\beta_n)$ over all the possible values of β_n:

$$P_n(i) = \int_{\beta_n} P_n(i/\beta) f(\beta/\psi) d\beta$$

where ψ are the parameters for the mean and variance of β.

Regarding the estimation of the RCL model, Bayesian procedures are used as they give the analyst a parameter for each sample individual and avoid the problems of convergence of algorithms of the classical estimation [11]. Following this author, the likelihood *L* of observed choice y_n for an individual *n* conditional on parameters *b* and *W* (average and variance of β_n, respectively) is expressed as:

$$L(y_n / b, W) = \frac{e^{X_t \beta_n}}{\sum_{j=1}^{J} e^{X_t \beta_n}} \phi(\beta_n / b, W)$$

where ϕ is the function of Normal distribution.

Let *k(b,W)* be the prior distribution of parameters *b* and *W*. In general, it is assumed that *b* has a Normal distribution and *W* an Inverted Gamma distribution (or Inverted Wishart distribution in the case of multi-variation) of type $f(W)=W^{-(v+1)/2}e^{-vs/2W}$ with *v* being the degrees of freedom and *s* a parameter of scale to be estimated. Bayes' rule allows the analyst to obtain the posterior distribution $K(b,W,\beta_n/Y)$ for the group of choices *Y* of the sample individuals (n=1,..., N) as:

$$K(b, W, \beta_n / Y) \propto \prod_{n=1}^{N} L(y_n / b, W) k(b, W)$$

The posterior distribution has three parameter types to estimate $\theta=\{b,W,\beta_n\}$: the average *b*, the variance *W*, and the parameters of each individual β_n, from which we obtain the utility functions of each individual and, therefore, the preference structure. The estimation of the parameters is obtained through the following expression

$$\hat{\theta} = \int_{\theta} \theta \cdot K(\theta / Y) d\theta$$

This integral has no closed solution, which leads the researcher to use a procedure of estimation by simulation. Therefore, θ is estimated as the average of the simulated drawings. However, the posterior distribution $K(\theta/Y)$ does not always take the form of a known distribution from which one could immediately take draws. Train [12], in the case of choice models, suggests the use of Monte Carlo Markov Chains; specifically, the sample simulation algorithms of Gibbs[2] and Metropolis-Hasting[3] for the draws of the density function. Train [13] also demonstrates that the estimator of the simulated average of the posterior distribution is consistent, asymptomatically normal and equivalent to the estimator of maximum likelihood.

3.2 Sample and Variables

To accomplish the research objectives proposed, 34 teachers at the University of Alicante were interviewed within the project "*REDES* for research and formation in university teaching" promoted by the Institute for Educational Science and School of Labour Relations during the academic year 2007/2008. A survey was sent to all teachers at the School of Labour Relations of the University of Alicante. Therefore, a census sampling was applied as the whole population at that school was considered as the sample. The response percentage (49.3%) is considered to be large enough to support the statistical significance of the results.

In order to make the choice model operational the variables used are defined, distinguishing between the dependent and independent variables.

1) Dependent variable. a) *Type of evaluation method.* The evaluation method is measured by a categorical variable that takes value 1 if the teacher follows the "final exam" method (the traditional one), value 2 if s/he follows "continuous assessment" and value 3 if s/he combines "continuous assessment plus final exam". Category 1 is taken as the reference alternative to estimate the models.

2) Independent variables. a) *Type of teaching method:* Both "master class" and "cooperative learning" are measured by a dummy variables that takes value 1 if the individual has followed such procedures and 0 otherwise; b) *Professional status*. Several dichotomous variables are used to represent teachers' professional status: "Asociado" (associate professor), "Titular de Universidad" (tenured university lecturers), "Titular de Escuela Universitaria" (tenured university school lecturers), "Colaborador", "Contratado Doctor" and "Ayudante"[4].To estimate the models the category "Titular de

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[2] This procedure follows this scheme: let ξ_1 and ξ_2 be two random variables, whose joint density function is $f(\xi_1,\xi_2)$ and conditional density function $f(\xi_1/\xi_2)$ and $f(\xi_2/\xi_1)$, respectively. Gibbs algorithm obtains iteratively draws from these conditional density functions through the following process: 1) It stems from a starting value ξ_1^0; 2) a value of ξ_2 is extracted from $f(\xi_2/\xi_1^0)$ and denoted as ξ_2^0; 3)a new value for ξ_1, i.e. ξ_1^1 is obtained from $f(\xi_1/\xi_2^0)$; 4) ξ_2^1 is extracted from $f(\xi_2/\xi_1^1)$; and so on. For a large enough number of draws, conditionals functions converge to the joint density function.

[3] The Metropolis-Hasting algorithm is used for the individual parameter estimates. It is based on draws from a density function $f(\xi)$ from the following process: 1) A starting value is taken ξ^0; 2) A new possible value for ξ^1 is selected, such that $\xi_p^1=\xi^0+\eta$ where η is a draw from a distribution $g(\eta)$ with zero mean (a Normal distribution is usually employed). 3) The density function is calculated at the testing point ξ_p^1 and is compared with the density of the starting value ξ^0. If $f(\xi_p^1)>f(\xi^0)$ the value ξ_p^1 is accepted as value for ξ^1, and the process goes on to step 4. If $f(\xi_p^1) \leq f(\xi^0)$ the value ξ_p^1 is accepted as value for ξ^1 with probability $f(\xi_p^1)/f(\xi^0)$ and is rejected with probability 1-$f(\xi_p^1)/f(\xi^0)$. In order to determine whether it is accepted or rejected, a draw from a uniform variable μ is performed. If $\mu \leq f(\xi_p^1)/f(\xi^0)$ the value ξ_p^1 is accepted as value for ξ^1; otherwise, ξ_p^1 is rejected and ξ^0 is then used as value for ξ^1. 4) A new testing value ξ^2 is selected, such that $\xi_p^2=\xi^1+\eta$, where η is a new draw from $g(\eta)$. 5) Step 3's selection rule is applied. 6) This process is repeated iteratively

[4] Profesores Titulares (both tenured university and tenured university school lectures) are the permanent agents in the university with civil servant status. The other profiles ("asociado",

Universidad” is used as a reference; c) Gender. A dummy variable is created with 1 if female and 0 if male; and d) *Type of subject*. Three dichotomous variables are employed to reflect the “core, compulsory and optional” character of the subject. The last one is used as a reference.

4 RESULTS

The estimation of Logit Models with Random Coefficients has reached the results in Table 1. Models 1 and 2 represent the effect of the teaching method on the evaluation method employed, and Model 3 shows the influence of professional status, type of subject and gender.

Table 1. Explanatory factors of evaluation methods

	Variables	Model 1		Model 2		Model 3	
Effect of teaching method on evaluation method	**Master class**	-7.959[a]	3.837				
		(0.625)	(2.785)				
	Cooperative Learning	165.22[d]	91412				
		(97.85)	(62303.6)				
	Master class (Cont. assess.)			-7.734[b]	44.807		
				(2.455)	(29.73)		
	Master class (Cont. assess. + Final Ex)			-6.664	8.184		
				(5.305)	(36.92)		
	Cooperative Leaning (Cont. assess.)			10.661[a]	1.371		
				(2.574)	(2.032)		
	Cooperative Leaning (Cont. assess. + Final Ex)			8.881[d]	84.925		
				(4.654)	(139.0)		
Professional status effect	**“Asociado”**					-4.337[a]	3.200[d]
						(0.907)	(1.823)
	“Tit. de Esc. Univ.”					0.961[b]	1.119
						(0.364)	(1.182)
	“Colaborador”					-5.201[a]	1.625
						(1.252)	(4.743)
	“Contratado Doctor”					8.550[a]	1.913
						(0.535)	(1.356)
	“Ayudante”					10.419[a]	2.300
						(0.662)	(1.495)
Gender	**Gender**					-100.68	97703.05
						(114.3)	(73902.1)
Subject type effect	**Compulsory**					-2.803[a]	3.455
						(0.735)	(2.548)
	Core					-13.430[c]	451.282
						(6.375)	(304.00)
Consts.	**Constant 2**	-6.143[a]	1.138	-12.032[a]	3.371	-9.473[c]	176.36[d]
		(0.346)	(0.955)	(3.453)	(2.568)	(4.217)	(106.35)
	Constant 3	-5.281[c]	98.252[c]	-81.131	97820.065	3.479[a]	2.650[d]
		(2.397)	(46.80)	(75.103)	(69324.7)	(0.875)	(1.537)

a=prob<0.1%; b=prob<1%; c=prob<5%; d=prob<10%

In Model 1, we can observe a significant negative parameter for the teaching method “master class”. It implies a negative impact on the probability of using “continuous assessment” and “continuous assessment plus final exam”. As for “cooperative learning”, a significant positive

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“colaborador”, “contratado doctor”, and “ayudante”) have a contractual relationship with the university. All carry out their tasks full time, except “asociado” and “colaborador”. Actually, “contratado doctor” and “ayudante” are the figures that can lead teachers to get a tenure.

parameter is obtained, showing a positive influence on both “continuous assessment” and “continuous assessment plus final exam”. These results are in line with the idea that teachers who already show a certain engagement in the ESHE, manifested by the new teaching technologies used, show a tendency to integrate all the novelty of the process holistically (teaching method plus continuous assessment method).

However, it is interesting to analyse the different effects of “master class” and “cooperative learning” on both “continuous assessment” and “continuous assessment plus final exam” separately. To this end, Model 2 is estimated: the generic negative effect detected for “master class” in Model 1 is actually capturing its influence on “continuous assessment”. As shown in Model 2, it is the only parameter that is significant and negative. As for the relationship between “master class” and “continuous assessment plus final exam”, the parameter is not significant.

The positive effect of “cooperative learning” on “continuous assessment” and “continuous assessment plus final exam” is found for both cases: we obtain significantly positive parameters. Having a more detailed look at these relationships, we can see that the effect of “cooperative learning” is higher for “continuous assessment” than for “continuous assessment plus final exam”. This means that a teacher who applies the cooperative learning method tends to apply *pure* continuous assessment with higher probability than a hybrid of evaluation methods.

Regarding professional status (Model 3), all the categories show significant parameters. Specifically, positive parameters are observed for “Titular de Escuela Universitaria”, “Contratado Doctor” and “Ayudante”, and negative parameters for “Asociado” and “Colaborador”. These results show that the first three present a bigger tendency to apply ESHE’s principles in the evaluation method chosen. Note the especially high parameters detected for the categories “Contratado Doctor” and “Ayudantes” compared to “Titular de Escuela Universitaria”, which means that, even though they all are positive, the degree of engagement of the first two is much stronger than the latter. In fact, we can observe that labour stability as well as the prospect of gaining it can have an influence on the degree of engagement: “Ayudantes” are more involved than “Contratados Doctores”, followed by “Titulares de Escuela Universitaria”. At the end of the row are “Asociados” and “Colaboradores”, whose involvement in the variables of analysis (use of evaluation method) is negative.

Finally, the variable “gender” does not seem to exert any influence, as its parameter is not significant. Concerning subject character, teachers tend to apply continuous assessment in optional subjects, followed by compulsory subjects and, further, core subjects. Given the experimental character of the application of these new evaluation methods at the University of Alicante, it seems quite obvious that optional subjects are used as guinea pigs.

5 CONCLUSIONS

The importance of the analysis of continuous assessment resides on the fact that it emerges as a clear-cut quality index for teaching-learning process in the university system and, consequently, it shows a great potential as a tool to favour convergence among university degrees in the frame of the ESHE. In this sense, identifying the factors that determine a stronger predisposition towards its use is fundamental in order to establish appropriate strategies. The empirical application carried out on a sample of teachers at the University of Alicante has allowed us to observe the following main results: i) “cooperative learning” is a determinant factor both for “continuous assessment” and for “continuous assessment plus final exam”; and ii) professional status has an influence on teachers’ degree of engagement in such a way that stability prospects favour the use of ESHE’s principles. As a fundamental implication, we can say that teaching institutions must establish inducements for their teaching staff that have to be stimulating for each type of teacher: as the response to the ESHE is heterogeneous, enticement programs varying in terms of type as well as intensity are needed.

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