ITALIAN PHD PROGRAMME SYSTEM: EVALUATING EXTERNAL EFFECTIVENESS BY STRUCTURAL EQUATION MODELS

Matilde Bini[1]
Department of Human Science, European University of Rome, Italy

Bruno Bertaccini
Department of Statistics "G. Parenti", University of Florence, Italy

Lucio Masserini
Statistical Observatory, University of Pisa, Italy

Abstract. *The analysis of the contribution of the PhD title to the PhDs employment condition is an important tool for evaluating the quality and the effectiveness of PhD programmes. For this reason, monitoring PhDs careers becomes fundamental for explaining the mismatch between third level education and labour market*[2]*. The aim of this paper is to assess the external effectiveness of PhD programmes using a Structural Equation Model. The analysis is performed with data from a survey on "Current situation and employment prospects of PhDs". The proposed measure of "external effectiveness" is a latent variable stemming from satisfaction with the employment status of PhDs who achieved the title in 2008.*

Keywords: *External effectiveness, Latent variables, PhD placement, Structural equation models.*

1. INTRODUCTION

Philosophy Doctor (PhD) programmes have been introduced in the Italian university system by the decree of the President of the Republic 382/1980 as third level of higher education and was subsequently regulated by the Law 210/1998 and by the Ministerial Decree 224/1999. The issue of internal evaluation in universities was introduced by the laws 168/89 and 537/93. The former law provides for the implementation of forms of internal control on efficiency and on management results, the latter established internal evaluation units in universities.

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[1] Matide Bini, email: mbini@unier.it

[2] Post-graduate university education is named level III education.

The evaluation of the quality of the university system can be represented following the general scheme in Fig. 1, proposed by Lockheed & Hanushek (1994) and generalised by Chiandotto (2004, 2008).

	DURING THE UNIVERSITY EXPERIENCE	AFTER THE UNIVERSITY EXPERIENCE
IN OUTCOMES TERMS	**Internal Effectiveness** effect of the PhD programme on learning ability of the student	**External Effectiveness** effect of the PhD programme on working ability
SATISFACTION	*of the student with respect to the programme*	*of the PhD with respect to the working conditions*
IN MONETARY TERMS	**Internal Efficiency** costs and revenue analysis	**External Efficiency** economic earnings after attending the PhD programme
SATISFACTION	*of PhD with respect to the employed resources*	*of PhD with respect to economic conditions*

Figure 1: Evaluation scheme of efficacy and effectiveness of PhD programmes

According to this approach, the estimated overall performance of an educational system can be decomposed into three distinct stages: the first is the assessment of how resources are employed to get the expected result (efficiency analysis); the second is the assessment of the results and the level of achievement of objectives (effectiveness analysis); the third is the assessment of the subjective perception of the subjects involved in educational processes. These evaluations can be made with an internal or external perspective, depending on whether we are interested on the results and achievements when graduates are still in the university system or they are outside, typically in the labour market, respectively.

This paper focuses on the assessment of the results obtained by PhDs in the labour market, which constitutes an analysis of external effectiveness. More specifically, external effectiveness is analysed by evaluating the level of satisfaction with the current employment status with respect to a set of attributes, using data from the research "Current conditions and employment prospects of PhDs" sponsored by the National Committee for the Evaluation of

the University System (CNVSU, 2010) to the Department of Statistics "G. Parenti" of the University of Florence. The analysis focuses on the PhDs who achieved their title in 2008 and are currently working.

The analysis of external effectiveness of second and third level educational processes can be performed taking into account a number of factors, including the level of satisfaction with the current job, and it can be presented using Structural Equation Models (SEM), an extensive class of models that also accommodates multi-level data structures. The use of a SEM approach allows to analyse multivariate relationships between variables (exogenous and endogenous) through a system of linear equations; moreover, it is possible to decompose the effects of a variable on other variables into direct and indirect effects, as well as to model latent variables. Recent studies on external effectiveness performed using SEM (Chiandotto *et al*., 2007 and 2010; Chiandotto and Masserini, 2011) provided useful references for the SEM model proposed in this work. In the paper of Chiandotto and Masserini for example, the hypothesised relationship between the latent variable *external effectiveness* and the observed indicators (measurement model) is defined using three variables: consistency with studies, utilization of acquires skills and compliance with cultural interests. A two-level structural equation model was performed, where PhDs and PhD programmes were considered, respectively, as first level and as second level units.

The present analysis starts from the work of Chiandotto and Masserini, by defining an alternative and wider measure of external effectiveness. Such a measure includes two additional variables in the measurement model: skills acquisition and satisfaction with respect to PhD title, i.e. if the PhD title is (or not) considered effective with respect to the current employment status. The choice of an alternative measure of external effectiveness allows us to have a wider evaluation of this dimension and it is to be highlighted that a unique definition of this concept does not exist in literature. However, in this paper a previous two-level analysis has been performed and showed not statistically significant results, unlike the study of Chiandotto and Masserini where a different measure of external effectiveness has been considered.

2. STRUCTURAL EQUATION MODELS

SEM is a multivariate technique used to test complex relationships between observed (measured) and unobserved (latent) variables as well as relationships between two or more latent variables. A SEM is characterised by two

components: a *structural* model, designed to explain the relationships between the latent variables and between the latent and the observed variables, and a *measurement* model, to explain the relationships among latent variables and observed indicators. The structural model can be expressed by the following equation:

$$\boldsymbol{\eta} = \mathbf{B}\boldsymbol{\eta} + \boldsymbol{\Gamma}\boldsymbol{\xi} + \boldsymbol{\zeta} \tag{1}$$

where $\boldsymbol{\eta}$ is a $m \times 1$ vector of endogenous latent variables; $\mathbf{B}$ is an $m \times m$ matrix for the endogenous latent variables; $\boldsymbol{\Gamma}$ is an $m \times n$ matrix of regression coefficients among the endogenous and exogenous latent variables; $\boldsymbol{\xi}$ is an $n \times 1$ vector of exogenous latent variables; $\boldsymbol{\zeta}$ is an $m \times 1$ vector of errors.

The measurement model is defined by two equations, respectively for the endogenous (2) and exogenous (3) latent variables:

$$\mathbf{x} = \boldsymbol{\Lambda}_x \boldsymbol{\xi} + \boldsymbol{\delta} \tag{2}$$

$$\mathbf{y} = \boldsymbol{\Lambda}_y \boldsymbol{\eta} + \boldsymbol{\varepsilon} \tag{3}$$

where $\mathbf{y}$ is a $p \times 1$ vector of the observed indicators for the endogenous latent variables; $\boldsymbol{\Lambda}_y$ is a $p \times m$ factor loadings matrix for the endogenous latent variables; $\boldsymbol{\varepsilon}$ is a $p \times 1$ vector of error terms. Similarly, $\mathbf{x}$ is a $q \times 1$ vector of observed indicators for the exogenous latent variables; $\boldsymbol{\Lambda}_x$ is a $q \times n$ factor loadings matrix for the exogenous latent variables; $\boldsymbol{\delta}$ is a $q \times 1$ vector of error terms (for further details, see Bollen, 1989).

When the exogenous variables are not affected by measurement errors (or when errors are negligible), the measurement model (2) is simplified as (Muthén, 1984):

$$\boldsymbol{\eta} = \mathbf{B}\boldsymbol{\eta} + \boldsymbol{\Gamma}\mathbf{x} + \boldsymbol{\zeta} \tag{4}$$

This implies that exogenous variables are not affected by measurement errors (or with negligible errors). So the measurement model (2) simplifies.

In SEM approaches sampled data are usually assumed to follow a multivariate normal distribution, so that the vector of the means and the matrix of covariance contain all the information required for the estimation procedure. In this respect, the widely used estimation method is Maximum Likelihood (ML). When data are non-normal, some alternative estimation procedures can be used, such as the Asymptotically Distribution Free (ADF, see Browne, 1982;

1984) based on the Weight Least Squares fit function. In addition, Asparouhov and Muthén (2004) proposed three maximum likelihood estimators based the E-M algorithm: maximum likelihood (ML) and maximum likelihood with robust standard errors and chi-square (MLR, MLF). Each estimator is characterised by a specific method for the computation of standard errors. In particular, the MLR estimator approximates the Fisher Information matrix using a sandwich estimator derived by the combination of the ML and MLF information matrices. Moreover, the MLR estimator computes an unbiased estimate of the covariance matrix without requiring normally distributed data, and produces a robust chi-square test for the model goodness of fit (for details see Muthén, 2004).

When data are ordinal, the observations can be considered as imprecise measures of underlying normally distributed (latent) variables (Muthén, 1984; Bollen, 1989). Under this assumption it is possible to compute polychoric correlations (correlations between non observed normal variables estimated from observed ordinal variables) (Olsson, 1979; Jöreskog, 1994). In this case, parameters are estimated by the WLS fit function, providing that the sample size is high enough (Muthén, 1984). Alternatively, it is possible to ignore the categorical nature of the variables, providing that the number of categories is at least 5 and data show an approximately normal distribution (Bollen, 1989). Under this condition, ML factor loadings are just underestimated (Muthén and Kaplan, 1985; Babakus *et al.*, 1987).

Whenever we test the goodness of fit of the model with a measure based on the chi-square distribution, and the sample size is very large, the test could suggest the rejection of the model even if it appears to describe the data satisfactorily. Conversely, when the sample is limited in size, there is a risk of accepting the model even if the fit is poor. For this reason, a series of indices have been proposed in the literature for measuring the goodness of fit of a model; often such indices take into account not only the model fitting but also its simplicity, usually expressed in terms of the number of model parameters.

Two proposed measures, both taking into account the complexity of the model, are the Tucker and Lewis Index - TLI (Tucker and Lewis, 1973), also known as NNFI (NonNormed Fit Index), and NFI (Normed Fit Index, see Bentler and Bonett, 1980)[3]. Another common measure is the Comparative Fit

[3] Jöreskog and Sörbom (1984) proposed two indexes named GFI (Goodness of Fit) and AGFI (Adjusted GFI); the last one is a modified version of the GFI that takes into account the complexity of the model.

Index - CFI whose values are less affected by the sample size (Bentler, 1990; Bollen, 1990; Hu and Bentler, 1995, 1998). All these measures take values between 0 and 1, where 1 indicates perfect fit. In literature there has been concern that the recommended cutoff values for all fit indices of 0.90 are too low and that higher values, such as 0.95 should be used. Hu and Bentler (1999) empirically examine various cutoffs for many of these measures. Another widely used measure of goodness of fit is the Root Mean Square Error of Approximation index (RMSEA); for this index, values smaller than 0.05 indicate a satisfactory fitting (for a review of some of these indices see Bollen, 1989).

3. MEASURING THE EXTERNAL EFFECTIVENESS OF PHD GRADUATES

The external effectiveness of an educational process can be measured with the success rate of individuals in the labour market, related to their capabilities, knowledge and skills acquired during their university studies. Typically, the success in the labour market can be measured using several indicators such as the probability of employment, the time to get the first job, the probability to find a job consistent with the acquired skills and the level of job satisfaction. In this study we use as measure of the external effectiveness of PhD programmes the evaluation of the employment status of PhDs, one year after achieving the title. The data set used in this analysis comes from the research project titled "Current situations and employment prospects of PhDs". The survey population was composed of 9696 units (PhDs) and the respons rate was 43,6%. The analysis concerns PhDs who achieved the title in 2008 and who are currently working. The sample size is 3488 PhD students who were interviewed one year after the end of their programmes. The data set contains several information on job condition.

The assessment of the employment conditions of PhDs is performed by measuring the degree of satisfaction of some relevant aspects, using a ten ordered points scale from 1 = “not at all satisfied” to 10 = “extremely satisfied”. Each score is considered as an approximation of a continuous indicator. The external effectiveness of PhD programmes is measured by these indicators: *consistency with studies*, *skills acquisition*, *utilization of the acquired skills*, *compliance with the cultural interests* and *compared to the PhD title*, where the latter indicator measures how much the competencies acquired during the PhD programme are used in the performing a job. In other words, assuming other

factors to be constant, the PhD title can be considered effective with respect to the current employment status if the activities of PhDs are consistent with their studies, if the skills acquired during the studies are actually used, if some more skills are acquired during the job experience, if the type of work is consistent with the cultural interests and if the job activities are adequate to the PhD competencies.

The satisfaction of PhD education with respect to the PhD's employment status represents the endogenous variable to be analysed, named external effectiveness and denoted with symbol (E). The hypothesised relationships between the latent variable E and the observed indicators, which represents the measurement model, are initially defined by a confirmatory factor model (Jöreskog, 1969). Such indicators are assumed to be correlated due to the presence of latent variable.

The E is measured with the mentioned indicators. It is also influenced by a number of variables, some of them are directly measurable (manifest variables), while others are not directly measurable (latent variables). The manifest variables are gender (named "gender"; 0 = "female" and 1 = "male"), age (named "age"; 0 = "less or equal to 32 years old" and 1 = "more than 32 years old"), scholarship (named "sch_ship"; 0 = "no" and 1 = "yes"), period of study spent abroad (named "time_abroad"; 0 = "no" and 1 = "yes"), employment status (named "job_status"; 0 = "not employed as researcher" and 1 = "employed as researcher") and searching for a job during the last three months from the date of interview (named "search_job"; 0 = "no" and 1 = "yes").

Among the latent variables affecting the external effectiveness, job satisfaction (JS), expectations (prospects and career) (EXP) and job participation (JP), as a measure of involvement in job activities, are included in the model. Similarly for the External effectiveness, these variables were identified through a nonstandard confirmatory factor analysis (Kline, 2011).

3.1 THE COMPLETE AND FINAL MODEL

Modifications applied to the measurement and structural part of the model for subsequent estimation steps have generated the model shown in this section (equations 4-10).

The latent variables E, JS, EXP and JP characterise the structural part of the model.

Formally, the variable E is measured as follows:

$$y_{y_p,i} = \lambda_{y_p,Ei}\eta_{ESi} + \varepsilon_{y_p,Ei} \qquad p = 1,...,5;\ \text{i=1,…, n.} \tag{4}$$

where *p* indicates the *p-th* variable, *i* the sample unit and *n* the sample size.

For the variable JS, the proposed indicators are *Level of the current wage* (y_6), *Correspondence to the tasks performed* (y_7), *Correspondence with the competencies acquired* (y_8) and *Overall satisfaction* (y_9):

$$y_{y_p,i} = \lambda_{y_p,JSi}\eta_{JSi} + \varepsilon_{y_p,JSi} \qquad p = 6,...,9;\ \text{i=1,…, n.} \tag{5}$$

For the variable EXP, the hypothesised indicators are *Level of the current wage* (y_{10}), *Opportunities of wage increase* (y_{11}), *Career opportunities* (y_{12}), *Job stability* (y_{13}), *Involvement in decision-making* (y_{14}), and *Overall satisfaction* (y_{15}):

$$y_{y_p,i} = \lambda_{y_p,EXPi}\eta_{EXPi} + \varepsilon_{y_p,EXPi} \qquad p = 10,...,15. \tag{6}$$

The first three indicators and *Overall satisfaction* reflect aspects which are relevant during the entire working life period, while the fourth indicator seems to be important especially at the beginning of the career because the first occupation is often characterized by precarious forms of employment. As regards *Involvement in decision-making*, this indicator measures how much the responsibility of a worker increases in a job position and we assume that this has an effect on expectations. Finally, for JP variable, the proposed indicators are *Skills acquisition* (y_{11}), *Compliance with the cultural interests* (y_{12}), *Independence and job autonomy* (y_{13}) and *Involvement in decision-making* (y_{14}):

$$y_{y_p,i} = \lambda_{y_p,JPi}\eta_{JPi} + \varepsilon_{y_p,JPi} \qquad p = 11,...,14. \tag{7}$$

These indicators are clearly related to job participation. More precisely, the last indicator denotes the condition to be involved in making decisions processes. Also the covariate *Searching for a new job during the last three months* as well as the variable indicating whether a PhD is employed as researcher in university or in public agency/institution, are used to explain the JP variable.

A total of four latent variables, thirteen observed response variables and two observed explanatory variables are used.

The structural model is defined with the following expressions, according to the relationships highlighted in Figure 2.

$$\eta_{E,i} = \beta_{EXP,E}\eta_{EXP_i} + \beta_{JP,E}\eta_{JPi} + \gamma_{E,job\_status}x_{job\_status_i} + \\ + \gamma_{E,time\_abroad}x_{time\_abroad_i} + \zeta_i. \tag{8}$$

The latent variable J*S* is a system of relationships expressed in extended form as follows:

$$\eta_{JS,i} = \beta_{JP,JS}\eta_{JP_i} + \zeta_i. \tag{9}$$

The latent variable EXP is a system of relationships expressed in extended form as follows:

$$\eta_{EXP,i} = \beta_{JP,EXP}\eta_{EXP_i} + \zeta_i. \tag{10}$$

4. RESULTS

Data analysis was performed considering the response variables as continuous. In addition, for the model estimation we decided to use the MLR estimator since it produces parameter estimates, standard errors and a chi-square test statistic that are robust with respect to non-normality distribution of the data. The analysis has been carried out using the software MPlus 5.21.

Tabb. 1, 2 and 3 report the estimated coefficients for the measurement model, the correlation between the observed indicators and the estimated coefficients of the structural model, respectively. In Tab. 1, R^2 coefficient is also shown as a measure of how much the observed indicator is explained by the latent variable. Fig. 2 shows the estimated model, with standardised estimates for the relationships between manifest and latent variables, among the latent variables and the factor loading for the measurement model. Accordingly to the typical notation, the ellipse represents the latent variable while the rectangles represent the observed indicators, both indicators and explanatory variables. The straight directional arrows starting from the latent variable represent the relationship between the latent variable and the observed indicators, the arrows pointing to the observed indicators represent the measurement errors whereas the bidirectional curved arrows represent the correlations between the observed indicators.

Chi-square test of model fit yielded a value of 483.787, with 77 degree of freedom and a *p*-value of 0.0000. This significance is probably affected by the sample size and the goodness of fit is evaluated with the other descriptive

indices. All these measures show a good fit of the model: CFI and TLI indices are respectively 0.979 and 0.968; RMSEA estimate is 0.040 (90% C.I. 0.036-0.043) and SRMR index is 0.028.

Table 1: Measurement model

Latent variables and indicators	*Est*	*Std err*	*p*	*Std est*	R^2
External effectiveness (E)					
Consistency with studies	1.00	–	–	0.84	0.71
Utilization of the acquired skills	1.05	0.02	0.000	0.93	0.86
Skills acquisition	0.41	0.04	0.000	0.38	0.58
Compliance with the cultural interests	0.80	0.05	0.000	0.71	0.70
Compared to the PhD title	0.37	0.03	0.000	0.27	0.51
Job Satisfaction (JS)					
Level of the current wage	1.00	–	–	0.12	0.42
Compared to the tasks performed	6.85	1.12	0.000	0.85	0.73
Compared to the PhD title	5.33	1.04	0.000	0.51	0.51
Overall	4.55	0.83	0.000	0.66	0.63
Expectations (EXP)					
Level of the current wage	1.00	–	–	0.59	0.42
Opportunities of wage increase	1.60	0.08	0.000	0.85	0.71
Career opportunities	1.72	0.09	0.000	0.88	0.77
Job stability	1.33	0.08	0.000	0.57	0.33
Involvement in decision-making	0.24	0.04	0.000	0.13	0.39
Overall	0.30	0.03	0.000	0.22	0.63
Job Participation (JP)					
Skills acquisition	1.00	–	–	0.45	0.58
Compliance with the cultural interests	0.41	0.09	0.000	0.17	0.70
Independence and job autonomy	1.47	0.11	0.000	0.63	0.40
Involvement in decision-making	1.41	0.12	0.000	0.55	0.39

Current condition and employment prospects of PhDs survey, 2008 (CNVSU, 2010)

Table 2: Estimates of correlation coefficients between observed indicators

Indicators	***r***	***Std err***	***p***	***Std est***
Level of the current wage *vs* Opportunities of wage increase	0.36	0.10	0.000	0.20
Level of the current wage *vs* Career opportunities	-0.53	0.08	0.000	-0.31
Job stability *vs* Overall	0.20	0.05	0.000	0.09
Consistency with studies *vs* Skills acquisition	-0.10	0.04	0.017	-0.07
Consistency with studies *vs* Compliance with the cultural interests	-0.43	0.08	0.000	-0.34
Utilization of the acquired skills *vs* Compliance with the cultural interests	-0.63	0.09	0.000	-0.73
Compliance with the cultural interests *vs* Independence and job autonomy	0.24	0.05	0.000	0.14
Independence and job autonomy *vs* Involvement in decision-making	0.85	0.08	0.000	0.32

Current condition and employment prospects of PhDs survey, 2008 (CNVSU, 2010)

Table 3: Estimates of regression coefficients between the latent and the observed variables

Latent and observed variables	***b***	***Std err***	***p***	***Std est***
External effectiveness (E) respect to	-	-	-	-
Expectations (EXP)	-0.42	0.05	0.000	-0.274
Job Participation (P)	1.70	0.11	0.000	0.81
Period of study spent abroad	0.12	0.05	0.025	0.03
Employment status	0.04	0.02	0.018	0.04
Job Satisfaction (JS) respect to	-	-	-	-
Job Participation (JP)	0.24	0.05	0.000	0.89
Expectations (A) respect to	-	-		-
Job Participation (JP)	0.72	0.07	0.000	0.53

Current condition and employment prospects of PhDs survey, 2008 (CNVSU, 2010)

The measurement part of the SEM model shows a very good fit: CFI and TLI indices are respectively 0.987 and 0.977; RMSEA estimate is 0.039 (90% C.I. 0.035-0.044) and SRMR index is 0.022.

In the measurement model, the indicators with higher factor loadings on the latent variables are:

- for the E variable, *Utilization of the acquired skills* (0.926), *Consistency with studies* (0.844) and *Compliance with the cultural interests* (0.709);
- for the EXP variable, *Opportunities of wage increases* (0.846) and *Career opportunities* (0.878);
- for the JP variable, *Independence and job autonomy* (0.630) and *Involvement in decision-making* (0.549);
- for the JS variable, *Compared to performed tasks* (0.853) and *Overall satisfaction* (0.661).

Concerning the structural part, the model shows that job participation has higher, positive and direct effect on external effectiveness (0.815), while expectation has a negative and direct effect (-0.274), supporting the hypothesis that the condition of being involved in a job increases the external effectiveness. The positive effect of job participation on expectations (0.526) means that current job conditions produce expectations for a future career.

As a consequence, the total effect of JP on the external effectiveness is lower than the direct effect $(0.670 = 0.815 - (0.526 \cdot 0.274))$. Among the manifest variables, gender, age, scholarship and searching for a new job do not have a significant effect on the external effectiveness. The employment status as researcher and the period of studies spent abroad directly affect the external effectiveness with a positive but weak effect.

Job participation also explains job satisfaction (0.894), confirming that the involvement in a job activity increases the satisfaction for the job condition. Obviously, the search for a new job is associated with a lower level of satisfaction for the current job (0.078).

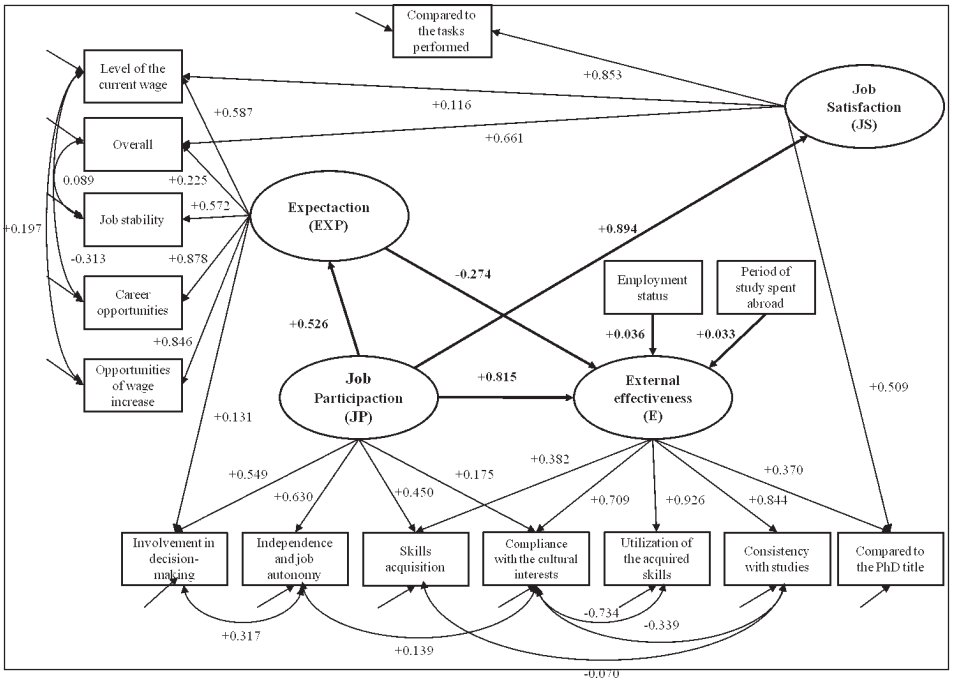

Figure 2: Relationships between the latent variable "External effectiveness" and the observed indicators. Current condition and employment prospects of PhDs survey, 2008 (CNVSU, 2010)

5. CONCLUSIONS

The interest on quality assessment of educational activities performed in Italian universities is established by law. In particular, it suggests to perform internal controls on the efficiency of processes as well as on the effectiveness of results of university management. With respect to the third level university educational processes, the success achieved in the labour market by PhD graduates can be considered as a measure of their effectiveness.

As well known, the external effectiveness of an educational process is difficult to be measured, because many aspects contribute to its definition.

This study focuses on the satisfaction with the several aspects of the current job and proposes the use of a structural equation model to assess the external effectiveness of PhD programmes, measured as a latent variable.

The employment status is usually characterised by several indicators related to satisfaction with the job conditions. This paper considers some of them, such as *consistency with studies*, *utilisation of the acquired skills*, *skills acquisition*,

compliance with the cultural interests and *compared to the PhD title*, as indicators of the quality of a job.

The SEM approach applied in this study yields some satisfactory and plausible results that validate the relationships hypothesised in the model.

The structural part of the model highlights the crucial role played by job participation on external effectiveness. Job participation has also a positive effect on job satisfaction and expectations.

The employment status as researcher increases the external effectiveness, although with a significant but weak effect. Also the experience abroad during PhD studies reveals to be an important factor for improving PhD effectiveness. This last result could be useful for improving activities of planning and management of the third level of university education.

Finally, all these upshots can be considered as preliminary and invite to carry out more detailed and deeper analyses on the external effectiveness of the level III educational process.

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