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MICROECONOMETRIC EVALUATION OF UNDERGRADUATE STUDENTS' RESULTS A MATCHING METHODOLOGY APPLICATION TO A PORTUGUESE POLYTECHNIC

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Abstract

During the academic years of 2004/05 and 2005/06 a new teaching methodology, inspired in the Bologna's Treaty, was implemented in one of the nine undergraduate programmes offered by the School of Technology and Management of *Bragança (Portugal)*. The aim was to increase the positive results for the students, concerning the acquisition of knowledge and skills.

To expose one undergraduate programme to a treatment – this is the teaching methodology - without expose the others created the conditions to a process of microeconometric evaluation that aims to quantify the causal effect of the exposition to the treatment. Following the lessons of the evaluation literature, the present paper adopts a propensity score matching methodology choosing as the interest parameter the average treatment on the treated (ATT). To compare only what is comparable, the evaluation was carried out on those subjects that were common among all the undergraduate programmes, like mathematics or statistics, or subjects that were common among the undergraduate programmes in the management's scientific area, like accounting or marketing.

Results show a positive effect of the treatment on those students who had been exposed to the teaching philosophy in 2004/05. Indeed the treated students present a bigger percentage of positive results comparing with the non treated colleagues. However, the results in terms of the grades' quality are less obvious. Even if the treated students achieve a positive grade, this grade is often smaller than the grade achieved by the colleagues. Results for 2005/06 are not so clear.

JEL Codes: C14, C21, A22
Keywords: Matching, Propensity Score, Microeconometrics, Program Evaluation, Average Treatment Effects

1-Introduction

The 2004/05 academic year was characterized, in the School of Technology and Management of the Polytechnic Institute of *Bragança (ESTIG-IPB*), by the implementation of the Bologna's Treaty in one of the nine undergraduate courses offered by the institution - the undergraduate course of *Informática de Gestão (IG)* which combines computer science and management. The changes in the course comprised not only a different structure but also a new teaching philosophy, namely at the methodological level, aiming to improve the positive results for the students. The main methodological changes included the compulsory obligation for students to participate in the classes, the continuous student's results evaluation and a more personal follow-up of the student. The methodology continued to be implemented only in that undergraduate programme in the 2005/06 academic year having been only extended to the remaining undergraduate courses two years after its introduction.

The authors intend to give their contribution to the discussion related to the teaching methodological methods. The discussion does not apply only to the institution where they work but also in the university system, in general. Therefore they present an impact microeconometric evaluation of the methodological changes in the results of those who where subject to them. The evaluation and the consequent outcome is the result of an objective assessment. It adopts a scientific methodology that allows us to conclude about the effectiveness of the introduction of a new teaching philosophy and offers the political makers a powerful analysis tool.

The introduction of a new teaching methodology – which in the future we will call treatment – to one undergraduate course leaving the others unchangeable creates the conditions to quantify the causal effect of the exposure to the treatment in the results.

Usually, the statistical methods applied to quantify the effects of an exposition to a treatment refer to statistical measures of association like the correlation coefficient between the treatment variable and the result variables. The association between two variables, however, does not always mean causality. Thus, we will apply an evaluation method suggested in the international literature of causal effects to empirically evaluate the impact of social programmes – the propensity score matching methodology. This methodology is very intuitive. It is a technique that for the elements in the group of treatment elements in the group not subject to the treatment, with the same observable characteristics, will be found. The matched elements will present only one difference – the participation on the treatment – so, the difference between their results can be caused by the treatment.

The majority of the observable characteristics for the students in the different undergraduate courses offered by *ESTiG-IPB* are administrative data, registered by the institution's information system and made available for the present evaluation. Other characteristics, personal and not objective, could be only obtained by questionnaire which was impossible to apply since this is an *ex-post* evaluation process.

Each academic year was evaluated independently. It aim to confirm, or not, the results obtained. For the 2004/05 academic year we found positive results in terms of approval rates especially when undergraduate courses in the neighbourhood of the scientific are analysed. However the same positive results were difficult to find when the quality of the approval rates where analysed. The treated students presented, on average, positive classifications lower than the ones obtained by their non treated colleagues. One year after the introduction of the teaching methodology the results are not as good. They are however positive, in general, and the quality of the positive results seemed to improve.

The present work is divided as follows. In the next section the econometric methodology will be presented and explained. The empirical application of the econometric methodology, to the problem under evaluation, is presented in section 3. Section 4, concludes.

2. The evaluation problem and the matching solution

2.1 – The evaluation problem

The evaluation problem of social programmes has been widely publicised and it is generally presented as a missing data problem. It can be formalized in a simple way. At a given moment in time, one student is in one of two potential situations (D), each one of them gives rise to a result (Y): in situation 1, the student participates in the treatment; in situation 0 he does not participate. The result of this formulation is presented in the Rubin Model:

$$Y = DY_1 + (1-D)Y_0 \qquad (1)$$

So it makes sense to associate both the results and think of their difference as the impact of the programme participation on the student, that is, the causal effect of the programme participation on him is given by the expression:

$$\Delta = Y_1 - Y_0 \qquad (2)$$

The evaluation problem arises because for a particular student, in a particular moment in time, it is impossible to observe his participation in the treatment (D=1) and, at the same time, his non-participation (D=0). The individual either participates in the programme under evaluation or not! This means that only one of the results is observed giving rise to the evaluation problem in social policies. It is not possible to know the causal effect of a programme for a given individual because there is no opposite evidence (the counterfactual corresponding to what would have happened in the absence of treatment). The estimation of a treatment effect relies on the artificial construction of the counterfactual result. This means the inference of a potential result that would have been observed if the individual had not been treated (Rubin, 1974; Rosenbaum & Rubin, 1983).

To understand the impact of the introduction of a new teaching philosophy, on the probability of those who had been treated, one needs to infer about the same probability if they had not participated. So, like in several other international research works, the interest parameter is the average treatment effect on the treated (ATT). This parameter estimates the average impact among those participating in the programme under evaluation:

$$\Delta P \equiv E(\Delta|D=1) = E(Y_1 - Y_0|D=1) = E(Y_1|D=1) - E(Y_0|D=1) \qquad (3)$$

2.2. The matching method

The matching method has been extensively refined in the most recent evaluation literature. It became now a valuable tool in empirical methodology, namely in non-experimental evaluations. The method is intuitively appealing. A student who participates in the programme is matched with a non-participant student who presents the same observational characteristics, so the difference between their results could be attributed to the programme Deheija & Wahba (2002). However, in a non-experimental evaluation the matching process could be a complex one due to selection problems that could bias the results. Therefore the matching process must rest on strong assumptions. One of these assumptions of identification is the Conditional Independence Assumption (CIA) that assumes that treatment assignment (D), conditional on observables (X), is independent of the potential results (Y). In formal notation the assumption corresponds to:

$$(Y_1, Y_0) \perp D|X \qquad (4)$$

Under the CIA, the treatment and comparison groups are comparable, on average, when conditioning on X.

$$E(Y_1|D=1, X) = E(Y_0|D=0, X) = E(Y_0|X) \qquad (5)$$

A practical implementation problem arises when the vector X is highly dimensional and contains continuous variables. But Rosenbaum and Rubin (1983) showed that match with a scalar function, such as the propensity score, P(X), is sufficient to balance the covariates X, between the treatment and comparison individuals. P(X) is one uni-dimensional variable defined as the conditional probability of participation given the vector of observed characteristics. Therefore, if CIA is conditional on X, it will also be conditional on the propensity score:

$$(Y_1, Y_0) \perp D|P(X), \text{ with } P(X) = \Pr(D=1|X) \qquad (6)$$

The alternative matching estimators comprise the definition of a closeness criterion, a neighbourhood, and the selection of a suitable weight function to associate the comparison individual to each treated individual. In this paper the choice of the comparison group lies in matched control observations which consist in the most similar non-participants – the nearest neighbour matching.

3. Empirical evaluation process

3.1. Selection of subjects and outcomes

From the presentation of the propensity score matching methodology it becomes clear that the adaptation of the econometric theory to this particular evaluation requires comparing only what is comparable. In the *ESTiG-IPB* institution, in the two academic years of reference, nine undergraduate courses with several specificities were offered. Nonetheless they had many similarities. The IG course had some subjects in common with the other eight courses some subjects. Therefore only the results of those subjects were evaluated. The subjects were: Algebra, Mathematics I, Mathematics II, Statistics, Operational Research, Introduction to Computer Science, Accounting I, Accounting II and Marketing.

The school success was measured: (i) by the percentage of students with classifications equal or higher than 10, and (ii) by the average of the positive classifications. The goal is not only to assess the success using the number of positive classifications but also assess the quality of that positive value to better understand the real impact of the introduction of the Bologna's Treaty.

3.1 – Causal Effect of the introduction of a new teaching methodology in the rate of positive classification

From the available data the observable variables described in the following Tables were selected.

In Table 1 is presented the distribution of the selected characteristics by the selected subjects, for the treatment group (TG) and for the comparison groups (CG), in the 2004/05 academic year. The Table 2 presents the same distribution for the academic year of 2005/06.

The different distribution of observable characteristics, as we can detect in Table 1 and Table 2, shows the importance of a matching process among the students to understand what is the real causal effect of the programme in the IG students. Indeed, the difference among the students in terms of observable characteristics could be in the origin of the difference among the results. So, to affirm the difference among the results of the students from different undergraduate courses is a consequence of the introduction of the policy in the IG course and not in the others is abusive and can originate interpretation mistakes.

As a result of the observed differences in the variables a *logit* binomial model was estrimated to compute the probability of a student being a IG student[1]. This is, to estimate the propensity score that will allow the matching among students. From the *logit* estimation we conclude that, although, not all the variables are statistically significant at the individual level they present joint statistical significance. These results show they are relevant to determine the probability of a student apply to the IG course. Actually it is possible to show (Table 3) the results of the rate of correct prediction[2] for participation obtained from the *logit* model. We considered that the rate of correct prediction is, in general, pretty good denoting that the selected variables are an excellent departure to find in the comparison groups good matches to the IG students,

[1] The results of the *logit* models will not be presented due to their extension.

[2] The models do not produce correct prediction rates equal to 100% and we do not expect that since we believe the models could be improved with subjective information not available for this particular research study.

according to the propensity score conditioned in a vector of selected observable characteristics.

After estimating the propensity score the matching methodology was implemented and the matches for the treated students were found in the comparison groups. Now the average of the IG students' results, in each subject, can be compared with the average of the results of the matched comparison students. The average of the results for the students in the comparison groups represents the results the IG students would have obtained if they had not been subject to the new teaching methodology. So, it is possible to estimate a more rigorous approximation to the real causal effect of the introduction of the policy on those who were subject to it.

The results of the matching methodology are presented in Table 5. However before we comment it is important to make reference to the quality of the matching procedure. Table 4 shows the results for the standardized absolute average bias[3] for the set of observable characteristics, between the treatment group and each comparison group before and after the matching procedure. The values are relatively high before matching but decrease after the procedure. Such reduction is a good indicator of the quality of the matching procedure and in practice means that it was possible to find in the comparison groups students equal to the treatment students, concerning the selected characteristics.

In Table 5 we can start to observe the causal effect of the teaching methodology on the IG students during the introduction year, the academic year of 2004/05, assuming the possibility that the student is attending the subject in any of the other undergraduate courses offered by the institution. With the exception of Statistics, Marketing and Accounting I the IG students would had obtained better results. In Algebra, Mathematics I and Operational Research they would have obtained a larger number of positive classifications if they were registered in another course of the institution. However if we compare the treated students only with the colleagues in the management courses the results show they benefited from being an IG student rather than a student from another management course. Analysing the academic year of 2005/06, the results appeared to be less positive for both groups of comparison. The results estimated for the previous year were not confirmed.

3.2 – Causal effect of the introduction of a new teaching methodology in the average value of positive classifications

To estimate the quality of the success the students with a positive classification were the only ones selected. For these students the distribution of observable characteristics among groups can be observed in Table 6 and Table 7 for the academic years of 2004/05 and 2006/07, respectively. The number of

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[3] Standardized Bias: $\dfrac{\left(\overline{X}_1 - \overline{X}_0\right)}{\sqrt{\left(V_1(X_1)+V_0(X_0)\right)/2}}$, where $\overline{X}_1\left(V_1\right)$ is the average (variance) in the treatment group and $\overline{X}_0\left(V_0\right)$ is the same for the comparison group.

student decreased and consequently the matching procedure did not perform as well. It is possible to observe in Table 8 a worse adjustment among treated students and comparison ones.

The results of the matching procedure are presented in Table 9. The first perception with only a few exceptions is that the IG students have a smaller probability to obtain better positive classifications than their colleagues attending the subjects in other courses. If the results for the 2004/05 academic year are not good for the treated students the results for the following year are even poorer if they are compared with colleagues from all scientific areas. Still they improve if they are compared with the colleagues in the management scientific area.

4. Conclusions

The estimations allow us to conclude that for the introduction year the teaching philosophy, as defended by the Bologna's Treaty, was important to improve the rates of positive classifications of those who where subjected to it. This result is not totally confirmed by the results of the second year of implementation. The second year results could be the consequence of a time dilution of the positive results for those who where subject to the new methodology. They could also be the result of positive externalities that where extended to the institution as an all and only arise in the second year of implementation of a new teaching methodology. When analysing the average value of the positive classifications the results were not satisfactory for 2004/05 but have improved over time for the neighbouring scientific study area of the treated students.

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Annex: Tables

Table 1 *Distribution of the observable characteristics for the 2004/05 year*

Subjects	Groups	Students	Age	% Sex (Male)	% Region (North)	% Nationality (Portuguese)	% Tuition Fee (No)	% Student Union (Yes)	% Scholarship (Yes)
Algebra	TG	49	25.3	71.4	20.4	77.6	4.1	18.4	6.1
	CG – All Courses	525	24.8	71.0	27.2	85.5	2.1	26.5	22.3
	CG - Management	118	26.1	41.5	29.7	85.6	0.8	47.5	33.1
Mathematics I	TG	59	24.7	67.8	18.6	78.0	5.1	20.3	8.5
	CG – All Courses	794	24.9	64.2	24.4	85.3	2.0	27.6	22.2
	CG - Management	299	25.6	41.8	23.4	83.9	1.3	35.1	27.8
Mathematics II	TG	62	24.9	69.4	21.0	77.4	4.8	17.7	9.7
	CG – All Courses	-----	-----	-----	-----	-----	-----	-----	-----
	CG - Management	321	25.8	43.6	24.3	83.8	0.9	34.3	26.2
Statistics	TG	47	25.4	48.9	25.5	89.4	2.1	34.0	25.5
	CG – All Courses	621	25.7	57.5	27.2	85.7	1.3	41.1	28.5
	CG - Management	217	26.2	37.8	27.2	86.6	1.4	46.5	34.1
Operational Research	TG	26	25.4	50.0	34.6	92.3	3.8	19.2	26.9
	CG – All Courses	419	26.1	55.6	27.9	88.5	1.2	39.4	28.4
	CG - Management	167	26.2	38.3	27.5	86.8	1.2	49.1	36.5
Introduction computer science	TG	23	25.6	73.9	21.7	73.9	4.3	4.3	21.7
	CG – All Courses	-----	-----	-----	-----	-----	-----	-----	-----
	CG - Management	150	25.4	36.7	20.0	80.0	0.7	13.3	24.7
Marketing	TG	43	25.0	39.5	27.9	79.1	0.0	20.9	37.2
	CG – All Courses	78	26.6	25.6	29.5	76.9	0.0	39.7	35.9
	CG - Management	71	26.7	28.2	31.0	74.6	0.0	40.8	32.4
Accounting I	TG	40	25.1	65.8	13.2	71.1	0.0	18.4	7.9
	CG – All Courses	78	24.5	47.4	20.5	80.8	0.0	14.1	19.2
	CG - Management	71	24.7	50.7	22.5	80.3	0.0	14.1	14.1
Accounting II	TG	57	25.8	63.6	25.5	76.4	0.0	18.2	7.3
	CG – All Courses	-----	-----	-----	-----	-----	-----	-----	-----
	CG - Management	97	24.9	44.3	18.6	79.4	0.0	22.7	16.5

Table 2 *Distribution of the observable characteristics for the 2005/06 year*

Subjects	Groups	Students	Age	% Sex (Male)	% Region (North)	% Nationality (Portuguese)	% Tuition Fee (No)	% Student Union (Yes)	% Scholarship (Yes)
Algebra	TG	25	26.2	80	12.0	80.0	8.0	20.0	-----
	CG – All Courses	331	24.6	66.5	25.4	86.1	6.3	27.8	-----
	CG - Management	110	25.7	38.2	27.3	88.2	5.5	39.1	-----
Mathematics I	TG	35	24.9	65.7	11.4	85.7	8.6	22.9	-----
	CG – All Courses	423	25.0	64.8	24.6	84.6	6.1	28.8	-----
	CG - Management	190	25.7	44.7	24.7	83.7	6.3	35.3	-----
Mathematics II	TG	39	24.8	64.1	17.9	87.2	10.3	20.5	-----
	CG – All Courses	-----	-----	-----	-----	-----	-----	-----	-----
	CG - Management	210	25.7	47.1	27.6	83.8	6.2	36.7	-----
Statistics	TG	45	24.9	60.0	28.9	91.1	6.7	31.1	-----
	CG – All Courses	626	25.1	56.1	27.2	85.3	5.0	37.1	-----
	CG - Management	217	25.5	39.2	29.0	86.2	3.7	45.2	-----
Operational Research	TG	29	24.9	48.3	24.1	82.8	6.9	20.7	-----
	CG – All Courses	361	25.4	55.4	27.1	86.7	6.1	36.8	-----
	CG - Management	41	25.6	41.1	30.5	85.1	4.3	45.4	-----
Introduction computer science	TG	9	24.9	55.6	0.0	66.7	11.1	0.0	-----
	CG – All Courses	-----	-----	-----	-----	-----	-----	-----	-----
	CG - Management	70	26.1	32.6	0.0	81.4	9.3	0.0	-----
Marketing	TG	16	24.8	43.8	50.0	100.0	6.3	31.3	-----
	CG – All Courses	71	24.8	32.8	23.0	100.0	3.3	42.6	-----
	CG - Management	63	25.0	33.3	25.9	100.0	3.7	42.6	-----
Accounting I	TG	21	25.1	66.7	9.5	71.4	9.5	14.3	-----
	CG – All Courses	110	24.8	45.5	23.6	80.0	10.9	16.4	-----
	CG - Management	99	25.1	44.4	24.2	79.8	10.1	17.2	-----
Accounting II	TG	27	25.6	77.8	14.8	81.5	11.1	14.8	-----
	CG – All Courses	-----	-----	-----	-----	-----	-----	-----	-----
	CG - Management	92	25.1	43.5	28.3	82.6	5.4	30.4	-----

Table 3 *Correct Prediction Rate for participation of students in the IG course.*

Rate of Correct Prediction (%)	Undergraduate Courses		Algebra	Mathematics I	Mathematics II	Statistics	Operational Research	Introduction Computer Science	Marketing	Accounting I	Accounting II
	All	2004/05	77.55	62.71	-----	63.83	73.08	-----	72.09	76.32	----
		2005/06	76	71.43	-----	64.44	72.41	-----	62.5	76.19	-----
	Management	2004/05	71.43	67.8	66.13	57.45	76.92	69.57	74.42	76.32	61.82
		2005/06	80	62.86	56.41	55.56	72.41	88.89	68.75	76.19	74.07

Table 4 *Average Absolute bias between the treatment group and the comparison groups before and after the matching procedure.*

	GC	Bias	Algebra	Mathematics I	Mathematics II	Statistics	Operational Research	Introduction Computer Science	Marketing	Accounting I	Accounting II
All Courses	2004/05	Before	18.58	16.87	-----	9.86	17.58	-----	21.35	23.6	-----
		After	0.54	6.58	-----	9.94	12.6	-----	5.82	10.98	-----
	2005/06	Before	24.55	10.85	-----	9.48	13.93	-----	19.52	19.67	-----
		After	13.63	6.22	-----	9.8	14.6	-----	15.77	16.78	-----
Management Courses	2004/05	Before	39.92	30.06	29.66	14.83	25.45	23.68	23.87	19.95	21.03
		After	8.43	4.81	8.37	13.14	10.07	22.83	13.43	18.35	14.37
	2005/06	Before	36.45	23.32	23.35	19.27	19.5	18.86	19.12	18.98	30.08
		After	15.25	11.4	9.57	8.2	10.33	0.45	1.37	13.23	12.75

Table 5 *Percentage of students with a positive classification.*

	Comparison Courses											
	All Courses						Management Courses					
	GT		GC		Difference (Δ)		GT		GC		Difference (Δ)	
	Academic year		Academic year		Academic year		Academic year		Academic year		Academic year	
	2004/05	2005/06	2004/05	2005/06	2004/05	2005/06	2004/05	2005/06	2004/05	2005/06	2004/05	2005/06
Algebra	26.5	24.0	30.6	8.0	– 4.1	16.0	26.5	26.1	16.3	8.7	10.2	17.4
Mathematics I	18.6	17.1	30.5	28.6	– 11.9	– 11.4	19.0	17.1	13.8	17.1	5.2	0.0
Mathematics II	-----	-----	-----	-----	-----	-----	27.9	30.8	11.5	10.3	16.4	20.5
Statistics	53.2	46.7	46.8	40.0	6.4	6.7	53.2	46.7	19.1	33.3	34.0	13.3
Operational Research	34.6	6.9	53.8	34.5	– 19.2	– 27.6	34.6	7.1	23.1	21.4	11.5	– 14.3
Introduction Computer Science	-----	-----	-----	-----	-----	-----	30.4	33.3	26.1	22.2	4.3	11.1
Marketing	92.9	86.7	73.8	100.0	19.0	– 13.3	95.1	86.7	65.9	93.3	29.3	– 6.7
Accounting I	73.0	36.8	27.0	21.1	45.9	15.8	73.0	36.8	29.7	21.1	43.2	15.8
Accounting II	-----	-----	-----	-----	-----	-----	56.4	25.0	16.4	12.5	40.0	12.5

Table 6 *Distribution of the observable characteristics for the 2004/05 year*

Subjects	Groups	Students	Age	% Sex (Male)	% Region (North)	% Nationality (Portuguese)	% Tuition Fee (No)	% Student Union (Yes)	% Scholarship (Yes)
Algebra	TG	13	23.8	30.8	23.1	92.3	0.0	30.8	7.7
	CG – All Courses	125	23.3	57.6	32.0	93.6	0.0	27.2	49.6
	CG - Management	43	24.0	30.2	34.9	93.0	0.0	44.2	58.1
Mathematics I	TG	11	23.6	36.4	27.3	63.6	0.0	27.3	18.2
	CG – All Courses	229	23.9	56.3	23.1	88.6	0.0	31.0	39.7
	CG - Management	62	24.3	24.2	25.8	85.5	0.0	50.0	56.5
Mathematics II	TG	8	23.9	37.5	37.5	62.5	0.0	25.0	25.0
	CG – All Courses	-----	-----	-----	-----	-----	-----	-----	-----
	CG - Management	57	24.5	24.6	21.1	84.2	0.0	42.1	47.4
Statistics	TG	13	25.2	38.5	23.1	92.3	0.0	30.8	46.2
	CG – All Courses	71	24.8	39.4	26.8	87.3	0.0	38.0	43.7
	CG - Management	16	24.5	0.0	31.3	93.8	0.0	31.3	68.8
Operational Research	TG	9	24.4	33.3	33.3	88.9	0.0	11.1	55.6
	CG – All Courses	179	25.0	52.0	24.6	91.1	0.0	37.4	36.9
	CG - Management	55	24.6	16.4	23.6	96.4	0.0	47.3	56.4
Introduction computer science	TG	7	26.1	85.7	42.9	85.7	0.0	0.0	42.9
	CG – All Courses	-----	-----	-----	-----	-----	-----	-----	-----
	CG - Management	49	23.7	40.8	10.2	81.6	0.0	18.4	40.8
Marketing	TG	39	24.9	33.3	25.6	76.9	0.0	20.5	35.9
	CG – All Courses	56	25.9	23.2	30.4	82.1	0.0	46.4	46.4
	CG - Management	49	26.0	26.5	32.7	79.6	0.0	49.0	42.9
Accounting I	TG	13	24.5	53.8	23.1	84.6	0.0	30.8	7.7
	CG – All Courses	23	23.4	30.4	17.4	87.0	0.0	17.4	39.1
	CG - Management	18	23.4	33.3	22.2	83.3	0.0	16.7	27.8
Accounting II	TG	19	25.2	36.8	26.3	84.2	0.0	26.3	10.5
	CG – All Courses	-----	-----	-----	-----	-----	-----	-----	-----
	CG - Management	32	23.9	37.5	18.8	78.1	0.0	37.5	25.0

Table 7 *Distribution of the observable characteristics for the 2005/06 year*

Subjects	Groups	Students	Age	% Sex (Male)	% Region (North)	% Nationality (Portuguese)	% Tuition Fee (No)	% Student Union (Yes)	% Scholarship (Yes)
Algebra	TG	6	25.3	50.0	16.7	66.7	0.0	16.7	-----
	CG – All Courses	65	23.3	52.3	26.2	26.2	0.0	33.9	-----
	CG - Management	25	24.0	28.0	32.0	80.0	0.0	36.0	-----
Mathematics I	TG	6	24.5	33.3	16.7	83.3	0.0	50.0	-----
	CG – All Courses	118	23.9	69.5	24.6	81.4	1.7	31.4	-----
	CG - Management	32	25.0	50.0	25.0	71.9	0.0	40.6	-----
Mathematics II	TG	12	24.3	25.0	33.3	83.3	0.0	25.0	-----
	CG – All Courses	-----	-----	-----	-----	-----	-----	-----	-----
	CG - Management	35	25.5	37.1	31.4	71.4	0.0	51.4	-----
Statistics	TG	10	24.6	50.0	50.0	100.0	0.0	30.0	-----
	CG – All Courses	101	24.6	50.5	30.7	86.1	1.0	40.6	-----
	CG - Management	39	24.7	33.3	25.6	87.2	0.0	53.8	-----
Operational Research	TG	2	28.5	100.0	0.0	50.0	0.0	0.0	-----
	CG – All Courses	94	24.5	57.4	23.4	87.2	4.3	36.2	-----
	CG - Management	16	24.3	43.8	12.5	75.0	0.0	37.5	-----
Introduction computer science	TG	3	23.7	0.0	0.0	66.7	33.3	0.0	-----
	CG – All Courses	-----	-----	-----	-----	-----	-----	-----	-----
	CG - Management	17	26.9	23.5	0.0	88.2	0.0	0.0	-----
Marketing	TG	13	24.2	38.5	46.2	100.0	0.0	23.1	-----
	CG – All Courses	50	24.6	36.0	24.0	100.0	2.0	46.0	-----
	CG - Management	44	24.8	36.4	27.3	100.0	2.3	45.5	-----
Accounting I	TG	8	25.4	62.5	12.5	62.5	12.5	25.0	-----
	CG – All Courses	47	24.7	40.4	19.1	78.7	6.4	19.1	-----
	CG - Management	44	24.9	40.9	20.5	79.5	4.5	18.2	-----
Accounting II	TG	7	24.1	57.1	0.0	71.4	14.3	14.3	-----
	CG – All Courses	-----	-----	-----	-----	-----	-----	-----	-----
	CG - Management	33	23.9	27.3	36.4	78.8	0.0	30.3	-----

(Columns Students through Scholarship are grouped under "Observable Characteristics".)

Table 8 *Average Absolute bias between the treatment group and the comparison groups before and after the matching procedure.*

	GC	Bias	Algebra	Mathematics I	Mathematics II	Statistics	Operational Research	Introduction Computer Science	Marketing	Accounting I	Accounting II
All Courses	2004/05	Before	35.96	29.21	-----	9.85	30.2	-----	25.87	38.2	-----
		After	1.38	24.50	-----	28.37	20.68	-----	10.57	32.53	-----
	2005/06	Before	36.18	29.48	-----	22.3	78.3	-----	22.57	24.22	-----
		After	59.24	1.05	-----	25.03	74.88	-----	14.8	33.88	-----
Management Courses	2004/05	Before	31.43	39.03	36.28	25.53	29.73	54.47	24.35	30.35	24.18
		After	17.25	39.50	40.81	51.25	34.35	30.43	18.9	19.8	40.68
	2005/06	Before	38.26	18.50	23.55	31.3	69.75	46.43	22.31	25.67	46.72
		After	36.44	38.28	23.55	11.65	48.33	29.28	6.12	21.08	15.08

Table 9 *Average value of positive classifications.*

	Comparison Courses											
	All Courses						Management Courses					
	GT		GC		Difference (Δ)		GT		GC		Difference (Δ)	
	Academic year		Academic year		Academic year		Academic year		Academic year		Academic year	
	2004/05	2005/06	2004/05	2005/06	2004/05	2005/06	2004/05	2005/06	2004/05	2005/06	2004/05	2005/06
Algebra	11.50	11.67	11.50	12.83	0.00	– 1.16	11.38	11.67	11.38	12.83	0.00	– 1.16
Mathematics I	11.27	11.17	11.91	11.83	– 0.64	– 0.66	11.27	11.17	11.45	11.00	– 0.18	0.17
Mathematics II	-----	-----	-----	-----	-----	-----	11.75	10.58	12.13	14.50	– 0.38	– 3.92
Statistics	10.73	12	10.45	11.4	0.27	– 1.16	10.73	12.00	10.18	11.70	0.55	0.30
Operational Research	11.00	10.50	11.33	10.50	– 0.33	0.00	11.00	10.50	13.22	12.50	– 2.22	– 2.00
Introduction Computer Science	-----	-----	-----	-----	-----	-----	12.33	10.33	10.67	12.67	1.67	– 2.34
Marketing	11.31	11.77	11.54	12.77	– 0.23	– 1.00	11.31	11.77	11.51	11.69	– 0.21	0.08
Accounting I	10.45	11.14	11.00	11.14	– 0.55	0.00	10.45	11.14	10.91	11.29	– 0.45	– 0.14
Accounting II	-----	-----	-----	-----	-----	-----	11.21	12.00	11.84	10.83	– 0.63	1.17