Causal analysis of rewards and quality commitment in higher education context

Причинно-следственный анализ системы вознаграждения и обязательств по обеспечению качества в контексте высшего образования

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Аннотация

Данная работа содержит результаты исследования причинно-следственной связи между вознаграждением работников университета и их отношением к обеспечению качества услуг. Исследование проводилось на базе Американского университета культуры и образования в Ливане в течение 6 месяцев. На трех факультетах университета были введены различные уровни вознаграждения, а отношение работников университета к обеспечению качества услуг было измерено до и после введения новых видов вознаграждения. Результаты первого и второго измерений были проанализированы при помощи метода разности разностей и сопоставления. В соответствии с результатами среднее воздействие на подвергшихся воздействию очень существенно (p-величины < 0,01) и варьируется между 0,626 и 0,669 для разных методов оценки, то есть отношение работников к обеспечению качества почти на один уровень выше (по шкале от 1 до 5) по сравнению с ситуацией, когда стимулирование отсутствует. Эти открытия подчеркивают важность развития системы вознаграждения в учреждениях высшего образования для укрепления положительного отношения работников университета к обязательствам по обеспечению качества услуг.

Ключевые слова: вознаграждение, внутреннее вознаграждение, качество, обязательства по обеспечению качества, профессорско-преподавательский состав, учреждения высшего образования (УВО), среднее воздействие на подвергшихся воздействию (ATT), метод разности разностей (DID).

Abstract

This research investigated causal inferences between rewards and university staffs attitudes toward quality commitment over a 6-month period at the American University of Culture and Education in Lebanon. Different levels of rewards were administered to three faculties and university staffs' attitudes toward quality were measured before and after reward administration. Results of first and second measurement were analyzed using techniques of Difference in Difference and matching. The results revealed that the Average treatment on treated is strongly significant (p-values < 0.01) and varies between 0.626 and 0.669 for different methods of estimation. This means that staffs attitudes toward quality commitment is almost one level higher (on the grade from 1 to 5) if compared to situation without incentives. These findings underscore the importance of developing reward schemes in higher education institutions to reinforce university staffs' attitudes toward quality.

Keywords: Rewards, Intrinsic Rewards, Quality, Quality Commitment, Academic staff, Higher education institutions (HEI), Average Treatment on Treated (ATT), Difference In Difference (DID).

Поступила в редакцию / Received: 29.02.2016
Web: http://elibrary.miu.by/journals!/item.eiup/issue.45/article.12.html

Introduction

Quality has become on the top of most agendas and improving quality is the most important task facing any higher education institution [1]. Higher Education Institutions (HEI) are being encouraged to take a developmental approach to quality [2], because «Quality» in the form of assurance processes was often met with resistance, and Staffs of HEI are partners in quality development as much as senior administrators [3]. Quality is the responsibility of every employee, and their commitment to quality is fundamentally important [4]. This is why HEIs are recommended to define incentive and reward schemes to stimulate the staff adoption of quality procedures [3].

In this regard, a causal research is conducted to identify potential inference for rewards on staff commitment to quality in higher education. The study gains its importance as a first move in the Lebanese higher education context, and intended to examine the extent to which staffs attitude toward quality is a function of offered incentives, does a varying level of incentives produce a varying level of change in staff commitment to quality?

We applied two popular approaches in causal analysis for estimating average treatment on treated (ATT): difference -in-difference (DID) and matching.

The paper proceeds with research design description, experiment description, introduction to modeling methodology and discussion of results.

1. Research Design

While the study explains the nature of relationships among rewards and staffs attitude toward quality commitment in higher education context, it's engaged in testing the following hypothesis:

H0: The greater the level of incentives received by staffs, the greater the extent of staff's attitudes change towards quality commitment. Alternative hypothesis can be formulated like this: H1: There is no causal inference for incentives/rewards on quality commitment.

On the other hand, this investigation is trying to examine the causal inference for incentives / rewards on staffs of higher education commitment to quality. The study took place in the natural environment at the American University of Culture and Education where work settings proceeded normally.

The American university of Culture and Education constitutes of 200 academic staff and 60 administrative staff distributed among eight branches/ campuses all around Lebanon. The data used in two phases of this study were gathered from Tyr campus before and after the introduction of reward system (sample size =84), and the Unit of analysis: Individuals, Dyads and groups (faculty). As the unit of analysis is a function of the research question posed, and is an integral part of the research design [5].

The time horizon of the study extended to six month from April 2015 to October 2015, where work settings proceeded normally. As a longitudinal study, data were gathered from the same sample to ensure a true panel [6] before and after the introduction of reward system using the same procedure for collecting survey data within each faculty. The quality commitment scale was included within a survey instrument containing a mixture of standardized instruments and items designed specifically for the organization in question. Questionnaires were administered by the researcher to academic staff members on two stages, before (M0) and after launching reward schemes (M1) to the target sample and consent to take part in the survey was obtained after the researcher explained the purpose of the survey. Confidentiality was assured, and completed questionnaires were removed from the study site for processing. Feedback was provided on the main findings of the survey to all academic staff who took part.

2. Experiment design

The experiment on the impact of rewards on staffs' attitude toward quality commitment took place in three different faculties at the university; the faculty of Education, faculty of Engineering and the faculty of Business. Rewards were carefully selected based on the findings of an empirical investigation on Academic Reward Systems in Lebanon [7]. The model of experiment was intended to measure the varying level of commitment among these three faculties after introducing varying levels of reward to each faculty as follows.

2.1. Faculty of Education

A set of rewards were officially launched in coordination with the university management and the head of the faculty of Education, A formal letter signed by the university officials targeted all members of the faculty of Education, including a three main rewards parallel with the expected performance criteria's, basis and responsibility of evaluation. The three main rewards are:

1) Researcher of the semester Award;
2) Discipline Award;
3) Instructor of the semester award.

In addition, some privileges were granted specifically to all staffs of the faculty of Education, the privileges are:

1) Ability to select which courses to teach per semester.
2) Two training sessions to be held during the rest of 2015 at the university. The training program will be designed to fit your professional needs; you will have the main voice in setting its priorities.
3) A regular meeting with the university director (at the end of each semester) to communicate your suggestions on potential developments on quality issues at the faculty of Education.
4) Your right to get a regular feedback from the faculty of Education head of department on your progress.
5) The right to report about any quality misconduct to the university director directly in a secured way.

2.2. Faculty of Engineering

Other set of rewards were officially launched in accordance with the university management and the head of the faculty of Engineering, A formal letter signed by the university officials targeted all members of the faculty of Engineering, including a two main rewards parallel with the expected performance criteria's, basis and responsibility of evaluation. The two main rewards are:

1) Researcher of the year Award;
2) Instructor of the semester Award.

The distinguishing characteristic among the offered rewards to the faculty of English and the faculty of Engineering is that faculty of Engineering members receive only two awards with no other privileges.

2.3. Faculty of Business

As per the experiment, faculty of Business staff members was intentionally left without any kind of rewards. As a control faculty, neither rewards nor privileges were granted to this faculty.

Descriptive statistics on results of the study presented in [8].

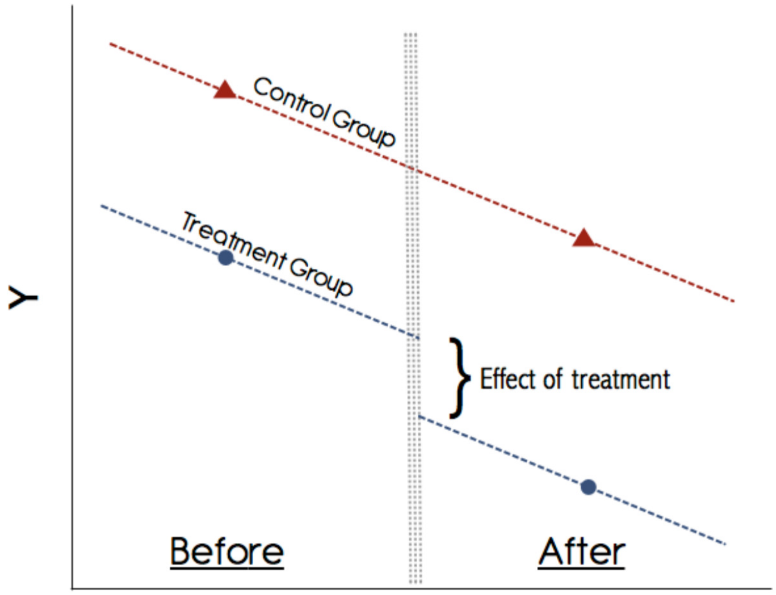

Figure – Average Treatment on Treated Effect

3. Modeling

We applied several approaches to estimation of ATT (Average Treatment on Treated Effect): difference-in-difference (DID) and matching.

3.1. Difference-in-difference

DID estimation uses four data points to deduce the impact of a policy change or some other shock (i.e. treatment) on the treated population: the effect of the treatment on the treated. The structure of the experiment implies that the treatment group and control group have similar characteristics and are trending in the same way over time. This means that the counterfactual (unobserved scenario) is that had the treated group not received treatment, its mean value would be the same distance from the control group in the second period. See the diagram below; the four data points are the observed mean (average) of each group. These are the only data points necessary to calculate the effect of the treatment on the treated. The dotted lines represent the trend that is not observed by the researcher. Notice that although the means are different, they both have the same time trend (i.e. slope).

Since the work by [9], the use of difference-in-differences methods has become very widespread. The simplest set up is one where outcomes are observed for two groups for two time periods. One of the groups is exposed to a treatment in the second period but not in the first period. The second group is not exposed to the treatment during either period. In the case where the same units within a group are observed in each time period, the average gain in the second (control) group is substracted from the average gain in the first (treatment) group. This removes biases in second period comparisons between the treatment and control group that could be the result from permanent differences between those groups, as well as biases from comparisons over time in the treatment group that could be the result of trends.

With repeated cross sections, we can write the model for a generic member of any of groups as:

$$y = \beta_0 + \beta_1 dB + \delta_0 d_2 + \delta_1 d_2 \cdot dB + u$$

Where y is the outcome of interest, d_2 is a dummy variable for the second time period. The dummy variable dB captures possible differences between the treatment and control groups prior to the policy change. The time period dummy d_2 captures aggregate factors that would cause changes in v even in the absence of a policy change. The coefficient of interest δ_1, multiplies the interaction term $d_2 \cdot dB$ which is the same as a dummy variable equal to one for those observations in the treatment group in the second period. The difference-in-differences estimate is

$$\delta_1 = (d_{B,2} - d_{B,1}) - (d_{A,2} - d_{A,1})$$

Inference based on even moderate sample sizes in each of the four groups is straightforward, and is easily made robust to different group/time period variances in the regression framework.

3.2. Matching

Matching has become an increasingly popular method of causal inference in many fields including statistics [10], medicine [11, 12], economics [13, 14], political science [15, 16, 17], sociology [18, 19, 20, 21] and even law [22]. There is, however, no consensus on how exactly matching ought to be done and how to measure the success of the matching procedure. A wide variety of matching procedures have been proposed, and Matching implements many of them.

When using matching methods to estimate causal effects, a central problem is deciding how best to perform the matching. Two common approaches are propensity score matching [23] and multivariate matching based

Table 1 – Difference-in-difference estimations

	Dependent variable: y		
	(1)	(2)	(3)
time	-0,010 (0,140)	-0,010 (0,068)	-0,010 (0,067)
Tr	0,125 (0,117)	0,017 (0,057)	0,017 (0,057)
Q3		0,049 (0,073)	
Q7		-0,045 (0,028)	-0,039 (0,024)
Q8		-0,034 (0,040)	
Q9		0,028 (0,042)	
y0		0,897*** (0,039)	0,893*** (0,039)
time: Tr	0,669*** (0,166)	0,669*** (0,080)	0,669*** (0,080)
Constant	3,274*** (0,099)	0,353** (0,171)	0,410*** (0,143)
Observations	168	168	168
R^2	0,345	0,852	0,850
Adjusted R^2	0,333	0,844	0,846
Residual Std. Error	0,485 (df = 164)	0,234 (df = 159)	0,233 (df = 162)
F Statistic	28,795*** (df = 3; 164)	114,120*** (df = 8; 159)	184,026*** (df = 5; 162)
Note:	*p < 0.1; **p < 0.05; ***p < 0.01		

on Mahalanobis distance [24, 25, 26]. Matching methods based on the propensity score (estimated by logistic regression), Mahalanobis distance or a combination of the two have appealing theoretical properties if covariates have ellipsoidal distributions – e.g., distributions such as the normal or t. If the covariates are so distributed, these methods (more generally affinely invariant matching methods) have the property of «equal percent bias reduction» (EPBR) [27, 28, 29]. When this property holds, matching will reduce bias in all linear combinations of the covariates. If the EPBR property does not hold, then, in general, matching will increase the bias of some linear functions of the covariates even if all univariate means are closer in the matched data than the unmatched [27]. Unfortunately, the EPBR property rarely holds with actual data.

Diamond and Sekhon [30] and Sekhon and Grieve [31] propose a matching algorithm, genetic matching (GenMatch), that maximizes the balance of observed covariates between treated and control groups. GenMatch is a generalization of propensity score and Mahalanobis distance matching, and it has been used by a variety of researchers (e.g., [18, 32, 33, 34, 35, 36, 37, 38, 39]. The algorithm uses a genetic algorithm [40, 41] to optimize balance as much as possible given the data. The method is nonparametric and does not depend on knowing or estimating the propensity score, but the method is improved when a propensity score is incorporated.

4. Results

The dataset used for models estimation consists of following variables:

1) Averaged answer to 10 questions related to staff commitment to quality (y0) measured before experiment. Each answer is coded from 1 to 5, where higher values indicate stronger staff commitment. See [18] for details on each question.
2) Averaged answer to 10 questions related to staff commitment to quality (y) measured after experiment – this is out dependent variable.
3) Treatment variable (Tr) indicating that person was treated (Tr = 1, Faculties of Engineering and Education) or wasn't treated (Tr = 0, Faculty of Business).
4) Time variable, equal to 0 for initial measure (M0) and equal to 1 for second measure (M1) after incentives were distributed.
5) Demographics variables: Q3 – for person role (Teaching Stuff or Administrative Staff), Q7 – staff level (Junior, Middle or Senior), Q8 – part-timer or full-timer, Q9 – gender.

4.1. Difference-in-difference

DID estimation are presented in Table 1, measure of interest is coefficient for time and Tr multiplication. In this case it's positive and strongly significant. The value of 0,669 indicates that those respondents who received treatment are almost one step better to acquire quality standards of the university on 1 to 5 scale. It's also notable that there is no discrimination on gender, staff role or level.

4.2. Matching

Non-experimental design was used to prove the estimated ATT. We used matching on confounding variables with dataset described above (Table 2).

Table 2 – Matching on confounding variables

Estimate	0,69167
AI SE	0,12641
T-stat	5,4716
p.val	4,4607e^{-08}
Original number of observations	84
Original number of treated obs	60
Matched number of observations	60
Matched number of observations (unweighted)	144

The estimate is still positive, strongly significant and very close to the one we get for DID estimation – 0.69167. It confirms that treated personal of university tend to precept the quality politics on one grade higher level than those who doesn't receive incentives.

Conclusion

The study proved that ATT (Average treatment on treated) is strongly significant (p-value < 0.01) and varies between 0.6 and 0.7 this means that attitudes toward quality commitment is almost one level higher (on the grade from 1 to 5) if compared to situation without incentives.

In accordance with the above findings, staffs attitudes toward quality commitment could be modified through effective administration of incentives/ rewards to staff. Higher education institutions have a valuable option to motivate staffs commitment to quality rather than imposing quality standards, controlling and monitoring its adoption.

Concerning the hypothesis, it was hypothesized that the greater the level of incentives received by staffs, the greater the extent of staff's attitudes change towards quality commitment. This is proved by positive signs of ATT estimations. As for the second hypothesis, change in staffs' attitudes toward quality in the faculty of Business (who didn't receive incentives) was insignificant.

These findings underscore the importance of developing reward schemes in Lebanese higher education institutions to motivate university staffs' adoption of quality standards. As for future research, further studies to investigate the change in staff adoption of quality as a function of increased level of received incentives is recommended.

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