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Designing and programming a graphical interface to evaluate *treatments* in economics experiments

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Abstract. In this paper, we develop a graphical interface that allows to calculate the efficacy of one or more *treatments* before adopting an experimental economics design. The graphical interface is built with Java according to a model-based *treatment* design. The aim is twofold. We are first interested in designing *treatments* in order to increase their efficacy, evaluating how experimental factors can affect the *treatment* process design. The second aim is to enhance the internal and external validity of the experiment to be run. The general idea behind this research is to implement a Graphical Experimenter Interface (GEI) capable to support economists when deciding which experimental *treatment* design to adopt and thus which factors to include.

Keywords: Experimental economics, model-based *treatment* design, computational economics.
JEL classification: C90, C91, C93, C99.

1 Introduction

In the context of economics experiments, a *treatment* is generally an artificial variation applied to randomly selected subset of experimental subjects having a causal effect on some outcome, and this subset compared to a randomly selected control group. Experimental research, indeed, enables economists to go beyond descriptive and predictive analytics, and attempts to determine what caused effects, providing information on cause-and-effect relationships between variables[1]. Among the aims of an experimental design is to ensure that the experiment is capable of detecting the *treatment* effects considered [4]. Regarding the effects in the experiments, we can define an effect as a notion of the counterfactual. A possible effect of a *treatment* or

[1] A large body of scientific literature is concerned with modelling the effects of a *treatment* on an outcome of interest [see 1, 2, 3]. In economics experiments, therefore, the experimenter selects variables which may affect the dependent variable and, thus, she considers them treatment variables (independent variables). The experimenter observes the effect on the dependent variable generated by one or more variations or manipulations of independent variables, ruling out any competing explanation.

treatment effect may be the difference between what did happen when the *treatment* was introduced and what would have happened had it not been introduced. Nevertheless, we focus on experimental designs *"[…] based on the random assignment of a purposeful "treatment" or manipulation. We include studies where treatment is deterministically assigned in a way that can be viewed as equivalent to random, such as assigning every second name in a list, or choosing a permutation of potential subjects that optimizes the balance between treatment and control groups."* Card *et al*. [5] pp. 40-41. In search of greater relevance, therefore, we argue that there is still much to learn from designing *treatments* increasingly turning to the experimental method in the field of economics. In line with this aim, we develop a "material" model[2] to predict the potential outcomes of *treatment*. This model provides potential outcomes that allow experimenters to predict efficacy of *treatments*. Indeed, *"the goal of any evaluation method for "treatment effects" is to construct the proper counterfactual, and economists have spent years examining approaches to this problem."* Harrison G.W. and List J.A. [7] p. 1014. Following [7], more specifically, a *treatment* is a process relying on the modifications of the baseline conditions in the experimental factors. As yet, the existing literature on experimental economics has principally converged on the effects that *treatments* yield in terms of experimental results (*treatment* effect) [8]. Nevertheless, a *treatment* is always endogenously generated by experimenters in economics before yielding results (*treatment* design) [9]. In particular, we investigate the role of *treatment* as a possible combination of one or more constitutive factors to design an economic experiment and in order to validate its outcome. The broad objective of our research project is to involve, and to draw preliminary conclusions about, two interrelated research themes. The first regards the preliminary evaluation of the *treatment* design in terms of efficacy [9, 10]; the second concerns the internal and external validity of an experimental study in terms of baseline and non-baseline characteristics of the experimental factors [11, 12]. On the one hand, we analyse the first theme by formulating a model which consists of two sub-models based on experimental factors included into the three experimental design contexts [13]. Drawing upon the model formulated, on the other hand, we consider the second theme by means of an evaluation index that relates the experimental factors to control and *treatment* groups within the design to be implemented. We devote most of our space to modelling experimental factors in *treatment* design because we feel it is otherwise under-emphasized both in economics and its applications [4]. In doing so, we present a model to evaluate *treatments* in economics experiments that allows experimenters to identify the preliminary efficacy of a *treatment* design. We initially describe a setting in which one *treatment* group is considered with one control group. We then extend this setting for examining the relationship between the modes of experimental factors and all possible experimental group. The idea is to measure the potential outcomes of *treatment* and control groups that are randomized for different subject pools (students and no students). To support this idea, we develop a graphical

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[2] In fact, "*a "material" model is a model of flesh and blood, the exogenous variables of which are controlled by the experimental design in order to see how the endogenous variables react to changes in the treatment variables*." Schmidt J. [6] p. 15. Although the model is general and can be applied to several experimental contexts, we introduce it in the context of designing economics experiments.

interface using Java code as a tool that facilitates experimenters to design a variety of *treatments* before adopting an experimental economics design. We named this tool *Graphical Experimenter Interface* (GEI). The layout of the paper is as follows. In Section 2, we present the model-based *treatment* design consisting in two sub-models. Section 3, presents relevant work in designing and programming a graphical interface in order to put the proposed model into context. Finally, in Section 4 we draw some conclusions and outline directions for future research and developments.

2 The model

In this section, we develop a model for designing *treatment* in economics experiments according to well-defined validation criteria [7-11-12, 14]. The purpose of the model is to test the preliminary efficacy of an experimental *treatment*, in other words we aim to determine whether or not the *treatment* actually works under certain conditions established by the experimenter. Card *et al* [5] claim for the use of between-group designs including at least one *treatment* group and one control group. However, the potential outcome framework allows to incorporate more than two groups. In a binary *treatment* setting causal effects are assessments of pairs of potential outcomes for the same experimental group, where a given group can only be assigned to one level of *treatment*. In a multiple *treatment* setting, causal effects are ultimately based on assessments of different units with different levels of *treatment*. Typically, experimenters in economics divide experimental subjects into one or more *treatment* group and a control group, manipulating one or more experimental factors. Factors that are manipulated represent the independent variable, whereas the outcome of the experiment corresponds to the dependent variable [14, 15]. The experimenter can then compare the *treatment* group to the control group in order to understand whether the manipulation of the independent variable affects the dependent variable. In our research project, we aim to determine whether the manipulation of the independent variable (hereafter *treatment*) can show its efficacy or whether one *treatment* is more effective than another. This is the novelty of our research and, therefore, we formulate and develop a multi-factor model, *Design of Treatment* (DOT), which describes and synthesizes the process of *treatment* in the experimental economics framework. To this aim, we organise the model into two parts: the first is made up of a non-parametric *Fractional Factor* (FF) sub-model; the second is formed by a parametric *Multi-Treatment* (MT) sub-model. Both these parts work before the experiment is carried out (*treatment* design phase) and, thus, during the experimental design process [16]. More specifically, by considering all possible combinations of experimental factors, we use FF sub-model to construct all possible experimental groups (control and *treatment* groups)[3], then we generalize FF in MT model in order to allow the experimenter to select the *treatment* groups from the set of possible combinations of all possible *treatments*, evaluating their potential efficacy afterwards.

[3] For *treatment group* we intend the group of experimental subjects to which the experimenter applies a *treatment*. For *treatment* we intend the change of one (single *treatment*) or more experimental factors (multiple *treatment*) compared to the value of those same factors tested in the control group or baseline group (group of basic experimental subjects).

2.1 The Fractional Factor model

Basing upon the experimental factors, we use FF sub-model to explore the preliminary efficacy of *treatment* in various types of experimental design. In FF sub-model, therefore, we first describe, and then evaluate, all possible control and *treatment* groups by using experimental factors which are manipulated by the experimenter[4]. These factors are used to construct several experimental vectors which identify all possible control and *treatment* groups. In line with [7], each vector consists of four experimental factors: x_1 indicates the experimental design context[5] (three categories: lab, field, extra-lab designs); x_2 refers to the nature of *commodity* (artificial or physical goods); x_3 indicates the nature of the *task* (baseline task or varied task); x_4 refers to the nature of the *stake* (null, fixed, random, or variable stakes). In addition to these factors, let us denote control and *treatment* groups with T_j. This term identifies the type of the experimental group, control or *treatment*, to which the experimental subjects are assigned. Bearing in mind the theory-testing view of science (for good discussions of theory-testing approach and its relevance for experimental economics, among others see [9-18, 19][6], in FF model we focus on a between-subject design [5] following two main steps. First, we set up an evaluation index (EVI) by using a threefold validation criteria [11-12, 14] for the three categories of the experimental design context[7]. Based on these criteria, we assess i) how the variations of experimental factors may affect the preliminary efficacy of the experimental groups (values of EVI);

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[4] According to Shadish *et al.* [17], a *treatment* should not be applied to nonmanipulable experimental variables. For example, the authors suggest not to consider gender to be a cause in an experiment because it cannot be manipulated due to the presence of so many co-variates based on life experience. A stronger inference is possible if experimenters are able to manipulate independent variables such as the dosage in medical investigations or the word choice in media messages.

[5] This first factor (x_1) summarizes three factors originally considered by [7]: i) subject pool, ii) information, and iii) environment. Indeed, among the original six factors taken into account in [7], only the three aforementioned factors can determine the experimental design context. If we do not summarize them, moreover, we obtain some vectors non-representative of the possible control and *treatment* groups. The opportunity to summarize these three factors enables us to exclude non-representative vectors and, at the same time, to overcome related problems of redundancy with experimental factors.

[6] The connection between economics experiments and economic theories is very close. In this regard, there is a broad consensus among economists on the fact that economics experiments can be run to test economic theories [20-21, 22]. According to [13, 23], when testing theories, experimenters can design laboratory, extra-lab and field contexts which, in a certain way, remind the economic theories – only for what is needed in regard to a particular knowledge of the world insofar as the economic theory itself does – while, in other ways, it represents the world in a different way, by replacing unrealistic assumptions with experimental subjects' actual behavior.

[7] We aim to represent the complementarity of lab and field designs, also including the extra-lab environment in order to represent the mechanism of *treatment* according to internal and external validity criteria [7-9, 12]. The matrices include no. 12 vectors that is to say no. 12 possible *control groups* and no. 24 *treatment groups* that is to say no. 24 possible *treatment groups*. Therefore, we have no. 36 possible experimental groups.

and ii) the difference between a *treatment* group and a control group in terms of effect size (this difference is approximated with a constant ***c***). Since this is a non-parametric sub-model, the experimenter cannot modify the scale of values of EVI. Second, we consider the values of EVI in order to estimate $\hat{y}$ outcomes that are determined through a multiple linear regression model. We assume a linear model in which we exclude that there is interference between the variables x_1, x_2, x_3, x_4:

$$y_j = \sum_{k=0}^{4}(\beta_k x_{j,k}) + cT_j + \varepsilon_j = (\beta_0 + \beta_1 x_{j,1} + \cdots + \beta_4 x_{j,4}) + cT_j + \varepsilon_j \qquad (1)$$

where y_j is the preliminary efficacy of the experimental group considered, with j = 1, 2, ... , 36; c is a constant term equal to 0.10; T_j is coded as a dummy that takes value 1 in a *treatment* group and 0 in a control group; ε_j is the random error. In other words:

$$y_j = \hat{y}_{CG} \text{ with } T_j = 0 \text{ (control group)}$$

$$\text{and } y_j = \hat{y}_{CG} + cT_j \text{ with } T_j = 1 \text{ (\textit{treatment} group) and } \varepsilon_j \sim 0$$

In a matrix form, the proof (1) becomes:

$$Y = XB + cT + E \qquad (2)$$

We estimate the parameters of FF sub-model to minimize the squared errors of prediction. For FF sub-model, the predictions are:

$$y = 0.26 + 0.08\, x_1 + 0.31\, x_2 + 0.09\, x_3 + 0.23\, x_4 + 0.10\, T \qquad (3)$$

We illustrate below the generalization given by the theoretical matrix which provides a formulation of the multiple regression model shown in (2).

Fig. 1. Generalization: the theoretical matrix of the model.

$$\begin{bmatrix} y_1 \\ \vdots \\ y_{36} \end{bmatrix} = \begin{bmatrix} 1 & x_{1,1} & x_{1,2} & x_{1,3} & x_{1,4} \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ 1 & x_{36,1} & x_{36,2} & x_{36,3} & x_{36,4} \end{bmatrix} \cdot \begin{bmatrix} \beta_0 \\ \vdots \\ \beta_4 \end{bmatrix} + c \begin{bmatrix} T_1 \\ \vdots \\ T_{36} \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \vdots \\ \varepsilon_{36} \end{bmatrix}$$

$$\begin{bmatrix} 0.15 \\ \vdots \\ 1.00 \end{bmatrix} = \begin{bmatrix} 1 & -1 & 0 & 0 & 0 \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix} \cdot \begin{bmatrix} 0.26 \\ \vdots \\ 0.23 \end{bmatrix} + 0.10 \begin{bmatrix} 0 \\ \vdots \\ 1 \end{bmatrix} + \begin{bmatrix} -0.03 \\ \vdots \\ -0.07 \end{bmatrix}$$

Results of the statistical analysis performed confirm a goodness of R square (0.8361).

2.2 The Multiple Treatment model

In the case of two or more *treatments*, we use MT sub-model which considers only *treatment* groups. The aim of MT is to study the combinations of *treatment* groups and to select which and how many *treatment* groups should be designed in order to evaluate the preliminary efficacy of multiple *treatment* combinations. The evaluation of the effects of multiple *treatment* combinations is done according to a linear combination of the various experimental factors that have been manipulated. Therefore, each *treatment* is represented by a vector:

$$f_i(x_1,\ x_2,\ x_3,\ x_4,\ y) \tag{4a}$$

Variables $x_1,\ x_2,\ x_3,\ x_4$ and (1) are linked by a linear relation and together they can be considered as coordinates of a point identified by a radius-vector:

$$f_i(x_j, y) \tag{4b}$$

Each linear combination of (4b) produces a new vector (radius-vector):

$$f(x_j, y) = p_1 f_1(x_j, y_1) + p_2 f_2(x_j, y_z) \quad \text{with j = 1, 2, 3, 4} \tag{5}$$

or more generally:

$$f_i(x_j, y) = \sum_k p_k f_k(x_j, y_k) \tag{6}$$

Consequently, the coefficients of the linear combinations p_k can be determined using the same weight for each *treatment* group, so that $\sum_{k=1}^{n} p_k = 1$. The result of the average of *treatments* is given by:

$$f(x_j, y) = \frac{1}{n}\left[\sum_{j=1}^{n} f_i(x_j, y_k)\right] \tag{7}$$

As we preliminary evaluate the efficacy of multiple *treatment* combinations, the evaluation of the efficacy of a multiple-*treatment* is as follows:

$$\hat{y} = \frac{1}{n}\left[\sum_{j=1}^{n} \hat{y}_i\right] \tag{8}$$

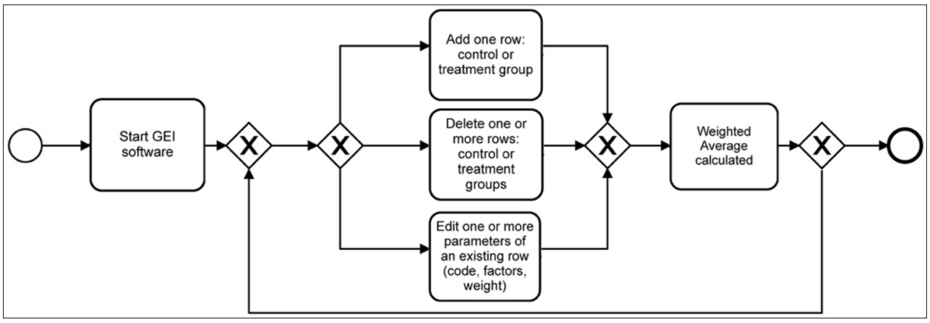
Finally, all possible multiple-*treatment* combinations are given by ***n*** combinations in class ***k***: $\binom{n}{k} = \frac{n!}{k!(n-k)!}$

3 Putting the model into context: a software application

At this stage of the work, we make the model accessible to experimental economists through the development of a graphical Java interface. Basing upon DOT model, in this section we address the creation of a software application named GEI which is designed to engage experimenters to preliminary evaluate the efficacy of their *treatment* designs. Using GEI is straightforward consistent with the prediction of the model presented in Section 2. The experimenter has many components in GEI that allow flexibility in designing input screens. The experimenter specifies one or more *treatment* design to develop and which factors to include in order to preliminary detect the efficacy of the design. The experimenter can also decide to include a control design and GEI estimates the efficacy of the total design. In Figure 2, we present the general algorithm according to which GEI is made, so as to represent every process related to GEI by focusing on a *top-down* technique. At the beginning, the experimenter selects the type of group of interest. Both in the *control group* and the *treat-*

ment group, the experimenter can select the modes of the factors (see section 2.1): in the case of *control*, she can set up the modes of factors *environment*, *commodity* and *stake*; in the case of *treatment*, she has to decide the number of *treatments* and then the modes of factors *environment*, *commodity*, *task* and *stake*.

Fig. 2. The flowchart of the general algorithm at the base of GEI



As we show in Figures 3 and 4, each row of GEI includes a possible experimental group (control or *treatment* group). We can consider two main phases in GEI: during the first, the experimenter launches the software and then decides whether to add a row (control or *treatment* group), delete one or more rows (control or *treatment* groups), or edit one or more parameters of an existing row. These parameters consist of i) experimental factor(s) (see sub-Section 2.1), ii) weight (one for each group), and more generally iii) code (one for each group). During the second phase, GEI calculates the weighted average efficacy of *treatment* groups. The cycle of GEI repeats itself or terminates if the experimenter does not need to continue.

Fig. 3. Experimenter's decision between *treatment* group or control group

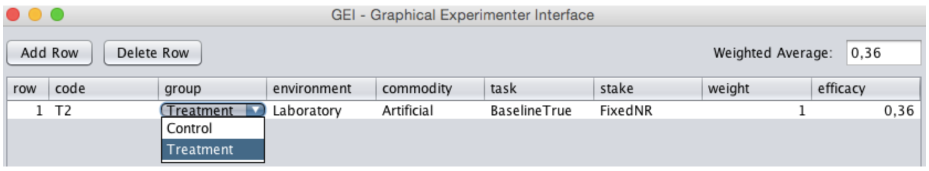
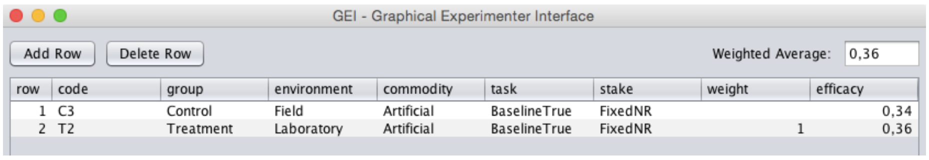
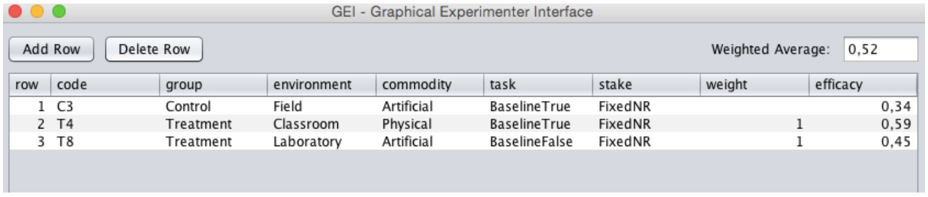


Fig. 4. Experimenter's decision: a single *treatment* with a control group



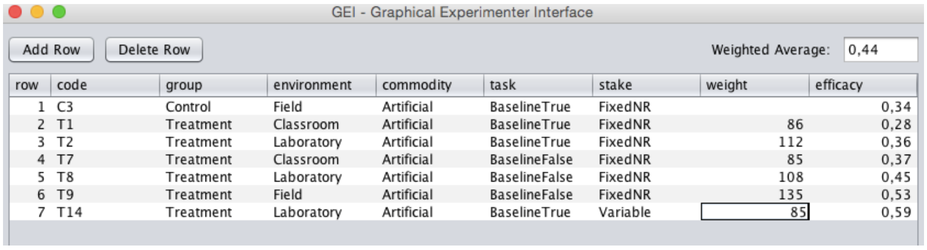
In Figure 3, we present an example of the first row or the initializing line which corresponds to the choice that the experiment makes in the decision between *treatment* group or control group. In Figure 4, we illustrate the case of a single *treatment* and a control group associated to it. When the *treatment* group is only one, the output provided by GEI corresponds to what is shown in Figure 4. When the *treatment* group is more than one, the experimenter has to decide how many *treatment* groups to include and their *weights*. In this last case, indeed, the experimenter can use MT sub-model in two ways: in the first (see Figure 5), the experimenter considers each *treatment* group giving the same *weight* to each of them, thus GEI automatically gives the same weight equal to 1 (weight = 1) to all *treatment* groups; in the second (see Figure 6), the experimenter assigns a subjective *weight* to each *treatment* group on the basis of other elements related to the design but unrelated to the experimental factors (*e.g.*, the number of the experimental subjects *assigned to the treatment group* or the work activity carried out by the same subjects).

Fig. 5. Experimenter's decision: a double *treatment* with a control group



row	code	group	environment	commodity	task	stake	weight	efficacy
1	C3	Control	Field	Artificial	BaselineTrue	FixedNR		0,34
2	T4	Treatment	Classroom	Physical	BaselineTrue	FixedNR	1	0,59
3	T8	Treatment	Laboratory	Artificial	BaselineFalse	FixedNR	1	0,45

Fig. 6. Experimenter's decision: a multiple *treatment* with a control group (with weighted average *treatments* based on the number of experimental subjects involved)



row	code	group	environment	commodity	task	stake	weight	efficacy
1	C3	Control	Field	Artificial	BaselineTrue	FixedNR		0,34
2	T1	Treatment	Classroom	Artificial	BaselineTrue	FixedNR	86	0,28
3	T2	Treatment	Laboratory	Artificial	BaselineTrue	FixedNR	112	0,36
4	T7	Treatment	Classroom	Artificial	BaselineFalse	FixedNR	85	0,37
5	T8	Treatment	Laboratory	Artificial	BaselineFalse	FixedNR	108	0,45
6	T9	Treatment	Field	Artificial	BaselineFalse	FixedNR	135	0,53
7	T14	Treatment	Laboratory	Artificial	BaselineTrue	Variable	85	0,59

4 Conclusions and future research

In the course of this paper, we present a software application designed and developed for experimental economists in order to optimize their design of *treatment* before running an experiment. More in detail, we introduce a graphical interface that may be useful for experimenters interested in estimating the efficacy of *treatment* (potential *treatment* effects) in economics experiments. At this stage, the software is configured based on a model for designing *treatment*; we adapt the software to the needs of experimental economists when they organize *ex ante* one or more *treatments* of interest concerning theory-testing and between-subject designs [16, 24]. The model is based on the trade-off between internal validity, which concerns the question whether the experimenters are drawing the right inferences within the experiment, and external validity, which concerns the question whether the experimenters are drawing the right conclusions from the experiment about the real-life world [6]. As future work, we intend to scale up the model in order to handle any possible experimental designs in economics. On the one hand, we aim to further develop *extra-lab* designs for analysing both *classroom* and *internet* experiments [25, 26]. On the other hand, we seek to include in the model a *within subject* design by which to apply a *treatment* to the same subject pool in a deferred mode [27]. To achieve this end, we suggest the implementation of values of EVI required by the model. More specifically, we promote the idea that there is often more than one scale of values of EVI that can vary according to the type of economic experiments to be performed [28]. We consider this to be a promising starting point for developing our model and for future research.

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