An evaluation of export promotion programmes with repeated multiple treatments

Valutazione di programmi di promozione dell'export con trattamenti multipli ripetuti

Chiara Bocci and Marco Mariani

Abstract Export promotion programmes usually consist of the provision of multiple services and aids, including consultancy, trade missions and international fairs and business-to-business meetings, of which firms can take advantage either simultaneously or at different moments in time. This constitutes an unusually complex setting for programme evaluation. Relying on assumptions of sequential ignorability extended to the multiple-treatment framework, and exploiting the programme participation data of an Italian region (Tuscany), we estimate the treatment effect of different services and aids on multiple aspects of the firms export performance using a marginal structural model that adjusts for dynamic confounding by means of inverse-probability-of-treatment weights.

Abstract *I programmi di promozione dell'export consistono tipicamente nella fornitura di vari servizi e aiuti, tra cui consulenze specialistiche, partecipazioni a fiere internazionali e incontri business-to-business, che le imprese possono utilizzare sia simultaneamente che in diversi momenti temporali. Questo ambito costituisce un setting complesso per la programme evaluation. Basandosi sull'assunzione di ignorabilitá sequenziale estesa all'ambito dei trattamenti multipli, si utilizzano i dati di un programma regionale di promozione dell'export per stimare, attraverso un modello strutturale marginale, gli effetti causali delle principali forme di supporto sui diversi aspetti della performance esportativa delle imprese, Tale modello affronta il problema del confondimento dinamico attraverso l'utilizzo di pesi inverse-probability-of-treatment.*

Key words: causal inference, multiple treatments, sequential ignorability, marginal structural models

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1 Introduction

Marginal structural models are a popular tool used for causal inference in epidemiology, where treatments are often taken in sequences, which raises issues of time-dependent, or dynamic, confounding [3, 7]. Surprisingly, their use is not common yet for the evaluation of economic and social programmes: for example, marginal structural models are not covered by the review by Imbens and Wooldridge [4] on the "econometrics of programme evaluation", a review that is popular with economists and social scientists.

In longitudinal observational settings, dynamic confounding arises when variables that can be affected by past treatments can, in their turn, affect future treatment receipt. Under these circumstances, a possible identification assumption is that of sequential conditional ignorability. This assumption represents an extension to the longitudinal setting of the conditional ignorability assumption (or unconfoundedness) of cross-sectional settings [8]. Ignorability is now invoked at each point in time, conditional on the past histories of treatment, outcome and covariates.

Under sequential ignorability, several approaches have been thought in order to estimate treatment effects. Marginal structural models are one of these approaches.

Although treatments in micro-economic policy hardly resemble a medical therapy that involves the repeated intake of a drug over time, there is a wide range of situations in which individuals or firms take one, or more, treatment at different time points. A typical example are unemployment subsidies and active labour market policies, which support the income of individuals and promote their job search every time they are outside of regular employment spells (e.g. [6]).

With respect to enterprise or innovation policy, one might think of a repeated receipt of a particular type of aid (e.g. R&D or investment grant) or also to the more complex situation where firms take different supports over time.

An area of policy where the latter situation is quite common is that of export promotion programmes. These usually consist of the provision to firms of a vast array of services and aids, including specialised consultancy, participation in trade missions and international fairs, organisation of business-to-business meetings or the set-up of temporary selling outlets, of which firms can take advantage either simultaneously or at different moments in time.

Note that, in the presence of different types of treatment, the sequential ignorability assumption needs to be extended to a multiple-treatment setting. This goal is easily achieved by transposing the generalisation of unconfoundedness put forward by [5] in a sequential setting.

Focusing on the programme participation data of an Italian region (Tuscany), we try to establish what services and aids are more effective in promoting the firms performance in subsequent years in terms of foreign sales, expansion of the number of markets served and of the range of products sold abroad. Particular attention in the analysis is devoted to establish if effects are heterogeneous across interesting sub-populations of participating firms, such as first-time and habitual exporters.

2 Marginal structural models

Under sequential ignorability, we can rely on “longitudinal” propensity scores in order to summarise, at each point in time, the past histories of treatment, outcome and covariates [1, 7]. Similarly to what happens in other propensity-score-based approaches, marginal structural models require first to model the treatment receipt as a function of the past histories of treatment, outcome and covariates, which returns a propensity score, and then to use the obtained propensity scores as an adjustment device in a second model where the outcome of interest is a function of treatments. This adjustment occurs by inverse-probability-of-treatment weighting.

Before recalling these aspects in greater detail, it is worth to clarify the assumption of sequential ignorability in the presence of multiple treatments. First, suppose that unit i can be assigned to one of m treatments $a_1,...,a_m$. In a cross-sectional setting, this unit is associated with m potential outcomes $Y_i(A=a_1),...,Y_i(A=a_m)$, of which only one is actually observed depending on the treatment received. In this setting, the ignorability assumption states that these potential outcomes are independent of treatment assignment mechanism, conditional on a vector of pre-treatment observable covariates $\mathbf{L}_i$ [5].

In a longitudinal setting, the unit i is followed for a total of T times and it can receive some treatment $A(t)$, e.g. $a_1,a_2,...,a_m$, at multiple points $t=1,...,T$. Under these circumstances, ignorability needs to be assumed at each point in time t, in a sequential fashion. Let $\bar{A}_i(t-1)$ and $\bar{\mathbf{L}}_i(t-1)$ be, respectively, the unit's treatment history and the unit's covariates history up to moment t. The sequential ignorability assumption states that the m potential outcomes in t are independent of the current treatment assignment mechanism, conditional on the unit's past history of treatments and covariates, the latter including past observed outcomes:

$$Y_i\left[A_i(t)=a_1\right],...,Y_i\left[A_i(t)=a_m\right] \perp A_i(t)|\bar{A}_i(t-1),\bar{\mathbf{L}}_i(t-1).$$

Under this assumption, the longitudinal propensity score at each time t is

$$Pr\left[A(t)=a(t)|\bar{A}(t-1)=\bar{a}(t-1),\bar{\mathbf{L}}(t-1)=\bar{\mathbf{l}}(t-1)\right]$$

and can be estimated by mean of a generalised linear model suitable for multinomial variables.

As shown in [7], stabilised inverse-probability-of-treatment weights can then be obtained as follows:

$$sw_i(t)=\prod_{k=0}^{t}\frac{Pr\left[A_i(k)=a_i(k)|\bar{A}_i(k-1)=\bar{a}_i(k-1),\mathbf{V}_i=\mathbf{v}_i\right]}{Pr\left[A_i(k)=a_i(k)|\bar{A}_i(k-1)=\bar{a}_i(k-1),\bar{\mathbf{L}}_i(k-1)=\bar{\mathbf{l}}_i(k-1),\mathbf{V}_i=\mathbf{v}_i\right]}$$

where covariates are now split in two parts: a vector of time-invariant covariates $\mathbf{V}_i$ and a vector of time-varying covariates $\bar{\mathbf{L}}_i(t-1)$ detailing the unit's history.

The stabilised weights above are finally used to build a weighted estimator of the coefficients of a structural regression model where the outcome of interest is a function of treatments.

3 Application and results

The application focuses on a complex public strategy of export promotion implemented in 2006–2012 by Tuscany's regional government, either by the direct provision on subsidies or via a public agency that supplies smaller firms with free specialised supports, including export-oriented consultancy, participation in international fairs or involvement in organised business-to-business meetings. A main characteristic of this program is that firms were allowed to take multiple supports, also repeatedly over time. In fact the repeated intake of multiple treatments occurred rather frequently and, therefore, cannot be neglected in the analysis.

We are interested in estimating the average treatment effects of all these supports, versus the non-treatment situation, on three main outcome variables: increase in foreign sales, in the number of markets served and in the number of products sold abroad. The non-treatment situation is reconstructed using a set of never-treated firms, selected by means of matched sampling techniques [9] so that we obtain a never-treated twin for each firm that will receive support in the future. The data on both treated and untreated firms are derived from two important datasets, SDOE and ASIA, held by the Italian Chambers of Commerce and by ISTAT respectively.

We express the outcomes in terms of first differences $\Delta Y_{i,t} = Y_{i,t} - Y_{i,t-1}$ in order to discard individual fixed effects. Therefore, the average treatment effects represent differences in differences (and not differences in means):

$$ATE_{DID,a-0} = E\left[\Delta Y_{A=a} - \Delta Y_{A=0} | \bar{A}, \bar{\mathbf{L}}, \mathbf{V}\right].$$

Outcomes have been reconstructed for each treated or untreated firm at each time starting from the SDOE yearly dataset, which is available for our analysis from 2005 to 2012. This archive reports details on each single export flow (exporting firm, type of good according to the NC8 classification, destination market, etc.) that originates from Italy in a series of years. Since the programmes under scrutiny aimed at promoting export towards non-EU countries, EU markets are excluded when measuring the three outcomes of interest. Moreover, as the export benefits of the supports are likely to require some time in order to arise, we estimate treatment effects not only when the supports are actually received $(t+0)$, but also one year later $(t+1)$. Longitudinal firm records reconstructed from SDOE are then merged with the ASIA dataset in order to link them to a number of background firm characteristics.

Using this information related to 1,648 small and medium-sized firms that were treated at least once in the observation period, as well as an equal number of never-treated twins, and following the procedure outlined in Section 2, we estimate the inverse-probability-of-treatment weights, whose distribution is plotted in Figure 1. Then, we specify for each outcome the following marginal structural model (with $h = 0,1$)

$$\begin{aligned}\Delta Y_{i,t+h} = {} & \beta_0 + \beta_1 Y_{i,0}^{Market} + \beta_2 Y_{i,0}^{Product} + \beta_3 Y_{i,0}^{Sales} + \beta_4 D_{i,0} + \beta_5 A_{i,t}^{F} + \beta_6 A_{i,t}^{B} + \\ & + \beta_7 A_{i,t}^{C} + \beta_8 A_{i,t}^{S} + \beta_9 (D_{i,0} A_{i,t}^{F}) + \beta_{10} (D_{i,0} A_{i,t}^{B}) + \beta_{11} (D_{i,0} A_{i,t}^{C}) + \beta_{12} (D_{i,0} A_{i,t}^{S}) + \varepsilon_i\end{aligned}$$

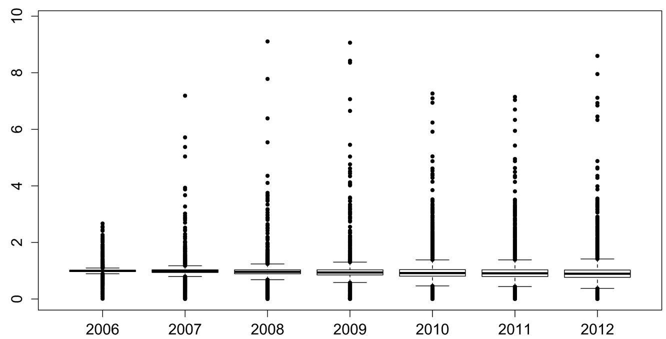

Fig. 1 Box-plots of the inverse probability-of-treatment weights for the years 2006-2012

that includes baseline levels of the outcome variables ($Y_{i,0}^{Market}, Y_{i,0}^{Product}, Y_{i,0}^{Sales}$), indicators for each type of treatment (A^F stands for participation in a trade fair, A^B for business-to-business meeting, A^C for specialised consultancy and A^S for export subsidy), a dummy for the fact that the firm has some previous export experience, and interactions between this dummy and the treatment indicators. By weighted least squares we obtain the coefficients and then the average treatment effects of interest, which are reported in Table 1 accompanied by p-values based on standard errors that are cluster-robust at the firm level [2].

We find that the programmes have no statistically significant effect on foreign sales, therefore the $ATEs$ related to this outcome are not reported in the table. Instead, with respect to the number of non-EU markets served and to the number of products sold there, the situation is much more interesting.

For a first-time exporter, the receipt of a subsidy helps much more than the participation in trade fairs, business-to-business meetings or the receipt of specialised consultancy. This is because the subsidy provides inexperienced firms with money they can invest in implementing a complex attempt of entry into foreign markets, an entry that can be impracticable relying on the other services and supports alone. On the contrary, firms already experienced in foreign markets that have higher know-how to exploit trade opportunities can take advantage of fairs, business-to-business meetings or specialised consultancies, whereas it seems inappropriate to provide them with direct subsidies.

4 Conclusions

Our results support the idea that export promotion programmes can be useful to let small and medium-sized firms attempt first exploratory approaches to new markets

Table 1 Average treatment effects on the number of non-European markets served and on the number of products sold in non-European markets.

	Markets						Products					
	$t+0$			$t+1$			$t+0$			$t+1$		
Treatment	ATE^M	p-value[a]		ATE^M	p-value[a]		ATE^P	p-value[a]		ATE^P	p-value[a]	
HABITUAL EXPORTERS ($D_0 = 0$)												
Fair	0.293	0.014	*	-0.258	0.114		0.373	0.117		0.007	0.980	
B2B	-0.047	0.701		0.346	0.008	**	-0.092	0.651		0.734	0.000	***
Consultancy	0.188	0.039	*	0.005	0.957		0.197	0.179		-0.075	0.682	
Subsidy	0.994	0.000	***	-0.337	0.033	*	1.027	0.000	***	0.015	0.961	
FIRST-TIME EXPORTERS ($D_0 = 1$)												
Fair	0.185	0.237		0.561	0.182		0.116	0.756		-0.477	0.239	
B2B	0.019	0.845		0.001	0.995		0.135	0.446		-0.080	0.737	
Consultancy	0.135	0.057	°	0.123	0.142		0.136	0.165		0.042	0.736	
Subsidy	0.383	0.047	*	0.025	0.796		1.033	0.020	*	-0.196	0.416	

[a] Signif. codes: '***' 0.1% '**' 1% '*' 5% '°' 10%

or try the introduction of new products into new or existing foreign markets. That said, however, they do not seem to help firms in improving substantially their penetration in foreign markets. Therefore, we can conclude that these programmes, rather than fostering the volume of foreign sales, are more suitable to accompany firms that try to implement some diversification of markets and products sold abroad.

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