Assessing the Impact of Financial Aids to Firms: Causal Inference in the presence of Interference

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Introduction

Regional and national development policies are an important tool for setting up and supporting local enterprise. Policy makers at national or sub-national level plan interventions aiming at removing barriers (e.g., credit rationing) and promoting investments and firms' performances, such as occupation and turnover. We consider the problem of assessing the effectiveness of financial aids provided to firms. An assumption usually made in policy evaluation studies is the Stable Unit Treatment Value Assumption (SUTVA). SUTVA combines the "no-interference" assumption that one unit's treatment assignment does not affect another unit's outcomes with the assumption that there are "no hidden versions" of the treatment. However, firms operating in the same geographical area and sector of activity are likely to interact each other, so SUTVA may be violated. Here, we assume that the "no hidden versions of treatments" assumption is met, and we focus on violations of SUTVA due to interference, an issue that has rarely been addressed in the causal inference literature. Exceptions include Verbitsky and Raudenbush (2004), Hong and Raudenbush (2006), Sobel (2006), Rosenbaum (2007), Hudgens and Halloran (2008). We address this problem, by explicitly modeling interactions among units. This approach involves specifying which firms interact with each other, and the relative magnitudes of these interactions. Some previous studies assumed that interactions are limited to units within well-defined groups, with the intensity of the interactions being equal within the same group (e.g., Hong and Raudenbush, 2006). We extend this approach, allowing that intensity of interactions depends on a distance metric, based on geographical distance and firms' characteristics. This idea is in line with extensive literature on social interactions (see, for instance, Brock and Durlauf (2000) for a survey), where interactions are often found to be stronger for geographically, or economically, or socially close units.

We apply our approach to data from a policy intervention implemented in Italy on Tuscan artisans firms. Given the characteristics of the Tuscan labour market, where most artisan firms are small-sized, and generally operate in a limited geographical area, it is crucial to consider possible spill-over effects of the policy.

Potential Outcomes Framework

Consider a group of units (firms), index by $i = 1, \ldots, N$. Let T_i be a binary treatment indicator, taking value 1 if firm i received the benefit (treated firm) and 0 otherwise. Let $\mathbf{T}$ be the $N-$dimensional vector of assignment with ith element T_i, and let $\mathbf{T}_{-i}$ be the vector of assignment with T_i removed. Let $Y_i(\mathbf{T}) \equiv Y_i(T_i, \mathbf{T}_{-i})$ denote the potential outcome on the firm i' performance (e.g., turnover, number of employees, production innovation) given the treatment vector $\mathbf{T}$. In the potential outcomes framework, SUTVA is an usually invoked assumption:

Assumption 1 *(SUTVA, Rubin, 1980, 1990)*

$$\textit{If } T_i = T_i',\ \textit{then } Y_i(\mathbf{T}) = Y_i(\mathbf{T}') \textit{ for all } \mathbf{T}, \mathbf{T}' \in \{0,1\}^{2N}$$

Therefore, under SUTVA, $Y_i(T_i, \mathbf{T}_{-i})$ can be simply written as $Y_i(T_i)$, and so there exist just two potential outcomes, $Y_i(0)$ and $Y_i(1)$, for each firm.

In our policy evaluation case, SUTVA implies that each firm assigned to the treated group receives the same benefit from the policy ("no versions of treatments") and that potential outcomes for each firm do not depend on the treatment assignment of the other firms ("no interference"). This lack-of-interaction assumption might be plausible in many applications, but there are also many cases in which interactions between units are a major concern and the assumption is not plausible. For example, it is reasonable to think that a policy intervention affecting the performance of one firm potentially has an effect also on the performance of other firms. Firms operating in the same geographical area and sector of activity are likely to interact each other. This implies that assigning an incentive to a firm may affect also its competitors, violating the no-interference assumption. Here, we focus on violations of SUTVA due to interference, but we assume that the no versions of treatments assumption is met.

Causal Inference in the Presence of Interference

Without SUTVA potential outcomes for each firm are not two anymore, but 2^N, because they also depend on the treatment assignment of all the other firms. In this setup, an individual causal effect may be defined as a comparison between any two potential outcomes: $Y_i(T_i, \mathbf{T}_{-i})$ versus $Y_i(T_i', \mathbf{T}'_{-i})$, $T_i, T_i' \in \{0,1\}$, and $\mathbf{T}_{-i}, \mathbf{T}'_{-i} \in \{0,1\}^{2(N-1)}$.

We introduce some additional notation in order to account for firms' activity sector. Suppose that there are K activity sectors and denote by N_j the number of firms in sector j, $j = 1, \ldots, K$. The vector of treatment assignments $\mathbf{T}$ can be conveniently decomposed as follows: $\mathbf{T} = [\mathbf{T}^{(1)}, \ldots, \mathbf{T}^{(K)}]'$, where $\mathbf{T}^{(j)} = (T_{ij}^{(j)}, \mathbf{T}_{-ij}^{(j)})$ and ij represents firm i in sector j [1].

In our setting, it seems plausible to assume that interference exists among firms working in the same activity sector, while firms in different sectors do not interact. Formally,

Assumption 2 *(SUTVA 1)*

$$\textit{If } \mathbf{T}^{(j)} = \mathbf{T}'^{(j)},\ \textit{then } Y_{ij}(\mathbf{T}) = Y_{ij}(\mathbf{T}') \textit{ for all } \mathbf{T}, \mathbf{T}' \in \{0,1\}^{2N}$$

Assumption 2 implies that $Y_{ij}(\mathbf{T})$ is equal to $Y_{ij}(\mathbf{T}^{(j)})$, and so each firm has 2^{N_j} potential outcomes. Under Assumption 2 interference only exists within activity sectors, therefore each firm has generally different potential outcomes corresponding to alternative allocations of the assignment for its competitors (firms belonging to the same activity sector), even if its own assignment does not change: $Y_{ij}(T_{ij}^{(j)}, \mathbf{T}_{-ij}^{(j)}) \neq Y_{ij}(T_{ij}^{(j)}, \mathbf{T}'^{(j)}_{-ij})$ if $\mathbf{T}_{ij}^{(j)} \neq \mathbf{T}'^{(j)}_{ij}$.

Even though interference is assumed to exist only within activity sectors, the number of potential outcomes for each firm could be anyway high depending on the value of N_j, implying that causal inference is not feasible without some additional assumptions. For instance, it might be reasonable to think that the strength of interference is not the same for all firms, but depends on firms' characteristics. As noted by Wooldridge and Imbens (2009), interactions may decline in importance depending

[1] In this paper we use square brackets to denote an ordered sequence of vectors and round brackets for a collection of elements.

on some distance metric, either geographical distance or proximity in some economic sense.

Here, we assume that for each firm ij, interference can be summarized by a m-valued function of treatment assignments of firm ij's competitors, $\mathbf{T}^{(j)}_{-ij}$: $f(\mathbf{T}^{(j)}_{-ij}) = [f_1(\mathbf{T}^{(j)}_{-ij}), \dots, f_m(\mathbf{T}^{(j)}_{-ij})]'$, so that, $Y_{ij}(T^{(j)}_{ij}, \mathbf{T}^{(j)}_{-ij}) = Y_{ij}(T^{(j)}_{ij}, f(\mathbf{T}^{(j)}_{-ij}))$. Formally, we make the following assumption:

Assumption 3 *(SUTVA 2)*

$$\textit{If } T^{(j)}_{ij} = T'^{(j)}_{ij} \textit{ and } f(\mathbf{T}^{(j)}_{-ij}) = f(\mathbf{T}'^{(j)}_{-ij}), \textit{ then } Y_{ij}(T^{(j)}_{ij}, f(\mathbf{T}^{(j)}_{-ij})) = Y_{ij}(T'^{(j)}_{ij}, f(\mathbf{T}'^{(j)}_{-ij}))$$

Alternative specifications of function f can be considered, also depending on subject matter knowledge. Background characteristics can be also included in the specification of such a function. For instance, simple functions f_r are linear combination of treatment assignments: $f_r(\mathbf{T}^{(j)}_{-ij}) = {}_r\mathbf{w}^{(ij)\prime}\mathbf{T}^{(j)}_{-ij}$, where ${}_r\mathbf{w}^{(ij)} = [{}_rw^{(ij)}_{1j}, \dots, {}_rw^{(ij)}_{(i-1)j}, {}_rw^{(ij)}_{(i+1)j}, \dots, {}_rw^{(ij)}_{N_jj}]$ is a $(N_j - 1)$-dimensional vector of weights for firm ij. A simple case is when each element of ${}_r\mathbf{w}^{(ij)}$ takes on two values, 0 and 1, depending on firms' characteristics. For instance, we might assign a zero weight to firms which are geographically faraway from ij, with respect to some pre-specified distance threshold. This amounts to assume that the assignment of firms with zero weight does not affect firm ij's potential outcomes. As a consequence the number of potential outcomes reduces. This situation can be reconducted to problem of causal inference with multivalued treatment variables, and widely used nonparametric approaches, such as matching (e.g., Imbens, 2000), can be still implemented. However, this specification for the weights might be somewhat restrictive. More generally, weights, ${}_r\mathbf{w}^{(ij)}$, might be specified as any real-value function. Specifically, we define weights as function of firms' characteristics. Let $\mathbf{Z}^{(j)}$ be the $N_j \times N_j-$dimensional matrix of variables affecting the strength of interference among firms in sector j, with ith row equal to $\mathbf{Z}^{(j)}_{ij}$. Then ${}_rw^{(ij)}_h = g_r(\mathbf{Z}^{(j)}_{ij}, \mathbf{Z}^{(j)}_{hj})$, with $h = 1, \dots, N_j$, $h \neq i$. In this case, a nonparametric approach might be difficult. We propose a modeling approach that explicitly uses these weights to account for interference.

Alternative causal estimands can be defined. Here we focus on average causal effects. In general, an average causal effect can be written as:

$$E\left[Y(T^{(j)}_{ij}, f(\mathbf{T}^{(j)}_{-ij})) - Y(T'^{(j)}_{ij}, f(\mathbf{T}'^{(j)}_{-ij}))\right].$$

For example, we could be simply interested in estimating the impact of a policy intervention on firm's performance, considering interference as a nuisance factor. In this case, focus will be on the following causal estimand:

$$E\left[E\left[Y(T^{(j)}_{ij} = 1, f) - Y(T'^{(j)}_{ij} = 0, f)\right]\right]$$

where the outer expectation is over the distribution of f. It could also be interesting to consider the effect of the policy under alternative pre-fixed levels of interference:

$$E\left[Y(T^{(j)}_{ij} = 1, f^*) - Y(T'^{(j)}_{ij} = 0, f^*)\right]$$

The variability of these effect with respect to the f^* could provide some evidence on the importance of the interference. A third possible causal estimand of interest can be defined by comparing potential outcomes that differ only because of a change in the level of interference:

$$E\left[Y(T^{(j)}_{ij}, f^*) - Y(T^{(j)}_{ij}, f'^*)\right] \qquad f^* \neq f'^*$$

Evidence on heterogeneity of these effects could be useful to plan future policy intervention. For example, if the policy benefit is reduced because the presence of geographically close treated competitors, then the policy maker could introduce some geographical constraints in the future allocation of benefits.

Estimation of the Impact of Financial Aids to Firms

We apply the approach described in the previous section to evaluate the impact of a small intervention in the form of financial aids to Tuscan small and medium handicraft firms, implemented within the framework of the Programs for the Development of Crafts in Tuscany (Regional Law n. 36, 4/4/95). Our treatment is the receipt of credit on investments, provided in years 2003 and 2004 by the Regional government at particular access conditions and at low cost in terms of interest rates. The dataset we use contains a wealth of information on firms pre-treatment characteristics, such as location, sector of activity and size, and many outcome variables measured in 2005, although we focus on sales as outcome. For details on the program, the survey plan and data, see Mauro and Mattei (2007).

Given that for this program firms were not randomly allocated to receive the benefits but they had to apply, we assume unconfoundedness of T conditional on a set of observed pre-treatment characteristics, and employ a matching strategy to create a sub-group of treated and control firms with the same distribution of observed pre-treatment characteristics. These include pre-treatment turnover (2002), number of employees (2002), geo-graphical area, legal status, sector of activity, age of the firm, age of the owner(s), gender of the owner(s), channel of distribution, and firm's market.

We also assume that the variables affecting interference are pre-treatment firm's size and geographical location, denoted by Z_1 and Z_2, respectively. Therefore, we set $m = 2$ and $f_r(\mathbf{T}^{(j)}_{-ij}) = {}_r\mathbf{w}^{(ij)\prime}\mathbf{T}^{(j)}_{-ij}$, $r = 1, 2$. The vector of weights ${}_1\mathbf{w}^{(ij)\prime}$ includes the Euclidean distances between firm ij's size and the size of the other firms in sector j. An element, ${}_2w^{(ij)}_{hj}$, of the vector of weights ${}_2\mathbf{w}^{(ij)\prime}$ is defined as the reciprocal of the geographical distance between firm ij and firm hj, $h \neq i$. Here, the geographical distance is the distance measured along the surface of the earth, and it is calculated as distance between centroids of municipalities where firms are located, which are defined by geographical coordinates in terms of latitude and longitude.

Let $\mathbf{T}^{obs} = [\mathbf{T}^{(1),obs}, \ldots, \mathbf{T}^{(K),obs}]'$ be the vector of treatment assignments, where $\mathbf{T}^{(j),obs} = (T^{(j),obs}_{ij}, \mathbf{T}^{(j),obs}_{-ij})$, and let Y^{obs}_{ij} the actual outcome for firm ij in sector j. Finally, let $\mathbf{X}$ be the $N \times K$ matrix of the pre-treatment variables with ijth row equal to $\mathbf{X}_{ij}$. We model the conditional expectation of Y^{obs}_{ij} given T^{obs}_{ij}, $f_r(\mathbf{T}^{(j),obs}_{-ij})$, $r = 1, 2$ and $\mathbf{X}_{ij}$ as a flexible function of its arguments. Formally,

$$E[Y^{obs}_{ij} | T^{(j),obs}_{ij}, f_1(\mathbf{T}^{(j),obs}_{-ij}), f_2(\mathbf{T}^{(j),obs}_{-ij}), \mathbf{X}_{ij}] = \alpha_0 + \alpha_1 \cdot T^{(j),obs}_{ij} + \alpha_3 \cdot f_1(\mathbf{T}^{(j),obs}_{-ij}) + \alpha_4 \cdot f_2(\mathbf{T}^{(j),obs}_{-ij}) + \alpha_5 \cdot f_1(\mathbf{T}^{(j),obs}_{-ij}) \cdot f_2(\mathbf{T}^{(j),obs}_{-ij}) + \alpha_6 \cdot T^{(j),obs}_{ij} \cdot f_2(\mathbf{T}^{(j),obs}_{-ij}) + \mathbf{X}_{ij} \cdot \beta$$

We estimate these parameters by ordinary least squares. Here we focus on the average treatment effect on the treated, therefore given the estimated parameters, we estimate the average potential outcome for a given allocation of the assignment $\mathbf{T} = [\mathbf{T}^{(1)}, \ldots, \mathbf{T}^{(K)}]'$ as

$$\hat{E}\left[Y(T^{(j)}_{ij}, f(\mathbf{T}^{(j)}_{-ij})) \mid T^{(j)}_{ij} = 1\right] = \frac{1}{N_T}\sum_{i=1}^{N_T}\Big[\hat{\alpha}_0 + \hat{\alpha}_1 \cdot T^{(j)}_{ij} + \hat{\alpha}_3 \cdot f_1(\mathbf{T}^{(j)}_{-ij}) + \hat{\alpha}_4 \cdot f_2(\mathbf{T}^{(j)}_{-ij}) + \hat{\alpha}_5 \cdot f_1(\mathbf{T}^{(j)}_{-ij}) \cdot f_2(\mathbf{T}^{(j)}_{-ij}) + \hat{\alpha}_6 \cdot T^{(j)}_{ij} \cdot f_2(\mathbf{T}^{(j)}_{-ij}) + \mathbf{X}_{ij} \cdot \hat{\beta}\Big],$$

and the average potential outcome for a given allocation of the assignment $\mathbf{T} = [\mathbf{T}^{(1)}, \ldots, \mathbf{T}^{(K)}]'$ and a pre-fixed interference level f^* as

$$\hat{E}\left[Y(T^{(j)}_{ij}, f^*) \mid T^{(j)}_{ij} = 1\right] = \frac{1}{N_T}\sum_{i=1}^{N_T} \hat{\alpha}_0 + \hat{\alpha}_1 \cdot T^{(j)}_{ij} + \hat{\alpha}_3 \cdot f^*_1 + \hat{\alpha}_4 \cdot f^*_2 + \hat{\alpha}_5 \cdot f^*_1 \cdot f^*_2 + \hat{\alpha}_6 \cdot T^{(j)}_{ij} \cdot f^*_2 + \mathbf{X}_{ij} \cdot \hat{\beta}$$

Table 1. Some Causal Estimates

Estimand	Estimate	SE
$E\left[Y(T_{ij}^{(j)}=1, f^*=(3,0)) - Y(T_{ij}^{\prime(j)}=0, f^*=(3,0)) \mid T_{ij}^{(j)}=1\right]$	0.92	0.413
$E\left[Y(T_{ij}^{(j)}=1, f^*=(3,1)) - Y(T_{ij}^{\prime(j)}=0, f^*=(3,1)) \mid T_{ij}^{(j)}=1\right]$	0.36	0.402
$E\left[Y(T_{ij}^{(j)}=1, f^*=(3,2)) - Y(T_{ij}^{\prime(j)}=0, f^*=(3,2)) \mid T_{ij}^{(j)}=1\right]$	-0.20	0.404
$E\left[E\left[Y(T_{ij}^{(j)}=1, f) - Y(T_{ij}^{\prime(j)}=0, f) \mid T_{ij}^{(j)}=1\right]\right]$	0.37	0.040

where N_T is the number of treated firms.

Table 1 shows the estimates for some causal estimands. As for the first three estimands, we considered the effect of the treatment on the treated under pre-fixed values of f_1 and f_2. In particular, f_1 is fixed at 3, that corresponds approximately to its average, while f_2 assumes values 0, 1 and 2, corresponding, respectively, to the lowest, the median and the third quartile of the empirical distribution of f_2. The first estimated causal effect is positive and substantial from an economic point of view: treated firms had on average 0.92 employers more than non treated ones. Provided that we are considering small firms, this is a big impact. As the strength of interference increases (second and third estimands), the effect reduces. This is consistent with the idea that the beneficial effect of the policy for a firm is reduced when its geographically close competitors are also treated. Finally, we consider the average causal effect of the policy for treated firms averaging over the distribution of f. We find that the effect is positive and as expected lies between the interference level-specific effects.

Concluding remarks

Our paper discusses the problem of estimating the effect of policies targeted to firms in the presence of possible externalities. We discuss weaker versions of SUTVA and define causal estimands of possible interest. Our results show that the impact of interference can be considerable and should not be neglected. A limitation of our analysis is that the outcome considered so far, number of employees, might not capture well the effect of the policy, especially in the short run. We plan to consider alternative firms' performance measures, such as turnover, and to adopt alternative estimation strategies in order to assess the robustness of our results.

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