Evidence of Treatment Spillovers Within Markets

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Les 14 et 15 février 2013 - Paris
February 14th and 15th, 2013 - Paris
• **Is it efficient to increase the proportion** of individuals treated by ALMPs?

• **Maybe not**, if policies have **negative indirect effects** on non-treated people. How can we evaluate such effects?

• Causal evaluation of public policies (and more broadly, of treatments) rely on **two main assumptions**:
  – **CIA**: conditional independence between treatment and outcomes;
  – **SUTVA**: no influence of an individual’s treatment status on another individual’s potential outcome.

• **!!! Many policies generate interactions between individuals** => **SUTVA may not hold.**
A growing evidence of *externalities of public policies*, and thus of SUTVA violations. Some rely on structural calibrated models

- Davidson and Woodbury *(1993)* => displacement effects of a re-employment bonus;
- Heckman, Lochner and Taber *(1999)* => equilibrium effects of tuition subsidies;
- Lise, Seitz and Smith *(2004)* => global impact of the *Self-Sufficiency Program* in Canada.
Some recent papers attempt to measure externalities directly through randomized or natural experiments:

- Duflo and Saez (2003) evaluate the diffusion of information on a retirement savings program, with a two step experimental design;
- Crépon et. al. (2013) measure the displacement effects of a reinforced placement assistance program, also with a two step experimental design;
- Gautier et. al. (2012) show negative effects of an activation program on non-participants using a difference-in-difference model.

Experiments are costly => is it possible to measure treatments spillovers (and hence to test the SUTVA) in a non-experimental setting?
What we do in this paper

• **We extend the standard evaluation model**, allowing for individual outcomes to depend not only on the subject’s treatment status but **also on the distribution of treatments in the population**.

• **We define a range of treatment effects**, and **show their identification under a pair of CIA**.

• Using data from the French unemployment agency, we study the effect of the proportion of trained jobseekers within a given market on the probability to leave unemployment.

• To overcome the issue of treatment allocation across markets, we use **detailed information on local labor demand**, together with the longitudinal dimension of our data.
The Model

- The economy consists of \( M \) markets, denoted by \( m \).
- An individual \( i \) belongs to only one market \( m = m(i) \).
- We consider a binary treatment \( Z = 0, 1 \) and an outcome \( Y \):
  \[ Y_i = Y (Z_i, Q_{m(i)}), \]
  where \( Q_{m(i)} \) is a function of \( Z_j, j \in m(i) \).
- In our empirical application: \( Q_m \) is the proportion of treated individuals in market \( m \).
Outcomes and treatment effects

• We define $Y_i(z, q)$ as the potential outcome for individual $i$ that applies if $Z_i = z$ and $Q_{m(i)} = q$.

• The evaluation of the causal effect of $q$ on the average treatment effect in the market is based on the averages of these individual potential outcomes:

$$Y_{z,q} = E_M \{E [Y_i (z, q) | M]\}, \quad \forall (z, q)$$

• The functions $Y_{z,q}$ directly lead to average treatment effects:

$$\delta_{z,z'}^{q,q'} = Y_{z,q} - Y_{z',q'}$$

• The effects of the treatment are then fully described by the set:

$$\{\delta_{q,q'}^{1,0}, \delta_{q,q'}^{0,0}, \delta_{q,q'}^{1,1}\}$$
Two identifying assumptions

- **At the individual level** we assume that we can observe a set $X$ of individual characteristics, that allows for the following CIA:

  \[ Y_i(z, q) \perp Z_i \mid X_i, M_i = m, Q_m = q, \forall z, q, m, i \]

- **At the market level** we assume that conditionally on a set of market characteristics $W_m$, the market potential outcomes are independent of the treatment status (here, the proportion of treated):

  \[ E[Y_i(z, q) \mid M_i = m] \perp Q_m \mid W_m, \forall m, z, q \]
Estimation in two steps

- In our empirical application we make use of matching methods. With matching, interactions between treatment and control groups are most likely.


Application to training policies: data

- **FNA (Fichier National des Assedic), which registers:**
  - all individual unemployment spells in France since 1990;
  - all training spells during unemployment;
  - a range of individual characteristics, among which the jobseekers’ occupation.

- **BMO (Enquête Besoins de Main d’Oeuvre):** survey which collects, from 2001 on, firms’ job opening predictions at a very detailed level.

- **We start in 2002 for two reasons:**
  - Unemployment insurance reform in 2001 => changes in the rules of participation to training;
  - match between FNA and BMO.
Individual level

• We consider the unemployment inflows of $T_0 = 2002$ and $T_0 = 2004$.
  – $Z_i = 1 \{i \text{ enters a training program within } d_Z \text{ months}\}$.
  – $Y_i = 1 \{i \text{ leaves unemployment within } d_Y \text{ months}\}$.

• The individual controls $X$ are:
  – age, $1\{\text{male}\}$, $1\{\text{previous occupation} = \text{occupation of job searched}\}$
  – duration of affiliation to the unemployment insurance system,
  – unemployment benefits and reference wage,
  – month when unemployment started.

• During $[T_0 - 2, T_0]$ and $[T_0 - 7, T_0 - 2]$:
  – # unemployment spells,
  – time spent unemployed/in training,
  – % of spells with training.
Market level

- Markets are characterized by: an occupation $o$, a region $r$, a year $t$.
- 308 markets. Smallest (resp. largest) market has 324 (resp. 24 262) individuals.
- Treatment rate $Q_m$ varies from 2% to 14%.
- Market characteristics $W_m$:
  - $\theta_m = (#\ \text{vacancies})/(#\ \text{unemployed workers})$: local labor market tightness;
  - $X_m$: mean of each individual characteristics at the market level;
  - a fixed unobserved region effect.
Results: outcomes vs. $Q$ ($d_z=6; d_Y=12$)
Treatment effects vs. $q$ ($d_Z=6$; $d_Y=12$)
Sources of interactions and policy implications

• **Negative crowding-out** effect for both treated and non-treated individuals?
  ⇒ Marginally expanding resources for training should be considered with caution.

• **Positive labor demand effect** for non-treated individuals?
  ⇒ Outcomes for \( q > 0.14 \) remain undetermined.
  ⇒ What effect of a change in the scale of training programs?
Conclusion

• We propose a two step method to identify treatment externalities in a non-experimental framework.
• We find direct evidence of SUTVA violation in the context of ALMP evaluation.
• Application to training policies show that treatment effects are decreasing with the proportion of treated individuals.
• A more structural investigation is needed to understand the nature of the interactions at work.