Decomposing Policy and Treatment Effects with Duration Outcomes: How do economic conditions and finding a job affect criminal recidivism?

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This paper presents an econometric framework which identifies the causal effects of a treatment policy regime and of the actual implementation of treatment when the outcome of interest is a duration variable. More specifically, we consider a situation where individuals are randomized to a *policy regime* upon entering a state at time 0. The policy regime dictates a stochastic propensity to future treatment among agents. Thereafter, at different moments in time and depending upon their policy regime, surviving agents are randomized to actually receive treatment. We are interested in how the policy regime and the treatment influence the outcome which is the time an individual exits the initial state. More specifically, our dynamic potential outcomes framework provides non-parametric identification of: (i) the ex-ante effect of the policy regime on duration to exit, (ii) the relative ex-post effect of actually receiving treatment on the duration to exit with a given policy regime, and (iii) the ex-post interaction effect of the policy regime and actually receiving treatment on the duration to exit from the initial state, (iv) the direct effect of the policy regime on the duration to treatment. In contrast to previous work discussing ex-ante and ex-post effects (Abbring and van den Berg ; Bozio, Costa Dias, van den Berg, 2014), this paper proposes new nonparametric assumptions on the timing of exit which ensure that the decomposition of causal effects pertains to the same sub-population of untreated survivors. The paper ties into the growing literature on dynamic treatment effects and mediation analysis (Abbring & van den Berg, 2005; Heckman & Abbring 2007; Robins, 1997; Gill and Robins, 2001; Frölich and Huber, 2015). It is closest to Abbring & Van den Berg (2015) but the latter imposes much more structure on the model.

An example of such a setting corresponds to a case where the econometrician observes individuals entering unemployment. They may or may not receive later in time a job market training - the treatment - provided that they are still unemployed. At the beginning of their spell, they are randomized between two policy regimes. For instance, one that assigns treatment with a constant hazard rate of 40% and one that assigns treatment to only 10% of individuals each period. We assume that individuals know which policy regime they were randomized into and that the latter may influence their exit decisions.

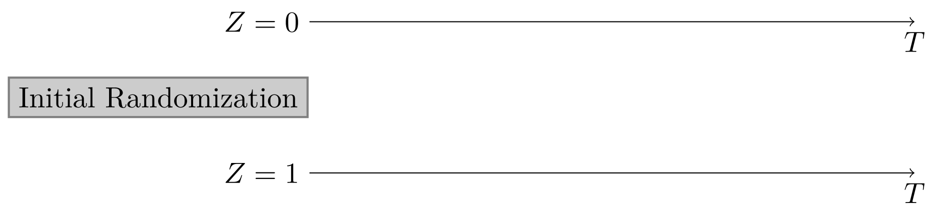

Figure 1: Randomization setting

In the paper, we adopt the standard semantic of duration models. That is, survival probabilities denote the probability of still being in the initial state - e.g. unemployed - at a given time. Conversely, exit probabilities refer to the probability to have exited unemployment at a given time. Survivors at t are individuals still in the original state at time t.

The paper starts with an economic model of job search that illustrates the different effects at play. Agents enter unemployment at time 0. Time is discrete and agents have a discount factor β. As long as they stay unemployed, individuals derive a reservation utility w_0 at each period. Also at each period, they have a probability - the poisson rate - λ to receive a job offer which salary is drawn from a distribution G. If they accept a job offer with associated income w, then they will receive a utility w at every subsequent period. We assume that individuals know λ and G. We derive a Bellman equation that enables us to characterize the reservation wage - the wage above which individuals accept any offer and below which they refuse any offer - in this model.

Additionally, we introduce a treatment in this model. If received, it shifts the distribution of job offers to the right, so that individuals actually want to receive the treatment. We consider the case where the probability of being allocated treatment is constant at each period and equal to π. We derive pre- and post-treatment reservation wages.

Then, (i) the ex-ante effect on the duration to exit with a given policy regime is the difference between the the two policy regimes pre-treatment hazard rates of exit. It may arise because individuals anticipate that they are more likely to receive treatment in a policy with a high π and thus are more likely to refuse a job offer so that they can receive treatment. In the model, this implies that the pre-treatment reservation wage is increasing in π.

The (ii) relative ex-post effect of actually receiving treatment on the duration to exit with a given policy regime is simply the treatment effect. It arises because the treatment shifts to the right the distribution of job offers. It is modelled by the fact that pre-treatment and post treatment hazard rate of exit are different.

Finally, to model (iii) the ex-post interaction effect of the policy regime and actually receiving treatment on the duration to exit from the initial state, we extend the model by assuming that individuals do not know G anymore but they think that the distribution of job offers is a normal with unit variance whose mean is the last job offer that they received. As the pre-treatment reservation wage for people within a high π policy regime is higher, people that actually get treated within a high π treatment policy are more likely to have got good job offers before treatment and thus have different anticipations at the time of treatment, which may in turn affect the treatment effect.

In a second section, we develop an econometric potential outcomes framework for the different effects. Let $T(s,z)$ be the potential duration to exit for an individual that is treated at time s under policy z. We denote by $S(z)$ the potential treatment of the individual under policy z. $T(+\infty, z)$ is the duration to exit for an agent that never receives treatment under policy z (notice that this is not necessarily equal to the duration to exit of an individual that is never assigned the treatment under a policy that never allocates the treatment because of the ex-ante effect). The hazard rate of a random variable R is noted θ_R. We assume the standard no anticipation assumption. It states that $\theta_{T(s,z)}(t) = \theta_{T(s',z)}(t)\ \forall t < s, s'$. It means that individual only anticipate the treatment up to the information contained in z i.e. they don't have any other valuable information about the timing of their treatment than the one of the policy regime.

We assume that both Z and $S(z)$ are randomized (The assumption that the treatment is randomized can be relaxed if the econometrician possesses an instrumental variable for it). So the ex-ante effect of the policy z vs z': $\mathbb{P}(T(+\infty, z') > t) - \mathbb{P}(T(+\infty, z) > t)$ is easily identified. Indeed, one just needs to compare the exit probabilities between the group $Z = z$ and the group $Z = z'$ as the policy Z is randomized.

The same is true of the relative ex-post effect on the survivors of actually receiving treatment at time s on the duration to exit within a given policy regime $\mathbb{P}(T(s,z) > t | T(+\infty, z) \geq s) - \mathbb{P}(T(\infty, z) > t | T(+\infty, z) \geq s)$. Indeed, assuming that for any time s we observe people treated and not treated at that time, the comparison between treated units at time s and not treated units at time s yields the treatment effect on the people who survided up to time s.

The main difficulty here is to identify the ex-post interaction effect of the policy regime and actually receiving treatment on the duration to exit from the initial state. To begin with, it is not clear which groups we should compare. A first thought could be to contrast treated at s under $Z = z$ with treated at s under $Z = z'$. However, this is not satisfactory for two reasons.

Firstly, (1) because "time" has a different meaning under both policies. To see this, it is useful to draw a parallel to biology consider for instance 2 countries: A where the life expectancy is 100 years and B where the life expectancy is 50 years. Imagine that we want to compare the effect of a given treatment to heal a sickness between the two countries. In this case, it does not make sense to compare the treatment effect on people aged 50 in country A to people aged 50 in country B because they are clearly not at the same point of their lives. In our economic setting, it is the same as the exit probabilities may differ between the two regimes.

Secondly, (2) there is an issue commonly called "dynamic selection". It basically states that the non-treated survivors at a given time s under $Z = z$ and $Z = z'$ do not represent the same population in terms of unobserved heterogeneity because the ex-ante effect interacts differently with individual characteristics between the two regimes.

To solve (1) we propose to compare individuals at times where the survival probabilities are equal. That is, we compare the treatment effect on non-treated survivors at s under $Z = 0$ to the treatment effect on non-treated survivors at s' under $Z = 1$ where s' is defined by

$$\mathbb{P}(T(+\infty, 0) \geq s) = \mathbb{P}(T(+\infty, 0) \geq s')$$

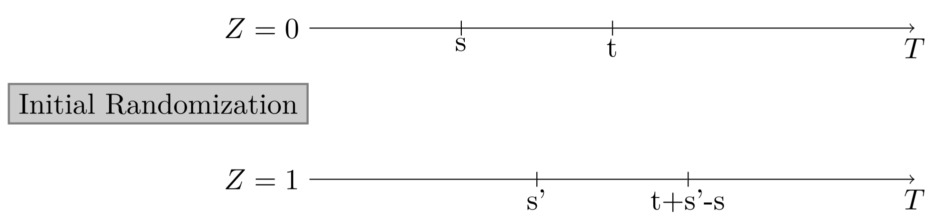

Figure 2: Comparison setting

This comparison choice is justified by the fact that s and s' correspond to equivalent points in their expected lives.

To solve (2), we provide 2 different sets of nonparametric assumptions that ensure that the population of non-treated survivors at s under $Z = z$ and at s' under $Z = z'$ are the same. In the first assumption, we assume that unobserved heterogeneity is summarized in a vector random variable V and we denote the observed covariates X. Then we propose to model the pre-treatment hazard rate as:

Assumption: Time equivalence

(i) $\theta^{T(\infty,z)}(t|X, V) = \lambda(t, z)\Psi(V, X)$

(ii) $\lim_{T\to\infty} \int_0^T \lambda(t)dt = +\infty$

(i) assumes that the hazard rate is multiplicative in a term that models the effect of time within policy regime z - the so-called baseline hazard - $\lambda(t, z)$ and a term that only depends on individual characteristics - $\Psi(V, X)$. This kind of proportionality assumption is standard in duration models. (ii) is a technical assumption that ensures that for every s we can find an s'. If it is relaxed, our identification results only hold for any s for which there exists a relevant s'.

Notice that the fact that the unobserved heterogeneity V is not time-varying can be relaxed here. In the paper, we propose a model with shocks to V that may represent adjustments of anticipation resulting from job offers (as in the economic model). Identification persists as long as the shocks have a symmetric effect on the survival probabilities.

An alternative assumption solving (2) assumes that V is scalar and that, under each regime, the highest V exit first and this happens continuously. As an example, consider that V can only take value 1,2 and 3, then this means that all the 3 will exit and the 2 will begin to exit when the 3 have finished to exit and so on...

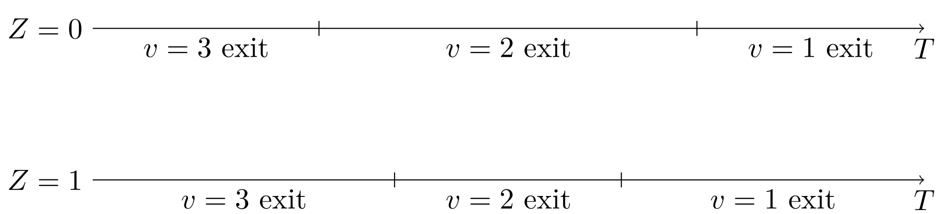

Figure 3: Exit times with 3 values of V

Under, one of the two described assumptions, the following ex-post interaction effect of the policy regime and actually receiving treatment is identified:

$$\mathbb{P}(T(s, z) < t | T(\infty, z) \geq s) - \mathbb{P}(T(s', z') < t + s' - s | T(\infty, z) \geq s)$$

The paper is finally augmented with an application. As we consider randomized experiments, data in our particular setting is scarce but we hope that employment agencies will consider our research as a good reason to run this kind of experiments. Because of these data constraints, we only consider an application to crime economics . We use Norwegian data to evaluate the treatment effect of finding a job (unfortunately this treatment is not randomized) on the duration to recidivism of ex-convicts. The policy regime is the unemployment rate in the region of the ex-convicts. Results are not yet available but should be ready soon. Our identification results will, for instance, enable us to plot treatment effects as function of the survival probabilities as in the following example:

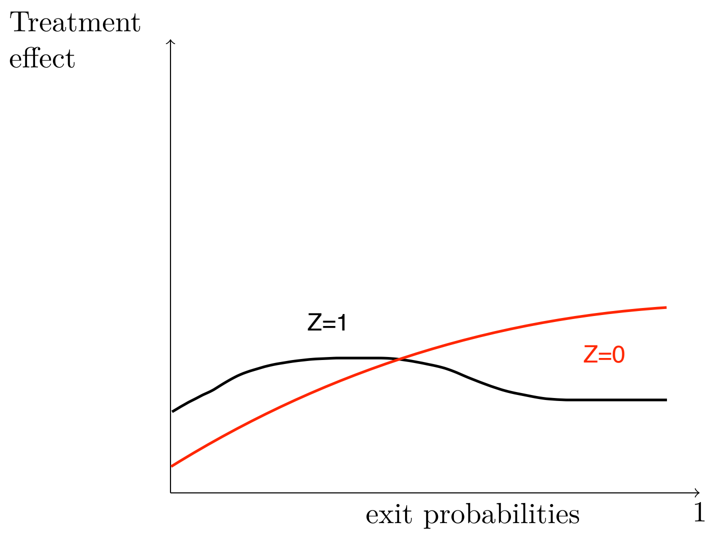

Figure 4: Treatment effects