Modelling Network Interference with Multi-valued Treatments: the Causal Effect of Immigration Policy on Crime Rates

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Abstract

Policy evaluation studies, which aim to assess the effect of an intervention, imply some statistical challenges: real-world scenarios provide treatments which have not been assigned randomly and the analysis might be further complicated by the presence of interference between units. Researchers have started to develop novel methods that allow to manage spillover mechanisms in observational studies, under binary treatments. But many policy evaluation studies require complex treatments, such as multi-valued treatments. For instance, in political sciences, evaluating the impact of policies implemented by administrative entities often implies a multi-valued approach, as the general political stance towards a specific issue varies over many dimensions. In this work, we extend the statistical framework about causal inference under network interference in observational studies, allowing for a multi-valued individual treatment and an interference structure shaped by a weighted network. Under multi-valued treatment, each unit is exposed to all levels of the treatment, due to the influence of his neighbors, according to the network weights. The estimation strategy is based on a joint multiple generalized propensity score and allows to estimate direct effects, controlling for both individual and network covariates. We follow the proposed methodology to analyze the impact of national immigration policy on crime rates. We define a multi-valued characterization of political attitudes towards migrants and we assume that the extent to which each country can be influenced by another is modeled by an appropriate indicator, that we call Interference Compound Index (ICI). Results suggest that implementing highly restrictive immigration policies leads to an increase of crime rates and the magnitude of estimated effects is stronger if we take into account multi-valued interference.

Keywords: causal inference, interference, complex networks, multi-valued treatment, multiple network exposure, immigration policies

1 Introduction

Policy evaluation studies aim to assess the effect of a treatment on an outcome variable. Social sciences such as economics or political sciences often evaluate complex treatments, which have not
been randomly assigned over the population. In some real-world situations, the analysis can be further complicated by the presence of interference between units. This phenomenon occurs because both economic and social agents are interconnected. Firms are connected by a wide mixture of juridical or commercial relationships including trading links, ownership or control ties and strategic alliances (Reinert et al. (2009)). On the other side, individuals also interact through various mechanisms involving friendship or parental links, working collaborations or informative communications. On top of that, even political entities result to be linked by way of explicit or veiled agreements, or according to their specific geographical and cultural collocation with respect to a reference environment. These relations are depicted by a network: the observed nodes are the elements of the population of interest, while network links represent the relations between them. Causal inference on a population of agents who are connected through a network faces some statistical challenges, involving how to take into account the spillover mechanism that reasonably arises. The standard Rubin’s Framework (Rubin (1980)), based on the idea of Potential Outcomes, relies on a key assumption, called Stable Unit Treatment Value Assumption (SUTVA), which rules out the presence of interference among units. But if agents are linked, experiments as well as observational studies may be affected by the presence of interference, which formally occurs when the treatment of one unit has an effect on the response of other units (in addition to the unit’s own outcome) (Cox (1958)). In the presence of interference, the causal effect of a treatment observed on one unit may be altered by the treatment received by other interfering units. For example, incentives targeted to single firms or companies may also benefit all those firms that are linked with them, according to juridical or economic relationships. In addition, policies implemented by single administrative entities also affect the outcomes of interfering territories. Dealing with interference is meaningful for two main reasons: first, wrongly assuming SUTVA can lead to deceptive conclusions about the real effect of an intervention; second, the relevance of the spillover effect can be itself the object of interest.

For this reason, in recent years, a growing community of statisticians has started reasoning about interconnected units, developing novel methods and techniques which allow to account for interference in causal inference studies. The existing works extend the standard Rubin’s framework so as to include the network information in the definition of individual potential outcomes. Most of these works examine interference in randomized trials. Rosenbaum (2007) illustrated the limitations of the present statistical tools in dealing with possible dependencies among units and developed non-parametric tests to evaluate treatment and spillover effects in the presence of interference. After a few years, Aronow (2012) presented a novel method to detect interference. Bowers et al. (2013) proposed tools to model various dependency scenarios and shew how to test hypotheses about causal effects according to the specific model that is supposed to depict interference. Recently, Aronow et al. (2017) rearranged the Horwitz-Thompson estimator allowing for the presence of interference so to obtain unbiased estimators for all the effects of interest, mains and spillovers. Athey et al. (2018) computed exact p-values for a variety of sharp null hypotheses about treatment
effect in an experimental design where units are connected in an observed network. Some other works focus on a particular type of interference known as \textit{partial (clustered) interference}, where units belong to exogenous groups and the spillover mechanism can occur only within clusters. The term ”partial” is used here to counterpoise this scheme of clustered dependencies with the ”general” interference scenario where units interact according to a network. Sobel (2006) formally introduced the partial interference assumption which states that units are grouped into classes and there is no interference between units belonging to different classes. Hudgens and Halloran (2008) investigated the role of interference in the spreading of infectious diseases, where the probability that a person becomes infected is lower if the proportion of vaccinated neighbors is high. Tchetgen and VanderWeele (2012) proposed novel estimands to evaluate group randomized studies. Barkley et al. (2017) addressed the issue of a possible treatment selection among connected individuals and proposed causal estimands allowing for clustered dependence in the treatment selection. Some researchers also investigated the role of interference in the design of experiments. For instance, Eckles et al. (2017) pointed out that wrongly assuming SUTVA lead to biased results and formalized a model of experiments in networks which implements novel techniques that allow to reduce this bias through the experimental design itself. Baird et al. (2018) formalized the optimal design of randomized controlled trials under partial interference. There are just a few articles that explicitly deal with general interference in \textit{observational studies}. Hong and Raudenbush (2006) evaluated the policy of retaining low-achieving children in kindergarten rather than promoting them to first grade, using a multilevel propensity score model. Lundin and Karlsson (2014) investigated the effect of a parenting support program, under partial interference. Forastiere et al. (2016) introduced a novel approach, based on joint propensity score (JPS), which allows to estimate the dose-response function in presence of interference. This work analyzes a binary treatment and models interference through an observed binary network. Del Prete et al. (2019) explored trade distortions in agricultural markets extending the JPS approach to the case of a continuous individual treatment.

The existing statistical literature that approaches interference in observational studies deals with binary treatments only. But many policy evaluation studies require the exploiting of more complex treatments, as, for example, treatments which are defined over more than two categories, known as multi-valued treatments. \textit{Multi-valued treatments} are highly diffused in nature. They are commonly used when the empirical aim consists in comparing various characterizations of an intervention and, above all, they are particularly employed in studies yearning to get the picture of complex and many-faceted phenomena, which may vary over multiple dimensions. For instance, evaluating the impact of different political attitudes towards puzzling macro-themes (immigration, national healthcare, economy) often calls for a multi-valued approach and requires also to keep into account of interference, since the treatment may spill among different political entities. Since our empirical attempt is to evaluate the impact of immigration policy, we expand the theoretical framework proposed by Forastiere et al. (2016) to the case of an individual multi-valued treatment, in observational studies. Generalization of the standard techniques (such as subclassification and
propensity score methods) for binary treatments to the multi-valued scenario is not straightforward and requires additional assumptions (Lopez et al. (2017), Yang et al. (2016), Linden et al. (2016)). The methodological approach becomes even more complicated if we decide to allow for the presence of interference, relaxing SUTVA and admitting first-order spillover effects. The key idea is that under a multi-valued treatment, in the presence of interference, each unit is individually assigned to a treatment level and, simultaneously, he can be exposed to all the treatment levels, due to the interaction with his neighbors. Therefore, each unit, in addition to his own treatment assignment, experiments a *multiple neighborhood exposure*, where each neighbor contributes in increasing the unit’s exposure to the treatment level he is actually assigned to. In addition, if the interference network provides some expressive weights that quantify the extent of dependencies, the multiple neighborhood exposure mapping will necessarily take them into account. Weighted networks are widely spread in real-world data. For instance, networks of transactions between entities are usually enriched by the information about transactions’ amount, social networks sometimes give a numerical measure of friendship between units, scientific collaborations networks often provide the number of collaborations, political networks frequently measure the strength of connections between administrative and political entities by specific not-binary indicators. Valued networks are particularly rich in terms of providing information and collapsing them to unweighted networks that simply signal the presence or absence of each link entails a considerable informative loss. Given the particular aim of our empirical application which attempts to model dependencies among countries, we decide to build up our framework so to be suitable also for weighted networks, making the extent of the neighborhood exposure related to the edges weights. In this scenario, each unit is exposed to an individual treatment, which is categorical with a given number of categories, and to a neighborhood treatment, which is a multivariate continuous variable that measures the unit exposure to all treatment levels, resulting from the interaction of his neighbors and given the strength of these interactions. Since we move in an observational study setting, where neither the individual treatment nor the neighborhood treatment are randomly assigned in the population, we propose an estimation strategy based on the usage of an extended version of the joint propensity score proposed by Forastiere et al. (2016). Our definition of propensity score, that we call *Joint Multiple Generalized Propensity Score (JMGPS)*, allows to suitably model the particular treatment we’ve introduced, efficiently handling the multiple neighborhood exposure. JMGPS represents the primary element of our proposed estimation strategy and it is used to impute missing potential outcomes through a purely parametric approach, in order to estimate the direct effects of interest.

We make use of this methodology for the analysis of the causal effect of immigration policies. In the last decades, the relevance of the immigration process has rapidly grown and shrew the way to the spreading of a wide and open debate about the effects of migration. Some political parties, single politicians and citizens all around the world do believe that immigration represents a risk for national identity and, moreover, that it leads to a lower social security. Consequently, they support governments that implement restrictive immigration policies. But the causal effect of immigration
policies on crime or social conditions in general has not been tested yet. In particular, there are no quantitative studies that involve and compare many countries, over a wide time frame. We analyze policies starting from the IMPIC (Immigration Policies in Comparison) dataset that numerically measures in terms of restrictiveness all the immigration policies that have been implemented in the OECD countries from 1980 and 2010. We include in the analysis 22 OECD countries that are located in Europe over the whole time frame covered by the IMPIC dataset. Our purpose is to investigate the impact of the promoted policy towards migrants on crime rates. SUTVA assumption appears not to be plausible in this empirical scenario. The political strategy towards migrants that a single country decides to implement may also affect crime outcomes of other countries. The possible spillover effect of the adopted political recipe towards immigration arises because migrants try to avoid countries with highly restrictive laws, and tend to move to states that appear to be more welcoming. Since migrants tend to move to countries with specific characteristics of their choice, the extent to which each country is affected by other countries’ policies depends on their level of similarity. Following this intuition, we derive an indicator summarizing the main factors which may prompt the spillover mechanism. These factors refer to various measures of similarity, which we reasonably believe to be the driving mechanisms of interference. Specifically, this index, that we call Interference Compound Index (ICI), gives a measure of potential interference between each pair of countries at a given year and combines information about Geographical Proximity and Cultural Similarity, which in turn are summarized by specific indicators. In this application, the treatment of interest represents the restrictiveness of immigration policies, which is measured in the IMPIC Dataset through the evaluation of a series of single policies. Each policy refers to regulations or control protocols. The former are all the binding legal provisions that create or constrain rights [Helbling et al. 2017], while the latter refer to the directives which have been adopted at the aim of monitoring whether the regulations are observed. Therefore, aggregating items referring to these two political dimensions, we obtain two indicators measuring the country-year restrictiveness towards migrants, with respect to regulations and control mechanisms separately. Using this information, we define a multi-valued treatment by looking at the joint value of the two indicators, for each country-year profile. This work is organized as follows. In Section 2 we focus on methodology. We first summarize the existing framework about causal inference under interference in observational studies and then we present our methodological novelties: we introduce a multi-valued treatment and we propose a novel tool that allows to model the neighborhood exposure in the presence of multi-valued treatment and weighted interference. We introduce the joint generalized multiple propensity score and we illustrate the employed estimation strategy. In Section 3 we motivate the importance of the empirical application, giving a broad overview of the existing literature and briefly describing data. Moreover, we give a more detailed characterization of the Interference Compound Index and we provide a deeper explanation on the definition of treatment nominal categories. In Section 4 we present the main empirical results. In the appendix, we collect the proofs of the theoretical propositions we present in Section 2, we give the precise definition of ICI and we present the detailed results of all the models we implement, also giving
some additional explanations about the transformation we apply to the neighborhood treatment variable, reporting some descriptives and checking the robustness of the main findings with respect to alternative definitions of the treatment variables.

2 Methodology

In this section we explain the main aspects of the employed methodology. We start from the existing framework about causal inference under interference (Subsection 2.1) and then we present the novel approach for multi-valued treatments (Subsection 2.2). Finally, we define the Joint Multiple Generalized Propensity Score (Subsection 2.3) together with its properties and we propose the estimation strategy (Subsection 2.4).

2.1 Causal Inference Under Network Interference

The main scope of causal inference is estimating the effect of a treatment on some outcome variable in a population of units. Let us consider a sample $N$ comprised by $N$ units. Denoted as $K$ the number of treatment levels, let $Z_i \in \{1, \ldots, K\}$ be a categorical variable representing the treatment assigned to unit $i$ and $Y_{i}^{\text{obs}}$ the observed outcome for the same unit. By $Z$ and $Y^{\text{obs}}$ we denote the corresponding vectors of the whole sample $N$. Moreover, $X_i$ denotes a vector of $P$ covariates (or pre-treatment variables) that are not influenced by the treatment assignment. Following the Rubin Causal Model (Rubin (1974), Rubin (1980)), we postulate, for each unit, the existence of $K$ potential outcomes, one for each treatment level, $Y_i(Z)$. Moreover, Rubin’s theoretical framework relies on the Stable Units Treatment Assumption (SUTVA) (Rubin (1986)). Under SUTVA, potential outcomes are well-defined so that they can be compared to estimate the treatment effect.

SUTVA is made up by two different components: (i) the Individualistic Treatment Response (ITR) (Manski (2013)) (or no interference) states that there is no interference between units, each unit’s potential outcomes are defined only by that unit’s own treatment; (ii) the consistency (or no multiple version of the treatment) states that there are no different versions of the treatment levels. As a consequence, the observed outcome is the one corresponding to the treatment that each unit $i$ has actually received: $Y_{i}^{\text{obs}} = Y_i(Z_i)$.

SUTVA completely rules out the presence of interference among units. However, in many real situations, this no-interference assumption is violated. This phenomenon can occur in various and heterogeneous frameworks. For instance, in economics, firms assigned to a program of incentives can be affected by incentives received by other firms. In epidemics, vaccines are known to benefit the whole community, including unprotected individuals, because they reduce the reservoir of infection and the infectiousness. Finally, in political sciences, policies implemented in some administrative region may have an effect also on the neighboring territories. All these examples refer to empirical situations in which one unit’s outcome may be influenced by other units’ treatment level. Figure[1] gives a graphical intuition of interference. In the no-interference case, each unit’s outcome
(red nodes) is affected only by his own treatment (blue nodes); in the presence of interference, neighboring units’ treatments also affect the individual outcome.

Figure 1: No-Interference vs Interference scenarios: blue nodes represent individual treatments, red nodes their corresponding outcomes.

When the spillover mechanism comes into play, wrongly assuming SUTVA leads to biased results and, consequently, to inaccurate or even misleading conclusions about the effects of interest. In order to model interference, we have to look at the relations between units. We consider an observed undirected network $G = (N, E)$, where $N$ is the set of nodes (the population of interest) and $E$ represents the set of edges indicating links between nodes. If we assume the plausible existence of first-order spillover effects only, then we primarily focus on the neighborhood of each node. For each node $i$, we identify a partition of $N$ into two subsets: i) the neighborhood of node $i$, $N_i$, that includes all the nodes $j$ such that exists a link between $j$ and $i$, $i \leftrightarrow j$; the ii) No-Neighborhood of node $i$, $N_{-i}$, including all the nodes $j$ such that doesn’t exists a link between $j$ and $i$, $i \leftrightarrow j$.

According to these partitions, we define, for each node $i$, the following partitions of the treatment vector and of the outcome vector, $(Z_i, Z_{N_i}, Z_{N_{-i}})$, $(Y_i, Y_{N_i}, Y_{N_{-i}})$. Figure 2 shows the neighborhood of a given node.

Figure 2: Neighborhood of a given vertex: the figure shows a given unit (yellow-colored unit) and highlights his own neighbors (red-colored units), in a population of connected agents.

Following Forastiere et al. (2016), admitting network dependencies in the analysis implies the
replacement of SUTVA by a neighborhood interference assumption which allows for the existence of first-order spillover effects between neighbors. Using the notation $Y_i(Z)$ for potential outcomes of unit $i$, we have:

**Stable Unit Treatment on Neighborhood Value Assumption (SUTNVA)**

1. **No Multiple Versions of Treatment (Consistency):** $Y_i(Z) = Y_i(Z^1) \quad \forall Z, Z^1$ such that $Z = Z^1$, that is, the mechanism used to assign the treatments does not matter.

2. **Neighborhood Interference:** A function $g_i : \{0, 1\}^{N_i} \rightarrow G$ exists such that for all $Z_{N_i}, Z^1_{N_i}$ and $Z_{N_i}, Z^1_{N_i}$ such that $g_i(Z_{N_i}) = g_i(Z^1_{N_i})$, the following relation holds:

$$Y_i(Z, Z_{N_i}, Z_{N_i}) = Y_i(Z, Z^1_{N_i}, Z^1_{N_i}).$$

This assumption basically states that there is interference and it is modelled by the function $g_i$.

Throughout, we indicate as $G_i$ the variable resulting from applying the function $g_i$ on the $i$'s neighbors’ treatment vector: $G_i = g_i(Z_{N_i})$. This variable, called neighborhood treatment, represents the unit’s exposure to the treatment, due to the influence of his neighbors. The function $g_i$ can be defined in many different ways, according to the interference mechanism that is assumed to take place. For instance, it can simply count the number of treated neighbors or it can measure the proportion of treated neighbors. Note that under SUTNVA interference is assumed to arise in the neighborhood of each vertex and that the possibility of any type of second-order interference is completely ruled out. This means that neighbors of neighbors of unit $i$ do not influence unit $i$ itself. This restriction over the dependency structure may appear to be too strong in some scenarios, but it results to be plausible in many empirical applications. In the presence of interference, each unit is affected by two treatments: the individual treatment $Z_i$ and the neighborhood treatment $G_i$. Therefore, we can state that each unit is affected by a joint treatment, that includes both the individual treatment $Z_i$ and the neighborhood treatment $G_i$. As a consequence, potential outcomes are indexed by both treatments: $Y_i(Z_i, G_i) = Y_i(Z_i = z, G_i = g)$. As in the standard framework, the only outcome we may observe is the one corresponding to the joint treatment that each unit $i$ is assigned to: $Y_{i}^{obs} = Y_i(Z_i, G_i)$.

Potential outcomes can be compared in order to estimate the direct effects of interest. In the presence of interference, these effects have to control for the neighborhood treatment. Keeping the neighborhood treatment fixed, the comparison is made between the different levels of the individual treatment $Z_i$:

$$\tau_{z'z}(g) = E[Y_i(Z_i = z', G_i = g) - Y_i(Z_i = z, G_i = g)].$$  \hspace{1cm} (1)
2.2 Multi-Valued Treatments in the presence of interference

This framework assumes the individual treatment to be defined as a binary variable. But in many real-world applications treatments are implicitly or explicitly multi-valued. In epidemics, researchers are interested in comparing between various doses of a particular drug or even between radically different therapeutic approaches (Linden et al. (2016)). In economics, firms are exposed to different types of incentives. In labor economics, whoever studies the social and individual returns to education is interested in assessing how different levels of education affect a person’s wage. In training programs, participants receive different hours of coaching and some trainings internally provide qualitatively different sub-branches (Cattaneo (2010)). Finally, political science evaluates adopted political strategies towards highly complex and multi-faceted issues which involve different sub-fields. In such scenarios, a common practice is to collapse the multi-valued treatment into a binary variable, but it implies a relevant loss in terms of information and it prevents the possibility of capturing differential effects across treatment levels (Cattaneo (2010)). For this reason, researchers have started to study how to extract causal information under multi-valued treatments, developing novel assumptions and techniques that extend standard tools as matching, subclassification, inverse probability weighting on the propensity score, also in the multi-valued scenario (Lopez et al. (2017)).

But no existing work suggests how to deal with interference in the multi-valued scenario. Under first-order spillover effects, each unit is exposed to a joint treatment whose second component represents the neighborhood treatment, thought as a numerical synthesis of the treatment status of his neighbors. In the binary setting, this synthesis is expressed by a single value, while when the individual treatment is defined over multiple categories this simplification cannot be proposed. Categorical treatments imply a more complex definition of the neighborhood treatment exposure, as the neighborhood treatment has to summarize the individual network exposure to each treatment level. Recalling the notation given in the previous subsection, the mathematical tool that we introduce to model the neighborhood treatment under multi-valued individual treatment is the Neighborhood Treatments Exposure Matrix $G$:

Definition 1 (Neighborhood Treatments Exposure Matrix (NTEM), $G$)

The NTEM is an $N \times K$ matrix $G$ that collects the unit neighborhood exposure to all the treatment levels:

$$G = \begin{pmatrix}
G_{1,1} & \ldots & G_{1,z} & \ldots & G_{1,K} \\
\vdots & \ddots & \vdots & \ddots & \vdots \\
G_{i,1} & \ldots & G_{i,z} & \ldots & G_{i,K} \\
\vdots & \ddots & \vdots & \ddots & \vdots \\
G_{N,1} & \ldots & G_{N,z} & \ldots & G_{N,K}
\end{pmatrix}.$$

Each element $G_{i,z} \in G$ indicates the exposure of unit $i$ to the treatment level $z$. Each row results to be the neighborhood treatment vector for the unit $i$, $G_i \in \mathbb{G}^K$. Therefore, the neighborhood treatment is not a scalar measure, as in the binary treatment environment. It is actually a $K$-dimensioned
vector whose components describe the unit’s neighborhood exposure to each treatment level.

If interference is modeled through a weighted network, the function \( g_i \) must take into account the weights, \( I_{ij} \), measuring the relevance of the link between \( i \) and the neighbor \( j \). For instance, given an individual treatment with \( K \) categories, we can set \( G_{i,z} = \sum_{j \in N_i} I_{ij} \delta_{zj} \), where \( \delta_{zj} \) is a dummy variable that equals 1 if \( Z_j = z \) and 0 otherwise.

Thus, each unit \( i \) is exposed to a joint treatment \((Z_i, G_i)\): the individual treatment \( Z_i \), which is a categorical variable with \( K \) levels and to the neighborhood multi-treatment \( G_i \), which is a \( K \)-variate variable. Hence, potential outcomes, for each unit \( i \), are indexed by the joint treatment: \( Y_i(Z_i, G_i) = Y_i(Z_i = z, G_i = g) \). The observed outcome is the one corresponding to the actual joint treatment each unit is exposed to: \( Y_{i,obs} = Y_i(Z_i, G_i) \).

Now, we have to explicitly define the effects of interest. Usually, when the empirical context provides a multi-valued treatment, researchers investigate binary comparisons, among each possible combination of the treatment levels (Lopez et al. (2017), Yang et al. (2016)). The number of the possible comparisons is \( \binom{K}{2} = \frac{K!}{(K-2)!2!} \). For instance, the direct effect of a given treatment \( z' \) with respect to the treatment \( z \), controlling for multi-valued interference, can be expressed as

\[
\tau_{z'z}(g) = E[Y_i(z', g) - Y_i(z, g)]
\]  

(2)

2.3 Joint Multiple Generalized Propensity Score (JMGPS)

In this work, we focus on observational studies, where neither the individual nor the neighborhood treatment are randomly assigned in the population. The general strategy in observational studies is taking into account of some individual baseline covariates so to make, conditioning on them, the treatment assignment becoming as good as random. The set of included covariates is chosen so that, conditioning on their information, we can exclude any dependence between treatment variable and potential outcomes. This assumption is known as unconfoundness (Rosenbaum and Rubin (1983)), it cannot be tested and it has no testable implications but it allows to have well-defined effects. In some empirical applications, researchers, instead of conditioning on the whole set of covariates, prefer to work with a scalar synthesis of them, called propensity score (Rosenbaum and Rubin (1983)). Propensity score is defined as the conditional probability of receiving each treatment level given the values of the covariates. In the binary treatment setting with no interference, propensity score is a balancing score and represents an univariate synthesis of the \( P \)-dimensional covariate space. As long as the balancing property holds, if the unconfoundness assumption is valid conditioning on individual covariates, it remains valid conditioning on the propensity score. Using this approach, researchers benefit of a relevant dimensionality reduction in the analysis. This general approach, which is well grounded in the standard causal inference literature, can be extended to the interference scenario. But the unconfoundness assumption has to be related to the joint treatment and the joint potential outcomes. Following the motivations proposed by Yang et al. (2016), we decide to rely on the weaker version of unconfoundness with respect to the individual
multi-valued treatment. Hence, instead of considering the actual multi-valued treatment variable \(Z_i\), we refer to \(K\) Treatment Indicator Variables which signal the presence (or absence) of a given treatment level \(z\), \(D_i(z)\). Thus, we advance the following assumption:

**Assumption 1 (Weak Unconfoundedness of the Joint Treatment)**

\[
P(D_i(z) = 1, G_i = g | Y_i(z, g), X_i) = P(D_i(z) = 1, G_i = g | X_i) \quad \forall z \in \{1, \ldots, K\} \quad \forall g \in G^K.\]

Note that, in presence of interference, \(X_i\) can include purely individual covariates as well as neighborhood covariates. From now on, we denote as \(X_i^{ind}\) the individual covariates and as \(X_i^{neigh}\) the neighborhood covariates.

Under Assumption 1 we introduce a suitable definition of joint propensity score. In the presence of interference, the propensity score is the joint probability of receiving a value \(z\) of the individual treatment and, simultaneously, being exposed to a value \(g\) of the neighborhood treatment, given the unit’s baseline covariates.

[Forastiere et al. (2016)] formally introduced propensity score under network interference. We expand their definition allowing for a multi-valued individual treatment and a multivariate neighborhood treatment. Therefore, we introduce the **Joint Multiple Generalized Propensity score (JMGPS)** as follows:

**Definition 2 (Joint Multiple Generalized Propensity score (JMGPS))**

\(\psi(z, g, x)\)

JMGPS is the probability of being jointly exposed to a \(K\)-variate individual treatment equal to \(z\) and to a \(K\)-dimensional neighborhood treatment equal to \(g\), conditioning on baseline covariates.

\[
\psi(z, g; x) = P(Z_i = z, G_i = g | X_i = x) = P(G_i = g | Z_i = z, X_i^g = x^g)P(Z_i = z | X_i^z = x^z) = \lambda(g; z, x^g)\phi(z; x^z),
\]

where \(\lambda(g; z, x^g)\) is the neighborhood propensity score and \(\phi(z; x^z)\) is the individual propensity score. \(X_i^z\) and \(X_i^g\) are vectors collecting covariates that affect the individual and the neighborhood treatment, respectively. Note that the two sets corresponding to the covariates included in \(X_i^z\) and \(X_i^g\) may differ. In particular, \(X_i^g\), can collect individual covariates as well as neighborhood covariates, while \(X_i^z\) includes individual variables only.

As the standard propensity score, the Joint Multiple Generalized Propensity Score is a balancing score, that is, it guarantees balance with respect to neighborhood and individual covariates.

**Proposition 1 (Balancing Property of JMGPS)**

The joint propensity score is a balancing score, that is

\[
P(Z_i = z, G_i = g | X_i) = P(Z_i = z, G_i = g | \psi(z, g; X_i)), \quad \forall z \in \{1, \ldots, K\} \text{ and } \forall g \in G^K.
\]
Proof in Appendix A.1

Furthermore, conditioning on JMGPS, we can exclude any dependency between the treatment variable and potential outcomes.

**Proposition 2 (Conditional Unconfoundedness of \( D_i(z) \) and \( G_i \) given JMGPS)**

Under Assumption 1 for all \( z \in \{1, \ldots, K\} \) and \( g \in \mathcal{G}^K \)

\[
P(D_i(z) = 1, G_i = g | Y_i(z, g), \psi(z, g; X_i)) = P(D_i(z) = 1, G_i = g | \psi(z, g; X_i)).
\]

Proof in Appendix A.2

Definition exhaustively calls the attention to the factorized nature that characterizes the JMGPS, which be splitted in the individual propensity score and the neighborhood propensity score. The following property points out that conditioning on the two components separately still guarantees the validity of the conditional unconfoundness property.

**Proposition 3 (Conditional Unconfoundedness of \( D_i(z) \) and \( G_i \) given individual and neighborhood propensity scores)**

Under Assumption 1 for all \( z \in \{1, \ldots, K\} \) and \( g \in \mathcal{G}^K \), we have

\[
P(D_i(z) = 1, G_i = g | Y_i(z, g), \phi(z; X_i^z), \lambda(g; z, X_i)) = P(D_i(z) = 1, G_i = g | \phi(z; X_i^z), \lambda(g; z, X_i)).
\]

Proof in Appendix A.3

### 2.4 Estimation Procedure

The JMGPS is the fundamental element of the estimation procedure that we propose here in this section. This procedure follows a parametric approach and imputes missing potential outcomes for all configurations of the joint treatment and then compares them for estimating the direct effects of interest. Standard errors and confidence intervals are computed using bootstrap methods.

The proposed estimation strategy can be summarized in few steps. As we adopt a parametric approach, the starting point is assuming a distribution for \( Z_i, G_i \) and \( Y_i \). Formally:

\[
Z_i \sim f^Z(X_i^z; \theta^Z),
\]

\[
G_i \sim f^G(Z_i, X_i^g; \theta^G),
\]

\[
Y_i(z, g) \sim f^Y(z, g, \phi(z; X_i^z), \lambda(g; z, X_i); \theta^Y).
\]

Of course, the multi-valued characterization of \( Z_i \) demands for the definition of a statistical model for categorical responses, with respect to the individual propensity score model. Furthermore, \( G_i \)
requires the definition of a multivariate model. Once accurately defined those parametric models, perform the following steps

1. Estimate the parameters $\theta^z$ and $\theta^g$ of the models for $Z_i$ and $G_i$;

2. Use the estimated parameters in Step 1, $\hat{\theta}^z$ and $\hat{\theta}^g$, to predict for each unit $i \in N$ the actual individual propensity score and the actual neighborhood propensity score, that is, the probabilities of being exposed to the individual treatment and the multivariate neighborhood treatment they have actually being exposed to:

   $$\hat{\Phi}_i = \phi(Z_i; X^z_i; \hat{\theta}^z),$$

   $$\hat{\Lambda}_i = \lambda(G_i; Z_i, X^g_i; \hat{\theta}^g).$$

3. Use the predicted propensity scores $\hat{\Phi}_i$ and $\hat{\Lambda}_i$, in order to estimate the parameters $\theta^y$ of the outcome model $Y_i(z, g)$:

   $$Y_i = f^y(Z_i, G_i, \hat{\Phi}_i, \hat{\Lambda}_i; \theta^y).$$

4. Consider the domain of the joint treatment ($Z_i = z, G_i = g$). In particular, $G_i$ is a $K$-dimensional continuous variable. In order to explore a multivariate domain one common practice is constructing a $K$-dimensional discrete grid that scours the possible values of $g$, over its $K$ components’ respective domain. Let us denote this grid as $\Gamma$, $\Gamma \subset \mathbb{G}^K$. For each possible value of the joint treatment, that is, for each combination $(Z_i = z, G_i = g)$ s.t $z \in \{1, \ldots, K\}$, $g \in \Gamma$ and for each unit $i \in N$,

   (a) Predict the Individual Propensity score corresponding to that level of $z$, $\hat{\phi}(z; X^z_i)$.

   (b) Predict the Neighborhood Propensity score corresponding to that level of $g$, $\hat{\lambda}(g; z, X^g_i)$.

   (c) Use that estimated parameters to impute the potential outcome $\hat{Y}_i(z, g)$, that is,

   $$\hat{Y}_i(z, g) = f^y(z, g, \hat{\phi}(z; X^z_i), \hat{\lambda}(g; z, X^g_i); \hat{\theta}^y).$$

5. Estimate the final direct effects of interest, avaranging potential outcomes over $\lambda(g; z, X^g_i)$:

   $$\hat{\tau}_{z'z} = \frac{1}{N} \sum_{i=1}^N \left[ \sum_{g \in \Gamma} (\hat{Y}_i(z', g) - \hat{Y}_i(z, g)) \right] \frac{\hat{\lambda}(g; z, X^g_i)}{\sum_{g' \in \Gamma} \hat{\lambda}(g'; z, X^g_i)}.$$

6. Compute variance through Bootstrap.

### 3 Empirical Application

In this section, we focus on the empirical application. We first enlighten the relevance of our empirical research question with respect to the existing literature about immigration (Subsection...
3.1 Empirical Research Question

In the last decades, interest about immigration has rapidly grown, so that it has become a major topic both in academic and real life debates (Helbling et al. (2017)). Immigration flows significantly increased, since many people attempted to move away from countries which have been suffering long periods of wars and bad economic conditions. The consequence of this process is that the world has become multicultural: migrants have started to be socially included into the hosting countries, launching a new job or even getting married. Moreover, migrants have diffused their own social and religious beliefs.

But immigration has entailed not only positive outcomes. Some countries which have embraced a relevant number of migrants, have experienced the rising of social tensions (Rudolph (2003)). Over the last decades, economic conditions gradually get worse: unemployment rates rose up, and real wages went down. In addition, people have noticed a relevant worsening in the perception of individual security. The conviction that immigration may have aggravated these negative processes has slowly taken root in the public opinion. Politicians and common citizens have started to evaluate problematic consequences about immigration and globalization. Worries about migration spread up in three main directions. First, native people perceive immigration as a risk for the preservation of national identity. Integration results to be not always easy and multiculturalism tend to be perceived more as a threat than as an opportunity. Second, as migrants move looking for better living conditions, they represent, in the common belief, adversary profiles for job. Finally, people tend to blame migrants for rising crime and neglect (Bigo (2002)).

In recent years, many researchers have started studying the effects of the increasing migration flows. For instance, Bove and Böhmelt (2016) has assessed the effect of migration on the diffusion of terrorism, while Rudolph (2006) has evaluated the effects on national security. Many epidemiological studies as Polissar (1980), Stillman et al. (2007) and Hildebrandt and McKenzie (2005) have analyzed the consequences on the spreading of some diseases and on public health, in its whole. Furthermore, Coleman (2008) and Keely (2000) have studied the causal effect of migration on some demographic outcomes. Ousey and Kubrin (2009), Bianchi et al. (2008), Bianchi et al. (2012), Stansfield (2016) have studied the impact of flows on crime. The existing works that exploit the causal link about migration flows and crime present findings which are conceptually in contrast to common perception, suggesting that increasing immigration flows don’t lead to higher crime rates. Some of them also state that there is actually a negative effect of immigration on crime.

The public discussion about migration has also involved the immigration policies that national governments implement at the aim of controlling and ruling the immigration process. Brochmann
and Hammar (1999) defined immigration policies as the "government’s statements of what it intends to do or not do (including laws, regulations, decisions or orders) in regards to the selection, admission, settlement and deportation of foreign citizens residing in the country". These policies can be more or less restrictive and, therefore, can discourage or encourage migrants, respectively. Some political parties of various countries all over the world support the idea that implementing restrictive immigration policies limits the negative effects of migrations and, consequently, leads to better living and economic conditions for the natives. On the other side, many politicians and intellectuals argue that the legislative system of a country should encourage immigrants and facilitate their settling.

In this work, we investigate the causal effect of immigration policies on crime rates. Specifically, we study the effect of the restrictiveness of the implemented immigration policy on one year lagged national crime rates, expressed in terms of homicides every 10,000 inhabitants. We approach this research question from a country level perspective: in particular, we focus on the subset of OECD countries that are located into the Continental Europe and we inspect their policies towards migrants from 1980 and 2010. These policies have been measured in terms of restrictiveness into the IMPIC(Immigration Policies in Comparison) Dataset (Helbling et al. (2017), Schmid and Helbling (2016)), that properly conceptualizes and quantitatively compares many national policies that affect migrants (Munck and Verkuilen (2002)). Starting from the restrictiveness measures supplied by the IMPIC Dataset and taking into account the conceptualization of the observed policies that the same dataset proposes, we evaluate the national immigration policy over two political dimensions: restrictiveness of regulations and restrictiveness of control strategies. From now on, we denote as Reg and Cont the two variables representing those two dimensions. We present a treatment variable that qualitatively distinguish country-year profiles with respect to these two measures and we pairwise compare different political strategies.

Our empirical analysis covers 22 OECD countries that are situated in the continental Europe. These countries are characterized by very different immigration experiences: there are countries that have experienced increasing immigration since one or two centuries (Great Britain, Germany, France), countries that recently turned from emigration to immigration (Italy, Spain) and countries that have experienced very limited immigration (Finland) (Helbling et al. (2017)). But, they are still highly comparable from an institutional point of view, as they’re all fully developed democracies and are all located in Europe. Figure 3 we show a map of the 24 included countries.

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124 OECD countries are located in the Continental Europe but we remove from the analysis Hungary and Estonia as they present extreme values of crime rate.
We believe that this is an innovative contribution to the existing literature about migration. Indeed, there are just some recent studies (Geddes and Scholten (2016), Messina (2007)) about immigration policies but they look at particular behaviors of individual countries or describe a small number of countries (Helbling et al. (2017)). Moreover, even if there are existing works that assess the effects of migration flows on crime rates, they focus on single countries comparing subnational administrative entities and they don’t take into account the national political strategy towards migrants.

In this empirical scenario, interference may play a relevant role. Migrants may choose to avoid highly restrictive countries and to settle in places where laws appear to be more welcoming. But we expect that they try to preserve some characteristics of their settling choice. Thus, the general idea is that dependence between two countries is related to their level of similarity. We assume that two mechanisms may rule interference: geographical proximity and cultural proximity. Thus, we build up a continuous indicator that analytically captures these driving mechanisms of interference. Each component contributes in determining the whole indicator according to a given weight. We test various configurations of the interference input weights in order to check the robustness of our results with respect to different restrictions about dependencies.

3.2 Data

This work merges different sources of Data. First, we use the IMPIC (Immigration Policies in Comparison) Dataset (Helbling et al. (2017)) that provides information about national immigration policies. In particular, the previously cited dataset includes data on migration policies for all the OECD countries over thirty years (from 1980 to 2010). Policies are measured with respect to their restrictiveness, from 0 (less restrictive) to 1 (highly restrictive). Data evaluate more than 50 policies for each country-year profile and aggregate items so to compute indicators of the general restrictiveness towards migrants with respect to the regulation and control protocols. The former
aspect is related to all the laws that discipline immigrants and their life in the hosting country, while the latter is referred to the mechanisms that help in monitoring whether the regulations are abided by (Schmid and Helbling (2016)).

Second, we handle various different datasets to assemble the *Interference Compound Index* (ICI), which measures the extent of dependency between each pair of countries at a given year. As we will fully discuss in the forthcoming section, this index is a convex combination of two complex indicators quantifying *geographical proximity* and *cultural similarity* between two countries at a given year. We build up the *geographical proximity indicator* starting from the CEPII Dist Dataset (Mayer and Zignago (2011)) which includes different measures of bilateral distances (in kilometers) and a dummy variable denoting pairwise contiguity. Furthermore, we explore *cultural similarity* between each pair of countries at a given year looking at the *linguistic similarity* through the CEPII Language Dataset (Melitz and Toubal (2014)) and at the *religious similarity* through CEPII Gravity Dataset (Fouquin et al. (2016)).

Third, we make use of some datasets that provide country-year features. Specifically, we collect information about crime rates relying on the *World Countries Homicide rate dataset* which comprises information about the country-year specific number of homicides per 10,000 inhabitants. In addition, we manage the *World Development Indicators* dataset, provided by the World Bank (Coppedge et al. (2018a), Lindberg et al. (2014) and Coppedge et al. (2018b)) which contains highly detailed country-year indicators referring to various aspects of society: they quantitatively mark out the economic situation, the demographic features, the state of the social welfare and democracy and even the level of equality, freedom and justice.

### 3.3 Modelling Interference: Interference Compound Index (ICI)

In the vast majority of policy evaluation studies, interference is modelled through an observed network which describes relations between agents. But sometimes getting information about the whole interference structure is not so immediate. For instance, in our empirical study we haven’t any explicit observed network which plausibly models interference. We have to define the interference structure thinking at the possible mechanisms that could make a different attitude in immigration policies in one country affecting the outcome levels of the other countries. The idea is that immigrants avoid highly restrictive countries and settle to areas that are similar to the first choice with respect to some characteristics, but more politically welcoming. Thus, the relevance of spillover between each pair of countries depends on their pairwise similarity. We assume that the kind of similarity that plays a role in this mechanism is the geographic proximity (meaning, the geographic distance between countries) and the cultural similarity. In some sense, we state that a migrant, who is willing to move, chooses the most welcoming alternative among the countries that are relatively near and culturally similar to the first choice option, that though implements highly restrictive laws. Therefore, we build up a composite indicator which numerically summarizes
these two mechanisms which we reasonably believe are the key prompters of dependency. The two components contribute to the determination of the global index according to some weights, $\alpha$ and $\beta$. This index, that we call \textit{Interference Compound Index (ICI)}, gives a unique information about how much one country $c$ interfer with a country $c'$ at time $t$. Formally:

\begin{definition} \textbf{(Interference Compound Index (ICI))} \\
ICI_{cc',t} = \alpha \times IG_{cc'} + \beta \times IC_{cc',t}
\end{definition}

where $IG_{cc'} \in [0,1]$ is the geographic proximity indicator which measures the geographical proximity between country $c$ and country $c'$ and $IC_{cc',t} \in [0,1]$ is the cultural similarity indicator that measures how much each pair of countries are culturally similar at time $t$. The constants $\alpha$ and $\beta$, with $\alpha + \beta = 1$, are the interference inputs weights that determine the extent of which each component contributes to the global index.

Note that, since the Interference Compound Index is a convex combination of two indicators bounded between 0 and 1, it is in turn bounded between 0 and 1, that is, $ICI_{cc',t} \in [0,1]$. More details about the construction of ICI can be found in the Appendix B. We test various allocations of ICI input weights ($\alpha, \beta$) to check the robustness of our results with respect to different assumptions over the interference structure. Following the same approach of many existing works in Economics and Social Sciences [Del Prete et al. (2019)], we have ruled out the presence of intertemporal links, that is we set $ICI((ct),(c't)) = 0 \forall c,c',t,t' \text{ with } t \neq t'$.

### 3.4 Defining the Treatment Categories

The observed population is characterized by country-year observations: we deal with $C = 22$ countries observed over $T = 30$ years where the initial time $t = 1$ is year 1980 while the ending time $t = T$ is year 2010. Therefore, the generic unit $i$ is a pair $(c,t)$ and the total number of units is $N = C \times T$.

IMPIC Dataset provides indicators which measure the country-year restrictiveness towards migrants with respect to \textit{regulations} and \textit{control} mechanisms. Let us denote as $reg_i$ the reported value of the restrictiveness in terms of regulations of the generic country-year profile $i = (c,t)$ and with $cont_i$ the corresponding value in terms of control. We define the nominal treatment categories looking at the joint distribution of the two indicators. In particular, denoting as $med_{Reg}$ and $med_{Cont}$ the median of the distribution of the regulations indicator and of the control one, respectively, we define the treatment categories as follows:

\begin{definition} \textbf{(Nominal Treatment Categories)} \\
\end{definition}
• $Z_i = A$ if $reg_i \leq med_{Reg}$ and $cont_i \leq med_{Cont}$: this category identifies profiles that are barely restrictive with respect to the two mechanisms.

• $Z_i = B1$ if $reg_i > med_{Reg}$ and $cont_i \leq med_{Cont}$: this category detects profiles which implement restrictive regulations but weak control strategies.

• $Z_i = B2$ if $reg_i \leq med_{Reg}$ and $cont_i > med_{Cont}$: this category indicates a welcoming attitude in terms of regulations but intense control protocols.

• $Z_i = C$ if $reg_i \geq med_{Reg}$ and $cont_i \geq med_{Cont}$: this category denotes an highly restrictive policy towards migrants with respect to both regulations and control.

Figure 4 provides a graphical idea of the previously described definition procedure. The left subfigure shows the density distributions of the regulation and control indexes: their corresponding median values are identified by dotted lines while black colored line represents the underlying distribution of the whole immigration policy index which results by a weighted mean of the former two (Helbling et al. (2017)). The right subfigure shows the individual treatment collocation starting from their own values of the regulation and control indexes.

Figure 4: Treatment Categories Definition

Hence, we deal with a $K$-valued individual treatment, where $K = 4$. Let us denote as $Z = \{Z_{ct}\}$, the $(N \times 1)$ multi-valued treatment vector where $Z_{ct} \in \{A, B1, B2, C\}$. Similarly, we indicate as $Y_{obs} = \{Y_{ct}^{obs}\}$ the $(N \times 1)$ observed (country,year) outcome vector. Furthermore, we take into account of the pre-treatment covariates matrix $X = N \times P$: each row of this matrix still

---

3Look in details how $Z$ and $Y$ vectors look like: $Z = [Z_{11}, \ldots, Z_{1T}; Z_{21}, \ldots, Z_{2T}; \ldots; Z_{C1}, \ldots, Z_{CT}]$; $Y_{obs} = [Y_{11}^{obs}, \ldots, Y_{1T}^{obs}; Y_{21}^{obs}, \ldots, Y_{2T}^{obs}; \ldots; Y_{C1}^{obs}, \ldots, Y_{CT}^{obs}]$.
represents a country-year observation, while each column refers to a specific baseline factor, denoted as $P$ the total number of included covariates. Following Definition 4 and assuming the Interference Compound Index as the ruling mechanism of dependencies, we explicit the neighborhood treatment $G_{ct}$ as

$$G_{ct} = \begin{pmatrix}
\sum_{c' \in N_{ct}} ICI_{cc',t} \delta_{Ac't} \\
\sum_{c' \in N_{ct}} ICI_{cc',t} \delta_{B1c't} \\
\sum_{c' \in N_{ct}} ICI_{cc',t} \delta_{B2c't} \\
\sum_{c' \in N_{ct}} ICI_{cc',t} \delta_{Cc't}
\end{pmatrix} = \begin{pmatrix}
G_{ctA} \\
G_{ctB1} \\
G_{ctB2} \\
G_{ctC}
\end{pmatrix},$$

where $\delta_{Ac't}, \delta_{B1c't}, \delta_{B2c't}, \delta_{Cc't}$ are dummy variables such that $\delta_{Ac't} = 1$ if $Z_{c't} = A$ and 0 otherwise; $\delta_{B1c't} = 1$ if $Z_{c't} = B1$ and 0 otherwise; $\delta_{B2c't} = 1$ if $Z_{c't} = B2$ and 0 otherwise; $\delta_{Cc't} = 1$ if $Z_{c't} = C$ and 0 otherwise. Consequently, the joint potential outcomes are defined as $Y_{ct}(Z_{ct}, G_{ct})$.

Figure 5 displays the distribution of the neighborhood treatment variable under the hypothesis of equal contribution to the ICI subcomponents in setting the whole indicator out, ($\alpha = \beta = \frac{1}{2}$).

The direct effects of interest are the pairwise comparisons between of the treatment levels, controlling for interference. In order to estimate the effects of interest, we follow the estimation procedure, based on the estimation of the joint multiple generalized propensity score, we have described in Section 2.

### 3.5 Joint Multiple Generalized Propensity Score (JMGPS) Estimation

We estimate the two components of JMGPS, relying on the factorization proposed by Forastiere et al. (2016). Both propensity scores can be seen as two peculiar version of generalized propensity score (GPS) proposed by Hirano and Imbens (2004).
3.5.1 Individual Propensity Score

The individual propensity score is the individual probability of receiving an individual treatment \( z \) conditioning on unit-level baseline covariates, that is,

\[
\phi(z; x^z) = P(Z_i = z|X_i^z = x^z).
\]

If the individual treatment is a categorical variable with \( K \) nominal categories the estimation strategy consists in fitting a model for categorical responses. The most common and immediate approach is applying a straight-forward Multinomial Logit Model (Agresti (2018), Long et al. (2006) and Menard (2002)). This model runs \( K - 1 \) independent binary logistic regression models, where one outcome is chosen to be a reference outcome. In particular, we have \( Z_i \in \{A,B1,B2,TC\} \) where \( A \) is the reference category. The fitted value of this model for each unit \( i \) is exactly his actual propensity score, meaning that the fitted value for unit \( i \) measures the exact probability of him to receive the individual treatment he is actually assigned to, given his baseline covariates and the model’s estimated parameters. Denoting with \( \hat{\theta}^z \) the vector that collects the estimated parameters, we explicitly express the estimated individual propensity score as \( \hat{\Phi}_i = \phi(Z_i; X_i^z; \hat{\theta}^z) \). Figures 6a and 6b provide a graphical intuition of the marginal and joint distribution of predicted propensity scores.

![Figure 6: Individual propensity score](image)

3.5.2 Neighborhood Propensity Score

In the considered empirical scenario, the neighborhood treatment is a quadrivariate continuous variable, \( G_{ct} \). One possible way to model propensity score with continuous treatments, is assuming a functional form for the treatment of interest where parameters are related to the individual
level covariates ([Wu et al., 2018], [Del Prete et al., 2019]). Since our treatment is a quadrivariate continuous variable, we have to move on a quadridimensional support.

We first apply a transformation on each component of the neighborhood multi treatment (more details can be found in the Appendix C) so that, after the transformation, we can state that the obtained variables $G_{i,z}^*$ follow a Normal distribution. Specifically, the four transformed components jointly follow a Quadrivariate-Normal distribution:

$$G_i^* \sim MN(\mu_{G_i}^*, \Sigma_{G^*}),$$

where the vector of the means is individual specific and related to the units’ covariates through some parameters,

$$\mu_{G_i}^* = \begin{bmatrix} \mu_{G_{i,A}^*}^*; \mu_{G_{i,B1}^*}^*; \mu_{G_{i,B2}^*}^*; \mu_{G_{i,C}^*}^* \end{bmatrix}$$

$$= \begin{bmatrix} \alpha_{G_{i,A}^*}^* + \beta_{G_{i,A}^*}^* T_i \theta; \alpha_{G_{i,B1}^*}^* + \beta_{G_{i,B1}^*}^* T_i \chi; \alpha_{G_{i,B2}^*}^* + \beta_{G_{i,B2}^*}^* T_i \chi; \alpha_{G_{i,C}^*}^* + \beta_{G_{i,C}^*}^* T_i \chi \end{bmatrix},$$

and the variance-covariates matrix looks like

$$\Sigma_{G^*} = \begin{pmatrix}
\sigma^2_{G_{i,A}^*} & \rho(G_{i,A}^*,G_{i,B1}^*)\sigma_{G_{i,A}^*}\sigma_{G_{i,B1}^*} & \rho(G_{i,A}^*,G_{i,B2}^*)\sigma_{G_{i,A}^*}\sigma_{G_{i,B2}^*} & \rho(G_{i,A}^*,G_{i,C}^*)\sigma_{G_{i,A}^*}\sigma_{G_{i,C}^*} \\
\rho(G_{i,A}^*,G_{i,B1}^*)\sigma_{G_{i,A}^*}\sigma_{G_{i,B1}^*} & \sigma^2_{G_{i,B1}^*} & \rho(G_{i,B1}^*,G_{i,B2}^*)\sigma_{G_{i,B1}^*}\sigma_{G_{i,B2}^*} & \rho(G_{i,B1}^*,G_{i,C}^*)\sigma_{G_{i,B1}^*}\sigma_{G_{i,C}^*} \\
\rho(G_{i,A}^*,G_{i,B2}^*)\sigma_{G_{i,A}^*}\sigma_{G_{i,B2}^*} & \rho(G_{i,B1}^*,G_{i,B2}^*)\sigma_{G_{i,B1}^*}\sigma_{G_{i,B2}^*} & \sigma^2_{G_{i,B2}^*} & \rho(G_{i,B2}^*,G_{i,C}^*)\sigma_{G_{i,B2}^*}\sigma_{G_{i,C}^*} \\
\rho(G_{i,A}^*,G_{i,C}^*)\sigma_{G_{i,A}^*}\sigma_{G_{i,C}^*} & \rho(G_{i,B1}^*,G_{i,C}^*)\sigma_{G_{i,B1}^*}\sigma_{G_{i,C}^*} & \rho(G_{i,B2}^*,G_{i,C}^*)\sigma_{G_{i,B2}^*}\sigma_{G_{i,C}^*} & \sigma^2_{G_{i,C}^*}
\end{pmatrix}.$$

In order to numerically derive the unit specific vector of the means we have to fit a model over $G_i^*$. We fit Multivariate Multiple Linear Regression Model, ([Davis, 1982], Duchesne and De Micheaux, 2010), regressing the (transformed) unit neighborhood treatment $G_i^*$ on the individual treatment $Z_i$ and on the predictors that are candidate to influence the neighborhood treatment, $X_i^*$. This procedure determines $\hat{\mu}_{G_i^*}$.

The variance-covariance matrix is estimated looking at the residuals of the model. In particular, we first compute residuals of the model and, then, we estimate the variance and covariance matrix of the residuals $\hat{\Sigma}_{G^*}$, that results to be an unbiased estimator of $\Sigma_{G^*}$. Therefore, neighborhood propensity score corresponds to the quantity

$$\hat{\Lambda}(g; z, X_i^*) = \frac{1}{(2\pi)^{\frac{n}{2}}|\hat{\Sigma}_{G^*}|^{\frac{1}{2}}} \exp \left[ -\frac{1}{2} (G_i^* - \hat{\mu}_{G_i^*})^T \hat{\Sigma}_{G^*}^{-1} (G_i^* - \hat{\mu}_{G_i^*}) \right].$$
4 Empirical Results

In this section, we illustrate the main empirical findings of this work. We evaluate the impact of immigration policy on crime rates dealing with a treatment of four categories and exploiting the pairwise comparisons between the treatment levels. We take into consideration four scenarios depicting the interference mechanism to check the robustness of results with respect to different \textit{a-priori} assumptions over dependencies. In particular, we check the following configurations of the interference input weights: i) $\alpha = \beta = \frac{1}{2}$, $(gc)$: both geographical proximity and cultural similarity shape dependencies between units, and contribute in determining the global interference compound index with equal weight; ii) $\alpha = 1, \beta = 0$, $(g)$: only geographical proximity drives interference; iii) $\alpha = 0, \beta = 1$, $(c)$: dependencies are prompted by cultural similarity only and iv) $\alpha = 0, \beta = 0$, $(noint)$: no interference mechanism comes into play.

We point out that we assume that there is a \textit{one-year lag effect} of baseline covariates on treatment and of treatment on outcome variables. We state that the covariates of one country $c$ at time $t$ affects his individual as well as neighborhood treatment at time $t + 1$ and that the joint treatment in turn affects the outcomes at time $t + 2$. Figure 7 provides an intuition of this conceptual idea.

![Figure 7: Variables Effects: timing](image)

There is no way to test this assumption, but a lagged process of causation seems plausible in the considered empirical scenario. In addition, in order to avoid reverse causality issues, in the propensity score estimation we control for no-lagged outcome variables. For instance, we consider the baseline covariates of one country at time $t$ to model his joint treatment at time $t + 1$ and consequently his outcome at time $t + 2$ and in the set of the pre-treatment variables at time $t$ we include the outcome at time $t$ as well.

Figures 8 and 9 graphically show the main empirical results, which are numerically reported in Table 1. The general conclusion is that severe approaches towards immigration imply higher crime rates, compared with a welcoming political receipt (A). This finding holds considering strategies which provide for a severe attitude with respect to regulations only (B1-A), systems where only control protocols are particularly strict (B2-A) and profiles adopting a restrictive legislative plan in terms of both regulations and control mechanisms (C-A). Observing the results, we can also...
state that ignoring the possible spillover mechanism leads to a downward bias in the estimates, thus relying on the SUTVA makes the size of the effects becomes smaller (noint). This conclusion is stable in all the constraints of interest. Allowing for the presence of interference increases the extent of the effects, and their robustness, with respect to the no-interference scenario. In particular, introducing the cultural similarity in the mechanism of dependencies points the way to an enhancement in terms of effects’ intensities (c). Geographical proximity mitigates the impact of interference on results, but also assuming that geography is the only prompter of the spillover mechanism steers to more sturdy conclusions, compared with the no-interference scenario (g and gc). These considerations hold in all the considered comparisons.

Figure 8: Forest plots, Direct Treatment Effects for the contrasts of interest: point estimates and 95% Confidence intervals. Colors signal the different assumption about interference: gc(lightblue), g(green), c(red), noint(purple)
Figure 9: Box Plots, estimated distributions of the effects of interest. Colors signal the different assumption about interference: $g_c$(lightblue), $g$(green), $c$(red),$noi$(purple)

Table 1: Direct Treatment Effects for the contrasts of interest: point estimates and 95% Confidence intervals

| Effects of Interest | (\(\alpha, \beta\)) | B1-A | B2-A | C-A |
|---------------------|---------------------|------|------|-----|
| \((\frac{1}{2}, \frac{1}{2})\) | 0.17774 *** 0.21145 *** 0.21145 *** | (0.17501;0.18008) (0.2007;0.21409) |
| \((1, 0)\) | 0.03281 *** 0.0451 *** 0.0451 *** | (0.02768;0.03721) (0.04062;0.0506) |
| \((0, 1)\) | 0.17778 *** 0.20191 *** 0.20191 *** | (0.17483;0.1803) (0.19934;0.20476) |
| \((0, 0)\) | 0.08228 *** 0.00647 *** 0.00647 *** | (0.07842;0.08657) (0.00213;0.01038) |

As we fully discuss in Appendix E these results are robust to different specifications of the multi-valued treatment (we introduce an alternative definition of the multi-valued treatment collapsing the B1 and B2 categories into one B category, so to delineate a treatment of three categories
Taking into consideration of a binary treatment (which we obtain simply differentiating the country-year profiles whose observed value of the general immigration policies indicator is above its reference median) still leads to positive results, independently on the assumption about interference. But in the last two scenarios, effects are significantly weaker. This conclusion exactly testifies the importance of adopting a multi-valued approach in such multi-faceted topics, whose complexity makes their analysis becoming kaleidoscopic.

These findings suggest that welcoming immigration policies may contribute in quetting down the social unrest between immigrants and natives. Thus, adopting a legislative system which allows migrants to be actively involved in the hosting community, conceding them civil and social rights, encourages the integration process and reduces frictions.

5 Concluding Remarks

This work extends the existing framework of causal inference under interference allowing for a multi-valued treatment and for an interference structure shaped through a weighted network. The methodological idea comes from the empirical necessity of taking into account of the possible spillover effects in the wide ensemble of applications which provide multi-valued treatments and complex network structures shaping the interference mechanism. For example, political science often approaches policy evaluation settings with a multi-valued strategy, as involved treatments often vary over multiple dimensions, so calling for an high level of complexity. For instance, evaluating the effect of national immigration policy on crime rates, as in the application we have proposed, forces to a composite approach and implies some technical difficulties, involving how to model and to include the plausible presence of interference between units. Given the multi-valued nature of the individual treatment, the neighborhood exposure cannot be summarized by a single measure, as in the binary setting. Our idea is to introduce a multi-valued network exposure, where each unit is exposed to each of the treatment levels, due to the weighted interaction he has with his neighbors. Information about the whole exposure mapping is depicted by the Neighborhood Treatments Exposure Matrix (NTEM). This framework implies an extended definition of the joint propensity score, called Joint Multiple Generalized Propensity Score (JMGPS), which models a multi-valued individual treatment and a multivariate neighborhood treatment. JMGPS is the key element of the proposed estimation strategy, which follows a parametric approach and allows to impute the missing potential outcomes taking into account of the multidimensional domain that characterizes the joint treatment variable. Direct effects of interest are pairwise comparisons of all treatment levels and they are computed comparing imputed potential outcomes controlling for the multi-valued network exposure. Our empirical findings show that implementing a welcoming immigration policy causes a reduction in crime rates. Ignoring multi-valued interference leads to weaker estimates.
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A Proofs

A.1 Balancing property of JMGPS

We have to prove that

\[ P(Z_i = z, G_i = g | X_i) = P(Z_i = z, G_i = g | \psi(z, g; X_i)) \]

The expression on the leften side exactly equals JMGPS, by definition, that is

\[ P(Z_i = z, G_i = g | X_i) = \psi(z, g; X_i) \]

We focus now on the righten side. By iterated equation we have that

\[ P(Z_i = z, G_i = g | X_i) = \mathbb{E}_{X_i} \left[ P(Z_i = z, G_i = g | X_i, \psi(z, g; X_i)) \right] \]

\[ = \mathbb{E}_{X_i} \left[ P(Z_i = z, G_i = g | X_i) | \psi(z, g; X_i) \right] \]

\[ = \mathbb{E}_{X_i} \left[ \psi(z, g; X_i) \right] = \psi(z, g; X_i) \]

The second equality holds as the joint multiple generalized propensity score, by definition, is functionally related to the characteristics \( X_i \). The third equality follows from the definition of JMGPS.

Both above expressions are equal to the joint multiple propensity score itself and, hence, they are also equal to each other.
A.2 Conditional unconfoundness of $D_i(z)$ and $G_i$ given JMGPS

We have to show that

$$P(D_i(z) = 1, G_i = g|Y_i(z, g), \psi(z, g; X_i)) = P(D_i(z) = 1, G_i = g|\psi(z, g; X_i)).$$

**Righten side.** We first focus on the expression that lies at the righten side. By the fact that $(D_i(z) = 1) = (Z_i = z)$ and Proposition 1, we have that

$$P(D_i(z) = 1, G_i = g|\psi(z, g; X_i)) = P(Z_i = z, G_i = g|\psi(z, g; X_i)) = \psi(z, g; X_i).$$

**Leften side.** By iterated equations, we have

$$P(D_i(z) = 1, G_i = g|Y_i(z, g), \psi(z, g; X_i))$$

$$= \mathbb{E}_X [P(D_i(z) = 1, G_i = g|X_i, \psi(z, g; X_i), Y_i(z, g))|Y_i(z, g), \psi(z, g; X_i)]$$

$$= \mathbb{E}_X [P(D_i(z) = 1, G_i = g|X_i, \psi(z, g; X_i))|Y_i(z, g), \psi(z, g; X_i)]$$

$$= \mathbb{E}_X [P(D_i(z) = 1, G_i = g|X_i)|Y_i(z, g), \psi(z, g; X_i)]$$

$$= \mathbb{E}_X [\psi(z, g; X_i)|Y_i(z, g), \psi(z, g; X_i)] = \psi(z, g; X_i),$$

The second equality is obtained taking into account that the joint multiple generalized propensity score is a function of covariates, the third equality results from applying the Assumption 1 while the forth equality holds recalling that $(D_i(z) = 1) = (Z_i = z)$ and Definition 2.

A.3 Conditional unconfoundness of $D_i(z)$ and $G_i$ given individual and neighborhood propensity score

We have to show that

$$P(D_i(z) = 1, G_i = g|Y_i(z, g), \phi(z; X_i^z), \lambda(g; z, X_i^g)) = P(D_i(z) = 1, G_i = g|\phi(z; X_i^z), \lambda(g; z, X_i^g)).$$

where $\phi(z; X_i^z) = P(D_i(z) = 1|X_i^z)$ and $\lambda(g; z, X_i^g) = P(G_i = g|z, X_i^g)$. We proceed showing that both sides of the equation equal the joint multiple generalized propensity score.

**Righten side.** By iterated equations, we have that

$$P(D_i(z) = 1, G_i = g|\phi(z; ; X_i^z), \lambda(g; z, X_i^g))$$

$$= \mathbb{E}_X [P(D_i(z) = 1, G_i = g|X_i, \phi(z; X_i^z), \lambda(g; z, X_i^g))|\phi(z; X_i^z), \lambda(g; z, X_i^g)]$$

$$= \mathbb{E}_X [P(D_i(z) = 1, G_i = g|X_i)|\phi(z; X_i^z), \lambda(g; z, X_i^g)]$$

$$= \mathbb{E}_X [\psi(z, g; X_i)|\phi(z; X_i^z), \lambda(g; z, X_i^g)] = \psi(z, g; X_i)$$

It results from the fact that both $\phi(z; X_i^z)$ and $\lambda(g; z, X_i^g)$ are function of $X_i$ (second equality) and
from the factorization of joint multiple generalized propensity score, \( \psi(z, g; X_i) = \phi(z; X_i^c)\lambda(g; z, X_i^g) \) (third equality).

**Leften side.** By iterated equations, we have that

\[
P(D_i(z) = 1, G_i = g|Y_i(z, g), \phi(z; X_i^c), \lambda(g; z, X_i^g))
\]

\[
= \mathbb{E}_X \left[ P(D_i(z) = 1, G_i = g|X_i, Y_i(z, g), \phi(z; X_i^c), \lambda(g; z, X_i^g))|Y_i(z, g), \phi(z; X_i^c), \lambda(g; z, X_i^g) \right]
\]

\[
= \mathbb{E}_X \left[ P(D_i(z) = 1, G_i = g|X_i, Y_i(z, g)|Y_i(z, g), \phi(z; X_i^c), \lambda(g; z, X_i^g)) \right]
\]

\[
= \mathbb{E}_X \left[ P(D_i(z) = 1, G_i = g|X_i)|Y_i(z, g), \phi(z; X_i^c), \lambda(g; z, X_i^g) \right]
\]

\[
= \mathbb{E}_X \left[ \psi(z, g; X_i)|Y_i(z, g), \psi(z, g; X_i) = \psi(z, g; X_i), \right.
\]

the second equality results from the fact that the two propensity scores are function of covariates, the third equality comes from Assumption 1, the fourth equality is obtained recalling that \( D_i(z) = 1 \) = \( Z_i = z \) and, finally, the last equality follows from the factorized nature of JMGPS.

**B Interference Compound Index (ICI) detailed construction**

ICI is formally defined as

\[
ICI_{cc',t} = \alpha \times IG_{cc'} + \beta \times IC_{cc',t}
\]

where \( IG \) denotes the geographical proximity indicator while \( IC \) states for the cultural similarity indicator. The former is time invariant, while the latter provides a temporal variation. Here, we discuss the detailed construction of these two indexes, which determine the interference structure.

We build up the geographical proximity index taking into account of two variables: a boundaries-related variable and a geographical distance-related variable. The former, that we denote by \( Sp \) counts the minimum number of states one needs to cross by, at the aim of reaching country \( c' \) starting from country \( c \). Thus, if we consider a graph collecting all the national states, this variable represents the length of the shortest path between \( c \) and \( c' \). The latter, that we denote as \( Dist^{std} \) is a standardized measure of geographic distance between the most populated cities belonging to the two countries. Formally, the geographical proximity indicator is computed as follows

\[
IG_{cc'} = 0.5 \times \frac{1}{Sp_{cc'}} + 0.5 \times (1 - Dist_{cc'}^{std}) = 0.5 \times \frac{1}{Sp_{cc'}} + 0.5 \times Prox_{cc'}^{std}
\]

On the other side, the cultural similarity indicator measures the level of cultural similarity between two countries \( c \) and \( c' \) at a given time \( t \). We summarize this aspect evaluating the linguistic

\footnote{We assume that the pairs of countries France and Great Britain, Ireland and Great Britain share a common boundary, as, even if they’re formally separated by the English Channel and the Irish Sea, respectively, they are very near and connections are extremely simple}
similarity and the religious similarity, through the variables *Ling* and *Relig*. These measures have been defined by the CEPII Linguistic Dataset [Melitz and Toubal (2014)] and CEPII Gravidata Dataset [Fouquin et al. (2016)], respectively. The *linguistic proximity indicator* gives a unique measure of how much the whole linguistic systems differ in the two countries, both in terms of the distribution of spoken languages over the population and in terms of the linguistic roots. The *religious similarity indicator* takes into account of the distribution of practised religions: an high value of this variable signals an high similarity in terms of prevalence of the various religious communities at time *t*.

\[ IC_{cc',t} = 0.5 \times Ling_{cc',t} + 0.5 \times Relig_{cc',t} \]

Figure 10 shows the density distributions of the two indicators that contribute in determining the Interference Compound Index, as well as of their respective sub-components.

![Density distributions of IC components](image)

(a) Geographical Proximity Indicator  
(b) Cultural similarity Indicator

Figure 10: ICI components density distributions

C  Transformation of the NTEM components

We run some checks about the normality of the components *G*<sub>i,z</sub>. The Shapiro Tests for Normality [Shapiro and Wilk (1965)], separately conducted on the four components, *G*<sub>i,A</sub>, *G*<sub>i,B1</sub>, *G*<sub>i,B2</sub>, *G*<sub>i,C</sub>, rejects the Normality null-Hypothesis.

Hence, we decide to apply a transformation to each of the *G*<sub>i,z</sub>. We conduct some tests experimenting various transformation methods and we compare them selecting the best approach according to the Pearson P statistic for Normality (divided by its degrees of freedom). We use repeated cross validation to estimate the out-of-sample performance of all these methods. Figure 11a shows the boxplots of the out of sample estimated normality statistics for all the techniques that we experiment, over the four variables of interest (under *α* = 1/2 and *β* = 1/2). We find out that the method
that performed better in handling the $G_{i,z}$ variables is the Ordered Quantile (ORQ) transformation, for all the various configurations of the ICI input weights. Figure 11B represents the tridimensional scatterplot of transformed variables.

![Figure 11: Best Normalizing method](image)

Ordered Quantile transformation (Bartlett 1947, Van der Waerden 1952) is based on ranks. Essentially, the values of a variable, judged as a vector, are mapped to their percentile, and then to the same percentile of the Standard Normal Distribution. As long as the number of ties is negligible, this method guarantees that the transformed variable follows a Normal Distribution. Formally, each variable $G_{i,z}$ is transformed according to the following formula:

$$G_{i,z}^* = \Phi^{-1} \left( \frac{\text{rank}(G_{i,z})}{N + 1} \right),$$

where $\Phi$ is the cumulative density function of a Standard Normal distribution, $N$ is the number of observations. We denote as $G_{i,z}^*$ the variable resulting from the Ordered Quantile transformation.

D Descriptives

This paragraph provides some descriptives. Figure 1 shows the density distributions of the indicators measuring the restrictiveness of regulations (Reg) and control strategies (Cont), over years. Regulations have become more welcoming over time while control strategies have turned to a more severe attitude.
(a) Regulations indicator  

(b) Control indicator

Figure 12: Indicators measuring the restrictiveness of immigration policies over years

Figure 13 represents the variation of the distributions of the Reg (violet), Control (blue) and ImPol (yellow) indicators in the 22 countries that we have included in the analysis.

Figure 14 consists to inspect the strictness of regulations and control implemented policies in each country-year profile.
Table 2 shows the basic descriptives of all the variables we have included in the analysis.

Table 2: Descriptive statistics

| Variable                        | Var. Label | N   | Mean  | St. dev | Min  | Pctl(25) | Pctl(75) | Max   |
|---------------------------------|------------|-----|-------|---------|-------|----------|----------|-------|
| Crime rate (every 10,000 inhab.)| rate       | 612 | 1.326 | 0.636   | 0.000 | 0.910    | 1.560    | 3.430 |
| Fertility rate                  | ferrate    | 612 | 1.675 | 0.498   | 0.000 | 1.440    | 1.840    | 4.360 |
| Power distributed to gender Index| powgend    | 612 | 1.876 | 0.973   | −0.854| 1.408    | 2.394    | 3.714 |
| Health equality Index           | eq_health  | 612 | 2.418 | 0.588   | 0.612 | 1.972    | 2.775    | 3.792 |
| Educational inequality Gini index (/60) | ineq_educ | 612 | 0.269 | 0.163   | 0.000 | 0.149    | 0.361    | 0.893 |
| Income inequality Gini index (/60) | ineq_inc  | 612 | 0.485 | 0.139   | 0.000 | 0.432    | 0.564    | 0.867 |
| Equal access index              | eq_access  | 612 | 0.871 | 0.137   | 0.290 | 0.856    | 0.945    | 0.986 |
| Equal distribution of resources index | eq_resdist | 612 | 0.924 | 0.070   | 0.588 | 0.908    | 0.964    | 0.986 |
| Civil participation index       | civilpart  | 612 | 0.641 | 0.111   | 0.161 | 0.616    | 0.690    | 0.885 |
| Access to justice index         | accjust    | 612 | 0.940 | 0.121   | 0.165 | 0.944    | 0.989    | 0.995 |
| State ownership of economy index| econcont   | 612 | 1.219 | 0.616   | −0.536| 0.890    | 1.636    | 2.731 |
| Freedom of expression index     | freeexp    | 612 | 0.934 | 0.128   | 0.128 | 0.955    | 0.979    | 0.991 |
| Freedom of religion index       | freerelig  | 612 | 1.958 | 0.751   | −1.003| 1.749    | 2.519    | 2.766 |
| Life expectancy (/ 100)          | lifeexp    | 612 | 0.746 | 0.126   | 0.000 | 0.749    | 0.785    | 0.824 |
| GDP per capita (/ 10,000)        | gdppe      | 612 | 2.666 | 1.154   | 0.610 | 1.954    | 3.373    | 8.192 |

Figure 15 shows the tridimensional plot of the two indicators measuring the restrictiveness.
towards migrants, and the corresponding the crime rate.

Figure 15: Tridimensional plot of the two indicators \( \text{Reg} \) and \( \text{Cont} \), with respect to the \( \text{Crime Rate} \).

E Results under different configurations of the treatment

This section shows results under alternative specifications of the treatment variable of interest. In particular, as Definition 5 clarifies, we test two secondary ways of detecting the treatment categories.

**Definition 5** Alternative specifications of the treatment variable Let us indicate \( Z^K_i \) a generic treatment variable defined over \( K \) categories. We consider the following treatment classifications

1. Multi-valued treatment with three categories, \( Z^{(3)}_i \), which have been defined collapsing the categories \( B1 \) and \( B2 \) of the original individual treatment variable.

   - \( Z^3_i = A \) if \( \text{reg}_i \leq \text{med}_{\text{reg}} \) and \( \text{cont}_i \leq \text{med}_{\text{cont}} \): this category identifies profiles that are barely restrictive with respect to the two mechanisms.
   - \( Z^3_i = C \) if \( \text{reg}_i \geq \text{med}_{\text{reg}} \) and \( \text{cont}_i \geq \text{med}_{\text{cont}} \): this category denotes an highly restrictive policy towards migrants with respect to both regulations and control.
   - \( Z^3_i = B \) otherwise

2. Binary treatment with two categories, \( Z^{(2)}_i \) defined as follows

   - \( Z^2_i = A \) if \( \text{impol}_i \leq \text{med}_{\text{Impol}} \)
   - \( Z^2_i = B \) if \( \text{impol}_i > \text{med}_{\text{Impol}} \)

\(^6\)note that the A and C categories exactly coincide with the A and C categories of the four-valued treatment
Figure 16 graphically represents these two alternative treatment characterizations.

(a) Multi-valued with three categories, \( Z^{(3)}_i \)  
(b) Binary with two categories, \( Z^{(2)}_i \)

![Graphical representation of treatment variable definitions](image)

**Figure 16: Alternative definitions of the treatment variable**

Table 3 shows results under these two definitions of the treatment variable. As it is immediate to observe, these results are robust with the main findings of this paper.

**Table 3: Results under different treatment definitions**

| Treatment categories | ICI \((\alpha, \beta)\) | Effects of Interest | \(3\) \((A, B, C)\) | \(2\) \((A, B)\) |
|----------------------|------------------------|---------------------|---------------------|---------------------|
|                      | \(\left(\frac{1}{2}, \frac{1}{3}\right)\) | \(B-A\) | \(0.06648 ***\) \((0.06485;0.06815)\) | \(0.03875 ***\) \((0.01424;0.06133)\) |
|                      | \(1, 0\)                | \(C-A\) | \(0.04986 ***\) \((0.04774;0.05196)\) | \(0.01781 ***\) \((0.01573;0.01987)\) |
|                      | \(0, 1\)                | \(B-A\) | \(0.03523 ***\) \((0.03452;0.03592)\) | \(0.04126 ***\) \((0.01686;0.06374)\) |
|                      | \(0, 0\)                | \(C-A\) | \(0.03587 ***\) \((0.01288;0.05705)\) | \(0.03506 ***\) \((0.01443;0.05789)\) |

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F Models Results

F.1 Model for Z

Table 4: Model for the individual treatment $Z_i$: multinomial logit

| Dependent variable: | B1                     | B2                     | C                     |
|---------------------|------------------------|------------------------|------------------------|
| (Intercept)         | 32.79243*** (12.78648) | -10.11091 (15.25728)  | 80.91698 (15.50048)   |
| rate                | 0.16626 (0.26154)      | 0.05287 (0.2613)      | 0.69135 (0.43628)     |
| ferrate             | 2.58746*** (0.96028)   | -1.67848 (1.06485)    | 4.32561*** (1.12471)  |
| powgend             | -3.09196*** (0.49015)  | 0.714 (0.41834)       | -0.54734 (0.51338)    |
| eq_health           | 0.10112 (0.69408)      | 2.75906*** (0.78272)  | 4.62427*** (1.1305)   |
| ineq_educ           | -2.09696 (2.33622)     | 5.29634*** (2.39962)  | -10.3432*** (2.70765) |
| ineq_inc            | 5.32876*** (2.59477)   | -9.08242*** (2.35931) | 10.89922*** (3.40414) |
| eq_access           | 28.56299*** (5.5844)   | -5.09848 (6.35618)    | 31.06497*** (7.08197) |
| eq_redist           | -40.91293*** (12.89674)| -38.18629*** (16.62724)| -114.90727*** (19.31919)|
| civilpart           | -9.59618*** (2.78319)  | 5.08124*** (2.47201)  | -6.36655 (4.05762)    |
| accjust             | -1.89435 (9.22897)     | -5.28742 (10.20244)   | -75.66229*** (12.17123) |
| ecocont             | 0.42103 (0.29668)      | -0.02385 (0.3009)     | -0.00473 (0.41129)    |
| freexp              | -15.37981*** (7.11022) | 45.12384*** (11.12141) | 46.82842*** (10.41181) |
| freerelig           | 1.26064*** (0.57401)   | 0.68092 (0.62653)     | -0.20062 (0.74503)    |
| lifexp              | 2.02242 (2.7095)       | 6.54206*** (2.64635)  | 12.97523*** (5.51876) |
| gdppc               | -0.8286*** (0.21716)   | -0.14708 (0.17659)    | -0.15251 (0.2456)     |

Note: *p<0.1; **p<0.05; ***p<0.01
### F.2 Model for G

Table 5: Models for the neighborhood treatment $G_i$: multivariate linear model

| Dependent variable: | Statistic | Statistic | Statistic |
|---------------------|-----------|-----------|-----------|
| $G^*$               |           |           |           |
| Omnibus Effect      | 35.31***  | 38.27***  | 41.42***  |
| (Intercept)         | 21.63 *** | 28.17***  | 9.79***   |
| $Z_i$               | 12.09 *** | 14.62***  | 9.81***   |
| rate                | 2.71 **   | 4.80 **   | 0.91      |
| ferrate             | 18.01 *** | 20.04 *** | 14.95 *** |
| powgend             | 3.76 ***  | 6.22 ***  | 3.44 ***  |
| eq_health           | 6.61 ***  | 12.35***  | 2.34 ***  |
| ineq Educ           | 0.38      | 0.07      | 5.43***   |
| ineq Inc            | 11.17 *** | 11.28 *** | 8.85***   |
| eq_access           | 7.81***   | 12.64***  | 3.32 ***  |
| eq_resdist          | 15.75 *** | 24.51***  | 4.97***   |
| civilpart           | 16.13 *** | 18.06***  | 14.58 *** |
| accjust             | 20.43 *** | 21.78 *** | 12.37     |
| econcont            | 16.66 *** | 16.39 *** | 20.85 *** |
| freeexp             | 15.85 *** | 16.85 *** | 9.86 ***  |
| freerelig           | 14.43 *** | 13.58 *** | 18.86 *** |
| lifeexp             | 1.01      | 0.64      | 4.51 ***  |
| gdppc               | 191.40*** | 196.56*** | 180.59*** |
| Vertex_centr        | 72.79***  | 81.82***  | 124.79*** |

ICI Input Weights

|        | $\alpha$ | $\beta$ |
|--------|----------|---------|
| $\alpha$ | 1/2      | 1       | 0       |
| $\beta$  | 1/2      | 0       | 1       |

*Note:* *p<0.1; **p<0.05; ***p<0.01
F.3 Models for Y

Table 6: Models for Y: linear model with time fixed effects

| Dependent variable: | Y |
|---------------------|---|
| $Z_{i,B1}$          | 0.18591**(0.08543) | 0.04817(0.09693) | 0.1866**(0.07333) |
| $Z_{i,B2}$          | 0.25183**(0.08896) | 0.20069**(0.08139) | 0.26622**(0.08028) |
| $Z_{i,C}$           | 0.20918*(0.11826)  | 0.04082(0.08269)  | 0.19946*(0.11675)  |
| $G_i^\ast$          | -0.44931(0.32531)  | 0.46268(0.32837)  | -0.92524**(0.28568) |
| $G_i^\ast$          | -0.26138(0.35755)  | -1.4981**(0.58176) | -0.00591(0.22521)  |
| $G_i^\ast$          | 0.9401**(0.47619)  | 1.80662***(0.53027) | 0.33123(0.3205)  |
| $G_i^\ast$          | 1.46947***(0.36545) | 0.55599(0.36047)  | 1.05639***(0.3828) |

Note: $^*$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

ICI Input Weights

| $\alpha$ | 1/2 | 1 | 0 |
|-----------|-----|---|---|
| $\beta$   | 1/2 | 0 | 1 |

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