The unintended consequences of well-intended measures: Swedish list of vulnerable areas and the impact on stigma on migration flows

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This project examines the impact that receiving a vulnerable area designation (*utsatta områden*) has on the flows of residents between the neighborhoods in Sweden. The vulnerable area designation was created by the Swedish Police Authority in 2015 with the intention of alleviating some of the negative effects of residential segregation and with an aim to focus resources on improving conditions in areas with most socio-economic challenges. Since its introduction, the police list of vulnerable areas has been updated every two years, receiving wide media coverage. Previous research indicated the list contributed to depreciation of housing value (Andersson et al. 2023). There was some concern that the list could contribute towards increasing segregation through its effect on migration flows in and out of the neighborhoods designed as vulnerable, because these areas would be perceived as less desirable residential locations. These effects could be strongest for residents who have the choice to move to non-vulnerable neighborhoods, that is households with more economic means, which could lead to further concentration of poverty and racialized marginalization (Wilson, 1987; Wacquant; 2015). In this study we attempt to examine if stigma association with neighborhoods being on the list has an effect on migration in and out of these areas. The methods used include staggered difference-in-difference analysis on migration rates as well as planned individual level analysis of residential mobility patterns.

The stigmatized spatial marking thesis

The main theoretical concept applied in this study is territorial stigma that is created by the perceptions of residents and outsiders about the inferior status of a neighborhood. It can be influenced by objective or subjective factors, from racial segregation and, poverty, to land use, and the built environment and biased news reporting. Neighborhood stigma may have long term consequences and undermine attempts to improve conditions in the area (Wacquant, Slater and Pereira, 2014). Scholars have long argued that ethnically segregated neighborhoods carry stigma, which is pointed to as one of the causes of disparate outcomes between areas (Kelaher et al. 2010). Individuals inform their understandings of areas based on the racialized construction of those neighborhoods and these understandings of place may carry stigma with them (Sampson and Raudenbush, 2004). When institutional actors, such as the police, create socially meaningful interventions they create the opportunity to either disrupt or solidify the racially informed and stigmatized understandings of different areas. Geographically delineated interventions such as the vulnerable areas designation, establish an institutionalized spatial marking (Faber, 2021), and legitimize the neighborhood hierarchies and outcomes that led to the designation in the first place. Moreover, neighborhood stigma may affect the inflow and outflows of people into and out of from the areas, which can contribute to further deterioration of conditions in the neighborhood. If so, it is possible that a reinforcing relationship of stigma is created between individuals and the areas that receive the designation, thereby deepening the inequalities that already exist there. There is evidence showing that spatial marking can have these types of unintended consequences on outcomes in other contexts, whether this is the case with marking neighborhoods as “vulnerable” in Sweden and its impact on crime victimization is an open question.

Data and Methods

To evaluate the effect of placing a neighborhood on the list of vulnerable areas we use Swedish register data 2010-2022 where we have coordinates for properties inhabited by each resident, this data is recoded on a 100-meter grid for end of December each year. We use DeSO (Demographic Statistical Areas created by Statistics Sweden) as neighborhood units and our outcome variables are the in-migration and out-migration rates for neighborhoods in a given year. These were created from coordinates data by examining the residents for each neighborhoods each year. Those who were residents in neighborhood n at time t but no longer residents there at time $t+1$ contributed to out-migration for time t, while those that were not residents in neighborhood n at t but were at $t+1$ contributed to in-migration at time $t+1$. It is important to emphasized that at this stage our analysis looks at internal migration patterns, thus excluding international migration.

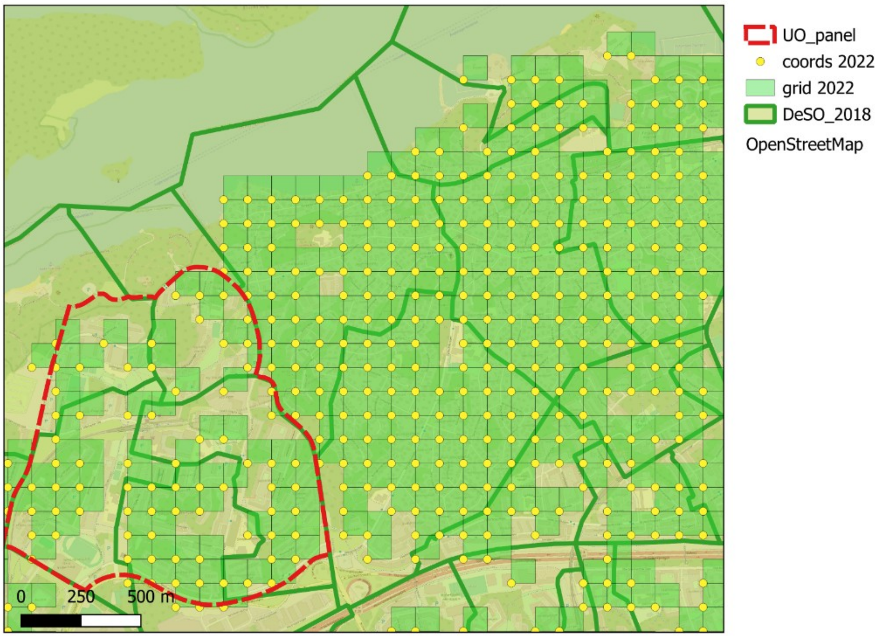

Figure 1 Data sources for part of Stockholm showing DeSO neighborhoods (DeSO_2018), vulnerable area boundaries (UO_panel) and well as individual coordinates on the 100 meter grid.

Finally, we use a panel of digitalized boundaries on vulnerable areas provided by the Swedish police to establish which neighborhoods were part of the list in each period and which were not. This was necessary as the police used their own geographies for creating the list, which did not nest with other administrative boundaries such as DeSO neighborhoods (see Figure 1). In our analysis neighborhoods which were treated were characterized as having at least 20% areal overlap with neighborhoods from the vulnerable area lists. Our analytical strategy relied on the use of difference in differenced with staggered treatment times (Callaway and Sant'Anna, 2021). This is because the list has new updates every two years, with new neighborhoods added to the treatment groups. Additionally, the method allows for estimating the treatment effect even when the parallel trend assumption is fulfilled only after conditioning on pre-treatment covariates. In our cases, these covariates will consist of the share of non-Western residents, share of young (below 18) as well as older (64+) residents, share on social benefits, share living at risk of poverty (below 60% of median disposable income), population density and whether there are other treated neighborhoods in the municipality where the neighborhood is located. For estimation we use package did in R and estimate the treatment effect of the treated units compared to units that were never threated.

Results

Below we present group-time average treatment effects on the areas that were treated obtained from staggered difference-indifference method.

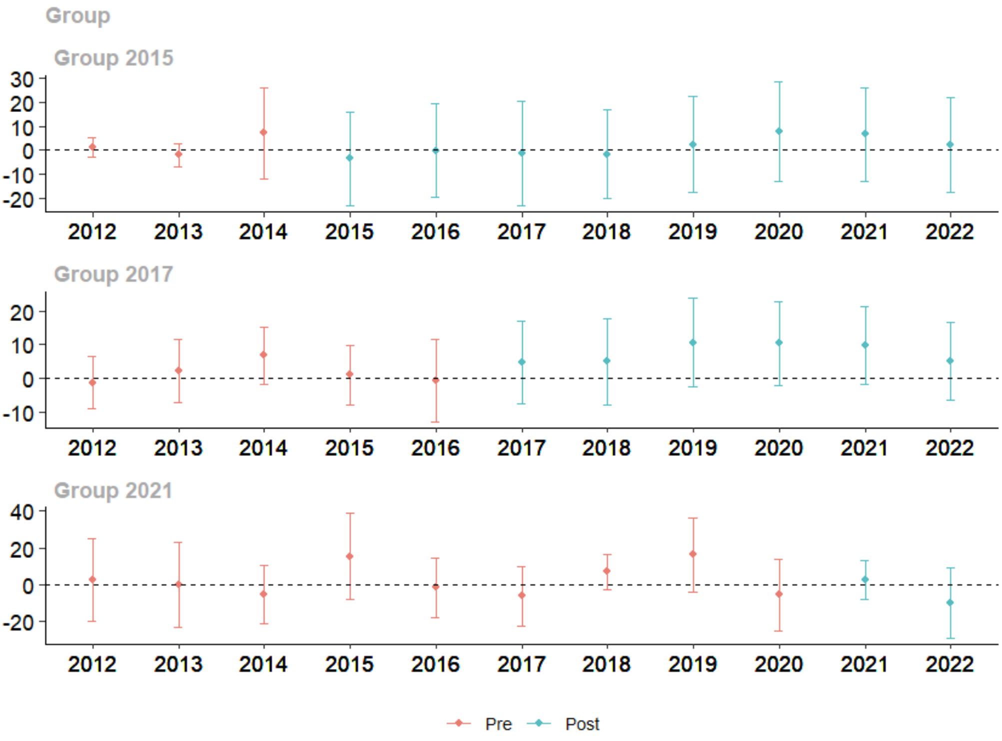

Figure 2 Group-time Average Treatment Effects for Out-migration

The pre-treatment point-estimates oscillate between negative and positive and the post-treatment estimates, while mostly positive, have confidence intervals that overlap with 0. For in-migration rate, we see that pre-treatment confidence intervals overlap with 0. Post-treatment point estimates are mostly positive and their confidence intervals do not overlap with 0.

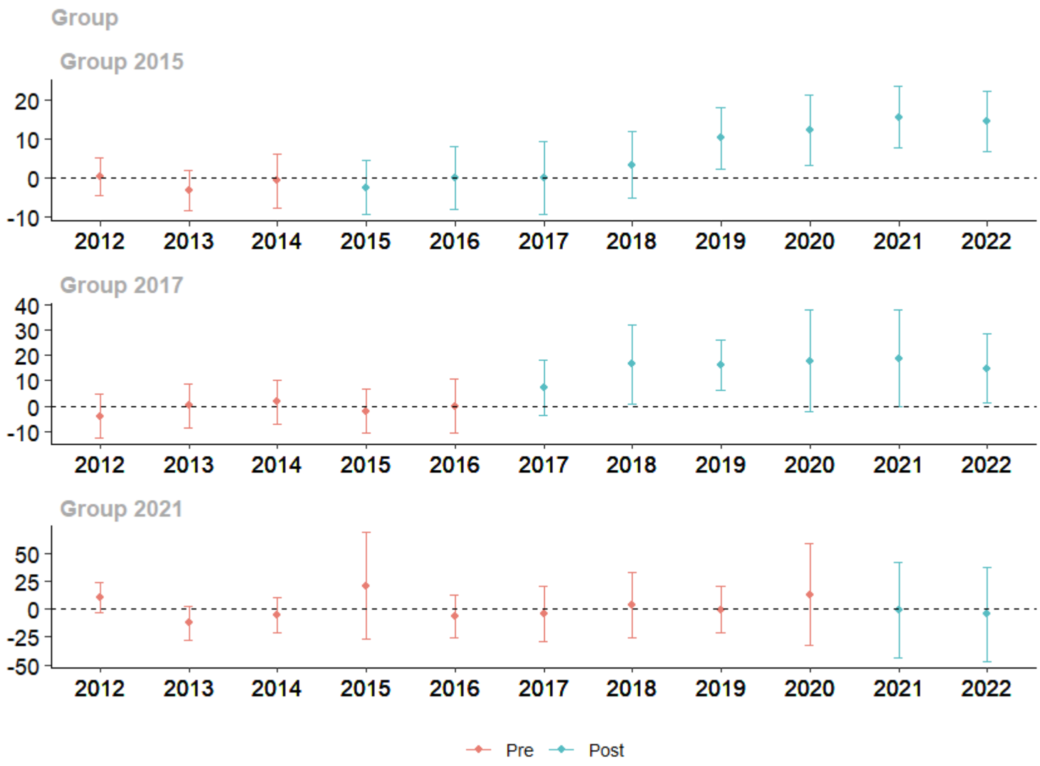

Figure 3 Group-time Average Treatment Effects for In-migration

In staggered difference in difference analysis a core requirement for causal inference is that the parallel trends assumption holds. This means that in the absence of treatment the outcome trends for treated and control group would evolve in parallel. The test for unconditional parallel trends gives a result that allows to reject this assumption, but this assumption holds conditionally after adjusting for covariates. The post-treatment estimates are mostly positive and some reach statistical significance for group 2017.

These results suggest that while out-migration from vulnerable areas is not much affected by the introduction of the policy, it is the in-migration that may have changes as a result of the list. This may seem surprising, but more checks are necessary to examine who are the individual most affected and which type of individuals most contribute toward this increased in-migration rates. For this the best approach is to move to individual level analysis where we can apply similar method to specific groups of individuals, for example those at risk of poverty, those with foreign background or those with school age children.

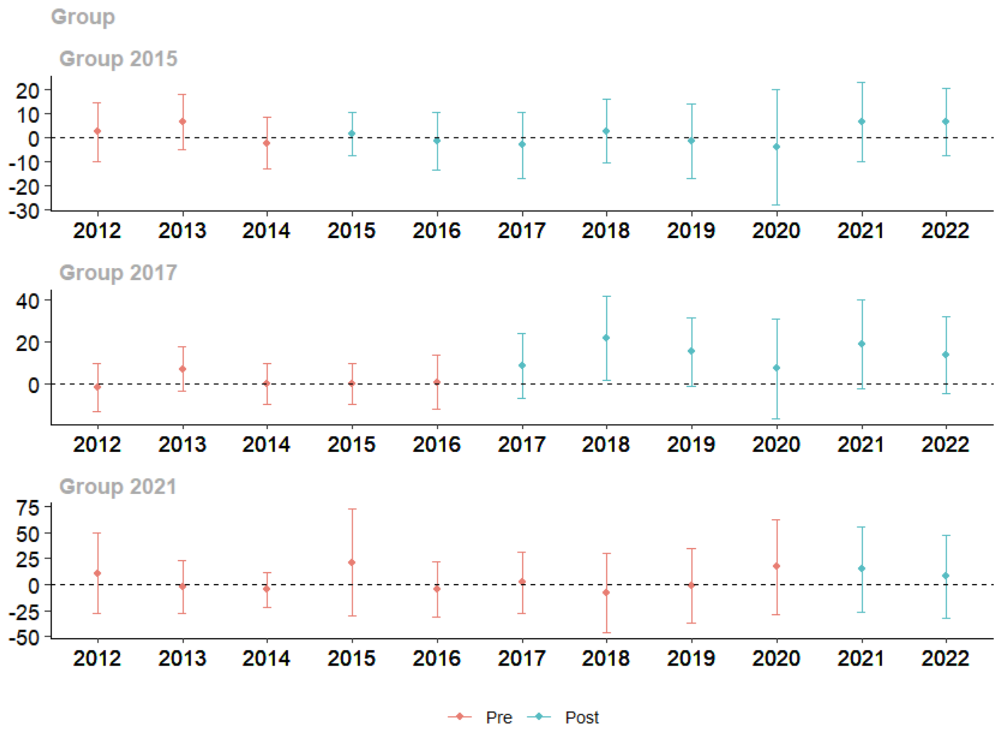

Figure 4 Group-time Average Treatment Effects for In-migration, conditioned on pre-treatment covariates

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