PAA 2019 Submission: Refugees and Environmental Degradation in Africa

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Refugees have been purported to leave their ecological footprint on the surrounding environment in multiple ways (Akokpari, 1998; Zommers and MacDonald, 2012). Land is often permanently cleared to construct a refugee camp. Those inhabiting camps may further extract forest resources for cooking or heating. Others might additionally utilize forest products to construct homes. However, the few quantitative studies documenting changes in physical landscape surrounding specific camps produce largely mixed results. Research in Sierra Leone and Darfur support claims of loss of forested land coverage (Alix-Garcia et al., 2013; Wilson, 2014; Kranz et al., 2015). On the contrary, Muller et al. (2016) show that Syrian refugees, who settled predominantly in camps and cities, had no impact on agriculture in Jordan.

The conventional narrative in the literature ignores economic mechanisms that could generate positive externalities on vegetation. It has been widely established that refugees increase the supply of cheaper goods and services in the informal economy, overwhelmingly augmenting the purchasing power of natives (Maystadt and Verwimp, 2014; Balkan and Tumen, 2016; Kreibaum, 2016; Taylor et al., 2016; Alix-Garcia et al., 2018; Maystadt and Duranton, 2018). Moreover, refugee inflows concurrently dampen the employment prospects of natives in the short-term by introducing competition for jobs and depressing market wages (Alix-Garcia and Bartlett, 2015; Ruiz and Vargas-Silva, 2015). Farmers in surrounding areas may take advantage of having a greater disposable income and a cheap labor force to expand production. At the same time, refugees and international workers bring additional consumers to both producers of agricultural and non-agricultural goods and services. Such increasing demand reinforces incentives for agricultural producers to expand their enterprises. Furthermore, natives in neighboring communities may diversify away from resource extraction activities to provide goods and services in the refugee economy.

A final factor to consider are the policies in which regulate the activities of refugees residing in camps. For example, some programs supported by NGOs and the United Nation's High Commissioner for Refugees (UNHCR) allocate refugees agricultural land adjacent to camps. Their agricultural practices can be indirectly affected through offerings of tools, seeds, and other things required to farm (Jacobsen, 1997). Use of unsustainable, customary practices and the shortening of fallowing cycles to compensate for meager land allotments can still threaten vegetation (Black and Sessay, 1997; Jacobsen, 1997). While the volition of refugees to remain engaged in farming in their asylum countries can underlie conversion of forested to agricultural land (Kranz et al., 2015), changes in equilibrium prices and access to markets may lead to agricultural intensification and encourage cultivation on idle (or marginal) land. Ultimately, the net effect on vegetation is ambiguous.

In this paper, we try to bridge the gap in the qualitative and quantitative literatures by trying to generalize the estimated effects of both refugee presence on vegetation in Africa. Specifically, we exploit data at the grid level for 53 African countries between 2000 and 2016. An instrumental variables approach is applied to account for the selection of refugees into poorly degraded areas, conditioning on pixel and year fixed effects. Both OLS and 2SLS estimates demonstrate that refugees do not exacerbate environmental degradation. On average, income effects seem to largely compensate for the direct environmental degradation induced by refugees. We plan to extend the analysis by conditioning the effect of refugee camps on heterogeneous characteristics in the receiving areas, as severity on vegetation likely depends on a variety of factors (Black, 1994).

Data

Geo-referenced data on 810 refugee camps and their number of residents are provided by the UNHCR over the period of 2000 to 2016, for a total of 9,356 observations. Although this dataset currently provides the most comprehensive view of camp locations, the reported numbers of refugees are limited to those residing in camps. Therefore, in using this data, we will be unable to extrapolate the environmental effects of refugees integrated in rural communities or cities.

The main challenge in using this dataset is that precise location information is only available for 61% of (or 493) camps. To address the error in measuring exposure to the universe of refugee camps, we apply an instrumental variables approach. The instrumental variable utilizes the UNHCR Population Statistics (UNHCR, 2018) time-series data on the number of refugees in year t in destination country i from origin country j. We, additionally, display estimates

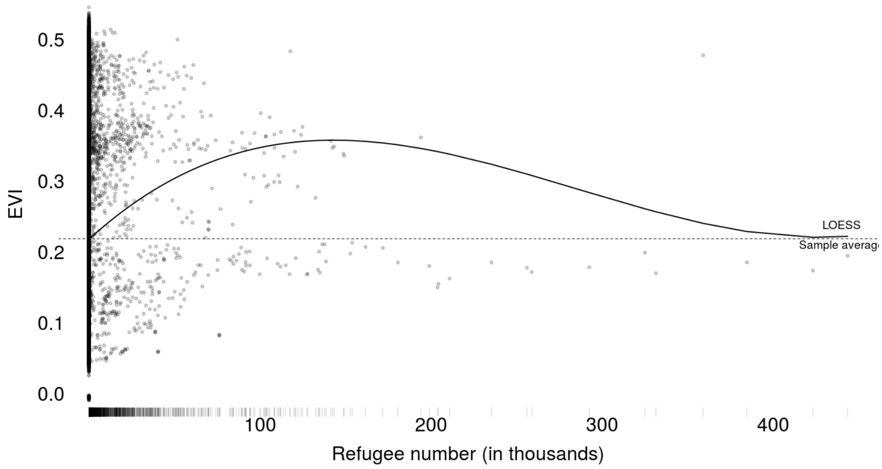

Figure 1: Raw data showing the untransformed refugee numbers and corresponding EVI value per grid-cell-year. Note that for the EVI higher values mean more vegeatation. Solid line shows local regression while dashed line indicates the sample mean.

from specifications that aggregate vegetation, refugee variables, and other explanatory factors over larger geographic units, such as the province level, for which precision of our refugee presence and intensity variables improve.

Environmental degradation is captured by the Enhanced Vegetation Index (EVI). EVI data is taken from NASA's MODIS observations (MOD13C2 v006), which provides monthly averages on a global 0.05°grid (Didan, 2015). Using the *MODIStsp* R package (Busetto and Ranghetti, 2016), we downloaded and processed the available data covering the period February 2000 to December 2016. Although the EVI data is available at a very fine resolution and high frequency, the refugee data that we had at our disposal is a bit coarser, both in terms of spatial and temporal resolution. Therefore, we aggregate the EVI data to the level of our unit of analysis (1°grid-cell), calculating the annual arithmetic mean for the vegetation index. We further aggregate the EVI to represent the annual variations in vegetation to mitigate the influence of seasonality on our estimated refugee effects.

To motivate our analysis, we plot the association between the raw levels of the EVI and refugee intensity (the number of refugees in a given grid-cell) in Figure 1. There appears to be a slight positive association between vegetation and refugee camps. Given the presence of outliers in the refugee data, we perform a non-linear transformation of the refugee variables before the analysis.

Methodology

We plan to formalize the relationship between the enhanced vegetation index EVI and the presence of refugees $Refugee$ in a pixel p at time t, conditional on a cell δ_p and time δ_t fixed effect by estimating the following regression equation:

$$EVI_{pt} = \alpha + \delta_p + \delta_t + \beta Refugee_{pt} + \gamma X_{pt} + \epsilon_{pt}. \tag{1}$$

The cell fixed effect controls for unobserved, location-specific factors that are likely to influence vegetation, such as the location's agro-ecological zone. The inclusion of a time fixed effect is meant to capture the role of temporal trends on vegetation. The natural induced time-varying factors that influence vegetation are implicitly accounted for in X, which includes the annual average temperature measured in degrees Kelvin and the annual daily average level of precipitation measured in millimeters. Inferences are based on standard errors clustered at the cell level and adjusted for spatial and time dependency of an unknown form (Conley, 1999). For the latter specifications, we assume spatial dependency disappears beyond a cutoff point of 55 and 110 kilometers (in separate specifications), allowing for two years of time dependency in both per Green (2003) and Hsiang (2010).

We quantify three relationships, each varying the definition of $Refugee$. The first model expresses $Refugee$ as the number of camps located in pixel p at time t. The second and third models specify $Refugee$ as the number of refugees and the share of the refugee population divided by the local population defined in 2000, respectively. Both refugee intensity variables are transformed by the Inverse Hyperbolic Sine (IHS). The IHS approximates the natural logarithm transformation, while including zero-valued observations (Alix-Garcia et al., 2018; Bellemare and Wichman, 2018).

There are three classical challenges noted in the economic literature on refugees which warrant the application of an instrumental variables (IV) strategy to identify β (Baez, 2011; Del Carpio and Wagner, 2015; Ruiz and Vargas-Silva, 2015). First, our main analysis focuses on refugee camps whose location has been estimated within 50 kilometers. Exposure to refugee camps may therefore suffer from measurement error. Second, bias can arise from omitted time-varying variables that determine vegetation. Third, the locations of refugee camps are unlikely to be exogenous. They may be instead situated in the worst places in terms of environmental conditions, leading to erroneous conclusions that refugee populations contribute to environmental deterioration.

Our IV approach relies on a just-identified first stage equation, given it is approximately median unbiased and less subject to weak instrumentation (Angrist and Pischke, 2009). Building on the aforementioned studies, equation (2) illustrates the single enclave IV adopted:

$$IV_{p(D)k(O)t} \quad = \quad \sum_{k \neq p} Refugee_{ODt} \times \left(\frac{1}{Distance_{pk}} \right) \times Q_{kt-1}. \tag{2}$$

The first term represents the number of refugees moving from country O to country D at time t. The second and third terms serve to exogenously allocate a greater number of refugees from a given origin to destinations based on existing pull and push factors. The second term presumes spatial proximity, intrinsic in the measure of the inverse distance between location k in origin country O and location p in destination country D, lures refugees to destinations relatively close to their origin. The third term suggests a greater number of refugees will come from locations exposed to higher levels of conflict Q_{kt-1} in the preceding year, where conflict levels are measured by the number of conflict events in the cell using the UCDP Georeferenced Event Dataset (Sundberg and Melander, 2013).

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