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Refugee influx and economic activity: evidence from Rohingya refugee camps in Bangladesh

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"Llegada de refugiados y actividad económica: el caso de los campos de refugiados *Rohingya en Bangladesh.*"

Resumen

Usando datos de iluminación nocturna y la ubicación de mercados históricamente importantes para comunidades locales en el sur de Bangladesh, estimamos el impacto de la inesperada llegada de refugiados en agosto de 2017 en la actividad económica de las comunidades locales. Para estimar este impacto, usamos diferencias en diferencias y encontramos que la llegada masiva de refugiados implico un aumento de 24% de la actividad económica en los mercados a 5 km de los campos de refugiado. Los resultados son robustos ante distintas especificaciones, usamos como controles la población alrededor de los mercados obtenida de la capa de alta resolución de población producida por CIENSIN y Facebook, y tiempos de viaje a través de la red de rutas locales. En este articulo argumentamos que el efecto fue producto de la llegada de refugiados junto a la respuesta de las agencias humanitarias. Este articulo contribuye a la literatura que documenta el impacto de refugiados en comunidades locales.

Palabras clave: Impactos de refugiados, Impacto de migraciones forzosas, iluminación nocturna, diferencias en diferencias, Rohingyas.

"*Refugee influx and economic activity: evidence from Rohingya refugee camps in Bangladesh.*"

Abstract

Using nighttime lights data and the location of historically important markets for host populations in Southern Bangladesh, we assess the impact of the sudden refugee influx in August 2017 in the economic activity for the local community. Using a difference in difference estimation, we find that a sudden refugee influx produced an increase of 24% in economic activity in host markets within 5 kilometers of refugee camps. The results are robust to different specifications, and we include as controls the population around markets from the High-Resolution Settlement Layer by CIENSIN and Facebook and travel times through the local road networks. We argue that the refugee influx plus the humanitarian response are responsible for this effect. This paper contributes to the literature documenting the impacts of refugees on host communities.

Keywords: Refugee impacts, Forced migration impacts, Nighttime lights, Difference in Difference, Rohingyas, Travel times, High Resolution Settlement Layer.

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Refugee influx and economic activity: evidence from Rohingya refugee camps in Bangladesh. [1]

1. Introduction

Around the world, 79.5 million people have fled their homes due to persecution, conflict, violence, human rights violations, or events seriously disturbing public order (UNHCR, 2020). On the other hand, communities receiving inflows debate about the implication, will the prices rise? Will salaries go down? Will the inflow kickstart the economy? In a context where 84% of forcefully displaced are in developing countries, the underlying questions for many actors are whether refugees help or hurt host communities that receive them.

Migration has been part of human history and will continue to rise[2], but the literature on the effects of the migrants in the host is scarce and suggest mixed results. Shedding light on this topic will help policymakers and humanitarian agencies to design better policies, address the shortcoming, and harvest the benefits of similar events in the future. This paper explores the effects of the sudden Rohingya refugee influx in the host communities' economic activity.

Late in 2017, Rohingya refugees fled from Myanmar to escape attacks by soldiers and pro-government militias and arrived in the district of Cox's Bazar of Bangladesh. Within four months, an influx of about 724,000[3] people joined other Rohingya who had fled earlier waves of violence, pushing the total number of displaced Rohingya in the area up to close to one million (Figure 1). By the end of 2018, around 918,000 Rohingya were hosted in close to 2000 campsites in two sub-districts in Cox's Bazar district. 81% of these refugees come from the most recent 2017 influx, with the remaining 19% coming from earlier arrivals.

The 2017 influx was unique on multiple dimensions: (i) its scale and speed, with 4 in 5 of all displaced Rohingya people arriving at the area in late 2017[4]; (ii) its size, relative to the host population, the influx represented an increase of 31.7% of the total population in Cox's Bazar and 154% of the population in the

[1] Acknowledgments: I want to thank Nethra Palaniswamy for encourage me to try this in the first place. Amelia Gibbons, my mentor, for the patience's, advice and useful comments. Jennifer Alix-Garcia, María Gabriela Ertola Navajas, Nandini Krishnan, Pablo Tillan, Robert Steven Banick and Walker Kosmidou-Bradley for all the comments.

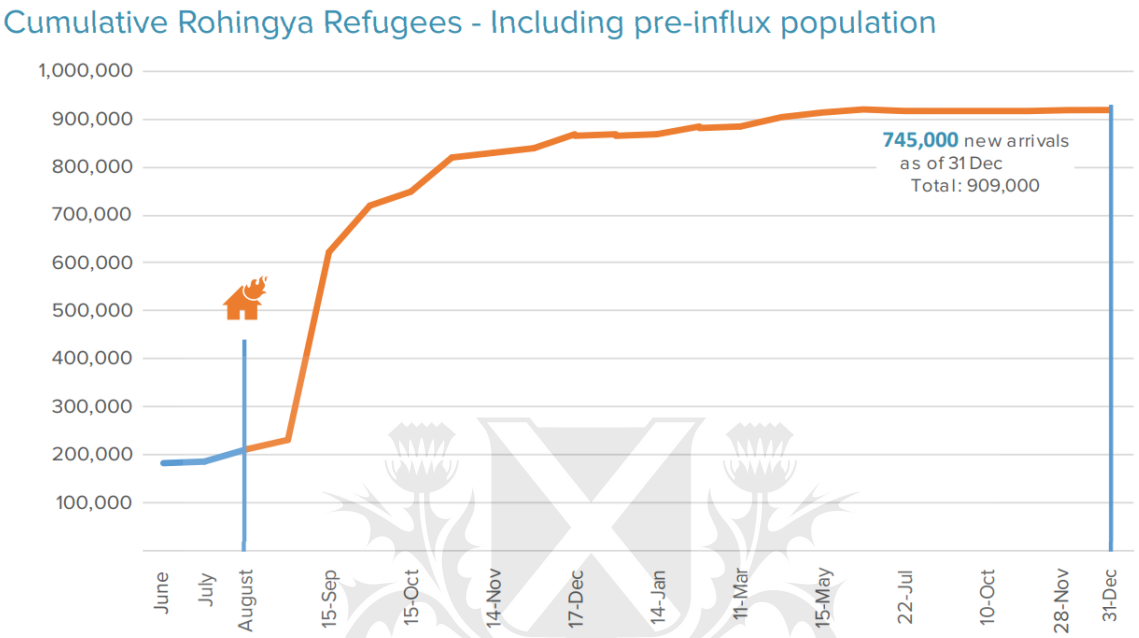
[2] For example, internal migration due to climate change could move around 143 million people from their homes by 2050 In Sub-Saharan Africa, South Asia, and Latin America (Rigaud et al., 2018).

[3] UNHCR Refugee population factsheet (As of 15 July 2019) http://data2.unhcr.org/en/situations/myanmar_refugees

[4] Own calculation based on UNHCR Refugee population factsheet (As of 15 July 2019).

sub-districts of Cox's Bazar that host refugee camps[5]; and (iii) its concentration of refugees is now the densest known in the world (11.7 square[6] meters per person).

Figure 1 *Total refugee population during 2017 in Cox's Bazar refugee camps.*



Source: (ISCG et al., 2019).

Since 2017, two sub-districts in Cox's Bazar district - Teknaf and Ukhia have been hosting large camp-based populations, which also accounted for a significant share of the total population in these areas. In Ukhia, Rohingya refugees account for as many as 4 out 5 persons; and in Teknaf, they account for 4 out of 10 persons[7]. Teknaf and Ukhia are among the three poorest sub-districts within Cox's Bazar[8] according to the last poverty estimation (Faizuddin et al., 2012) and populations within them have markedly poor access to markets (World Bank, 2020).

[5] Own calculation based on UNHCR Refugee population factsheet (As of 15 July 2019) and Bangladesh Bureau of Statistics population Census 2011.

[6] This is the density reported of Camp 3 in Ukhia in the UNHCR assessment "Settlement and protection profiling of all camps Ukhia/Teknaf, Cox's Bazar, Bangladesh Round 5 July 2019".

[7] Figures account for the total population of displaced Rohingya persons reported by the UNHCR (new and old arrivals).

[8] Host households in Cox's Bazar live in largely rural areas of the district, where consumption poverty is both high and significantly worse than the national average of 24.5%. Poverty rates outside the district capital of Cox's Bazar Sadar are higher than both the national and district averages; with the primary hosting subdistricts of Teknaf and Ukhia reporting small area poverty estimates of 30% and 40% respectively. In 2016, only 55% of adults over 18 in Cox's Bazar reported being literate. In addition, only half of all households reported access to electricity, and less than 3% reported access to piped water. According to the 2011 census, infrastructure and social indicators are also significantly worse both outside the district capital, as well as in the primary hosting sub-districts.

In this paper, using nighttime lights (NTL) data, we provide evidence of higher economic activity in markets run by the host population near the refugee camp, suggesting that the host communities near camps have seen more economic activity after the influx of refugees. The hypothesis that the sudden influxes of people bring new resources to the region, especially by the expansion in humanitarian aid. The aid provides means for the refugees to increase the demand and activity in local markets. In Cox's Bazar, the international assistance that refugees received includes in-kind and e-voucher transfers plus different cash for work programs.

The effects of refugee influxes on the welfare of host populations are complex. Alix-Garcia et al. (2017) suggest a framework separating effects via market mechanisms and outside the market mechanisms. Within the market, there are effects via demand and supply in goods, services, and labor. The changes in demand and supply impact the prices and incomes of host populations, thus affecting their welfare. In this paper, we focus on effects via a market mechanism, mainly we argue that more economic activity after the influx might have increased the income of hosts. The results confirm that positive effects can occur near refugee camps, and they can be more significant since there is more existing infrastructure and host markets with which to interact.

The paper follows this structure; Section 2 reviews briefly the literature. Section 3 describes the data used for the analysis and including some nuance of what nighttime light data could measure in a developing country context. Section 4 describes the analysis and run some robustness checks. Section 5 presents details on the scale and magnitude of the humanitarian assistance response in Cox's Bazar, and Section 6 concludes.

2. Literature

Economic activity quickly emerges even under challenging contexts; for instance, Radford (1945) describes the emergence of economic activity inside a camp of Prisoner of War in the Second World War were cigarettes were used as currency. We build on the existing literature that documents economic dynamics and effects of interaction between the refugee population and host communities. Specifically, in the refugee camp context, economic activity is generated within and around camps (Alloush et al., 2017). Refugees tend to receive humanitarian food and non-food aid and also derive income from agricultural production, wages, saving, and remittances (Alloush et al., 2017; Werker, 2007), thus they have resources to participate in local markets. Refugee camps can be subject to strict regulations which define their interactions and assimilation with hosts, this set of rules might distort their livelihoods and future perspectives (Betts et al., 2014)

The literature suggests heterogeneous economic and welfare effects in the local communities when analyzing refugee flows. The local governments and the international community response play a significant role in solving this issue (Chambers 1986, Whitaker 2002). In rural settings, an influx of population reduces the availability of land and other natural resources[9]. At the same time, usually, poor infrastructure available now require new and more substantial investments. Besides, sudden influxes might produce changes in demand, and these could push prices up if the supply of goods is not flexible (Alix-Garcia & Saah, 2009).

Refugees can increase aggregate demand for local products and bring in competitive labor to the local markets, thus generating economic growth (Rosenbach & Tiburcio, 2018). However, the way international aid is distributed is of crucial importance since it can stimulate local markets and provide opportunities and incentives for refugees and hosts (Khoudour & Andersson, 2017; Taylor et al., 2016).

In the case of Congolese refugees living in camps in Rwanda, sustained international aid plus the integration of the refugee in local labor markets have increased demand and boost the income of neighboring communities (Alloush et al., 2017; Taylor et al., 2016). In the same direction, Taylor et al. (2016) show how the average annual real income increase in the local Ugandan host communities when we factor in cash food assistance received by the international community. There is some long-term evidence also, for example, Maystadt & Verwimp (2014) study effects thirteen years after a massive influx of refugees. In particular, they show that Tanzanian households living close to the Rwandan and Burundian refugee camps have marginally higher consumption levels compared to villages without refugees. Alix-Garcia et al. (2018) mix NTL data and cross-section surveys to measure how in Kenya, villages nearby to Kakuma refugee camps,

[9] In Cox's Bazar the deforestation became eventually a problem until the humanitarian agencies stared supplying stoves and gas for cooking.

show higher economic activity (proxied by NTL data in the communities), and 25% higher household consumption levels when compared to farther away villages.

Verme & Schuettler, (2019) conduct a meta-analysis of the empirical results studying the impact of forced displacement on host communities. Only 1 in 5 of the 762 results analyzed, find a negative and significant effect on host welfare. In particular, higher prices and lower wages are the most likely adverse outcomes, although negative and significant results just appear in 40% and 35% of cases, respectively. The evidence of negative impacts on well-being and employment is scarcer, representing only 20% and 25% of cases, respectively.

In the case of Cox's Bazar, after the 2017 influx, evidence from the early phase of crisis pointed to short-term price inflation and a reduction in daily wages for unskilled host workers (Hill & Genoni, 2019; Rosenbach & Tiburcio, 2018). Since there are very few data sources available from the Cox Bazar area, it is hard to find a credible analysis of the impact of the 2017 influx in economic welfare for the host community.

3. Data section

Cox's Bazar data is scarce, DHS, HIES, MICS[10] surveys are not designed to produce disaggregated estimates within districts, and most of the data sets were collected in a pre-influx period. The primary sources for within-district analysis are the Population Census 2011, the Economic Census 2013, and the Agricultural Census 2008. After the influx, the administrative data from humanitarian agencies keeps track of the refugee population, but similar records for the host population are not available.

Given the scarcity of comparable data before and after the influx, we turn to monthly NTL data; this data is a reliable source of information at constant intervals before and after the influx. We obtain the NTL data monthly series from the Earth Observation Group (EOG) of the Payne Institute for Public Policy[11]. To produce the NTL estimates, the EOG relies on the data generated by the NASA – NOAA Joint Polar Satellite System (JPSS) partnership. The partnership launched in 2011 the Suomi National Polar Partnership (SNPP) satellite carrying the first Visible Infrared Imaging Radiometer Suite (VIIRS) instrument. The VIIRS instrument collects low light imaging data that is processed to provide a nightlight intensity measure for all the world in a grid of pixels of approximately 0.5 square kilometers. The sensor detects luminosity from outdoor and indoor use of light, fires, gas flares, and the aurora around 1:30 am every day, local time (Elvidge et al., 2013). In particular, we use version 1 of the monthly series that went by the stray-light correction procedure produced by the EOG. This data shows the locations where artificial lighting is present and a measure of the brightness as observed from space (Elvidge et al., 2017).

Nighttime light data has proven to be a good proxy of economic activities (Beyer et al., 2018; Chen & Nordhaus, 2015; Donaldson & Storeygard, 2016). But what does NTL data measure in a developing country? Henderson et al. (2012) suggest a significant advantage of NTL data is that they can be used to examine income growth and fluctuations at a very local scale and presets some case studies. For example, in Indonesia, NTL data fluctuates closely with the GDP during the Asia crisis suggesting it is a good proxy of short-term variations. To illustrate how a crisis event reflects in lights, they use the Rwanda Genocide, there is a dampening of light in 1994 and how the light intensity recovers its 1993 level in 1996. A different example of how NTL data can track changes at the local level is a gemstone discovery in Madagascar, the

[10] HIES stands for the Household Income and Expenditure Survey last fielded in 2016. DHS stands for Demographic and Health survey last fielded in 2017 and MICS stands for Multiple Indicator Cluster Surveys, fielded in 2013 and 2019 but designed to be representative at the district level which imped comparison within district. None of these surveys include refuge population in their sample frame.

[11] As of October 15, 2019, the National Centers for Environmental Information from NOAA has ceased production of the Global Nighttime Lights: annual and monthly composites using VIIRS Day/Night Band. These products, based on VIIRS observations, are now publicly available through the academic sector at the Colorado School of Mines, a public university in Golden, Colorado. Ongoing data will be available through the university's Payne Institute for Public Policy.

discovery kickstarted a shift in the growth of areas near the new gemstone sources that tractable thanks to the NTL data. In addition, literature suggest NTL data has been used in the region before: Beyer et al. (2018) assess the short-term impacts in the economic activity using NTL data of the 2015 earthquake in Nepal, demonetization in India and, violent conflict outbreaks in Afghanistan. On the other hand, NTL data has been used to explore the relationship between refugee population increase and welfare in host communities (Alix-Garcia et al., 2018).

The NTL intensity change in the Cox's Bazar area can be a product of the arrival of the refugees, and it does not have to imply that the host population is better off. To address the fact that light can also come from refugee camps, we use the location of host markets (more details below) and measure the total NTL around a 500-meter radius of each market for each month from February 2014 to December 2019.

In January 1984, the planning commission of Bangladesh published a "strategy for rural development". The strategy was based on focusing developmental resources on about 1400 markets designated as "growth centers," selected based on socio-economic priority and related ranking. In a 10-year revision in 1993, the Bangladesh Planning Commission expand the list of growth centers and add 700 markets to the list-making the final count 2100[12] (World Bank, 1996). In a 2005 review, the Government of Bangladesh (GoB) proposed new infrastructure and reiterated that the goal of these centers is to be the focal point of rural development (LGED, 2005). Growth centers are characterized by having a permanent multimodal structure, including shops, banks, storages, among others, as well as managing a large volume of trade (LGED, 2005).

Table 1 shows the number of growth center within the Cox's Bazar district and the distance to any Rohingya refugee camps in Cox's Bazar. To the best of our knowledge, there is no evidence that thoroughly explains the current location of the new camps. Still, it is reasonable to argue that the old refugee camps were attraction points at the beginning of the influx. Most of the area where new camps were built, was part of the Teknaf Wildlife Sanctuary. This area was not prepared for the major refugee influx, and indeed many refugees have been killed by elephants and other wildlife[13]. Furthermore, although the old camps

[12] The Growth Centers selection process: The process that was used to select the growth centers included some quantitative criteria such as population, area and number of unions, together with a requirement that the selected centers should be at a minimum of 4 miles apart. However, in the selection of the first 1400 centers, the local authorities were given the collated data so they could make the final selections. As a result, the local authorities also introduced some of their own preferences, so the final selection was partly based on the ranking system and partly on local decisions. The second lot of 700 additional growth centers selected in 1993 used the same grading system to decide the number in each thana and the final selection of the actual new centers was based on a grading system taking into account 31 parameters and a constraint of a minimum distance of 4 kilometers between centers (World Bank, 1996).

[13] See for example Ferdous (2018).

(Kutupalong and Nayapara) were first registered in the early 1990s[14] (Tan, 2017), nevertheless little is known about how the old refugee camps end up in a particular location. The information described above leads us to conclude that refugees camps locations do not explain growth center locations. Growth centers are spread across the district, as Figure 2 shows, and 5 of them are within a 5 kilometers (km) distance to a camp.

Table 1 Growth centers in Cox's Bazar district, by distance from Rohingya camps

Distance from camps	Number of Growth Centers
5 km	5
5 to 10 km	1
10 to 15 km	2
15 to 25 km	3
25 to 80 km	23
Total in Cox's Bazar	34

Source: Own calculations based on LGED and refugee population location data.

We obtain the Refugee camp location and boundaries (Figure 2) from the Inter Sector Coordination Group (ISCG). To get the location and counts of the Host population location, we used Facebook and CIESIN's High-Resolution Settlement Layer (HRSL)[15] . The HRSL provides estimates of human population distribution at a resolution of approximately 30 meters by 30 meters for the year 2015. The population estimates use recent census data and high-resolution satellite imagery. Using the location of the host population and the location of growth centers, we calculate the Host population within a 5 km radius of a market. As a measure of overall connectivity, we calculate the travel times in minutes from each growth center to the Cox's Bazar district capital following the proposal in World Bank (2020).

Table 2 groups key variable averages in two groups: markets near refugee camps and markets far from refugee camps, --when possible, we show the calculation before and after the influx of August 2017. Markets near refugee camps have, on average, similar travel time to the district capital when compared

[14] In 1991, thousands of Rohingyas fled from the Burmese military's Operation Pyi Thaya or Operation Clean and Beautiful Nation, although after UN intervention, many returned to Myanmar. Bangladesh have seen various Rohingyas influxes from Myanmar even before 1990's. The 1962 regime change in Myanmar lead to the official denial of citizenship in 1982 and persecution to Rohingyas by the Myanmar government (Skutsch, 2005).

[15] See Facebook Connectivity Lab and Center for International Earth Science Information Network - CIESIN - Columbia University. 2016. High Resolution Settlement Layer (HRSL), (2016).

with the rest of the markets (65 min vs. 66 min). Still, the average host population size in near camp markets is lower when compared with the rest of the markets (58,678 vs. 71,463).

When turning to the NTL data, markets within 5 km of a refugee camp show a lower average NTL radiance between February 2014 and July 2017 (before the influx) when compared with farther away markets (4.3 vs. 8.6). The difference in NTL intensity is maintained if we average the period after the influx (August 2017 to December 2019). However, markets nearby camps grow more on average more in relative and absolute terms.

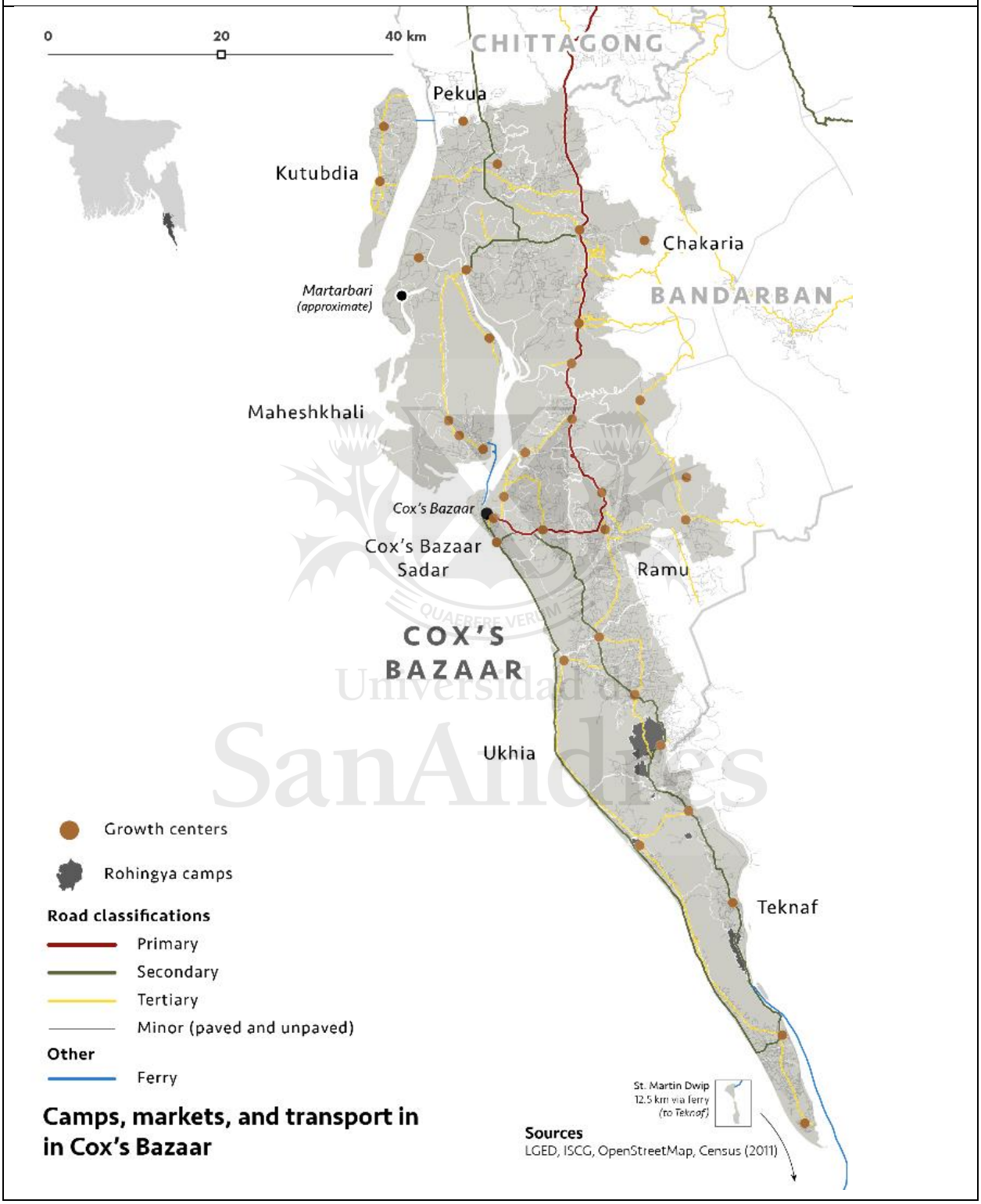
A different approach to check if there was a relative change in the economic activity of markets is to create a ranking for each month based on the luminosity. This ranking goes from 1 to 34 (1 is the lowest). The comparison of the average ranking shows that the markets nearby camps climbed on average, three places in the district ranking after the influx from 15 to 18.2.

Table 2 *Summary Statistics*

Variable	Less than 5 km from a refugee camp		More than 5 km from a refugee camp	
	Before August 2017	After August 2017	Before August 2017	After August 2017
Average Ranking	15	18.2	17.9	17.4
	(7.6)	(7.5)	(10.1)	(10.2)
Average NTL intensity	4.3	8.9	8.6	11.9
	(3.0)	(5.5)	(12.0)	(14.5)
Average refugee population size in Cox's Bazar	83,568	832,802	83,568	832,802
	(22,405)	(175,605)	(22,360)	(175,102)
Average refugee population size within 5 km	21,145	206,677	-	-
	(23,378)	(263,307)	-	-
	Less than 5 km from a refugee camp		More than 5 km from a refugee camp	
Average host population size within 5 km	58,678		71,463	
	(24,600)		(51,003)	
Average distance to a refugee camp	1.8		40.8	
	(1.6)		(20.0)	
Average travel time to Cox's Bazar Sadar	64.9		66.5	
	(17.8)		(45.08)	

Note: Own calculation. Standard deviations in parenthesis. NTL stands for nighttime light. The periods are from February 2014 to December 2019. The ranking using the NTL intensity was built on a monthly basis. It goes from 1 to 34, where 1 is the lowest intensity of NTL. Average time in minutes from a market to Cox's Bazar Sadar (the district capital). The average distance is in kilometers (km) measure from each market to the closest camp border.

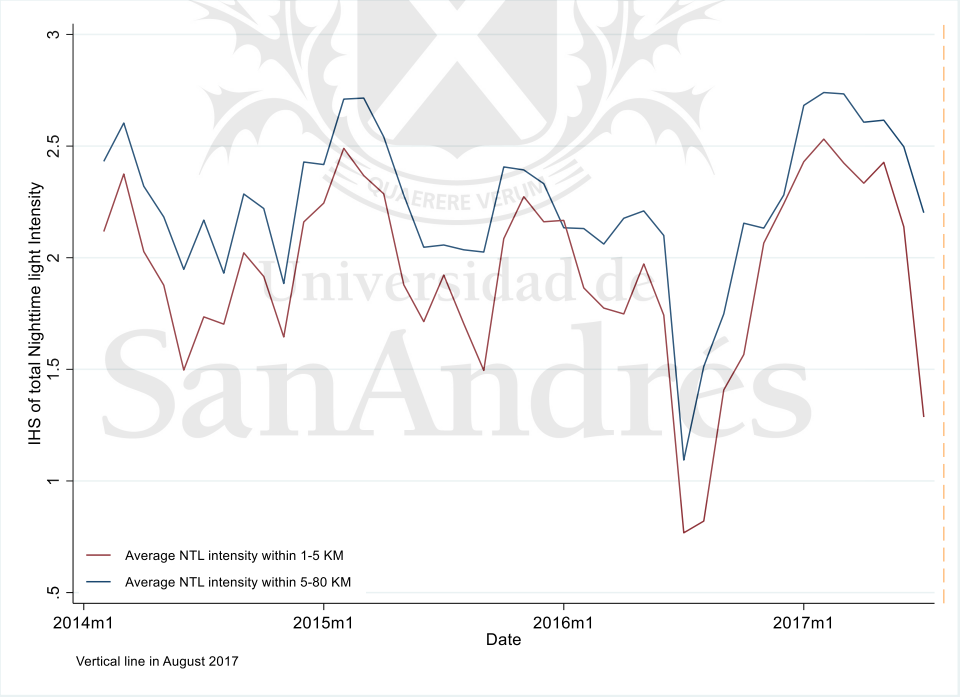
Figure 2: Cox's Bazar district in grey. Location of Growth centers, refugee camps, and major roads (Figure published in World Bank, 2020).



4. Estimation Strategy and Results

As stated, the hypothesis is that the major refugee influx accompanied by an expansion in humanitarian assistance in response to the Rohingya influx was followed by an increase of demand and activity in local markets. We use the data sources described above to measure changes in monthly nightlight intensity starting from February 2014 to December 2019 in a 500-meter buffer around growth centers. We believe this is a strong localized effect. Therefore, we chose a 5 km distance from camps to evaluate the effect of the influx in economic activity. Figure 3 presents the average NTL intensity overtime before the influx for markets within 5 km (in blue) and farther away from the camp (in red). Markets nearby camps are, on average, below the NTL intensity of markets camps farther away. NTL intensity depends on climatological conditions, and the monsoons season explains most of the drop in the series across years.

Figure 3 *Average monthly NTL for markets 5 km from a growth center and the rest of the markets before the influx.*



Note: Own calculation using NOAA VIRRS nightlight intensity data. The vertical line is in August 2017. To reduce variance and include zeros, we use the inverse hyperbolic sine (IHS) of the total nightlight intensity within the 500 meters buffer around the growth center. Results are consistent using a logarithmic fit.

Formally our estimation strategy is a difference in difference model:

$$Lights_{it} = \alpha + \theta Influx_t + \delta\ 5Km\ from\ camp_i + \beta Influx_t * (5\ Km\ from\ camp_i) + \gamma Connectivity_i * u_t + \phi Host\ population_i * u_t\ + u_t + \theta_i + \epsilon_{it}$$

where $Lights_{it}$ is the inverse hyperbolic sine (IHS) of the sum of the VIIRS luminosity in a 500 meters buffer around growth center i in month t. $5\ Km\ from\ camp_i$ is a dummy identifying the market within 5 km of a camp. $Influx_t$ is a dummy variable taking the value of one starting in August 2017. $Conectivity_i$ is the IHS of the travel time from growth center i to the district capital, we interact this with a year-month fixed effect as in (Alix-Garcia et al., 2018). Differences in economic activity and growth patterns might be explained by how markets are connected between them. Connectivity is a dynamic process, so the location fix effect would not solve this issue thoroughly. $Host\ population_i$ is the IHS of the host population living in a 5 km radius of growth center i according to the HRSL data. We also interacted $Host\ population_i$ with a year-month fixed effect, as connectivity different population sizes around a market can influence the economic activity; thus, we introduce this control. θ_i is the growth center fix effect, μ_t is a year-month fixed effect following the literature in NTL (Alix-Garcia et al., 2018; Baskaran et al., 2015; Chen & Nordhaus, 2015; Storeygard, 2016), and ϵ_{it} is an error term. To identify this relationship, we rely on across space and time variation and the fact that the August 2017 sudden influx is uncorrelated with the location of growth centers.

We report the results of the estimation in Table 3. Column 1 presents the estimations without any controls. Column 2 introduces market and year-month fixed effects. Columns 3 and 4 reproduce columns 1 and 2 but include the connectivity and host population controls. The four columns have a stable positive coefficient. All the coefficients are significant when using robust standard errors. However, estimates are not significant when clustering the standard errors at the market level, nor if we use a wild clusters[16] bootstrap estimation following Cameron & Miller (2015), note that the p-values when clustering at the market level are between 0.126 and 0.245[17] and between 0.122 and 0.316 using wild clusters. Markets nearby refugee camps after the influx are 24% brighter than what they would have been in the absence of the refugee influx. The results of the estimation stay in line with previous literature documenting the positive effect of refugee influxes in host communities. Refugees are a new source of demand for host products and services, and the humanitarian aid provides a low but steady flow of resources, evidence suggests a part of them end up in local businesses.

[16] We turn to wild clusters since we have "few" clusters, we have 34 markets, below, the 50 clusters suggested by the literature. In addition, of those 34 just 5 are treated, see Cameron & Miller (2015) for a broader discussion.

[17] If we calculate the standard errors using bootstrapping (10,000 reps) clustered at market level the p-values are around 0.152 and 0.259 for Table 3.

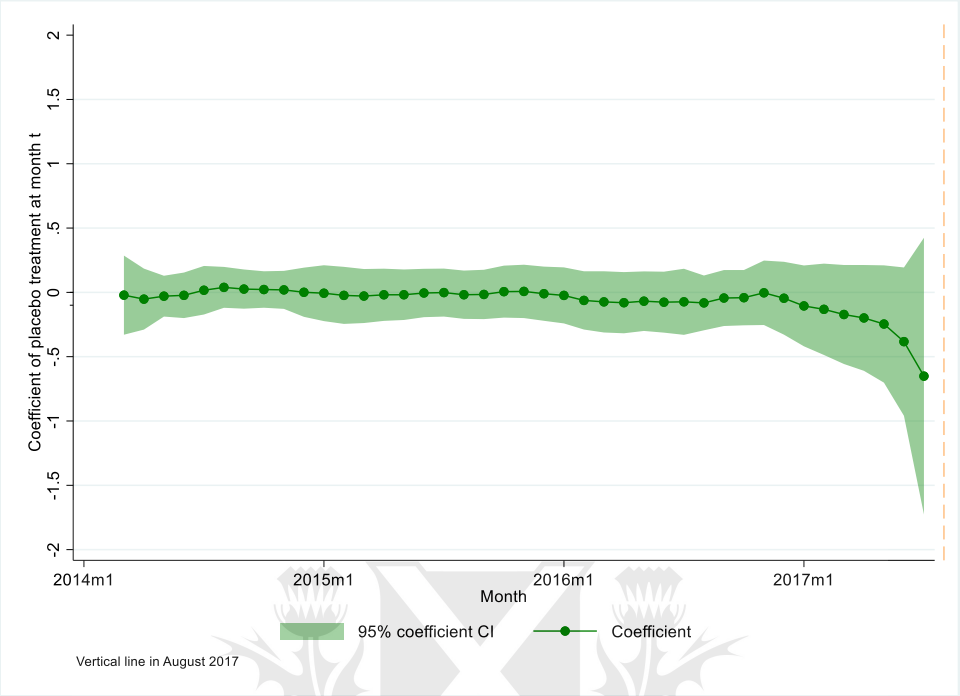
Table 3 *Regression results*

VARIABLES	(1) IHS(Lights)	(2) IHS(Lights)	(3) IHS(Lights)	(4) IHS(Lights)
0 to 5 km * Dummy August 2017	0.289	0.289	0.237	0.237
	(0.001)	(0.000)	(0.000)	(0.000)
	[0.126]	[0.134]	[0.235]	[0.245]
	{0.122}	{0.122}	{0.316}	{0.316}
Observations	2,414	2,414	2,414	2,414
R-squared	0.070	0.875	0.588	0.896
Host population Control	NO	NO	YES	YES
Connectivity control	NO	NO	YES	YES
Market FE	NO	YES	NO	YES
Year-Month FE	NO	YES	NO	YES

P-values using robust standard errors in parentheses. P-values using standard errors cluster at the market level in brackets. P-values calculated using wild cluster bootstrap in braces. The estimation is cluster at the market level, the bootstrap use 10,000 replications and uses Rademacher distribution.

A concern in the literature when using a difference in difference approach is the underlying assumption of parallel trends (Angrist & Pischke, 2009; Bertrand et al., 2004). Below we present two results suggesting we can assume there are parallel trends. The first is the placebo test (Angrist & Pischke, 2009), we estimate the effect of placebo treatment for each month before the influx, just excluding the first and the last month of the series (February 2014 and July 2017). For the placebo treatment estimation, we use the same specifications as in column 4 of Table 3. The results are estimated just using before influx observations. In total, we made 40 estimations, in Figure 4, we plot the coefficients as if the treatment would have taken place in month t. None of the coefficients were significantly different from zero, supporting the parallel trend assumption. When approaching August 2017, the coefficient estimates are noisier since there is a dive of the whole series (see Figure 3); this dive could be explained by the start of the rainy season in the area.

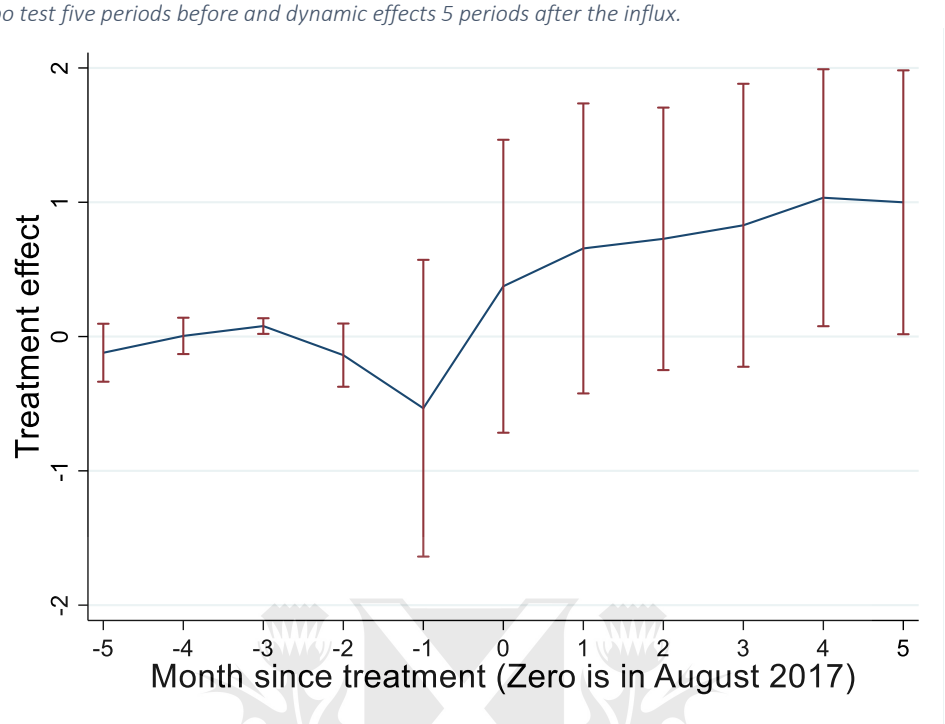
Figure 4 *Placebo test for different periods before the influx.*



Note: Own estimation. Circle in green is the coefficient of the placebo treatments in the corresponding month. In light green, the 95 % confidence intervals using cluster standard errors at the market level.

For the second result, we follow the proposal and implementation of de Chaisemartin & D'Haultfœuille, (Forthcoming). They propose an estimator that generalizes the standard difference in difference estimator while providing a way to estimate the placebo and dynamic effect of the treatments. We present the placebo estimates five periods before the influx and the dynamic effects five periods after the influx in Figure 5. Figure 5 presents the estimated coefficients, under parallel trend assumption, the placebo estimated coefficients should be around zero, as Figure 5 shows. On the other hand, the same figure let us see the dynamic effects after the treatment.

Figure 5:Placebo test five periods before and dynamic effects 5 periods after the influx.



Note: Treatment started in August 2017 (zero in August 2017). The treated observations are markets within 5 km of a refugee camp 95% confidence intervals in red, standard errors clustered at the market level, and calculated using Bootstraps (1000 reps). The regression includes all the control in column 4 of Table 3. For more details see de Chaisemartin & D'Haultfœuille, (Forthcoming).

Robustness Check

We explore four robustness checks. The first two address the fact that the refugee influx could have affected the broader Cox's Bazar. First, using the specifications as in column 4 of Table 3, we exclude the markets within 5 to 15 km since they might also be affected by the refugee influx. These markets could also have been affected by spillovers of refugees, making our previous estimations an underestimate of the effect. Column 1 of Table 4 presents the results of the estimation. The coefficients slightly drop, suggesting those markets were not generating an underestimation of the coefficients in Table 3.

In the second robustness check, again using the specifications as in column 4 of Table 3 we exclude markets in the district capital, 6 out of the 34 markets are in the Cox's Bazar district capital area. This area might also be affected by the spillovers of the influx since the humanitarian response staff, and offices flood the city. In Colum 2 of Table 4, the coefficient slightly increases. The increase suggests that our las estimation in Table 3 provides underestimated coefficients due to the spillover effects of the refugee influx in the capital area.

The third robustness check explores the possibility of the effect being more widespread; here, we use bigger reference areas from refugee camps. The aim of this is to provide more evidence suggesting that the observed effect is stronger near refugee camps. We explore two alternatives. First, we use markets within 15 km from camps. The results are positive and significant, but the coefficients are lower; we report the results in column 3 of Table 4. In the last columns of Table 4, we use all markets within 25 km of a camp, and there is no significant result.

Table 4 *Robustness check 1*

VARIABLES	(1) IHS(Lights)	(2) IHS(Lights)	(3) IHS(Lights)	(4) IHS(Lights)
0 to 5 km * Dummy August 2017	0.228	0.24		
	(0.000)	(0.000)		
	[0.269]	[0.253]		
	{0.354}	{0.318}		
0 to 15 km * Dummy August 2017			0.116	
			(0.002)	
			[0.427]	
			{0.550}	
0 to 25 km * Dummy August 2017				-0.015
				(0.654)
				[0.903]
				{0.923}
Observations	1,988	2,201	2,414	2414
R-squared	0.865	0.897	0.895	0.894
Excluding markets within 5 to 15 km of a camp	YES	NO	NO	NO
Excluding Cox's Bazar Sadar	NO	YES	NO	NO
Host population Control	YES	YES	YES	YES
Connectivity control	YES	YES	YES	YES
Market FE	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES

P-values using robust standard errors in parentheses. P-values using standard errors cluster at the market level in brackets. P-values calculated using wild cluster bootstrap in braces. The estimation is cluster at the market level, the bootstrap use 10,000 replications and uses Rademacher distribution.

The fourth robustness check is related to the buffer size chosen around a market to generate the NTL measure. The 500 meters buffer size is arbitrary. Nevertheless, we believe 500 meters gives a good measure of economic activity within the market and nearby. In Table 5, we present evidence that although

arbitrary, the buffer size is irrelevant to the magnitude and sign of the effect for markets within 5 km of a refugee camp. Colum 1 present the results using a 1 km buffer around the market using the full specification (Colum 4 of Table 3). Columns 2, 3, and 4 present the results for 2, 3, and 5 km buffers around markets, and the sign and magnitudes do not change.

Table 5 *Robustness check 2*

VARIABLES	(1) IHS(Lights) 1 km	(2) IHS(Lights) 2 km	(3) IHS(Lights) 3 km	(4) IHS(Lights) 5 km
0 to 5 km * Dummy August 2017	0.274	0.276	0.236	0.243
	(0.000)	(0.000)	(0.000)	(0.000)
	[0.253]	[0.247]	[0.271]	[0.115]
	{0.329}	{0.319}	{0.362}	{0.097}
Observations	2,414	2,414	2,414	2,414
R-squared	0.880	0.871	0.871	0.887
Host population Control	YES	YES	YES	YES
Connectivity control	YES	YES	YES	YES
Market FE	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES

P-values using robust standard errors in parentheses. P-values using standard errors cluster at the market level in brackets. P-values calculated using wild cluster bootstrap in braces. The estimation is cluster at the market level, the bootstrap use 10,000 replications and uses Rademacher distribution.

5. The humanitarian response

We explore three channels than may explain how the new refugee influx response could have driven the local economic growth. The first is a product of the substantial increase in humanitarian agencies operating in the area, producing new jobs and demand for services around the camp and in the district capital. Second, refugees receive as humanitarian assistance food and non-food items they then sell or barter to get resources to trade in local markets. Third, the cash for work programs implemented by humanitarian agencies, allow families to go to local markets to purchase goods and services mainly provided by the host population.

Table 6 Cox's Bazar Airport traffic

YEAR	Passenger ('000)	Freight/ mails (tons)
2014	87	3541
2015	107	2809
2016	154	2087
2017	256	1676
2018	539	3834

Own calculation based on Bangladesh Bureau of Statistics, Statistical Yearbook 2019

The first channel we explore is the arrival of humanitarian aid. The most recent influx of displaced Rohingya from Myanmar necessitated a large scale and immediate humanitarian response, averaging over 600 million USD per year (24 % of the GoB National budget for Social Security and Welfare[18]) since 2017. Food security and nutrition remain the single largest category of assistance, accounting for roughly 30% of all aid, which has been mostly successful in fulfilling the basic food needs of the Rohingya population in Teknaf and Ukhia camps (Figure 6 and Figure 7). However, the scale of available funding remains below requirements estimated by the UN (World Bank, 2020).

Understanding the impact of the expansion in humanitarian assistance on the local economy of Cox's Bazar is severely restricted by the lack of data. There is some suggestive evidence that the influx of humanitarian and development assistance, as well as workers and staff, have already shaped the local economy in meaningful ways. Air traffic between Cox's Bazar and Dhaka (capital of the country) has increased

[18] We use as reference the budget of fiscal year 2016-2017. It was comprised of 3,406.05 billion Bangladeshi takas. 5.8% of that budget was set to be use in Social Security and Welfare, see the Ministry of Finance-Government of the People's Republic of Bangladesh (2020).

substantially in people and cargo (Table 6). Between 2017 and 2018, passenger traffic at the airport increased 111%, and the number of passengers traveling on the Dhaka-Cox's Bazar route increased 40% (World Bank, 2020); anecdotal evidence also suggests that there is increased demand for real estate and accommodation in the district capital as well; and that there is higher traffic on the Cox's Bazar Sadar - Teknaf main road which connects the airport and the district headquarters to the camps. At the same time, there are new jobs available created by humanitarian agencies nearby the camps, for instance, households living near[19] refugee camps are more likely to report working in an NGO if compared with households living far away from camps (World Bank 2020).

Figure 6: Share of total funding by clusters in Cox's Bazar humanitarian response

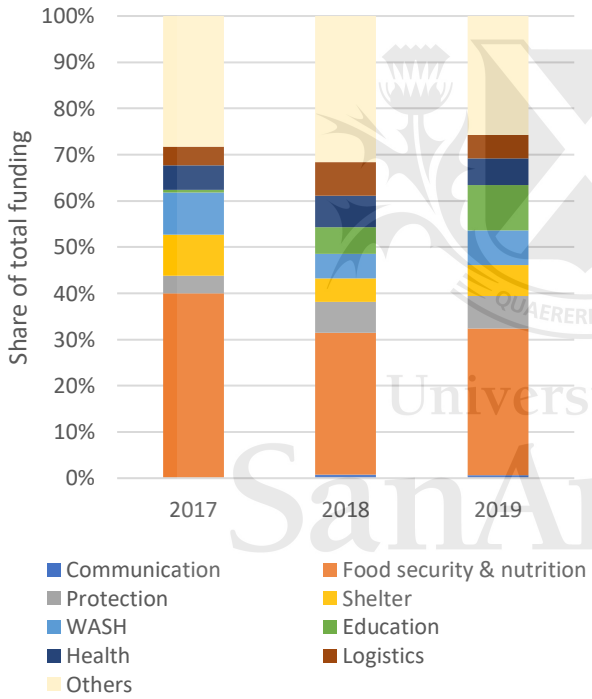
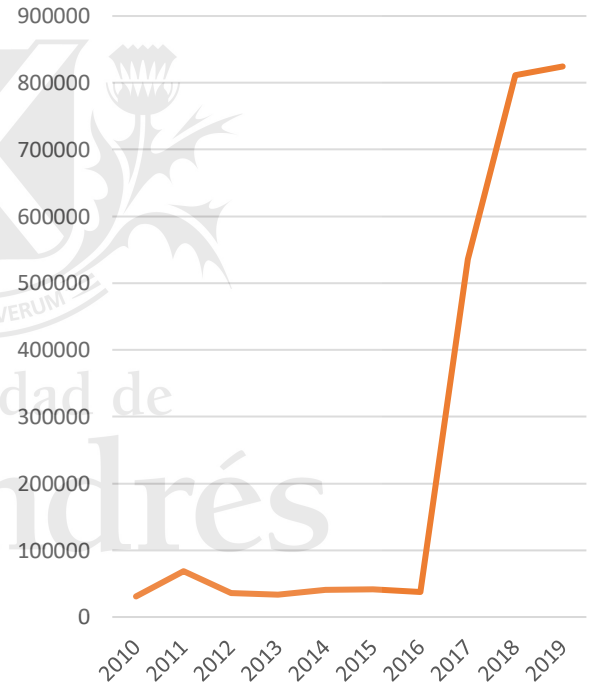


Figure 7: Evolution of funding in Cox's Bazar humanitarian response



Source: Own calculation, using data from OCHA[20]

To discuss the two channels left, we first provide more context on the humanitarian aid response, the humanitarian response after the refugee influx was able to provide shelter and essential services to the refugees. Still, the local regulation forbids recently arrived refugees to officially work and to receive Bengali-

[19] Here near a camp is define as living within 3-hour walking distance of camp.
[20] Data retrieved from https://data.humdata.org/dataset/e31467b1-0f37-40ea-b5be-558cf8c1b8aa on February 2020.

language education (World Bank 2020). The lack of opportunities makes refugees reliant on humanitarian assistance: 100% of refugee households receive some type of food or non-food aid, in particular, 80% of the daily caloric intake of refugees comes from food aid (World Bank 2020).

The World Food Program (WFP) is one of the institutions that provide food, shelter, and livelihood programs in the refugee camps. The WFP is responsible, among other things, for the in-kind and e-voucher food aid to refugees. In April 2020, WFP provided food assistance to 858,401 refugees: 684,561 via e-voucher and 173,840 via in-kind food distribution (WFP, 2020). Together they account for around 8.8 million USD per month[21]. The e-voucher modality provides an allocation of USD 9 (BDT[22] 770) per person per month to spend at the e-voucher outlets (WFP, 2020). While the in-kind is a fixed basket for 30 kilograms of rice, 9 kilograms of lentils, and 3 liters of cooking oil for every three members in a family, at WFP local point of sales prices,[23] this implies 6.27 USD (536 BDT) per capita.

The second channel we want to discuss, imply that refugee might be going to a secondary market with a part of their food aid; refugees around the world have been selling or bartering part of humanitarian assistance (Alix-Garcia et al., 2017; Taylor et al., 2016; World Bank, 2020). WFP has introduced a cap in some products to limit this behavior, but it is still a common practice. At least 21% of households report bartering the assistance received last month, and 32% of households report income from activities related to bartering or selling food aid (World Bank, 2020) Going to the secondary market with part of the aid received can provide a steady income for refugee families. Although it is still difficult to measure the precise amount of resources obtained through aid selling, literature has documented these behaviors in various refugee camps (Alix-Garcia et al., 2017; Alix-Garcia & Saah, 2009; Taylor et al., 2016; Verme & Schuettler, 2019). This source of income for refugees implies that refugees can go to local markets, thus expanding the host economic activity.

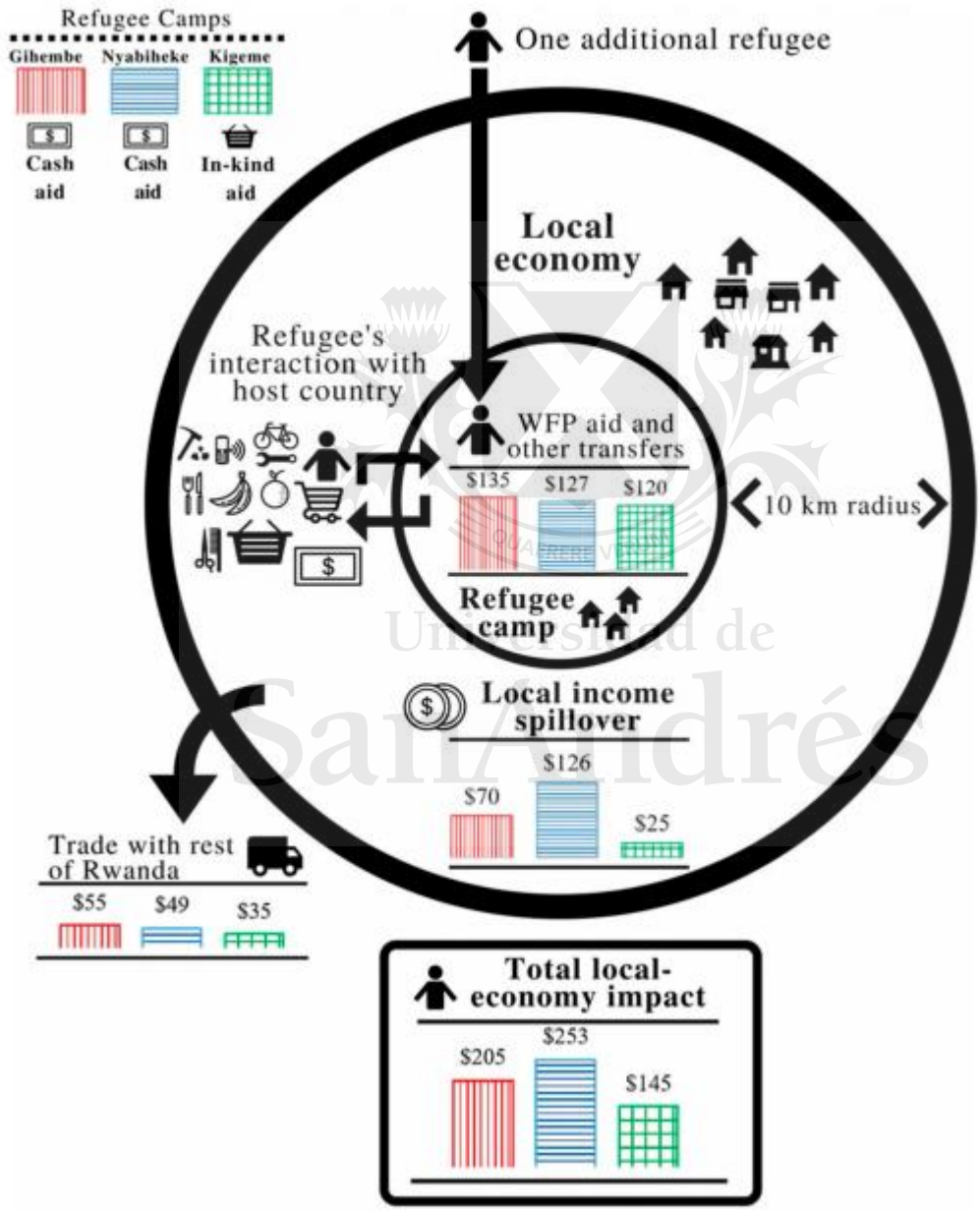
The third channel we want to discuss involves the cash for work programs, although a comprehensive record of the cash for work programs is not available since the start of the crisis, we can put some pieces of the puzzle together. In 2018, the Intern Sector Coordination Group (ISCG) and the GoB set conditions and rates for cash for work programs and volunteer labor to achieve operational objectives of different agencies (see Guidance on Refugee Volunteer Incentive Rates Rohingya Refugee Response V12, 2018). In the same document, the ISCG set rates for cash for work programs at 350 takas per day[24] for daily labors and some other engagements like semi-skilled volunteers, their monthly rates are set between 7,200 to

[21] Own estimation adding e-voucher and estimate equivalent of in-kind basket of 6.27 USD per capita.
[22] Bangladeshi Taka (BDT)
[23] Prices retrieved on the October 9, 2019. 1 kilogram of rice was 31 BDT 1 kilograms of lentils was 46 BDT and 1 liter of cooking oil was 88 BDT.
[24] The average daily rate for a comparable activity for host is around 500 per day see (Guidance on Refugee Volunteer Incentive Rates Rohingya Refugee Response V12, 2018).

12,600 BDT. Not all refugees had access to these programs, the labor force participation among refugees stands around in 32.6% (64% for men and 8.8% for women). Nevertheless, data shows that most of the refugees reporting labor work in construction and earthworks in a non-government organization (World Bank, 2020). Labor force participation is low when compared with hosts, and daily labor rates are lower than hosts. Still, resources are getting to refugee workers who can engage in market transactions, in refugee and host communities, boosting the local economy.

These three channels interact at the same time; in the literature, we can find an estimation of the multipliers effect of the aid received by refugees in local economies (Figure 8). More specifically, general equilibrium models to simulate the effect in Rwanda have calculated the impact of an extra refugee in the host economy (Taylor et al., 2016). The economic spillovers were kickstarted by food aid and other transfers. An additional adult refugee will generate an annual increase in the real, local economy between 205 to 253 USD, which is significantly more than the 120-126 USD that the refugee receives in aid directly (Taylor et al., 2016). We should take the benefits of an extra refugee in the case of Rwanda as a lower bound, as these models just take into account the resources directly transfer to refugees and do not include the resources used by the humanitarian agencies in the local operations (logistics, staff, etc.). We believe a similar process could be operating in Cox's Bazar, but for now, the lack of data is the major constrain to evaluate this in a more detailed manner.

Figure 8 *Impacts of an additional refugee on income within a 10-km radius of each camp and trade with the rest of Rwanda. The bars within the refugee camp represent the WFP aid and other transfers, including the income refugees bring with them. The bars in the local economy circle are real-income spillovers within a 10-km radius of each camp, created by refugees' interactions with local markets. The total local-economy impact is the sum of all real-income increases inside and outside the camps, including spillovers to host-country households and their feedback on refugee households, for example, through employment and the prices of goods and services. These impacts, shown in the box at the bottom of the figure (Center), significantly exceed the amount given in aid. The bars outside the circle (Left) show the stimulus to trade with the rest of Rwanda. Note: infographic taken from Economic impact of Refugees (Taylor et al., 2016).*



6. Conclusion

Significant evidence gaps remain in getting to a full understanding of the local economic impacts of the Rohingya refugee influx, which will need to be filled. Specifically, a detailed understanding of changes in economic activity in the district since the influx and understanding of winner and losers in the process can deepen humanitarian actors' understanding of specific mechanisms by which host communities are hurt or gain after a significant refugee influx.

In a context of scarcity of data, we turn to NTL to estimate the effect of a significant refugee influx in the host community economic activity. Specifically, we use the location of 34 host communities' local markets in Cox's Bazar district to generate a monthly series, from February 2014 to December 2019, of NTL around the markets. Given the location of the markets was defined more than 20 years ago, we believe the influx represents an exogenous shock to their economic activity. A difference in difference estimation showed that markets within 5 km of a refugee camp were 24% brighter than what they would have been in the absence of the refugees. The specification considers a measure of connectivity and the host population around the markets, and a time trend plus markets and year month fix effects. The results are robust if we include markets within 15 km, but they are of a lesser magnitude. If we increase the area used to measure the NTL around a market, the results do not change. A placebo was used; it did not yield any significant effect in the pretreatment period suggesting the assumption of a parallel trend is plausible.

The generation of new economic activity can be explained, to a certain degree, by the resources given to refugees through humanitarian aid received via food aid and non-food aid. As documented above, this is a significant amount of resources, most of them are certainly consumed by refugees, but the evidence of the economic activity growth in this paper suggest part of them have made their way to local markets.

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