Impact of Rohingya Refugees on Food Prices in Bangladesh: Evidence from a Natural Experiment

Ashraful Alam, Indranil Dutta, M. Emranul Haque, Ricardo Nogales

June 2020

Updated April 2022

Economics

School of Social Sciences

The University of Manchester

Manchester M13 9PL

Impact of Rohingya Refugees on Food Prices in Bangladesh: Evidence from a Natural Experiment [*]

Ashraful Alam[†]   Indranil Dutta[‡]   M. Emranul Haque[§]   Ricardo Nogales[¶]

Abstract

The Rohingya crisis is the fourth largest displacement of population in the world, with most refugees sheltering in neighbouring Bangladesh. We use this event as a natural experiment to examine the impact of the sudden influx of Rohingyas on food prices in the main host region of Bangladesh. We have pieced together a unique data set on food prices based on unpublished information at local government levels covering the pre- and post-influx period. We use a difference-in-difference approach to identify the impact of the refugee influx on the prices in the local area. Our baseline results indicate that overall food prices increased by 8 percent in the host sub-district of Ukhia, with prices of protein and vegetables increasing by 7 and 36 percent, respectively. For aid-supplied food products, such as cereals and lentils, we do find a statistically significant mitigating effect on prices. However, they were not substantial enough to reverse the increase in food prices.

Key Words: Bangladesh, Difference in Difference, Food Prices, Refugees, Rohingya

JEL Classification: C21, E31, H84, I31, J61

[†]Bangladesh Civil Service, Government of Bangladesh, E-mail: ashraf77.du@gmail.com
[‡]Corresponding author: Department of Economics, University of Manchester, UK. E-mail: i.dutta@manchester.ac.uk
[§]Department of Economics, University of Manchester, UK. E-mail:emranul.haque@manchester.ac.uk
[¶]Universidad Privada Boliviana and OPHI, University of Oxford. E-mail: rnogales@upb.edu

1 Introduction

The Rohingya crisis of 2017 forced close to 700,000 ethnic minority Rohingyas to flee the Rakhine state of Myanmar and seek refuge in Bangladesh. This made the Rohingya crisis among the top four of the largest displacements in the world by population groups.[1] It was a sudden mass exodus that happened within a very short period of just a few weeks, starting around late August of 2017 (UNHRC, 2018). We use this event as a natural experiment to examine how the sudden influx of Rohingyas impacted the local, regional economies of Bangladesh.[2] Through this analysis, we also shed light on the impact of displaced groups on host communities.

In particular, we examine the impact of the influx of Rohingya refugees on food prices in the main host region of Bangladesh, namely the Ukhia sub-district. There is a broad interest in studying the impact of the Rohingyas, given the scale of the influx and the high levels of poverty and malnutrition already present in the hosting regions (UN, 2018). The impact of the influx on food prices, however, is not apparent. It is reasonable to expect that among the early effects of this sudden arrival of refugees will be an increased demand for food in the host region resulting in high prices. Consequently, host communities and particularly their poorer sections may be significantly affected (Chambers, 1986). On the other hand, research (Lach, 2007; Zachariadis, 2012) indicates that the presence of immigrants leads to a lowering of consumer prices. Further, studies such as Balkan and Tumen (2016) and Tumen (2016) demonstrate that the influx of Syrian refugees led to a decline in consumer prices in the host regions of Turkey due to wage reduction from the increased labour supply in the informal markets.

In this paper, we follow studies such as Card (1990) and Tumen (2016) in using a difference-in-difference method to examine the impact of the Rohingya refugees on food prices. The Rohingya influx since August 2017 presents a unique opportunity. Unlike other refugee flows, they were limited to only two relatively small sub-districts of Bangladesh, Ukhia and Teknaf, near the border with Myanmar. There was no free movement of Rohingyas outside this region, and most of their activities were limited to the vicinity of the refugee camps. The Rohingyas were prohibited from participating in the labour market, too. This allows us to have a clearly defined host region. We undertake a rigorous process of matching the host region to a set of

---

[1] See UNHCR website: https://www.unhcr.org/globaltrends2018/
[2] See Tumen (2015) on the use of refugee influxes as natural experiments.

control sub-districts based on several variables such as agricultural productivity and wages, which impact demand and supply of food, and food prices.

Using 49 food items and comparing their prices between eight to twelve months pre- and post-influx in the host region to those in other similar regions (control sub-districts) in Bangladesh, we find that the mass influx of Rohingyas led to an increase in food prices in areas where refugees have settled. Similar increases in the prices of food due to refugee influx have also been observed in other parts of the world (Alix-Garcia et al. 2014, Ruiz and Vargas-Silva, 2017). The increase in prices that we observe holds across several food groups such as protein and vegetables and the overall food price index. We do not find any mitigating effect of the labour market through lower wages on food prices, perhaps because of the short-run focus of our analysis.

Our baseline results show that overall food prices increased in Ukhia by a significant 8 percent, and prices of protein and vegetables increased by 7 and 36 percent, respectively, relative to other similar sub-districts. News reports from the region during that time (Alam, 2018; Alsaffin, 2018) attests to the increase in prices of essential commodities that local populations faced. As expected, for aid supplied food products, such as cereals and lentils, we observe a decline in prices in the host region compared to other regions. So far, most of the studies on Rohingyas have mainly focussed on the labour market issues in the host regions of Bangladesh (UNDP, 2018). Hence, ours is the first paper to discuss the effects of the Rohingyas refugee influx on the host region's (food) prices. Our paper, thus, adds to the small and growing literature on the impact of Rohingya refugees on the host regions of Bangladesh (Filipski et al. 2019, UNDP, 2018). The main thrust of our results remains the same when we undertake several robustness checks. In this sense, it also contributes to the broader literature on the impact of displaced population on host regions.

Since Bangladesh does not conduct regular price surveys, we have pieced together a unique data set on food prices based on unpublished information at the local government levels. Our data is quite granular, where we have monthly information on prices at the sub-district levels of the host regions. This gives us two specific advantages. First, the sub-district level data allows us to estimate the effects of the refugee flow on food prices with more precision. It is important to focus at the sub-district level because not only the refugees are concentrated in particular sub-districts of Bangladesh, the factors that influence food prices such as agricultural

wages, transportation facilities, irrigated land, among others, are not similar across the sub-districts. Second, with the monthly information on food prices, we can observe any significant anticipated changes in the food prices in the host regions. This is relevant because the conflict had already started in different parts of the Rakhine state of Myanmar sometime before August 2017 (Annan et al. 2017) and there has been a previous history of Rohingyas seeking refuge in Bangladesh.

The plan of the paper is as follows. In the next section of the paper, we provide a context to the current influx of Rohingya refugees drawing on previous incidences. Section 3 discusses the data and Section 4 lays out the estimation strategy. Section 5 provides our main results, followed by a whole set of robustness checks in Section 6. Section 7 examines the impact of food aid, and a broader discussion of these results are presented in Section 8. We provide some concluding remarks in Section 9.

2 Refugee flow of Rohingyas

The Rohingyas are an ethnic Muslim community mainly from the northern part of Rakhine State of western Myanmar. The number of Rohingyas in Rakhine state is around 1.2 million, which is roughly 40 percent of the total population of that state. They have a long history of being displaced and seeking refuge in Bangladesh (Mahmoud et al., 2017). In 1974, the Ne Win military government enacted Emergency Immigration Act and officially declared the Rohingyas as foreigners in their land. A new citizenship law followed this in 1982 whereby the Rohingya were not recognised as an ethnic group of Myanmar. This denial of citizenship was the root cause of the forced migration faced by the Rohingya time and again (Holland et al., 2002, p. 10).

The first major wave of influx of the Rohingya to Bangladesh happened in 1978 when the then government of Myanmar launched an operation that triggered 200,000 Rohingyas to flee. In 1990, the military government of Myanmar launched a new operation in the Rakhine state, which led to another influx of 250,000 Rohingya refugees into Bangladesh between 1991 to 1992 (Holland et al., 2002). Through bilateral negotiation between Bangladesh and Myanmar during 1992-2005, around 237,000 Rohingyas were repatriated to the Rakhine state. Even after this repatriation, there were instances between 2005 and 2015 when Rohingyas sought refuge in Bangladesh (RRRC, 2018).

The recent influx of the Rohingya to Bangladesh started with renewed conflict in the southern part of the Rakhine state in Myanmar in October 2016 (Annan et al. 2017). The influx became negligible only towards the end of February 2017, according to the International Migration Office (IMO) (2017) report. A total of around 80,000 Rohingya refugees crossed into Bangladesh during that period. By July of 2017, around 212,000 Rohingyas lived in various sub-districts of Cox's Bazar (ICRG, 2017).

Figure 1: Map of Chittagong, Cox's Bazar and Myanmar
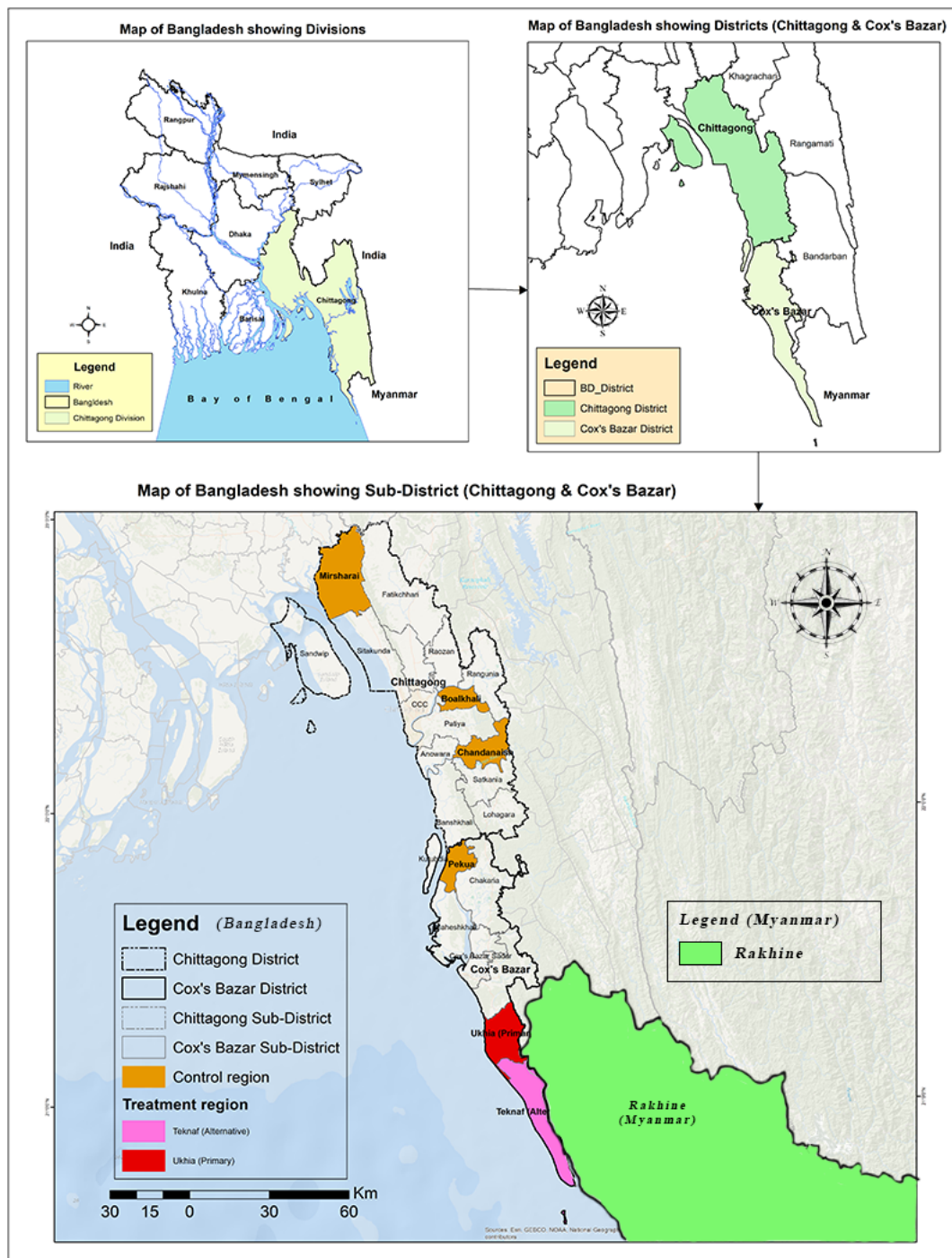
Source: Authors. The region in red and purple are the sub-districts of Ukhia and Teknaf where the influx of refugees happened. The regions in orange are the control sub-districts of Boalkhali, Chandanaish, Pekua and Mirsharai.

As seen from Figure 1, both Cox's Bazar district and Bandarban district of Bangladesh share a border with the Rakhine state of Myanmar. Given the mountainous terrain of Bandarban, the main influx of refugees had taken place in the coastal district of Cox's Bazar. In addition, as the Rohingyas share the same dialect as spoken in the Cox's Bazar region, there was a natural advantage for them to seek shelter in Cox's Bazar.

Our paper focuses on the largest and fastest influx of the Rohingya into Bangladesh which began in August 2017, when the conflict started in the northern parts of Rakhine state, close to the Bangladesh border.[3] Within the first few weeks, 73,000 Rohingyas sheltered in the Ukhia and Teknaf sub-districts of Cox's Bazar. The overall flow of the refugees is given in Table 1.

Table 1: **Rohingya Refugee Flow in Cox's Bazar District of Bangladesh: 2017-18**

Time	Refugee Influx	Percentage of Total Influx	Cumulative Influx
Before Aug-17	212,500	23.12	212,500
Aug-17	73,000	7.94	285,500
Sep-17	434,000	47.23	719,500
Oct-17	100,000	10.88	819,500
Nov-17	18,000	1.96	837,500
Dec-17	30,500	3.32	868,000
Jan-18	12,500	1.36	880,500
Feb-18	3,000	0.33	883,500
Mar-18	500	0.05	884,000
Apr-18	21,418	2.33	905,418
May-18	13,518	1.47	918,936
Total	918,936	100	

Source: Summary of the ISCG Situation Report 2 to 86 (2 September 2017 to 30 June 2018)

The main flow for this latest influx of refugees seems to have taken place between August and October 2017. As of 30 June 2018, more than 700,000 new refugees were sheltering in

[3]See UN-OCHA report https://www.unocha.org/rohingya-refugee-crisis

different refugee camps in Ukhia and Teknaf. In total, there were 32 refugee camps, with the largest among the camps being Kutupalong in Ukhia.[4] The total population of Cox's Bazar district within a few months had increased by 50 percent, bringing the population density to 1500 per square kilometre, far exceeding the national average of 1100 (UNDP, 2018). Around 80 percent of the refugees are concentrated in Ukhia, with the rest in Teknaf. As a result, the population in Ukhia increased close to 300 percent while the population of Teknaf increased around 50 percent.[5] From the rapid rise in population, it is reasonable to conclude that while the influx of refugees was substantial, it did not lead to a significant emigration of the native population from these sub-districts.

It is important to note that Bangladesh has not given refugee status to the Rohingyas (Bowden, 2018).[6] Thus, unlike other refugee situations such as the Syrian refugees in Turkey, the Rohingyas lack certain rights, including the right to free movement. Checkpoints and road patrols are in place making it difficult for Rohingyas to travel outside the two districts of Ukhia and Teknaf (UNDP 2018, p.73).[7] More importantly, Rohingyas do not have the right to work in Bangladesh (Alam, 2021). While there is growing evidence that Rohingyas are working as unskilled workers, particularly day labours, they are not legally allowed to do so. Their primary earnings are from self-employment, informal work, and local and international aid (Alam, 2021). Despite these limitations imposed on the refugees, the Government of Bangladesh had provided support to the refugees through various departments. Notably, they had allocated 2000 acres of forestry land for the refugees in Ukhia (UN, 2018, p.22). The governments of Bangladesh and Myanmar also had signed an agreement in November 2017 for the repatriation of Rohingyas, however, that has not been implemented.

3 Data

In Bangladesh, each month, the office of the District Marketing Officer collects data on average prices for 56 food items in major open markets in various sub-districts of the region.

---

[4]Some of these camps were established earlier. For instance, both Kutupalong in Ukhia and Leda in Teknaf started in 2007.

[5]According to UNDP (2018, Table 4.2), the total Bangladeshi population of Ukhia in 2017 was 198,000, while that of Teknaf was 367,000.

[6]Bangladesh is not a signatory to the 1951 Refugee Convention.

[7]Since 2019, the Bangladesh Government has tightened the restrictions on movement even more (Human Rights Watch (HRW), 2019. Available at: www.hrw.org/news/2019/09/07/bangladesh-clampdown-rohingya-refugees).

These data, although available to the public if requested, are not usually published. Out of those items, we were reliably able to collect monthly price data for 49 food items from the 16 local government sub-district offices from July 2016 to June 2018.[8] As mentioned in Section 2, there was a small influx of Rohingyas into Bangladesh in the second half of 2016 due to military operation in the southern part of the Rakhine state. To avoid any possibility of that influx impacting the common trends assumptions most of our analysis focuses from December 2016 till April 2018. This gives us around eight months on both sides of August 2017, when the sudden large-scale influx started. However, under robustness checks, we also present the results for the entire sample. Some of the food items are seasonal, and therefore, we do not have prices for them every month. Further, there is no information available to seasonally adjust our price data, although in the robustness section, we do control for seasonality using standard methods.

We have divided the 49 food items in our data into eight broad categories of cereals, pulses, fish, meat, vegetables, spices, oil, and other items.[9] Out of these, we focus on three broad food groups: cereals, proteins, and vegetables, which together carry substantial weight in the rural consumer price index of Bangladesh.[10] Cereals contain all different varieties of rice and flour; protein includes beef, chicken, eggs, fish, and mutton; and vegetables include seasonal vegetables and more staple items such as potatoes. The details of these are available in Appendix A (Table A3).

To assess how similar the various sub-districts of Chittagong - Cox's Bazar region are, we undertake comparisons across two different data sets. First, we collected information on a total of 19 variables for 21 sub-districts in the region, which capture a wide range of infrastructure and agriculture-related factors that may impact food prices. We use the latest available data from the District Statistics for 2011 report, published by the Bangladesh Bureau of Statistics in 2013 (BBS 2013a, 2013b). Second, we use the Bangladesh Household Income and Expenditure Survey for 2016 to compare food expenditures incurred by households in the Chittagong and

---

[8]We did not consider seven food items for various reasons. One rice item (Atop) was dropped because its price was mirroring the price of generic low-quality rice that we consider in our analysis. Further, we drop another item of rice (Najirshali) and five items of fish (Hilsha, Carp (2 varieties), Barbel, Shrimp) because of the large variability in prices, and we were unable to cross-check the prices. Right after the influx started in August 2017, a ban on fishing in River Naf, the main river for fishing in Cox's Bazar, was imposed (Sattar, 2019). Significant quantities of these fish are also exported. These impacts might have been confounding factors in our analysis.

[9]In doing so, we have followed the classification used by the Bangladesh Consumer Price Index.

[10]The weights are based on the 2005 rural consumer price index of Bangladesh (Bangladesh Bank, 2008).

Cox's Bazar district.

4 Empirical Strategy: Difference in Difference

In estimating the causal impact of the refugee flow on the food prices, we consider a difference-in-difference (DiD) strategy, which analyses the difference in prices between control and treatment regions before and after the event. In what follows, we consider August 2017 as the period from when the Rohingyas arrived in Bangladesh. This matches with the UN Declaration of the problem in August 2017.

We use a standard DiD model to estimate the impact of refugees on prices using the following equation:

$$ln(p_{ist}) = \alpha + \sum_{i \in N} \beta_i I_i + \sum_{s \in S} \gamma_s I_s + \delta(D_s \times P_t) + \sum_{t=t_0}^{t_f} \lambda_t I_t + \epsilon_{ist} \tag{1}$$

where $ln(p_{ist})$ is the log-price of food item i in sub-district s at time t. The set of considered food items is denoted as N, and that of considered sub-districts as S. I_i and I_s are dummy variables for food item i and sub-district s, respectively. Thus β_i represents food item fixed effects, and γ_s sub-district fixed effects. D_s is the treatment sub-district dummy variable, and P_t is a dummy variable for the post-treatment period. Thus δ represents the impact of refugee influx. In this baseline specification, trends are month-year fixed effects, λ_t, activated by dummy variables for time periods I_t covering all time points between t_0 and t_f. This could also be interpreted as a flexible trend since, compared to a linear trend, it takes into account non-trend time unobservables. Finally, ϵ_{ist} are error terms. While equation 1 with flexible time trends forms our baseline specification, as one of our robustness checks, we extend it to accommodate sub-district specific time trends, too.

In the context of forced displacements, there can be several threats to identification of the impact of interest (Balkan and Tumen, 2016). First, the treatment region where the refugees settle must not be entirely pre-determined, leading to other factors impacting price. Second, the influx of refugees could lead to the local population emigrating out of those regions thereby reducing the impact of the refugees. Third, the treatment and control region prices should have common trends before the influx of refugees. Hence, to address these threats, the challenge lies in determining reasonable treatment and control groups to compare the before and after effects of the influx of refugees.

In the sections below, we discuss our choice of the treatment region and the steps we take to address the issues related to the pre-determination of regions where refugees settled. As in most cases of forced displacement, the main influx of Rohingya refugees happened in the border regions of Bangladesh. This by itself is not an issue so long as the influx has been unanticipated and not endogenous to food prices. As discussed earlier in Section 2, there was also no substantial emigration out of the treatment region. The population of Ukhia considerably swelled with the influx. Third, through plotting the average prices of food groups and undertaking event study in later sections, we demonstrate that the prices between our treatment and control region followed a similar path before August 2017.

4.1 Treatment Region

For our analysis, we take Ukhia as our primary treatment region. The current influx of refugees mainly took place in Cox's Bazar district, with over 80 percent settled in camps in Ukhia and the rest going to the Teknaf sub-district. Thus, our primary analysis is focused on the area where the majority of the influx happened and where we may observe a sharper impact on food prices.

One reason why Ukhia may have been the preferred destination for refugees is that it already had a significant number of refugees from previous displacements compared to other sub-districts in Cox's Bazar. Ukhia accounted for around 50 percent of the refugees from previous displacements. However, among other plausible reasons for choosing a destination, better economic opportunities could also be a factor in which Teknaf would have been the preferred destination since it is a local business hub (UNDP, 2018). An ICRG (2017) report from the ground during the influx of refugees in 2017 mentions, "[Refugee] movements within Cox's Bazar remain highly fluid, with increasing concentration in Ukhia...". This broad evidence demonstrates that there were no clear and obvious reasons why refugees chose to settle in Ukhia over other sub-districts of Cox's Bazar. More importantly, there is no evidence that these decisions were based on food prices.

Nonetheless, we undertake additional robustness checks to address any issues with the treatment region. First, we include Teknaf as another treatment region in our analysis. The impact of the refugee influx on both Ukhia and Teknaf is estimated, where they are considered as two distinct treatment regions. Second, we also consider sub-district specific trends for our

primary analysis. In the absence of month-to-month information on the flow of Rohingyas to the different sub-districts, the sub-district specific trend controls for any sub-district specific time-variant factor that may impact prices.

4.2 Control Region

For our primary analysis, we consider the sub-districts of Boalkhali, Chandanaish, Mirsharai, and Pekua, belonging to the Chittagong and Cox's Bazar districts, as the control region. In arriving at the control region, we sought to find similar sub-districts to Ukhia, our main treatment region, from nearby areas not impacted by the influx of Rohingya refugees. First, we use general observations about the topography and economic conditions to match the control and the treatment regions. Second, we use a broad set of criteria and similarity scores to significantly narrow down the sub-districts that can be considered as potential control areas.

In terms of general observations, Cox's Bazar, a hilly and coastal district, is in the Chittagong division along with ten other districts, out of which only four, namely, Chittagong, Rangamati, Bandarban, and Khagrachari, are in the same region as Cox's Bazar. Among these four districts, only Chittagong is a coastal district like Cox's Bazar (see Figure 1 above). The topography of five hilly districts shows that Chittagong and Cox's Bazar districts are very similar in terms of land cover and usage. Most of the population of the other three hilly districts are tribes, and their lifestyle is quite different from that of Cox's Bazar (UNPO, 2018). Hence, we focus on Chittagong and Cox's Bazar districts.

To substantiate this, we use the HIES 2016 data to check for monthly household food expenditure in Chittagong and Cox's Bazar district. The survey collected food expenditure data from 720 households in each district, covering 116 food items across ten food groups. As shown in Appendix A Table A1, the results demonstrate that there are no significant differences in food expenditure between the two districts. To narrow down the control region further, we look for the closest match to Ukhia over several different variables that may impact the demand and supply of food items. This is important because city regions, such as Cox's Bazar Sadar, have very different dynamics that influence food prices than rural regions of Ukhia and Teknaf. We use the Mahalanobis distance measure, which is well suited to capture the dissimilarity between the regions based on the different variables of interest. The higher

the distance measure, the bigger is the dissimilarity between the regions.[11] Based on the BBS (2013a, 2013b) data for 2011, we consider 19 variables that cover a broad range of factors that impact both demand and supply of food items.[12]

As a first step of matching the regions, we use only those variables which are balanced.[13] A total of 15 different variables out of 19 satisfy the balance tests. We specify five different combinations of these variables extending from a baseline combination that considers all variables except three with the least variance. We then choose the top four sub-districts that fulfil the following two criteria in terms of Mahalanobis distance measure : (i) the sub-districts which are in the top three in terms of the closest match in at least one of the specifications, and (ii) those which also came lowest in terms of the sum of the ranks in all five combinations above. The rankings of the various sub-districts based on the Mahalanobis distance measure for five different specifications are in Appendix A, Table A2. For robustness checks, first, we consider all 14 sub-districts for which we have price information, and second to address spillover effects we consider a control region where we exclude two nearby sub-districts of Ramu and Cox's Bazar Sadar from the set of 14 sub-districts.

4.3 Common Trends of Prices

One of the crucial identifying criteria for DiD in our context is that the difference in prices between treatment and control regions would have been the same without the refugee flow. To reduce noise in the data and present a sharper picture of the common trends, we consider a three-month moving average of the prices, which is in line with other studies based on quarterly prices such as Tumen (2016).

---

[11]Consider a vector of variables for region A is $X : (x_1, x_2, ..., x_n)$ and the same vector of variables for region B is $Y : (y_1, y_2, ..., y_n)$, then the Mahalanobis distance measure is given by

$$d^M(X,Y) = \sqrt{(X-Y)S^{-1}(X-Y)}$$

where S is the variance-covariance matrix.

[12]We consider agricultural wages, productivity, and the amount of land under irrigation and cultivation in the region. The agro-climatic conditions are captured by the proportion of riverine and forest land. Resilience to weather shocks, the lack of which may otherwise impact food prices, is captured through the number of flood defences, cyclone shelters, and food warehouses. Transportation facilities are taken into account through the metalled roads, railways, and permanent waterways. We also consider prices in 2011 of staple food such as rice, wheat, flour, and potatoes.

[13]The balance test that we undertake checks whether the value of the variable for Ukhia lies within the range of values of the other region for the same variable.

Figure 2: Common Trends of Prices between Treatment and Control Regions
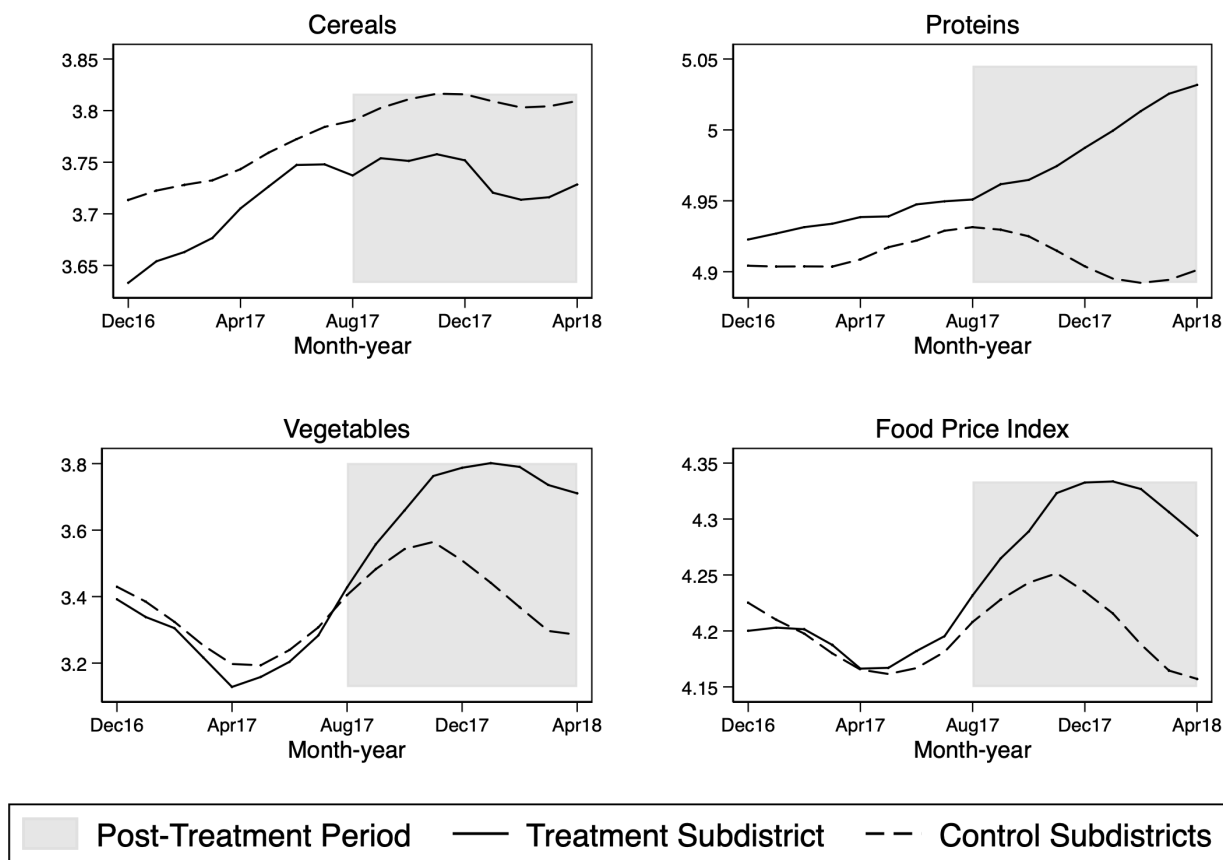
Note: Treatment period - August 2017; Control region includes sub-districts of Boalkhali, Chandanaish, Pekua, and Mirsharai; Treatment region is Ukhia.

We compare the average prices in the treatment sub-district of Ukhia and the average prices across all the four control sub-districts of Boalkhali, Chandanaish, Mirsharai and Pekua. Along with the overall Food Price Index (FPI), we also show the prices of the three important food groups that we consider in our analysis — cereals, protein, and vegetables. The results of the common trends are shown for the period December 2016 to April 2018 in Figure 2, where the treatment period starting with August 2017 is highlighted by a shaded area.

As evident from Figure 2, since the treatment date of August 2017, one can observe a widening gap between the prices in treatment and control regions for the various food groups and the FPI. In particular, we can see a clear divergence between the prices of Ukhia and the control sub-districts for protein, vegetables, and the FPI. For cereals, there is an initial narrowing of the gap, followed by a slight divergence. While the pre-trends for cereals and protein food groups can be considered linear, the pre-trends for vegetables and the FPI are

non-linear.

In the trends before August 2017, we observe some interesting patterns. For cereals, as we come towards August 2017, there is a slight widening of trends in the prices between the treatment and control regions because of a drop in prices in the Ukhia. When we disaggregated the patterns within cereals, we observed that the drop in prices in cereals before August 2017 is arising from generic low and medium-quality rice. We find a similar pattern with protein too, where the prices between the two regions remain stable, with a slight dip in the protein prices between the regions around July 2017 before it increases sharply from August onwards. On the other hand, vegetables display a different pattern, where initially the prices between the regions narrowed but remained more or less stable since. The differences in FPI between the treatment and control regions, was negligible, although we see a slight divergence beginning to emerge closer to August 2017.

The changes in prices around July is potentially associated with some anticipated effect of the looming refugee crisis. The fluctuation towards the beginning of the pre-treatment period, we suspect, reflects the adjustment in prices from the effects of the conflict in the southern part of the Rakhine state in the last quarter of 2016.[14] On the whole, however, these changes in prices are substantially smaller than those after the influx of refugees. While one cannot draw any strong conclusions from this, it might be taken to suggest that the differences in prices between the regions have remained more or less stable in the pre-treatment period.

5 Results

5.1 Regression Estimation

To estimate the causal effect, we consider equation (1), which represents the standard DiD model (Angrist and Pischke, 2009), as our baseline regression. In Table 2 below, we present the estimates for coefficient δ in equation (1), which measures the refugee effect[15]. In all cases,

---

[14]The current Rohingya conflict started in 2016 in the southern part of the Rakhine state (see Anan et al. 2017). By July 2017, Rohingyas were fleeing to other parts of the world, such as Malaysia.

[15]Each column represents a different configuration of set N in equation (1) – we have 49 food items when we consider All food groups, 6 for Cereals, 9 for Proteins and 10 for Vegetables (see Table A6 in the Appendix for more details). We consider a 17 month study period, and set S in equation (1) comprises 5 sub-districts – Ukhia, the treatment, and 4 control regions. Thus each of our estimations is based upon a panel dataset sized $N \times S \times$ length of the study period in months. The number of observations in the panel exactly corresponds to this calculation when it is fully balanced – as is the case for Cereals and Proteins. A lower number of observations depicts an unbalanced panel structure due to missing data – as is the case for Vegetables and All

13

standards errors are initially clustered at the sub-district level, and given the small number of clusters (sub-districts), they are further refined using a wild bootstrap procedure (Davidson & Flachaire, 2008; Liu, 1988)[16].

Table 2: Difference-in-Difference regressions: Treatment August 2017

	All Food Groups	Cereals	Proteins	Vegetables
	Estimation results for equation (1) – the baseline specification			
Impact	0.0798 ***	-0.0259 ***	0.0719 ***	0.3633 ***
Trend	Month-Year FE	Month-Year FE	Month-Year FE	Month-Year FE
Control Subdistricts	Best	Best	Best	Best
Pre-treatment period	Dec/16 - Jul/17	Dec/16 - Jul/17	Dec/16 - Jul/17	Dec/16 - Jul/17
Post-treatment period	Aug/17 - Apr/18	Aug/17 - Apr/18	Aug/17 - Apr/18	Aug/17 - Apr/18
Within R2	0.051	0.250	0.086	0.291
Obs.	4077	510	765	796

Notes: Wild bootstrap p-value: * <0.10; **<0.05; ***<0.001. Best control refers to Boalkhali, Chandanaish, Pekua, Mirsharai.

Table 2 shows a statistically significant increase in the prices of all food, protein, and vegetables in the refugee settled regions (treatment region) compared to the control region. Our baseline results with flexible time trends indicate that overall food prices in the treatment region increased by 8 percent; protein increased by 7.2 percent and vegetables increased by 36.3 percent since the influx. These are substantial increases in prices which is corroborated by news articles such as Sattar (2019), which highlight the increase in prices, particularly the sharp jump in vegetable prices.

However, when it comes to cereals, we find that there has been a 2.6 percent statistically significant decrease in prices. This decrease is mainly arising from the decrease in the price of low-quality rice. Without low-quality rice in our calculations, the impact of the influx on cereal prices becomes insignificant. In a later section, we shall attribute this to significant food-aid that came into the region.

---

food groups.

[16]In this procedure, the bootstrap sample of log-prices is generated using the estimated coefficients and residuals, denoted as $\hat{\epsilon}_{ist}$, obtained from the original model specification, with an added random error term $\hat{\epsilon}_{ist}\nu_{ist}$. Throughout our empirical analysis, ν_{ist} is a random variable with zero mean and unity variance, independently drawn for each sub-district – the cluster level in the initial estimation. Following usual empirical practice, regularly applied due to consistently proven adequacy through Monte-Carlo methods (see Davidson & Flachaire, 2008), we apply a parametric approach allowing ν_{ist} to follow a standard Gamma distribution. In all cases, our bootstrap samples consist of 5000 replications of the log-prices, which are used to compute wild-bootstrapped standard errors.

5.2 Event Study

In this section, we undertake an event study to understand the patterns of the prices changes over the various months. Through this, we also establish the common trends more accurately for the three food groups of cereals, protein and vegetables, and all food items. The event study plot depicts the treatment effect at each point of time relative to a based period. In Figure 3 below, the coefficients of the price difference for each month are plotted along with their 95 percent confidence intervals.[17]

Figure 3: Event study plot: December 2016- April 2018

● Estimated Coefficient

---
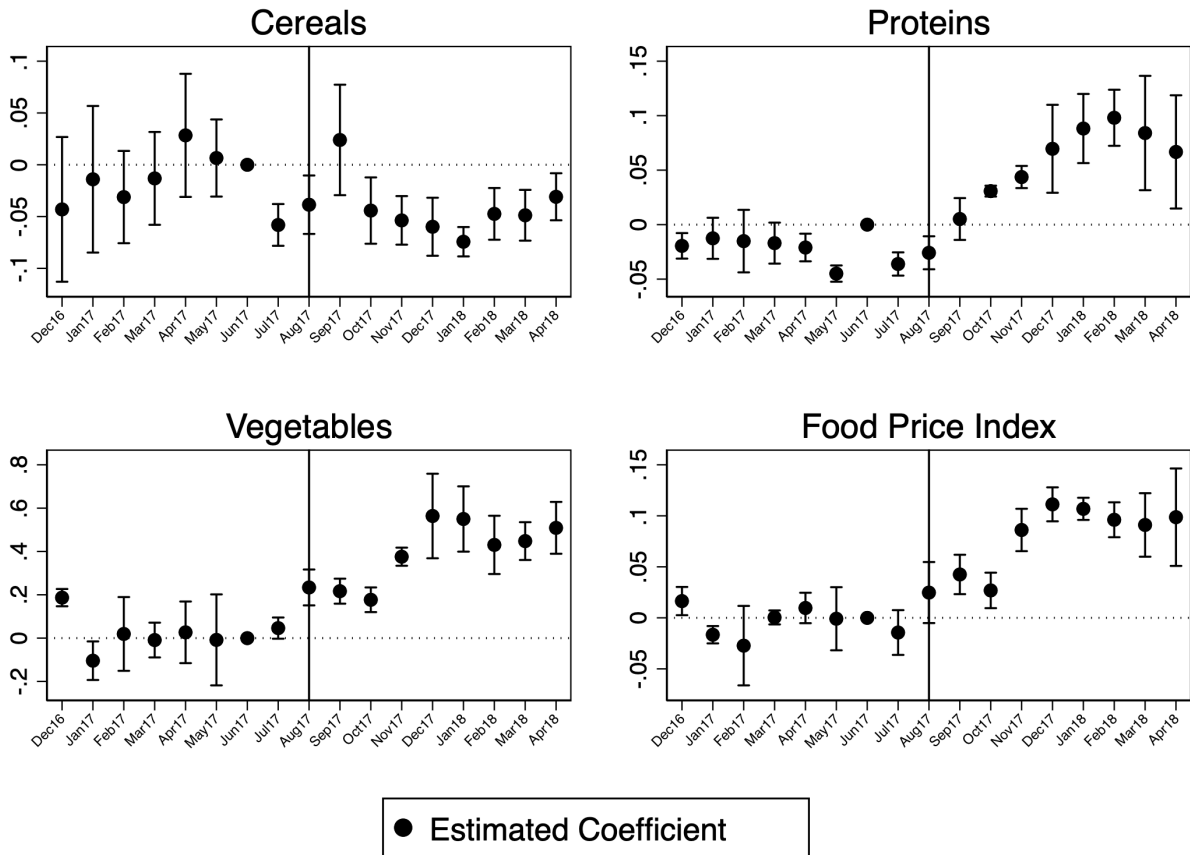
[17]We estimate an equation that is similar to our baseline specification (1). However, instead of the interaction between the treatment sub-district, D_s, and post-treatment dummies, we include interactions between D_s and time dummies associated with all possible leads and lags with respect to the treatment occurrence in August 2017 (see Autor, 2003). The equation we estimate is: $ln(p_{ist}) = \alpha + \sum_{i \in N} \beta_i I_i + \sum_{s \in S} \gamma_s I_s + \sum_{t=t_0}^{t_f} \theta_t(D_s \times I_t) + \sum_{t=t_0}^{t_f} \lambda_t I_t + u_{ist}$. In Table A4, we show the estimates of θ_t for different food groups - i.e. different definitions of set N, with Ukhia taken as the treatment sub-district, and June 2017 taken as the reference time period. We choose this reference because it is the period where prices are the closest in treatment and control groups (see Fig. 2). These estimations consider clustered standard errors by sub-district, which have been refined with a wild bootstrap procedure.

A solid vertical line represents the event date of August 2017. First, the patterns displayed in Figure 3, mirror what we found in the common trends in Figure 2. For protein, vegetables, and overall food price, we see an increase in prices post-August 2017 in the treatment region of Ukhia relative to the control region. However, for cereal prices, we observe a decline in the treatment region after the influx of refugees. This is also detected in our regression estimate in Table 2, where cereals show a decrease in prices. Second, we observe sharper changes in prices a few months down the line from the event date. For instance, although we find that overall food price indices increased right after August 2017, the coefficients display a sharper increase around November 2017. This is because, as shown in Table 1, Rohingyas continued to arrive in Ukhia during that time creating significant pressure on prices. September and October 2017 taken together roughly account for two-thirds of the post-August inflow of refugees. Third, and quite importantly, the lead coefficients, i.e. those before August 2017, are essentially zero for most months, thus broadly validating the common trends assumption.

6   Robustness Checks

To check for the robustness of our results above, we use an array of alternative specifications with different treatment dates, time trends, and samples, along with extended treatment and control regions. We also looked at the impact of seasonality and spillover effects. Their results are reported below.

6.1   Sub-district Specific Time Effects

Our baseline equation (1) specifies identical, common pre-treatment trends for both treatment and control sub-districts. Hence, our preferred specification relies on the pre-treatment parallel trends assumption, for which we presented compelling evidence. However, given that we have multiple sub-districts as the control group, which has been chosen based on a broad set of indicators, there is a possibility that the matching between the treatment and control group is not perfect. Hence, any significant price changes captured through DiD could be due to differences in the natural supply and demand pressures for the food items between the sub-districts rather than the actual event of refugee inflow (see Ulrick and Sacher, 2015). Thus, to check for robustness of our results from equation (1), we also estimate an equation that accommodates for sub-district time effects by including an interaction between I_t and I_s to

activate sub-district and time-varying coefficients denoted by $\tilde{\lambda}_{st}$ as follows[18]:

$$ln(p_{ist}) = \alpha + \sum_{i \in N} \beta_i I_i + \delta(D_s \times T_t) + \sum_{s \in S} \sum_{t=t_0}^{t_f - 1} \tilde{\lambda}_{st}(I_t \times I_s) + \tilde{\epsilon}_{ist} \tag{2}$$

The results from estimating this equation for the various food groups and all food items is presented in the table below.

Table 3: Difference-in-Difference regressions: Sub-district specific time trend

	All Food Groups	Cereals	Proteins	Vegetables
	Estimation results for equation (2)			
Impact	0.1319 ***	-0.0739 ***	0.1514 ***	0.4175 ***
Trend	Subd.TE	Subd.TE	Subd.TE	Subd.TE
Control Subdistricts	Best	Best	Best	Best
Pre-treatment period	Dec/16 - Jul/17	Dec/16 - Jul/17	Dec/16 - Jul/17	Dec/16 - Jul/17
Post-treatment period	Aug/17 - Apr/18	Aug/17 - Apr/18	Aug/17 - Apr/18	Aug/17 - Apr/18
Within R2	0.062	0.314	0.176	0.352
Obs.	4077	510	765	796

Notes: Wild bootstrap p-value: * <0.10; **<0.05; ***<0.001. Subd.TE = Sub-district specific time effect. Best control refers to Boalkhali, Chandanaish, Pekua, Mirsharai.

The estimates from equation (2) (see table 3) show similar results to the baseline specification. Sub-district specific time effects are controlling for time-varying changes within each sub-district. Hence, the estimates show the impact of the influx on prices conditional on changes in factors influencing the prices in each sub-district. Thus, an increase in the estimated effect is to be expected under this specification. Indeed, the results are stronger once the sub-district specific trends are considered. Overall, food prices increased by 13.2 percent, the price of protein increased by 15.2 percent, and vegetables by 41.8 percent. Cereal prices, as before declined, but now by a larger 7.4 percent. This consistency across different specifications demonstrates that since August 2017 in Ukhia, food prices have increased substantially.

6.2 Extended Sample

Our baseline analysis was conducted over a smaller set of control sub-districts and a shorter time period of December 2016 to April 2018. Both these were important for the identifying restrictions. In this section, we relax these two constraints, first by including all sub-districts

---

[18]Note that the time period considered for these sub-district specific effects goes from t_0 to $t_f - 1$ to avoid perfect collinearity between the set of sub-district specific trends and term $(D_s \times T_t)$.

for which we have information and next by use of the whole two-year period from July 2016 to June 2018, for which we have collected the data as our sample period. [19]

6.2.1 Extending Control Region

We have collected price information from 14 sub-districts of Cox's Bazar district and Chittagong district. For the Cox's Bazar we have information on the following sub-districts: Chakaria, Cox's Bazar Sadar, Maheshkhali, Pekua, and Ramu. For the Chittagong district, the sub-districts in our data set are as follows: Anowara, Banshkhali, Boalkhali, Chandanaish, Hathazari, Lohagora, Mirsharai, Patiya, Satkania. In the table below we run our baseline specification model, but with these 14 sub-districts being the control region.

Table 4: Difference-in-Difference regressions: All sub-districts (except for Teknaf) as control for Ukhia)

	All	Cereals	Proteins	Vegetables
Impact	0.0721 *	-0.0122	0.0606 **	0.3624 ***
Trend	Month-Year FE	Month-Year FE	Month-Year FE	Month-Year FE
Control Subdistricts	All	All	All	All
Pre-treatment period	Dec/16-Jul/17	Dec/16-Jul/17	Dec/16-Jul/17	Dec/16-Jul/17
Post-treatment period	Aug/17-Apr/18	Aug/17-Apr/18	Aug/17-Apr/18	Aug/17-Apr/18
Within R2	0.045	0.237	0.055	0.232
Obs.	12080	1530	2295	2426

Notes: Wild bootstrap p-value: * <0.10; **<0.05; ***<0.001. All control set refers to the inclusion of 14 sub-districts (except for Teknaf) as the control set for Ukhia.

The results with the expanded control region demonstrate that overall food prices increased by 7.2 percent, protein prices increased by 6 percent, and vegetable prices increased by 36.2 percent in the treatment region of Ukhia. Even with an expanded control region, the broad results of our analysis hold. We find a significant increase in food prices in the treatment region where refugees settled, compared to the control region. Interestingly, in contrast to the results under the *best* control region, the cereals coefficient is now insignificant. To rule out the possibility of this result arising from the spillover effects of refugees into neighbouring sub-districts, we run the same analysis as before but exclude from our control region two sub-districts, Ramu and Cox's Bazar Sadar, which are nearest to Ukhia (see Appendix B, Table

---

[19]Note that in Appendix A, Table A1 we show that food expenditure in Chittagong and Cox's Bazar sub-districts before the influx in 2016 were very similar in terms of food expenditure. This gives us some confidence that at least from the demand side the prices would be very similar in the sub-districts of Chittagong and Cox's Bazar. Hence, we can extend our control sample to include a wider set of sub-districts from both Chittagong and Cox's Bazar.

B1). The broad results are similar to what we find here in Table 5, with cereals still statistically insignificant. However, the lack of increase in cereal prices could still be indicative of downward pressure on prices due to direct food aid, but the effect not strong enough to reduce the prices significantly.

6.2.2 Extended Time and Control region

In this section, we included the full time period. This gives us 13 months pre-treatment period and 11 months post-treatment. All the other aspects of the analysis remain the same; in particular, the treatment region is Ukhia and the control region constitutes the 14 sub-districts. The results are presented in Table 5.[20]

Table 5: Difference-in-Difference regressions: All sub-districts (except for Teknaf) as control for Ukhia) – Full Period

	All	Cereals	Proteins	Vegetables
Impact	0.0911 **	0.0078	0.0618 **	0.4027 ***
Trend	Month-Year FE	Month-Year FE	Month-Year FE	Month-Year FE
Control Subdistrict set	All	All	All	All
Pre-treatment period	Jul/16-Jul/17	Jul/16-Jul/17	Jul/16-Jul/17	Jul/16-Jul/17
Post-treatment period	Aug/17-Jun/18	Aug/17-Jun/18	Aug/17-Jun/18	Aug/17-Jun/18
Within R2	0.040	0.284	0.105	0.210
Obs.	17075	2160	3240	3439

Notes: Wild bootstrap p-value: * <0.10; **<0.05; ***<0.001.

The estimation results show that when the entire sample period is considered, overall food prices in the treatment region increased by 10 percent, protein prices increased by 7.4 percent, vegetable prices increased by 38.5 percent after the refugee influx in August 2017. Interestingly, there is no decrease in cereal prices over the extended period, since the change in cereal prices is insignificant. This is, to an extent, the result of the variation in cereal prices over the extended period. The decrease in cereal prices that followed the sharp rise in prices in the first couple of months of the post-treatment period begins to reverse towards the end of the sample period. On the whole, the analysis over the longer time period supports our broad hypothesis that the prices of food items increased in Ukhia since the Rohingya influx of August 2017.

---

[20]Thus, we have the same number of items in each food group and 5 sub-districts. The length of the time period is now 23 months, which increases the number of observations relative to the previous specifications

6.3 Extended Treatment Region

We consider Teknaf, the other sub-district where 20 percent of the refugees settled, as a second treatment region for our final robustness check. Here, we have chosen Teknaf as a separate treatment region. The total number of refugees settled in Ukhia during our study period is around 560,000, which is close to three times the existing population of Ukhia (see discussion in Section 2). On the other hand, for Teknaf, which has a population of around 350,000, the August 2017 influx led to the arrival of around 140,000 refugees by the end of April 2018. Thus, both in terms of the absolute and relative size of the influx, Ukhia is distinct from Teknaf.

For this analysis we use the extended control region of 14 sub-districts and the time period from December 2016 to April 2018. We estimate the following equation:

$$ln(p_{ist}) = \alpha + \sum_{i \in N} \beta_i I_i + \sum_{s \in S} \gamma_s I_s + \delta^{UK}(D^{UK} \times P_t) + \delta^{TE}(D^{TE} \times P_t) + \sum_{t=t_0}^{t_f} \lambda_t I_t + u_{irt} \quad (3)$$

where D^{UK} and D^{TE} dummy variables for Ukhia and Teknaf, respectively, and δ^{UK} and δ^{TE} represent the impact of the refugee influx in Ukhia and Teknaf, respectively. All other elements in equation (3) are defined in the same way as in our baseline equation (1). The results from estimating equation (3) are presented in Table 6.[21]

Table 6: Difference-in-Difference regressions: Treatment effects on Ukhia & Teknaf

	All Food Groups	Cereals	Proteins	Vegetables
	Baseline specification with extended treatment region			
Impact Ukhia	0.0911 ***	0.0078	0.0618 ***	0.4021 ***
Impact Teknaf	0.0142 **	-0.0197 ***	0.0140 **	-0.0195
Trend	Month-Year FE	Month-Year FE	Month-Year FE	Month-Year FE
Control Subdistricts	All	All	All	All
Pre-treatment period	Jul/16 - Jul/17	Jul/16 - Jul/17	Jul/16 - Jul/17	Jul/16 - Jul/17
Post-treatment period	Aug/17 - Jun/18	Aug/17 - Jun/18	Aug/17 - Jun/18	Aug/17 - Jun/18
Within R2	0.040	0.279	0.104	0.210
Obs.	18178	2304	3456	3654

Notes: Wild bootstrap p-value: * <0.10; **<0.05; ***<0.001.

The impact of the refugee influx in the prices in Ukhia is similar to what we have seen

---

[21]The number of food items in each food group is the same as in previous specifications, and the length of the considered period is 17 months – as in the baseline specification. In this case, 6 sub-districts are included in the regressions – 2 as treatment and 4 as controls, explaining the size of the panel datasets.

before, with overall food prices increasing by 8 percent. Protein and vegetables increased by around 7 percent and 36 percent respectively, while price of cereals decreased by 2.6 percent. On the other hand, in Teknaf overall food prices increased by around 1.4 percent. Protein prices in Teknaf also increased by a similar amount. We also find a statistically significant decrease in the price of cereals by around 2 percent. Interestingly, vegetable prices in Teknaf did not register any significant change.

The broad pattern that emerges from the two-arm treatment is that the change in prices in Teknaf is smaller relative to Ukhia for all food groups. It reflects the relatively smaller increase in the population of Teknaf due to the refugee influx. Compared to an increase of population in Ukhia by around 300 percent, Teknaf saw a smaller increase of around 50 percent. Hence, the sudden increase in demand for food items in Teknaf was not as strong as in Ukhia. Further, it is quite likely that Teknaf was better able to meet the increased demand, being a significantly stronger hub of business and commerce compared to Ukhia (UNDP, 2018, p.52).

6.4 Seasonality

Given the monthly prices in our data, part of the price effect in our results may be due to seasonal price fluctuations. In the absence of specific seasonal weights in our data, we control for seasonality by including monthly dummies (Wooldridge, 2020). We consider the full sample, from July 2016 to June 2018, with Ukhia as the treatment region and all the sub-districts other than Teknaf as our control region. In this specification, we include a linear trend. The results are presented in Table 7.

Table 7: Difference-in-Difference regressions: Seasonal effects

	All Food Groups	Cereals	Proteins	Vegetables
Impact	0.0879***	0.0027	0.0610***	0.3975***
Trend type	Linear	Linear	Linear	Linear
Seasonal Dummies	Monthly	Monthly	Monthly	Monthly
Control Subdistricts	All	All	All	All
Pre-treatment period	Jul/16 - Jul/17	Jul/16 - Jul/17	Jul/16 - Jul/17	Jul/16 - Jul/17
Post-treatment period	Aug/17 - Jun/18	Aug/17 - Jun/18	Aug/17 - Jun/18	Aug/17 - Jun/18
Within R2	0.036	0.212	0.093	0.197
Observations	17075	2160	3240	3439

Notes: Wild bootstrap p-value: * <0.10; **<0.05; ***<0.001.

The overall food prices increased by 8.8 percent, protein prices increased by 6.1 percent, and

vegetable prices increased by 39.7 percent. As seen before, when we consider the full sample, cereals do not exhibit any statistically significant price increase. However, the broad pattern of the results demonstrates that even after controlling for seasonality, the prices in the treatment region of Ukhia had increased relative to the control regions after the influx of Rohingyas.

7 Impact of Food Aid on Prices

In this section, we examine the impact of food aid-related items on the prices in the treatment region. In a study on the impact of refugees from Burundi and Rwanda into Tanzania in 1993-1998, Alix-Garcia and Saah (2010) find that aid-related products supplied by aid organisations can compensate for the increased demand for those products if these are brought from outside the region. In the context of the Rohingya influx of August 2017, the World Food Programme (WFP) was the principal agency responsible for food aid. In the initial months, given the scale of the influx, they had borrowed directly from the Bangladesh Government reserves.[22] Thus, extra supplies were brought from outside the treatment region.[23] The main food aid in the initial months consisted of low-quality rice, red lentils, and soybean oil (packeted).[24]

We undertake two different ways of demonstrating the impact of food aid. First, we show how for each of the food aid item, the prices changed in Ukhia, relative to the control region, after August 2017. This is presented in Table 8 below.

Table 8: Difference-in-Difference regressions: Aid-related food items

	Aid-related food group	Low quality rice	Red lentils	Packeted soybean oil
Impact	-0.0998 **	-0.1654 **	-0.1439 **	0.0100 *
Trend	Month-Year FE	Month-Year FE	Month-Year FE	Month-Year FE
Control Subdistricts	Best	Best	Best	Best
Pre-treatment period	Dec/16-Jul/17	Dec/16-Jul/17	Dec/16-Jul/17	Dec/16-Jul/17
Post-treatment period	Aug/17 - Apr/18	Aug/17 - Apr/18	Aug/17 - Apr/18	Aug/17 - Apr/18
Within R2	0.176	0.674	0.779	0.799
Obs.	255	85	85	85

Notes: Wild bootstrap p-value: * <0.10; **<0.05; ***<0.001. Best control refers to Boalkhali, Chandanaish, Pekua, Mirsharai.

The first column contains all the three food aid items together. The number of observations

---

[22] We are highly grateful to Md. Shamsud Douza, Additional Refugee Relief and Repatriation Commissioner (Deputy Secretary), RRRC Office, Cox's Bazar, for this information and extensive discussion around food-aid to Rohingyas in the initial months.

[23] As the situation stabilised, more local partners were involved. However, these local partners imported the products from outside the region.

[24] As the refugee flow stabilised, e-vouchers, which could be used in participating retail stores, were slowly introduced.

for each food item is 85 (which arises from 5 regions over 17 months), taking the total to 255. It shows that for food-aid items, on the whole, prices decreased by around 10 percent. For low-quality rice and red lentils, the prices in Ukhia reduced by 16 percent and 14 percent respectively. On the other hand, packeted soybean oil prices increased just by one percent. From our data, we know that packeted soybean oil is among the more expensive oils, and although local (Bangladesh-based) brands were provided as part of food-aid, we expect the demand for packeted soybean oil to be inelastic overall. Thus, in the face of increased demand, the price of packeted soybean oil increased. However, if we expand the sample period and the control region of the analysis, then we do not find any increase in the price of packeted soybean oil (see Appendix B, Table B2), although the rest of the results of the expanded sample is consistent with our findings in Table 8.

Our second method of testing for the efficacy of food-aid is to compare the influx effect on overall food prices with and without food aid items. We also undertake the same process for all the cereals together, with and without low-quality rice. The results are presented in the table below.

Table 9: Difference-in-Difference regressions: Contrast of results with and without aid-related food items

	All Food Items		Cereals	
	Aid-related items included		Aid-related items included	
	Yes	No	Yes	No
Impact	0.0798 ***	0.0919 ***	-0.0259 **	0.0020
Trend	Month-Year FE	Month-Year FE	Month-Year FE	Month-Year FE
Control Subdistricts	Best	Best	Best	Best
Pre-treatment period	Dec/16 - Jul/17	Dec/16 - Jul/17	Dec/16 - Jul/17	Dec/16 - Jul/17
Post-treatment period	Aug/17 - Apr/18	Aug/17 - Apr/18	Aug/17 - Apr/18	Aug/17 - Apr/18
Within R2	0.051	0.057	0.250	0.241
Obs.	4077	3822	510	425

Notes: Wild bootstrap p-value: * <0.10; **<0.05; ***<0.001. Best control refers to Boalkhali, Chandanaish, Pekua, Mirsharai.

From Table 9, two broad results can be highlighted. First, the increase in prices for all food items is higher if we do not include food-aid items. Overall prices in Ukhia increased by 9.2 percent without food aid items, whereas with food-aid items included they increased by a smaller margin of 8 percent. Thus, the decline in the price of low-quality rice and red lentils in our sample has a mitigating impact on the overall food prices. Clearly, food aid has played a role in stemming the increase in food prices. Second, we see a similar pattern for

cereals. With food aid items (low-quality rice) included, cereal prices declined by 2.6 percent. If low-quality rice is excluded from cereals, we see that the refugee effect on cereal prices was statistically insignificant. For additional robustness checks, we also undertake the analysis on an expanded sample (see Appendix B, Table B3). We find a statistically significant increase in cereal prices when aid-related items are not included. The rest of the results from the analysis of the expanded sample are consistent with Table 9.

8   Discussion

Our analysis finds a significant increase in prices after August 2017 in Ukhia relative to the control region. This is not a surprise since survey by Bhatia et al. (2018) shows that refugees incurred debt mainly to buy food, and any additional income earned was intended for buying more food. Hence, Ukhia faced significant demand-side pressure on food prices after the influx. Food groups such as protein and vegetables, which were not supplied through food-aid, saw a substantial increase in their prices. For vegetables, in particular, there is evidence of high consumption from the local populace. According to GNPC (2010), the hosting regions consumed around 236.2-gram vegetables per day, which is the highest among other items except for cereals.[25] Further, there is some evidence to suggest that, despite a reduction in wage income in Ukhia, the refugee influx did not impact household expenditure in Ukhia and Teknaf (UNDP, 2018, p.84). This is perhaps because some households were able to switch to non-labour income through starting small businesses, but also perhaps through the selling of small assets and taking loans (UNDP, 2018, p.110). Thus, the continuing demand from the local population, along with the increased demand from the refugee population, led to a large increase in demand.

The increased demand for food, and vegetables, in particular, were not met by increased supply. One plausible reason may be that there has been a reduction in arable land due to refugee activities. Between August 2017 and March 2018, at least 100 hectares of cropland in Teknaf and Ukhia were damaged by refugee activities, and 76 hectares of arable land were occupied by refugee settlements and humanitarian agencies. Around 5000 acres of land in Ukhia has been rendered useless because of sandy soil flowing down from the mountain slopes,

---

[25]Among the other items, the consumption was as follows: red meat 18.7 grams per day, legumes and pulses, 63.7 grams per day, milk 32.1 grams per day, fruits 63.3 grams per day, sugar was 38 grams per day, and seafood was 22.5 grams per day.

which are being used for refugee housing purposes (UNDP, 2018, p. 84-85). In addition to this, as mentioned earlier, Rohingyas are not permitted to work in the local economy, and their economic activities are mostly restricted within the refugee camp areas. Therefore, any strong dampening effect on prices working through the labour market channels, as observed in other contexts (Balkan and Tumen, 2016), is missing. Yet, there is emerging evidence that wages, especially for jobs such as agricultural labourers where Rohingyas might be involved, decreased (UNDP, 2018, p.83-84). We believe that over the long-run these wage reductions will be reflected in the prices. However, given that this analysis focuses mainly on the nine months in the post-influx period, our data is not picking up any such effect.

What is surprising is the differences in food prices between Ukhia and Teknaf and the neighbouring sub-districts. Note that the increase in prices in Ukhia is also observed under a broader set of control region that includes neighbouring sub-districts (see Table 5 in Section 6.2). We interpret the existence of price differences in food items as evidence of a lack of arbitrage taking place in these markets. Given that they are neighbouring sub-districts, in the presence of arbitrage, where supply could be moved easily between the sub-districts, we would have expected prices of different food groups to be similar, particularly between Ukhia and Teknaf. But, as our analysis demonstrates, food prices in Teknaf are substantially lower than in Ukhia. One plausible explanation for this is that small and medium traders, who constitute majority of the traders, found it difficult to move products between various markets quickly due to lack of transportation and adequate storage facilities. In the Ukhia city bazaar, 100 percent of the traders surveyed by the WFP Report (2017, p.18) mentioned the cost of hiring transport was a reason for supply getting affected, and 56 percent complained about limited storage facilities.

One mitigating effect in reducing food prices has been food aid. Those items which were provided through food aid had a favourable impact on food prices. The amount of direct food aid given to the refugee families is shown in the table below.

Table 10: Direct Food-Aid Provided to Rohingya Refugee Households in Bangladesh

Items	Monthly Food Aid to Households		
	1-3 members	4-7 members	8+ members
Rice (Cereal) Kg	30	60	120
Lentil (Pulse) Kg	9	18	27
Soybean (Oil) Litre	3	6	12

Source: RRRC (2018), Ministry of Disaster Management and Relief, Bangladesh

Indeed, refugee households are given an adequate amount of basic rations. The extra demand created by the increase in the refugee population is being met by the increased supply of these items, which are being mainly procured from outside the region. The reduction in the open market prices of rice and lentils in Ukhia essentially tells us that supply of these items have increased relative to demand in the region. It is plausible that local traders have brought in an excess supply of rice and lentils in Ukhia in anticipation of the increase in demand. However, given that we did not find evidence that the refugee influx was anticipated, and the lack of adequate storage facilities that traders highlighted in the WFP Report (2017), this seems very unlikely.

The alternative explanation is that some of the aid-provided rice landed up in the open market, increasing the supply. There are several corroborating evidence from news articles and reports on Rohingyas selling their food-aid items in the nearby markets. For instance, Alsaffin (2018) reports that, "As part of their work, aid agencies deliver food essentials, such as rice, lentils and vegetable oil, to the camps' residents, some of whom, in turn, hawk the surplus items at black markets for a fraction of the price found in local markets, affecting market stability."Focus group discussions of various stakeholders, including Rohingyas, have revealed that rice, lentils, and oil were the most traded items by the Rohingyas leading to lower prices of those products in the local markets (see UNDP, 2018, p.71).

9   Conclusion

Using data from various local government administrative offices in Bangladesh, we find strong evidence that the sudden influx of Rohingyas from Myanmar to the Cox's Bazar area of

Bangladesh in August 2017 had led to an increase in the food prices in the Ukhia sub-district. Based on our baseline regression, overall food prices in the treatment region increased between 8 to 13 percent, and we observe substantial increases in prices in specific food groups too. To some extent, the food aid has been effective in mitigating the price rise. We find a significant increase in prices happened in food groups not covered through food-aid. However, note that our analysis here mainly focuses on food prices in the short run (nine months) after the initial influx of refugees. The long-run impact of the influx on prices might be very different, as shown in other contexts (Alix-Garcia et al. 2018, Maystadt and Verwimp 2014).

This increase in food prices is not a surprise since there has been a significant increase in demand. Additionally, mitigating factors, particularly through the labour market are missing. Host communities in the region may not have many reserves to weather the food prices shocks from this influx of refugees since they are themselves poor with 37.5 percent of people living below the poverty line and 10.7 percent of people suffering from acute malnutrition (FSIN 2018). Thus, an increase in food prices would have a detrimental impact on the welfare of the host region population in the short run, which is bound to increase resentment against refugees in host communities. Under such conditions, the task of hosting and integrating the refugees will become politically difficult unless effective policies to mitigate the economic impacts on host communities are undertaken.

References.

Akgunduz, Y. E., Van Den Berg, M., and Hassink, W. (2018),'The Impact of the Syrian Refugee Crisis on Firm Entry and Performance in Turkey', World Bank Economic Review, 32(1), 19-40.

Alam, J. (2021), The Status and Rights of the Rohingya as Refugees under International Refugee Law: Challenges for a Durable Solution, Journal of Immigrant and Refugee Studies, 19(2), 128-141, DOI: 10.1080/15562948.2020.1746872

Alam, M. (2018), How the Rohingya Crisis is Affecting Bangladesh and Why it Matters? Washington Post, February 12, 2018.

Alix-Garcia, J.and Saah, D. (2010), 'The Effects of Refugee Inflows in Host Communities: Evidence from Tanzania', World Bank Economic Review, 24(1), 148-170.

Alix-Garcia, J., Bartlett, A., and Saah, D. (2012) 'Displaced Populations, Humanitarian Assistance and Hosts: A Framework for Analyzing Impacts on Semi-urban Households', World Development, 40(2), pp. 373–386.

Alix-Garcia, J., Walker, S., Bartlett, A., Onder, H., and Sanghi, A.(2018), 'Do Refugee Camps Help or Hurt Hosts? The case of Kakuma, Kenya', Journal of Development Economics, 130, 66-83.

Alsaffin, L. (2018), Price Hikes and Jobs: How NGO's Affect the Economy in Cox's Bazar, Aljazeera News Feature, https://www.aljazeera.com/indepth/features/price-hikes-jobs-ngos-impact-economy-cox-bazar-180810090248437.html

Angrist, J., and Pischke, J-S. (2009), Mostly Harmless Econometrics: An Empiricist's Companion, Princeton University Press, Princeton.

Annan, K., Salame, G., Assum, L. van den, Mra, U. W., Lwin, U. A.,Shwe, T. H., Thida, M., Tint, D. S. K., and Lay, U. K. M. (2017), 'Towards a Peaceful, Fair and Prosperous Future for the People of Rakhine: Advisory Commission Final Report on Rakhine State', Available at: http://www.rakhinecommission.org/app/uploads/2017/08/FinalReport Eng.pdf (Accessed: 24 August 2018).

Autor, D. H. (2003). Outsourcing at will: The contribution of unjust dismissal doctrine to the growth of employment outsourcing. Journal of Labor Economics, 21(1), pp. 1-42.

Balkan, B. and Tumen, S. (2016) 'Immigration and Prices: Quasi-Experimental Evidence From Syrian Refugees in Turkey', Journal of Population Economics, 29(3), pp. 657–686.

Bangladesh Bank (2008), Inflation in Bangladesh: Does the Changing Consumption Pattern Affect Its Measurement? Policy Analysis Unit.

BBS (2013a), District Statistics 2011 - Chittagong, Bangladesh Bureau of Statistics, Dhaka.

BBS (2013b), District Statistics 2011 - Cox's Bazar, Bangladesh Bureau of Statistics, Dhaka.

Bhatia, A., Mahmud, A., Fuller, A., Shin, R., Morshed, K., Rahman, A., Shatil, T., Sultana, M., Balsari, S., and Leaning, J. (2018), 'A Rapid NeedsAssessment Among the Rohingya and Host Communities in Cox's Bazar, Bangladesh: A Randomized Survey', OSF Preprints. Open Science Framework, p. 21.

Bowden, M. (2019), The current context to the Rohingya crisis in Bangladesh, Humanitarian Practice Network. Avaialble at: https://odihpn.org/magazine/current-context-rohingya-crisis-bangladesh

Card, D. (1990) 'The Impact of the Mariel Boatlift on the Miami Labor Market', Industrial and Labor Relations Review, 43(2), p. 245.

Chambers, R. (1986) 'Hidden Losers? The Impact of Rural Refugees and Refugee Programs on Poorer Hosts', International Migration Review, 20(74), pp. 245–263.

Davidson, R., Flachaire, E. (2008). The wild bootstrap, tamed at last. Journal of Econometrics, 146(1), pp. 162–169.

Filipski, M., Tiburcio, E., Dorosh, P., Hoddinott, J., Rosenbach, G. (2019), 'Modelling the Economic Impact of the Rohingya Influx in Southern Bangladesh', International Food Policy Research Institute (IFPRI), Discussion Paper 01862

FSIN (2018), Global Report on Food Crises 2018, Food Security Information Network, Rome. Available at: https://www.wfp.org/publications/global-report-food-crises-2018 (Accessed: January 2020)

GNPC (2010) Global Dietary Database, Global Nutrition and Policy Consortium. Available at: https://www.globaldietarydatabase.org/dietary-data-by-country.html (Accessed: 27 August 2018).

Holland, M. S. F., Fronti, S., March, H. (2002) '10 Years for the Rohingya Refugees in Bangladesh: Past , Present and Future', Médecins Sans Frontières-Holland, (March), pp. 1–45. Available at: https://www.msf.org/ten-years-rohingya-refugeespast-present-and-future-report-summary

ICRG (2017), 'Situation Report: Rohingya Refugee Crisis, Cox's Bazar', Inter Sector Coordination Group, December.

IPUMS (2020) Minnesota Population Center. Integrated Public Use Microdata Series, International: Version 7.3, Bangladesh Population and Housing Census, 2011 . Minneapolis, MN. https://doi.org/10.18128/D020.V7.2

Lach, S. (2007) 'Immigration and Prices', Journal of Political Economy, 115(4), pp. 548–587.

Liu, R. Y. (1988). Bootstrap procedures under some non-iid models. Annals of Statistics, 16(4), pp. 1696–1708.

Mahmood, S. S., Wroe, E., Fuller, A., and Leaning, J. (2017) 'The Rohingya People of Myanmar: Health, Human Rights, and Identity', The Lancet, pp. 1841–1850.

Maystadt, J.-F. and Verwimp, P. (2014) 'Winners and Losers among a Refugee-Hosting Population', Economic Development and Cultural Change, 62(4), pp. 769–809.

RRRC (2018) Report on the Activities of Humanitarian Assistance to the Rohingya Refugee for the year 2017-18. Cox's Bazar.

Ruiz, I. and Vargas-Silva, C. (2017) 'The Consequences of Forced Migration for Host Communities in Africa', Revue d' Economie du Developement, 25(3), p. 135.

Shakeeb, A. (2017) Rohingya crisis explained in maps, Al Jazeera. Available at: shorturl.at/lrAD1 (Accessed: 15 August 2018).

Tumen, S. (2015) The Use of Natural Experiments in Migration Research. IZA World of Labor: 191 doi: 10.15185/izawol.191

Tumen, S. (2016) 'The Economic Impact of Syrian Refugees on Host Countries: Quasi-Experimental Evidence from Turkey', American Economic Review, 106(5), pp. 456–460.

Ulrick, S. W. and Sacher, S. B. (2015). 'Inferring Anti-Competitive Price Effects from Difference-in-Difference Analysis: A Caveat', Journal of Competition Law Economics, 11(4), 999–1012.

UN (2018), Joint Response Plan for the Rohinya Humanitarian Crisis, Inter-Sector Coordination Group and Strategic Executive Group, United Nations. Available at: www.humanitarianresponse.info/en/operations/bangladesh

UNDP (2018), Impacts of the Rohingya Refugee Influx on Host Communities, United Nations Development Programme, Bangladesh.

UNHRC (2018), Report of the Independent International Fact-Finding Mission on Myanmar, UN Human Rights Council.

UNPO (2018), Chittagong Hill Tracts. Washington. Available at: http://unpo.org/members/7867 (Accessed: 18 August 2018).

Waseem, M. (2017), 'Taxes, Informality and Income Shifting: Evidence from a Recent Pakistani Tax Reform', Journal of Public Economics, 157, 41-77.

Wooldridge. J. (2020), Introductory Econometrics: A Modern Approach, 7th Edition, Cengage, US.

WFP (2017), Market Assessment in Cox's Bazar – Implications for Market-Based Intervention Targeted towards Rohingya Refugeess and Host Communities, World Food Programme Report.

Zachariadis, M. (2012) 'Immigration and International Prices', Journal of International Economics, 87(2), pp. 298–311.

A Appendix

Figure 4: Balance check of matching variables – Treatment=Ukhia; Control=Boalkhali, Chandanaish, Pekua and Mirsharai
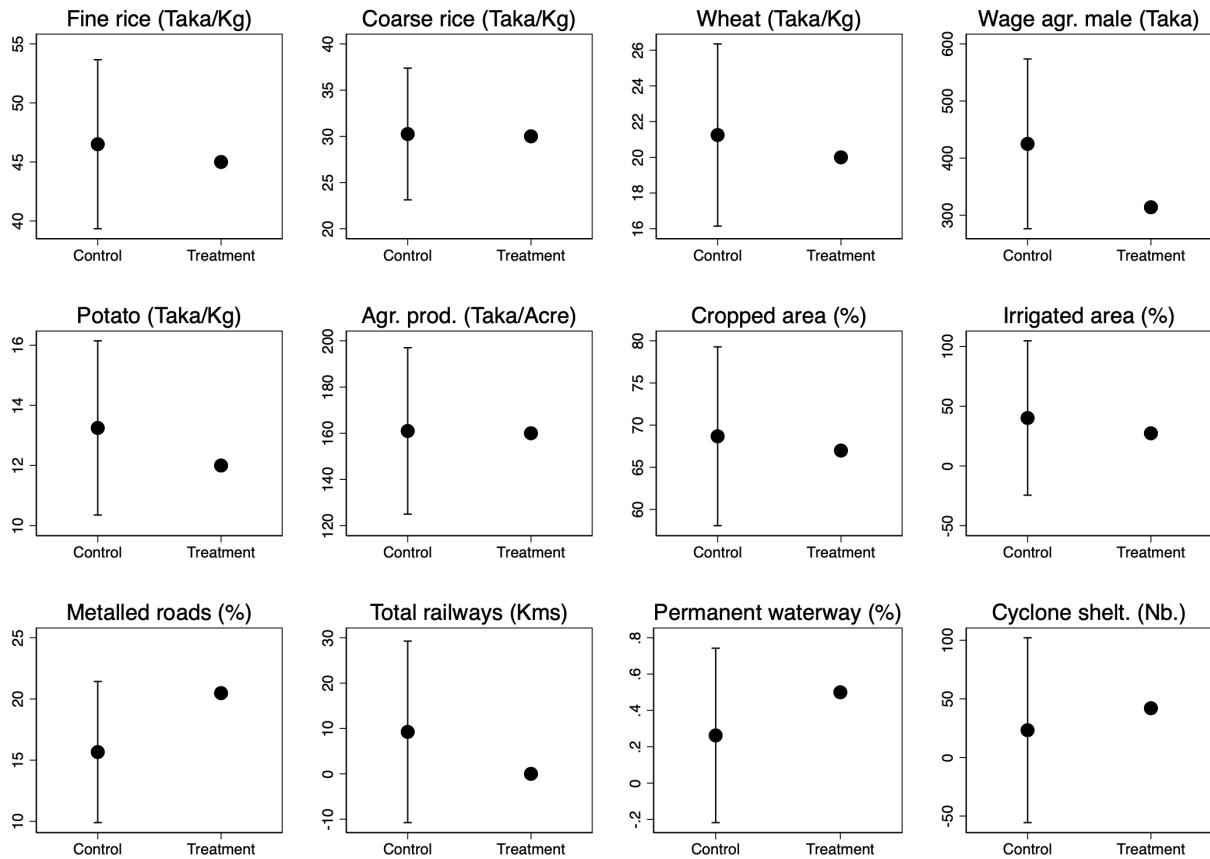
Table A1: Monthly Household Food Expenditure (in Taka) in Chittagong and Cox's Bazar District -2016

	Obs	Mean	Std Err.	Std. Dev.	[95% Conf.	Interval]
Chittagong	720	852.340	11.065	296.907	830.616	874.064
Cox's Bazar	720	858.550	16.401	440.090	826.350	890.750
Diff.		-6.210	19.78		-45.020	32.600
p-value		0.754				

Note: Authors calculation based on Household Expenditure and Income Survey, Bangladesh, 2016.

Table A2: Mahalanobis Distance Rankings (Ukhia – Balanced Variables)

Final rank	Upazilla	Sum	R1	R2	R3	R4	R5
1	**Boalkhali**	**6**	**1**	**2**	**1**	**1**	**1**
2	**Pekua**	**11**	**3**	**1**	**3**	**2**	**2**
3	**Chandanaish**	**15**	**2**	**4**	**2**	**4**	**3**
4	**Mirsharai**	**21**	**5**	**3**	**5**	**3**	**5**
5	Moheshkhali	30	6	9	6	5	4
6	Lohagara	32	8	5	7	6	6
7	Chakaria	33	4	10	4	8	7
8	Hathazari	50	10	11	13	7	9
9	Satkania	52	9	7	9	12	15
10	Ramu	56	11	14	12	9	10
11	Fatikchhari	57	7	21	8	13	8
12	Patiya	58	15	6	14	11	12
13	Raozan	59	13	8	11	14	13
14	Anowara	65	12	13	10	16	14
15	Rangunia	66	14	15	16	10	11
16	Kutubdia	80	17	12	17	17	17
17	Sandwip	88	19	18	20	15	16
18	Banshkhali	91	20	16	19	18	18
19	Chittagong City Corp.	91	16	20	15	21	19
20	Cox's Bazar Sadar	93	18	17	18	19	21
21	Sitakunda	101	21	19	21	20	20

Note: Authors calculation based on BBS (2013)

R1: Daily average wage rate of male labour in agriculture (in taka); Fine rice price (Miniket variety) per kg (in taka); Coarse rice price per kg (in taka); Wheat price per kg (in taka); Potato price per kg (in taka); Agricultural productivity per acre of land; Percentage of cropped area (cropped area/operated area); Percentage of irrigated area (irrigated area/operated area); Percentage of metalled road (metalled road/total road); Railways (broad gauge, meter gauge and dual guage) (kms); Percentage of permanent water ways (permanent waterways/total waterway); Number of cyclone shelters.

R2: R1+ Number of flood shelters; Number of food warehouses; Population Density per square km.

R3: R1 + Number of flood shelters.

R4: R1+ Number of food warehouse.

R5: R1+ Density per square km.

Table A3: List of Food Items

Cereals	Pulses	Protein	Vegetables	Oil	Spices	Others
Chinigura	Achor	Beef	Aubergine	Mustard	Chilli (Normal)	Milk (Loose)
Flour (Loose)	Split Bengal Gram	Chicken (Farm)	Bitter Gourd	Palm	Chilli (Quality)	Milk (Packet)
Flour (Packet)	Kheshari	Chicken (Organic)	Pointed Gourd	Soybean (Loose)	Garlic (Imported)	Sugar
Miniket	Red Lentil (Good quality)	Chicken (Cockrel)	Yard Long Beans	Soybean (Packet)	Garlic (Local)	
Rice (Medium quality)	Red Lentil (Normal)	Duck Egg	Papaya		Ginger	
Rice (Low quality)	Yellow Lentil	Egg (Farm)	Potato		Green Chilli	
		Egg (Local)	Pumpkin		Onion (Imported)	
		Fish (Pangash)	Spinach (Green)		Onion (Local)	
		Mutton	Spinach (Red)		Salt (Open)	
			Tomato		Salt (Packet)	
					Turmeric	

Source: Office of the District Marketing Officer, Cox's Bazar and Chittagong, Govt. of Bangladesh

Table A4: Event study Regression Estimates: December 2016-April 2018

	All Food Groups	Cereals	Proteins	Vegetables
Treat. X lag(-8)	0.0164	-0.0431	-0.0195*	0.1869***
Treat. X lag(-7)	-0.0165*	-0.014	-0.0125	-0.1043*
Treat. X lag(-6)	-0.0272	-0.0312	-0.0151	0.0193
Treat. X lag(-5)	0.0004	-0.0131	-0.0170	-0.0090
Treat. X lag(-4)	0.0097	0.0284	-0.0210*	0.0267
Treat. X lag(-3)	-0.0009	0.0065	-0.0449***	-0.0082
Treat. X lag(-2)	0.0000	0.0000	0.0000	0.0000
Treat. X lag(-1)	-0.0144	-0.0581**	-0.0361***	0.0462
Treat. X lag(0)	0.0248	-0.0385*	-0.0258*	0.2338**
Treat. X lead(+1)	0.0425*	0.0240	0.0052	0.2167***
Treat. X lead(+2)	0.0269*	-0.0442*	0.0308***	0.1770**
Treat. X lead(+3)	0.0861**	-0.0537**	0.0437***	0.3758***
Treat. X lead(+4)	0.1113***	-0.0598**	0.0696*	0.5638**
Treat. X lead(+5)	0.1068***	-0.0743***	0.0882**	0.5499***
Treat. X lead(+6)	0.0961***	-0.0474**	0.0981***	0.4304**
Treat. X lead(+7)	0.0911**	-0.0488**	0.0841*	0.4479***
Treat. X lead(+8)	0.0987*	-0.0309*	0.0667*	0.5090***
Constant	4.2060***	3.7171***	4.9115***	3.3799***
Trend	Month-Year FE	Month-Year FE	Month-Year FE	Month-Year FE
Control Sub-districts	Best	Best	Best	Best
Pre-treatment period	Dec/16 - Jul/17	Dec/16 - Jul/17	Dec/16 - Jul/17	Dec/16 - Jul/17
Post-treatment period	Aug/17 - Apr/18	Aug/17 - Apr/18	Aug/17 - Apr/18	Aug/17 - Apr/18
Within R2	0.054	0.273	0.123	0.313
Observations	4077	510	765	796

Notes: Wild bootstrap p-value: * <0.10; **<0.05; ***<0.001. Best control refers to Boalkhali, Chandanaish, Pekua, Mirsharai. We use June 2018 as our reference period.

B Appendix

B.1 Spillover Effects

To address the issue of spillover effects we run our regression estimation as in Table 5, in the full time period, except that in the control group we do not consider the sub-districts of Ramu and Cox's Bazar Sadar. These two sub-districts border Ukhia, and despite police check-points there was always a possibility that refugees had moved to these nearby sub-districts.

Table B1: Difference-in-Difference regressions: Spillover Effect

	All	Cereals	Proteins	Vegetables
Impact	0.0896 **	0.0048	0.0628 **	0.3999 ***
Trend	Month-Year FE	Month-Year FE	Month-Year FE	Month-Year FE
Control Subdistricts	Spill	Spill	Spill	Spill
Pre-treatment period	Jul/16-Jul/17	Jul/16-Jul/17	Jul/16-Jul/17	Jul/16-Jul/17
Post-treatment period	Aug/17-Jun/18	Aug/17-Jun/18	Aug/17-Jun/18	Aug/17-Jun/18
Within R2	0.040	0.296	0.105	0.212
Obs.	15973	2016	3024	3224

Notes: Wild bootstrap p-value: * <0.10; **<0.05; ***<0.001. Spill includes all sub-districts except for Teknaf, Ramu and Cox's Bazar Sadar.

Although the results are similar to Table 5 discussed in the paper, as expected, we see that for most food groups, including all food items, the impact of the refugee influx on food prices is stronger when we remove possible spillover effects.

B.2 Impact of Aid

Next, we demonstrate the DiD estimates for aid related items for the full sample.

Table B2: Difference-in-Difference regressions: Aid-related food items

	Aid-related food group	Low quality rice	Red lentils	Packed soybean oil
Impact	-0.1205 *	-0.1598 ***	-0.1858 ***	-0.0158
Trend	Month-Year FE	Month-Year FE	Month-Year FE	Month-Year FE
Control Subdistrict	All	All	All	All
Pre-treatment period	Dec/16 - Jul/17	Dec/16 - Jul/17	Dec/16 - Jul/17	Dec/16 - Jul/17
Post-treatment period	Aug/16 - Apr/18	Aug/16 - Apr/18	Aug/16 - Apr/18	Aug/16 - Apr/18
Within R2	0.089	0.547	0.520	0.370
Obs.	765	255	255	255

Notes: Wild bootstrap p-value: * <0.10; **<0.05; ***<0.001.

Table B3: Difference-in-Difference regressions: Contrast of results with and without aid-related food items

	All Food Items		Cereals	
	Aid-related items included		Aid-related items included	
	Yes	No	Yes	No
Impact	0.0721 ***	0.0850 ***	-0.0122 **	0.0172 ***
Trend	Month-Year FE	Month-Year FE	Month-Year FE	Month-Year FE
Control Subdistrict	All	All	All	All
Pre-treatment period	Dec/16 - Jul/17	Dec/16 - Jul/17	Dec/16 - Jul/17	Dec/16 - Jul/17
Post-treatment period	Aug/16 - Apr/18	Aug/16 - Apr/18	Aug/16 - Apr/18	Aug/16 - Apr/18
Within R2	0.045	0.049	0.237	0.206
Obs.	12080	11315	1530	1275

Notes: Wild bootstrap p-value: * <0.10; **<0.05; ***<0.001.