# The Effects of Rohingya Refugees from Myanmar on Low-Skilled Wages in the Chittagong Division of Bangladesh

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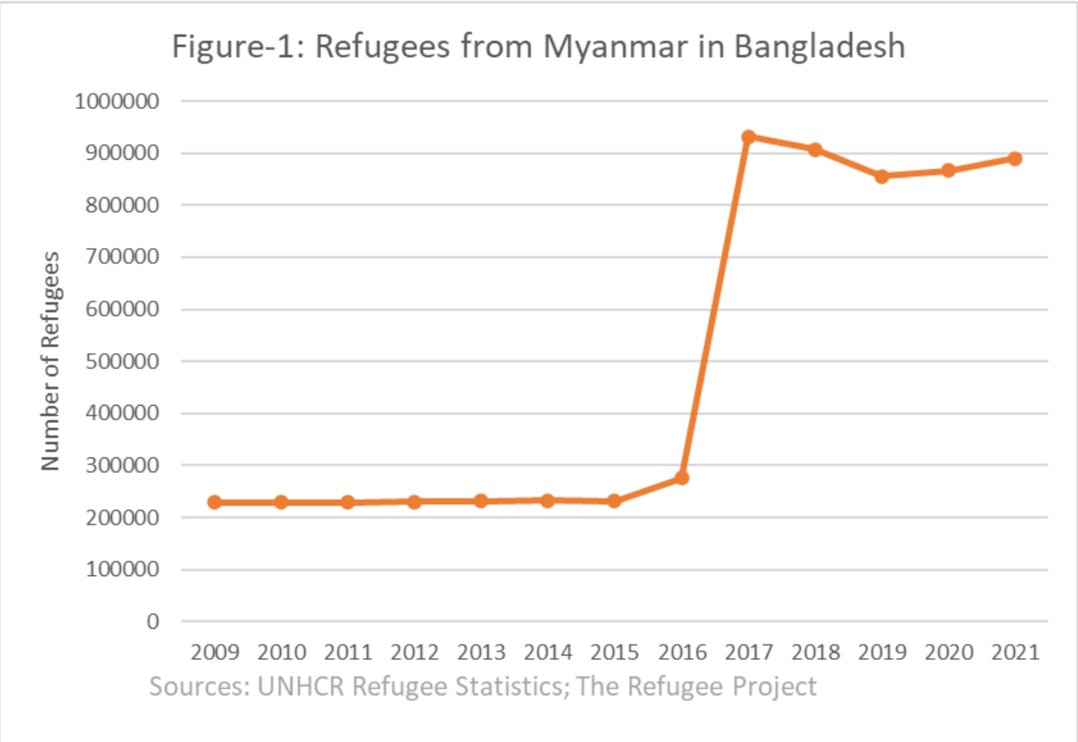
## Introduction

On the 25th of August 2017, the military of Myanmar initiated a large-scale genocide of Rohingya Muslims living in the country's Rakhine region. Over 650,000 Rohingya fled Myanmar and sought refuge in Southern Bangladesh in August and September of 2017, with over 90% of them settling in the latter nation's Chittagong division (UNHRC, 2021). IFPRI (2019) estimates suggest that this constituted an approximately 3% rise in the population of Chittagong, with the figure being over 30% for districts within Chittagong with particularly high refugee populations (Cox's Bazaar, for instance). This paper investigates how this influx – and the associated increase in labour supply – impacted the wages of low-skilled workers in Chittagong.




## Literature Review

Famously, Card (1990) found that a 7% increase in Miami's labour force brought about by an influx of 125,000 Cuban immigrants had no negative effect on wages of natives. Dustmann and Glitz (2015) similarly determined that economic effects of a refugee influx in the tradable sector do not manifest through factor price changes. Instead, the main channels are increases in size of enterprises that intensively use labour of the skill level represented by the refugees, or more intensive use of such labour by these enterprises.

Borjas and Monras (2017) found that wage impacts of refugee crises vary by worker groups: those with skills levels similar to refugees are likely to experience declining wages, while those for whom refugees are not good substitutes tend to benefit.

In the Bangladeshi context, the IFPRI (2019) used a Local Economy-Wide Impact Evaluation (LEWIE) model to simulate the Rohingya influx. Two scenarios were considered: (1) the refugees remain confined to the Cox's Bazaar district of Chittagong where most refugee camps are based, and (2) refugees disperse across Chittagong. In the former case, a 31.01% drop in wages was predicted in Cox's Bazaar, while in the latter, a less severe – but still substantial – 3.86% drop was predicted in wages at the Chittagong level. Notably, this negative estimate was arrived at even after accounting for the fact that almost 55% of Rohingya refugees are children (UNHRC, 2020).

## Empirical Analysis

I adopt a two-step empirical approach. First, identifying a control group with which to compare Chittagong. And second, comparing the post-influx wage trend in Chittagong with that of the control, ascribing any divergence to the crisis.

### Choice of Control

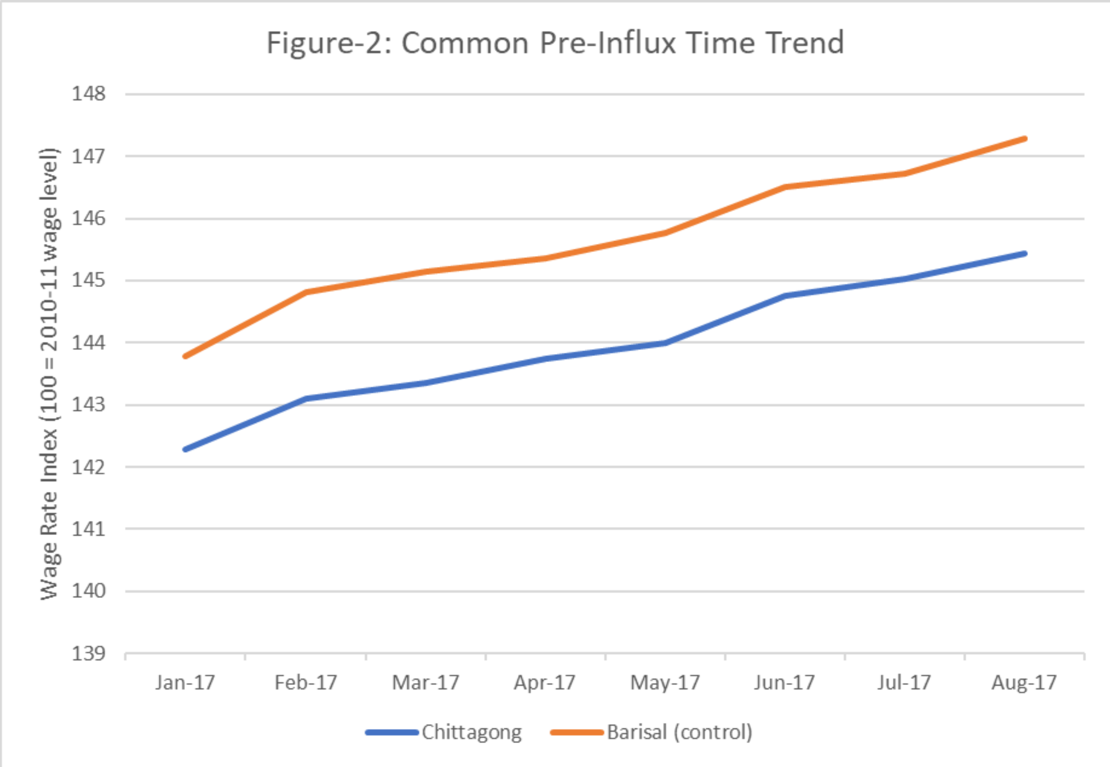
All divisions of Bangladesh apart from Chittagong form the pool of prospective controls. We are interested in a division wherein wages, (1) followed a similar trend to Chittagong pre-influx, and (2) were unlikely to have been affected by the influx.

Monthly data on each division's Wage Rate Index (WRI) – the Bangladesh Bureau of Statistics' (BBS) preferred measure of low-skilled wages – is leveraged to identify a division that meets (1). Table-1 shows the differences between Chittagong's WRI and each other division's WRI in each month of 2017 before the influx.

**Table-1: Wage Rate Index Differences (Chittagong - Stated Division)**

| | Dhaka | Rajshahi | Rangpur | Khulna | Barisal | Sylhet |
|---|---|---|---|---|---|---|
| Jan-17 | 0.73 | 1.29 | -1.68 | 0.14 | -1.5 | -3.09 |
| Feb-17 | 0.08 | 1.08 | -1.37 | -0.39 | -1.72 | -2.93 |
| Mar-17 | 0.01 | 0.82 | -1.39 | -0.64 | -1.78 | -3.2 |
| Apr-17 | 0.09 | 0.89 | -1.26 | -0.68 | -1.62 | -2.98 |
| May-17 | -0.16 | 0.99 | -1.42 | -0.81 | -1.76 | -3.06 |
| Jun-17 | -0.41 | 1.05 | -1.33 | -0.79 | -1.76 | -2.85 |
| Jul-17 | -0.64 | 0.86 | -1.55 | -0.91 | -1.71 | -2.87 |
| Aug-17 | -0.68 | 0.75 | -1.8 | -0.96 | -1.85 | -2.88 |
| Standard Deviations | **0.432023** | **0.162245** | **0.173853** | **0.335112** | **0.101088** | **0.116378** |

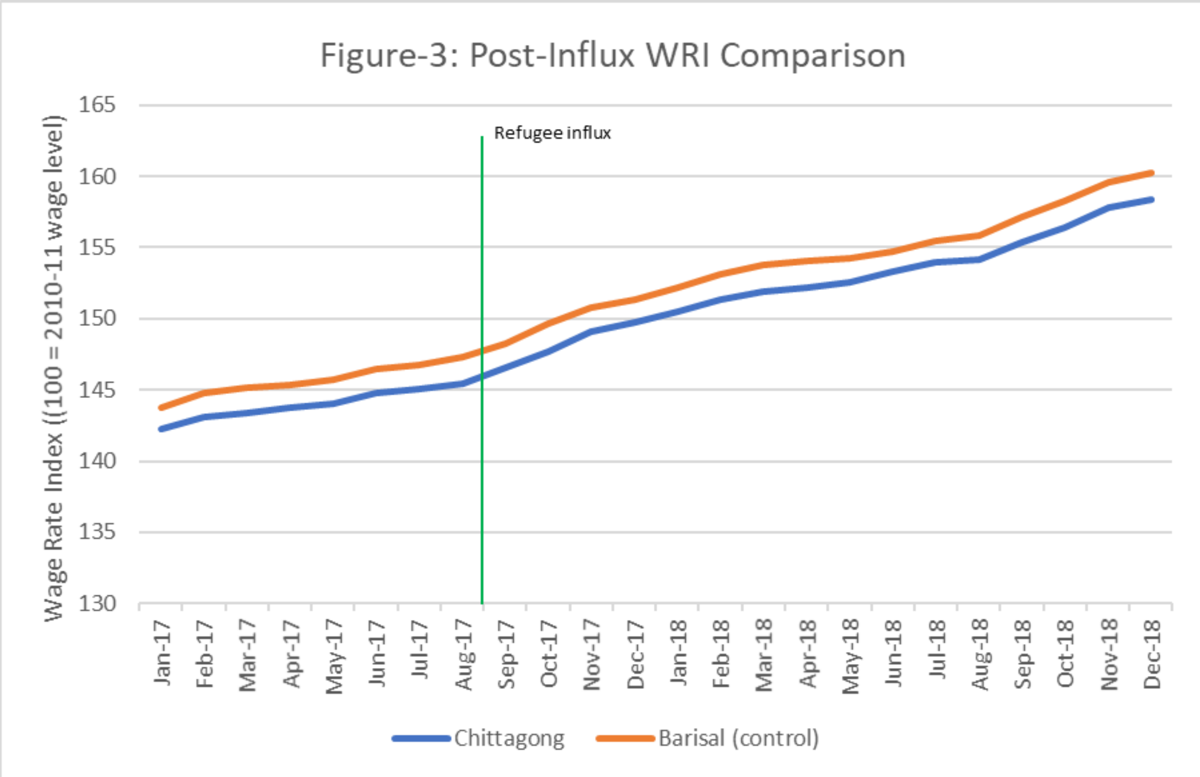
The final row displays the standard deviations of each division's WRI differentials with Chittagong. Evidently, this is lowest in Barisal, indicating that its pre-influx wage-trend was closest to Chittagong's (see Figure-2). Encouraged by the facts that almost none of the 2017 Rohingya refugees settled in Barisal, and Barisal shares no land border with Chittagong making migration of refugees into Barisal difficult, we adopt Barisal as our control (UNHRC, 2021; Nations Online Project, 2022).




## Comparison

The Easy Answer

Figure-3 shows the evolution of wages in Chittagong and Barisal prior to and following the influx. The lack of WRI divergence post-influx implies – interestingly – that the refugees had no impact on wages. However, this analysis could be misleading.




The Caveat

Unfortunately, the BBS does not make sufficiently clear what the '100' value in Barisal and Chittagong's respective WRI time-series corresponds to. While the base year (2010-11) is unambiguously specified, it is uncertain whether the base is Bangladesh's national average wage in 2010-11, or respectively, the local average wages in Barisal and Chittagong in 2010-11. The need therefore arises, for analysis that is robust to this potential heterogeneity in indexation to ensure comparability between Barisal and Chittagong's data.

A Robust Solution

The indexation problem is solved by using growth rates of the WRI between consecutive months instead of levels of the WRI. An analogy helps to clarify why: while one would be remiss to compare *levels* of the Consumer Price Index (CPI) across geographies, *growth rates* of the CPI – inflation rates – are indeed perfectly comparable.

Table-2 reproduces the analysis of Table-1, using growth rate differentials instead of level differentials. As indicated by the final row, Barisal remains the relevant control group.

| **Table-2: WRI Growth Rate Differences *** | | | | | | |
|---|---|---|---|---|---|---|
| | Dhaka | Rajshahi | Rangpur | Khulna | Barisal | Sylhet |
| Feb-17 | -0.46214 | -0.15416 | 0.221981 | -0.37343 | -0.14707 | 0.122165 |
| Mar-17 | -0.04905 | -0.18452 | -0.01206 | -0.17373 | -0.03919 | -0.18112 |
| Apr-17 | 0.055789 | 0.047584 | 0.092355 | -0.0266 | 0.113489 | 0.155897 |
| May-17 | -0.17415 | 0.068877 | -0.10877 | -0.08916 | -0.0943 | -0.05085 |
| Jun-17 | -0.17284 | 0.03835 | 0.066976 | 0.016725 | 0.006289 | 0.153636 |
| Jul-17 | -0.15792 | -0.13358 | -0.1489 | -0.08144 | 0.036368 | -0.00995 |
| Aug-17 | -0.02619 | -0.07803 | -0.1675 | -0.03246 | -0.09204 | -0.00114 |
| Standard Deviations | **0.153943** | **0.098474** | **0.133122** | **0.121726** | **0.082875** | **0.115412** |
| * Each data-point was obtained as follows: % change in Chittagong WRI from previous month - % change in stated division's WRI from previous month | | | | | | |

Difference-in-Differences Estimation

We now use regression analysis to determine how wage patterns in Chittagong were affected by the crisis. The relevant variables are as follows: *growthrate*, measuring %change in WRI from the previous month; time-dummies from *Feb-17 – Dec-18*, taking the value 1 if the observation in question is from that time period; *Treatment*, taking the value 1 if an observation relates to Chittagong and 0 if it relates to Barisal; and finally, time-treatment interaction dummies, defined as the product of a time-dummy and *Treatment*, taking value one if the observation is from Chittagong, in the period stated in the variable name (*TreatMonthYear*), and 0 otherwise.

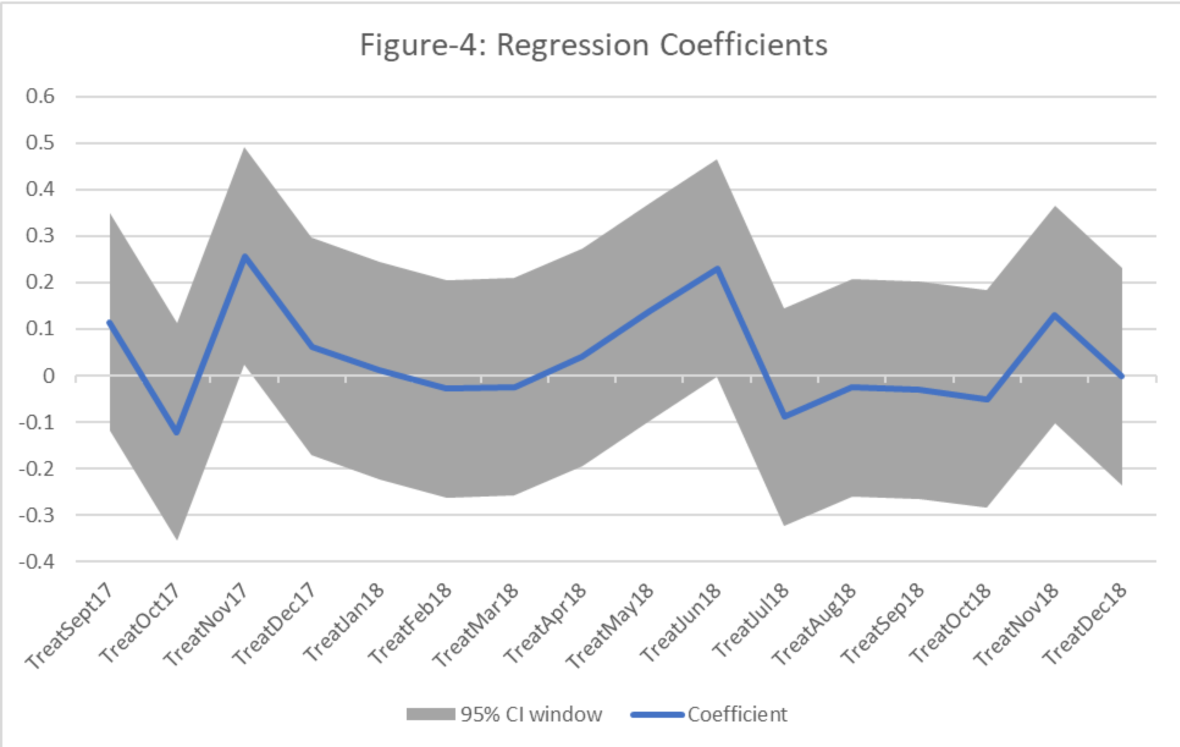
We regress *growthrate* on all the time-dummies (except *Feb-17* to avoid the dummy-variable trap), *Treatment*, and time-dummy interactions for periods after the influx (*TreatAug17* – *TreatDec18*). The exclusion of time-treatment interactions prior to the influx is predicated on the reasonable assumption of a common pre-influx *growthrate* trend in Chittagong and Barisal (supported by Table-2). The interpretation of various coefficients in this regression is explained in Table-3.

**Table 3: Coefficients and their Interpretation**

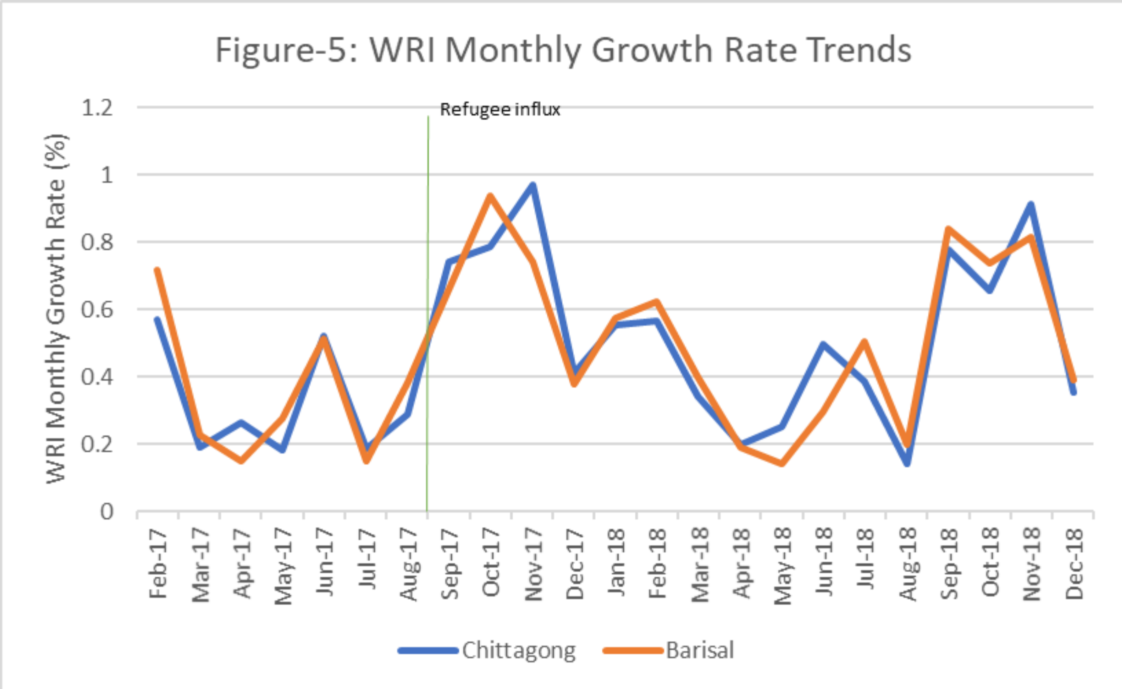
| **Coefficient** | **Interpretation** |
|---|---|
| Constant term | *growthrate* in Barisal in Feb-17 |
| Time-Dummies | Barisal *growthrate* in stated period minus Barisal *growthrate* in Feb-17 |
| Treatment | Pre-influx average difference between Barisal monthly *growthrate*s and Chittagong monthly *growthrate*s |
| Time-Treatment Interactions | Difference between Barisal *growthrate* and Chittagong *growthrate* in a given month post-influx that is NOT accounted for by pre-influx average growth rate difference |

If a coefficient of a time-treatment interaction is non-zero, we interpret the crisis to have affected Chittagong's wage patterns as the pre-influx growth rate differential does not equal the post-influx growth rate differential.

The regression output however (see Figure-4 and Appendix), shows that the coefficients of all but one time-treatment interactions (*TreatNov17*) are not statistically different from zero at the 5% significance level. The coefficient of *TreatNov17* is in fact statistically positive, indicating an unusually *high* growth rate in Chittagong relative to Barisal.




We therefore conclude that <u>the influx did not depress wages in Chittagong</u>. This is supported by Figure-5 which shows no marked divergence in growth rates in Chittagong and Barisal after the influx.




## Hypotheses and Conclusions

An immediately apparent explanation for our results is provided by the fact that, as per prevailing Bangladeshi legislation, the Rohingya are not allowed to work outside of refugee camps (Dempster and Sakib, 2021). Effective implementation of this restriction would mean that the influx constituted an increase in Chittagong's population, sans an increase in labour force. The larger population size would increase aggregate demand, exerting upward pressure on wages. The IFPRI (2019) however, estimates that 47% of Rohingya households were engaged in economic activities regardless, limiting the value of this hypothesis.

Another theory – supported by the UN Development Programme (2018) – suggests that the influx could have reduced wages in specific regions with high refugee populations, but these impacts were too localised to reflect in the aggregate Chittagong trend. However, this is contrary to economic intuition, which suggests that out-migration from low-wage areas in search of less saturated labour markets will depress wages in neighbouring geographies as well (Borjas, 2001). Consequently, localised effects *would* reflect in the aggregate trend.

A more realistic explanation is that most Rohingya worked in farms and fisheries in Myanmar, and thus have limited ability to influence wages in Chittagong, where these sectors are not very large or well-established (Rakhine Commission, 2017). Recall the literature review's allusion to the relation between skill-substitutability and wage-impacts of refugees.

A more worrying prospect is that the wage effects of the crisis were concentrated in the informal sector, as suggested by Altindag et al (2020), and the BBS data-collection did not adequately cover informal sector workers. While this would indeed be a significant caveat to our results, it is less concerning than it seems, for two reasons. Firstly, the BBS survey makes specific efforts to include workers from 44 informal sectors (BBS, 2022), and secondly, wage changes in the informal sector have spill-over effects on formal sector wages (author's reasoning based on Bassier, 2021): even if refugees entered informal employment, the wages of formal workers were unlikely to have been unaffected.

The final explanation we will consider is provided by the Rybczynski theorem, which posits that an increase in labour supply is accompanied by an expansion of labour-intensive sectors (in Chittagong, garments, textile, footwear, tourism) and contraction of capital-intensive sectors (in Chittagong, shipbuilding, industrial parts, electric and electronic goods) (Chittagong Chamber of Commerce & Industry, 2022; Rybczynski, 2015). If the theorem was operational in Chittagong, the deleterious effects of increased labour supply on wages would thus have been counterweighed by a rise in labour demand.

In conclusion, the influx did not affect wages of low-skilled workers in Chittagong, however, further research is needed to definitively identify why this was the case.

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## Appendix

Regression Output:

| **Variable** | **Coefficient** | **t-ratio** | **95% CI lower limit** | **95% CI upper limit** |
|---|---|---|---|---|
| Mar-17 | -0.43455 | -6.87 | -0.58943 | -0.27967 |
| Apr-17 | -0.43451 | -6.86 | -0.5894 | -0.27963 |
| May-17 | -0.41481 | -6.55 | -0.56969 | -0.25992 |
| Jun-17 | -0.12515 | -1.98 | -0.28003 | 0.029735 |
| Jul-17 | -0.47449 | -7.5 | -0.62937 | -0.31961 |
| Aug-17 | -0.3072 | -4.85 | -0.46208 | -0.15232 |
| Sep-17 | 0.000268 | 0 | -0.19389 | 0.194423 |
| Oct-17 | 0.279245 | 3.52 | 0.08509 | 0.4734 |
| Nov-17 | 0.083434 | 1.05 | -0.11072 | 0.277589 |
| Dec-17 | -0.28021 | -3.53 | -0.47437 | -0.08606 |
| Jan-18 | -0.08339 | -1.05 | -0.27755 | 0.11076 |

| | | | | |
|---|---|---|---|---|
| Feb-18 | -0.03412 | -0.43 | -0.22827 | 0.160037 |
| Mar-18 | -0.25999 | -3.28 | -0.45415 | -0.06584 |
| Apr-18 | -0.46969 | -5.92 | -0.66385 | -0.27554 |
| May-18 | -0.51549 | -6.5 | -0.70964 | -0.32133 |
| Jun-18 | -0.36012 | -4.54 | -0.55427 | -0.16596 |
| Jul-18 | -0.15419 | -1.94 | -0.34835 | 0.039962 |
| Aug-18 | -0.45895 | -5.78 | -0.65311 | -0.2648 |
| Sep-18 | 0.182417 | 2.3 | -0.01174 | 0.376571 |
| Oct-18 | 0.079945 | 1.01 | -0.11421 | 0.2741 |
| Nov-18 | 0.156663 | 1.97 | -0.03749 | 0.350818 |
| Dec-18 | -0.26978 | -3.4 | -0.46393 | -0.07562 |
| TreatSept17 | 0.114931 | 1.2 | -0.11923 | 0.349091 |
| TreatOct17 | -0.12174 | -1.27 | -0.3559 | 0.112415 |
| TreatNov17 | 0.257567 | 2.69 | 0.023407 | 0.491726 |
| TreatDec17 | 0.061959 | 0.65 | -0.1722 | 0.296119 |
| TreatJan18 | 0.010425 | 0.11 | -0.22374 | 0.244584 |
| TreatFeb18 | -0.02862 | -0.3 | -0.26278 | 0.205537 |

| | | | | |
|---|---|---|---|---|
| TreatMar18 | -0.0239 | -0.25 | -0.25806 | 0.210263 |
| TreatApr18 | 0.039802 | 0.42 | -0.19436 | 0.273961 |
| TreatMay18 | 0.137766 | 1.44 | -0.09639 | 0.371926 |
| TreatJun18 | 0.23081 | 2.41 | -0.00335 | 0.46497 |
| TreatJul18 | -0.08844 | -0.92 | -0.3226 | 0.145718 |
| TreatAug18 | -0.02551 | -0.27 | -0.25967 | 0.20865 |
| TreatSep18 | -0.03138 | -0.33 | -0.26554 | 0.20278 |
| TreatOct18 | -0.05078 | -0.53 | -0.28494 | 0.183379 |
| TreatNov18 | 0.130401 | 1.36 | -0.10376 | 0.364561 |
| TreatDec18 | -0.00274 | -0.03 | -0.2369 | 0.231419 |
| Treatment | -0.03092 | -0.91 | -0.11371 | 0.051866 |
| _cons | 0.658297 | 13.76 | 0.541217 | 0.775377 |