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# THE EFFECT OF VENEZUELAN MIGRATION ON EDUCATIONAL OUTCOMES IN COLOMBIA 

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#### Abstract

About 1.8 of the 5.2 million Venezuelans who have left their country due to political and economic turmoil have settled in neighboring Colombia. The extent to which the Colombian schooling system can absorb the massive demand for education of Venezuelan children is key for their future trajectory of human capital accumulation, as well as that of Colombian students in receiving communities. In this paper, we estimate the effect of Venezuelan migration on educational outcomes of children living in settlement municipalities in Colombia, and distinguish between the effect of the migration shock on native as well as on migrant students. Specifically, we estimate the effect of the migration shock on school enrollment, dropout/promotion rates and standardized test scores. Our identification relies on a plausibly exogenous measure of the predicted migration shock faced by each Colombian municipality every year. We find that the migration shock increased the enrollment of Venezuelan students in both public and private schools and in all school grades, but also generated negative spillovers related to failing promotion rates and increasing dropout. We document that these negative effects are explained by the differential enrollment capacity of schools, as well as by the deterioration of key school inputs.


## JEL Codes: F22, I25

Keywords: Migration, Education, Colombia, Venezuela

[^0]
## 1. Introduction

Economic and political turmoil, as well as a surge of criminal violence in Venezuela have induced a large migration wave of Venezuelans to Colombia. By July 2020, about a third of the almost 5.2 million Venezuelans who had fled the country because of the crisis, had registered in Colombia. Of these, more than 750 thousand had obtained a residence permit. ${ }^{1}$ Figure 1 reports the annual inflow of Venezuelans to Colombia. Between one fourth and one third of the Venezuelan migrants who settle in Colombia are children. ${ }^{2}$ Because of their status of refugees or crisis-driven migrants, these children have interrupted their education process. Upon settlement in hosting community a priority of the migrant household is likely to enroll them in school. The implied surge in the demand for schooling constitutes an important challenge for the Colombian education system. Indeed, the extent to which local schools can absorb and accommodate Venezuelan children will determine the accumulation of skills and human capital of the younger generations of both migrants and native kids in host communities.

In this paper, we estimate the impact of the Venezuelan migration shock on schooling outcomes in receiving Colombian municipalities. In particular, we use administrative data to study the effect of the Venezuelan migration on school enrollment, dropout rates, promotion rates, and test scores. We use individual-level administrative data to distinguish between native and migrant children, as well as in terms of gender and school characteristics such as their public or private ownership.

Our empirical strategy exploits two sources of exogenous variation in cumulative Venezuelan migration inflows at the municipality-year level. Cross-sectional municipal variation comes from the share of population within each receiving municipality that was born Venezuela and arrived before the political and economic crisis of that country began. Annual variation comes from the number of Venezuelans arriving to Colombia each year, as the crises worsened during the late Chavez' and the under Maduro' administration. The interaction of these two sources of variation corresponds to a plausibly exogenous predicted migrant shock measure. ${ }^{3}$

[^1]Our identification strategy exploits the fact that crisis-induced migrants tend to move disproportionately to municipalities where they have preexisting networks, formed before the beginning of the migration wave (??). Our identification assumption is that predicted migration shock is correlated with actual migration but do not affect educational outcomes independently or through any other channel. This is plausible after controlling for municipality-specific trends parametrized by key pre-determined municipality characteristics, which we choose using machine learning techniques.

We find that the migration shock increased the enrollment of both male and female foreign students. This effect is mainly driven by public schools, and it is stronger for younger kids, who enroll in primary school grades. We also find, however, negative externalities of the increased enrollment in terms of promotion rates and dropout rates. While falling promotion rates and increasing dropout occurs for both native and foreign students, the effects are larger for the former. Migrants, on the other hand, seem to exert more effort as suggested by their performance in standardized tests. Finally, we document that the mechanisms that explain these negative effects of the migration shock have to do with the deterioration of key school inputs in public schools. For instance, we show that the migration shock reduces the number of teachers and increases the ratio of pupils to teachers (and thus class size). Our results highlight important policy implications, which we discuss in the conclusion.

Our paper contributes to recent strand of the literature that studies the effect of exposure to refugees on educational outcomes of native children. Interestingly, most such papers find that the interaction with refugees does not affect the outcomes of native students. For example, ? finds that the inflow of Indochinese refugees in the U.S. at the end of the Vietnam War did not affect native children's academic achievement. In a similar fashion, ? find no effects on native students Florida public schools of Haitian migrants who fled after the 2010. ? find not effect of Syrian refugees on educational outcomes of Jordanian children. ? also find not effect of having refugees in the classroom on outcomes of Dutch students. ${ }^{4}$ Our paper also contributes to an extensive literature that studies how the characteristics of peers affect students' outcomes. Most

[^2]of these papers find that that low-ability and disruptive peers (e.g. exposed to Native violence) have negative impacts in student achievement (?????).

The remaining of the paper is organized as follows. Section 2 provides a brief discussion of the context. Section 3 describes the data sources used to assess the effect of Venezuelan migration flow on schooling outcomes in Colombia. Section 4 lays out the empirical strategy and discusses challenges to identification. Sections 5 and 6 present the results and the potential mechanisms respectively, and 7 concludes.

## 2. Context

2.1. The Venezuelan crisis. The beginning of the Venezuelan political crisis can be traced back to the election of Hugo Chávez as president on December 6, 1998. Chavez' socialist regime was characterized by constitutional amendments, land expropriations, the implementation of populist social programs, nationalizations, and restrictions on private businesses (?). These policies were continued -and in some cases strengthenedby Nicolás Maduro, who was elected president of Venezuela in 2013. Since then, shortages of food and basic necessities became common, and looting began to occur systematically throughout the country (?). Moreover, insecurity became endemic, repression of the opposition became common, and systematic human rights violations by public authorities were repeatedly reported by the international media (see ???). External factors such as plummeting oil prices since 2014 and international sanctions on Venezuela, have exacerbated the crisis. ${ }^{5}$

This situation triggered large waves of out-migration by Venezuelans, who most often moved to neighboring Colombia. According to the official statistics, since that start of the humanitarian crisis caused by Chavez' and Maduro's regimes, about 5.2 million Venezuelans have left their country. Of these, about 1.8 million have settled in Colombia. ${ }^{6}$

Initially, Venezuelan migrants consisted mainly of wealthy Venezuelans and entrepreneurs who came to invest in Colombia and fled to save their capital from expropriations and

[^3]from high inflation (?; ?). As the crisis intensified, however, the core of Venezuelan migration shifted to the less educated population, who report fleeing to escape violent crime, political repression, and to look for basic necessities for survival (?). Indeed, according to recent characterizations of Venezuelan migrants based on the Colombian household surveys of 2015 and 2016, over 80 percent of registered migrants have not completed a high school education, at least half are 25 years old or less, and they are balanced in terms of gender (see ?).
2.2. Colombia's education system and policy response. The education system in Colombia comprises one year of preschool, five years of primary education, four years of lower secondary education and two years of upper secondary education. In 2014, $87 \%$ of the schools in Colombia were public and out of those, $78 \%$ were located in rural areas (?). All children between five and fifteen years old are legally required to attend preschool plus nine years of compulsory basic schooling. However, it is estimated that $20 \%$ of the students do not continue studying beyond primary school (?), and only $65 \%$ of boys and $77 \%$ of girls complete lower secondary education (?).

The Colombian government has implemented several initiatives to facilitate the integration of Venezuelan children in public schools. For example, Decree 1288 of 2018 simplified the process for Venezuelans to validate their educational through standardized tests. This policy was designed with the objective of allowing migrant children to enroll in school grades according to both their age and prior academic achievement. In addition, also since 2018, the Colombian government allowed Venezuelan children to attend public schools regardless of the immigration status of their households.

Unfortunately, before 2018 the Colombian government did not keep systematic track of school enrollment by student nationality. The most recent statistics available for the city of Bogotá are suggest that, by 2019, half of migrant students were enrolled in primary level, a quarter in secondary and a fifth in preschool. Also, about $70 \%$ of Venezuelan students were between 4 and 12 years old -i.e. in preschool and primary ages- (Alcaldía de Bogotá, 2019). ${ }^{7}$ Importantly, our administrative individual-level

[^4]dataset does distinguish between Colombian and foreign students, and crucially, according to the 2018 population census $87 \%$ of foreigners who have settled in Colombia are from Venezuela. ${ }^{8}$

## 3. Data

3.1. Outcomes. To measure our outcome variables, we will combine two administrative datasets. First, we will compute school-level enrollment, dropout rates and promotion rates using the administrative registry of all the students in Colombia, enrolled in either public or private schools. This dataset is called R166-SIMAT and its source is the Colombian Ministry of Education. ${ }^{9}$ It is available for the period 20122018, and thus this is our sample period.

Importantly, R166-SIMAT includes the student ID that allows us to distinguish between Colombian and foreign students in order to explore the effects of the Venezuelan migration shock on both native and migrant students. Specifically, we identified as 'migrant' students with IDs different than the standard ID that the government issues to underage natives. These include special residence permits, visas, and border mobility cards. We also classified as migrant students who enrolled using a provisional ID, provided by the municipal Secretary of Education to undocumented children who want to enroll in a public institution. The vast majority of undocumented children are foreigners, most of whom are Venezuelans. Using R166-SIMAT we can construct the following school (or school/grade)-level variables:

1. (Log) Enrollment: the (log of the) total number of students enrolled per school (or school/grade) at the beginning of each academic year.

At the end of the academic year, total enrollment is broken into four categories: students who transferred to a different school during the academic year, student who dropped out from the school (and did not transfer to any school during that year),

[^5]student who were promoted to the next grade (or graduate from school), and students who failed the grade. Using this break-up, we can compute the following additional outcomes:
2. Dropout rate: the share of students who dropped out from each school during the academic year over the initial school enrollment for that year. Note that this corresponds to the intra-annual dropout rate as it measures the proportion of students that leave the school during an academic year. Also importantly, this is a true measure of dropout, as we net out the students who changed schools during the academic year. Formally, for grade $g$ of school $s$ and year $t$, we compute the dropout rate $(D R)$ as:
$$
D R_{s t}=\frac{\sum_{g=1}^{11} d_{g s t}}{\sum_{g=1}^{11} e_{g s t}}
$$
where $d_{g s t}$ is the number of dropouts from grade $g$ of school $s$ and year $t$ and $e_{g s t}$ is enrollment at the beginning of that grade/school/year (net of school switchers).
3. Promotion rate: the share of students who were promoted to the next grade relative to the initial enrollment (net of school switchers). Formally, we compute the promotion rate $P R$ as:
$$
P R_{s t}=\frac{\sum_{g=1}^{11} p_{g s t}}{\sum_{g=1}^{11} e_{g s t}}
$$
where $e_{g s t}$ is defined as above and $p_{g s t}$ is the number of students promoted in that grade/school/year.

R166-SIMAT also includes a registry of public school teachers for the period 20142018. We use these data to explore potential mechanisms (albeit for publics schools only) related to key supply measures such as the teacher/students ratio and the quality of teachers.

The second administrative dataset contains information on the scores obtained by students in the official high-school exit exam (called Saber 11) for the period 20052018. It comes from the Colombian Institute for the Promotion of Higher Education. From it, we computed math and language test scores. To facilitate the interpretation
and make scores comparable across years, we standardized the test scores to have mean zero and standard deviation one each year. Table 1 reports descriptive statistics of the main outcome variables.
3.2. Other data. We will also employ data on the total number of Venezuelans arriving annually in Colombia, available from the national migration authority (Migración Colombia). These data come from the information recorded at official migration points and thus it does not include any illegal or unregistered migration.

Finally, we have access to a large number of pre-determined municipal level controls (based on te 1993 and 2005 population censuses) that we use to control for differential trends parametrized by time-invariant municipal characteristics that may help predict the evolution of educational outcomes. Table 2 reports the descriptive statistics on these covariates.

## 4. Empirical Strategy

As forced migrants do not choose their arrival municipalities randomly, we cannot use a mean comparison to identify their effects on educational outcomes in host municipalities. Such a comparison would likely be biased. For example, if migrants go disproportionally to more prosperous municipalities and prosperity is positively associated with better school performance, such the bias would be positive. More generally, it is reasonable to assume that the decision of where to locate is associated with municipal characteristics that, in turn, are correlated with the quality of education.

Our empirical strategy, consequently, exploits the fact that, as the political crises intensified in Venezuela, migrants tend to move disproportionately to municipalities where they have networks, family, or acquaintances. This has been shown to be the case in a variety of contexts. ${ }^{10}$ In particular, we estimate the following augmented specification, which distinguishes the effects of the migration shock across nationality (native versus migrant students) and gender (females versus males).

[^6]\[

\left.$$
\begin{array}{r}
Y_{s m d t}=\lambda_{s}+\gamma_{d \times t}+\theta_{1} \text { Pr.Ven.Shock }_{m d t}^{1993}+\theta_{2} \text { Native }_{s m d t}+\theta_{3} \text { Female }_{s m d t}+  \tag{4.1}\\
\theta_{4}\left[\text { Pr.Ven.Shock }_{m d t}^{1993} \times \text { Native }_{s m d t}\right]+\theta_{5}\left[\text { Pr.Ven.Shock }_{m d t}^{1993} \times \text { Female }_{s m d t}\right]+ \\
\theta_{6}[\text { Pr.Ven.Shock } \\
m d t \\
1993
\end{array}
$$ Native_{s m d t} \times Female_{s m d t}\right]+\theta_{7}\left[Native_{s m d t} \times Female_{s m d t}\right]++\sum_{c \in \mathbf{X}_{\mathbf{m d}}} \delta^{\prime}\left(c \times \phi_{t}\right)+\epsilon_{s m d t}, ~ \$
\]

where $Y_{s m d t}$ is any of several educational outcomes in school $s$ from municipality $m$ of department $d$ and year $t ; \lambda_{s}$ and $\gamma_{d \times t}$ are respectively school fixed effects and department $\times$ year fixed effects. These control, respectively, for any time-invariant school-level heterogeneity that may be correlated with educational outcomes and for any aggregate shock that may affect in the same way all the municipalities of the same department. Pr.Ven.Shock ${ }_{m d t}^{193}$ is our predicted cumulative migration inflow to municipality $m$ of department $d$ and year $t$, based on the 1993 census. Native ${ }_{s m d t}\left(\right.$ Female $\left._{s m d t}\right)$ identifies the subgroup of Colombian (Female) students in school $s . \mathbf{X}_{\mathbf{m d}}$ is a vector of pre-determined municipality-specific characteristics which we interact with the year fixed effects represented by $\phi_{t}$. This interaction effectively controls for municipalspecific changes over time, parametrized by the set of control included in $\mathbf{X}_{\mathbf{m d}}$. It is worth noting that the municipality characteristics included in this set are not chosen in an $a d$ hoc way. Rather, following ?, the controls are selected using machine learning techniques. In this way we are agnostic about which municipality characteristics are more related to educational outcomes in areas that have hosted Venezuelan migrants. Finally, the error term, $\epsilon_{s m d t}$, is estimated allowing for serial correlation within municipalities.

Our measure of the predicted migration shock follows the standard practice in the literature (see ? and ? for the pioneer approaches and? for a review of the literature on applications) and exploits the disproportionate levels of cumulative migrant inflows to areas with previous settlements of similar identity groups. Specifically, our measure is constructed as:

Pr.Ven.Shock ${ }_{m d t}^{1993}=\left[\frac{1}{\text { Population }_{m d}^{1993}}\left(\right.\right.$ Tot. Ven. Inflow $_{t} \times$ Venezuelan Share $\left.\left._{m d}^{1993}\right)\right] \times 100$
where Tot. Ven. Inflow ${ }_{t}$ is the aggregate number of (legal) Venezuelans entering Colombia every year (as recorded by migration authorities), Population $m_{d}^{1993}$ is the total population of municipality $m$ in 1993, which is kept fixed prior to the migration shock to avoid further endogeneity concerns. Venezuelan Share ${ }_{m d}^{1993}$ is the share of Venezuelans living in municipality $m$ according to the 1993 population census to the total number of Venezuelans living in Colombia. ${ }^{11}$

$$
\text { Venezuelan Share }_{m d}^{1993}=\frac{\text { Venezuelan } \mathrm{Pop}_{m d}^{1993}}{\sum_{m} \text { Venezuelan } \mathrm{Pop}_{m d}^{1993}}
$$

For robustness, we aggregate our outcome variables at the municipality level and re-estimate equation 4.1 changing the school fixed effects for municipality fixed effects.
4.1. Challenges to Identification. Our identification relies on the plausibly exogeneity of our predicted migration shock. We now discuss potential threats to this assumption, and how we have dealt with them. First, it is worth noting that we are not using the predicted cumulative inflows as an instrument of the actual inflows of Venezuelans to each municipality/year. This is because there are no administrative records of where do the arriving Venezuelan nationals settle on a yearly basis. We therefore use the predicted shock to estimate a reduced-form equation. The magnitude of our results should therefore be interpreted with caution, as it only captures the numerator of a standard 2SLS estimator.

The first assumption that we rely on for identification is, therefore, that the predicted migration is strongly correlated with the (unobserved) actual Venezuelan migration. We can test this assumption for 2018, when the last population census took place in Colombia. Figures 3 and 4 show the municipal distribution of, respectively, the observed number of the Venezuelans and the predicted figure for 2018. The distribution looks very similar in both maps, and indeed the correlation is 0.67 . We are thus confident that our predicted migration shock has predictive power. ${ }^{12}$

[^7]Secondly, the 1993-based predicted inflow measure needs not to be correlated with contemporaneous schooling outcomes through any channel different than actual Venezuelan migration. Regarding this assumption, it is worth noting that, because our estimates include fixed effects by municipality as well as by department×year, they are confounded neither by time-invariant differences across municipalities nor by annual aggregate department-level shocks. ${ }^{13}$ This is, however, not enough to achieve identification. It may well be the case that pre-shock migrants disproportionally settle in places with characteristics that explain future educational outcomes. Indeed, as noted by ?, identification in the Bartik/Shift-Share-type instruments comes mainly from the cross-sectional ("share") variation, so it is important to check the extent to which the initial shares (o migrants) are correlated with potential confounders prior to the current migration wave. To this end, following ?, we use machine learning to select the most robust determinants of Venezuelan settlements according to the 1993 census and include in our main specification the interaction between each of these and the year fixed effects. By doing so, we flexibly control for municipal-specific trends, parametrized by a large set of pre-determined characteristics that predict early settlements. ${ }^{14}$

One additional recent criticism to the validity of using early migrants networks to study the impacts of migration in that is settings in which migration is serially correlated, past migration causes both current outcomes and current migration, and thus the short and long run effects of migration are confounded (?). Our empirical strategy is not sensitive to this threat because the inflows crisis-driven Venezuelan migrants are not stable in time, they are sudden and large in scale as a consequence of the intensification of the internal and the Venezuelan crises.

Overall, we are confident that our estimates can be interpreted identifying the causal effect of the Venezuelan migration shock on educational outcomes.

## 5. Results

5.1. Main results. We start by studying the effect of the Venezuelan migration shock on educational outcomes aggregated at the school level and averaging across all schools (Table 3). We then separate the result across public and private schools (Tables 4 and

[^8]5 respectively); between primary and secondary school grades (Tables 6 and 7 respectively); and across schools situated in relatively more urban or more rural municipalities (Tables 8 and 9 respectively). Panel A in each table includes no controls, and Panel B includes the set of controls optimally selected by the machine learning algorithm proposed by ?. All the results are robust to the inclusion of the controls, both in magnitude and in terms of statistical significance.

All the tables report the marginal effects of the migration shock on each type of student (across gender and nationality) to facilitate the interpretation of the findings. Because our main specification interacts the predicted migration shock with the school-level subgroup of native student and females (and it is saturated with all the underlying double interactions), interpreting the regression output is time-consuming. For reference, in the appendix we report Tables A. 1 to A.7, which are the regression output counterpart ofs Tables 3 to 9 . In those tables, the coefficient associated with the noninteracted migration shock ( $\theta_{1}$ in equation 4.1) is the effect of the shock for foreign males. The effect of the shock on foreign females is the sum of the former and the coefficient associated to the interaction between the shock and the Female indicator ( $\theta 5$ ). The effect on native males is the sum of the coefficient associated with the shock $\left(\theta_{1}\right)$ and that of its interaction with the Native indicator $\left(\theta_{4}\right)$. Finally the effect on native females is the sum of the coefficient associated with the shock and those associated with the two double interactions ( $\theta_{4}$ and $\theta_{5}$ ) and that of the triple interaction $\left(\theta_{6}\right)$. We compute these sums (and their corresponding standard errors), and for simplicity only refer to the marginal effects henceforth.

Starting with the effect of the Venezuelan migration shock across the aggregation of all school types (Table 3), we find very intuitive results for the case of enrollment. On average, the shock increased the school enrollment of both migrant men and women, but not of natives (Column 1). Focusing on Panel B, which includes the optimal set of controls interacted with the year fixed effects, we find that a one-standard-deviation increase in the predicted migration shock ( $=22.89$, see Panel B of Table 1) increases the enrollment of migrant male students by 9.38 students $(=22.89 \times 0.0041 \times 100)$, and that of migrant female students by 8.47 students. ${ }^{15}$ These effects are sizeable: they represent about 4 percent of total average enrollment (see Table 1). The estimated coefficients of the marginal effects of the migration shock on the enrollment of natives (men and women) are very close to zero.

[^9]We also find that the shock decreased promotion rates across the board (Column 2), making it harder for both native and migrant students to advance in their educational cycle. In terms of the economic size of the effect, a one-standard-deviation increase in the predicted migration shock decreases the promotion rate of foreign male students by 0.54 percent $(=22.89 \times 0.0235)$ and that of native males by 0.5 percent. These effects are rather small, and represent, respectively 2.4 percent and 4.7 percent of the group-specific standard deviation of the promotion rate (reported at the bottom of the Table). The effect of a one-standard-deviation increase in the predicted migration shock on the promotion rate of native female students is a decrease in 0.43 percent ( 4.6 percent of the group standard deviation). For the case of foreign females, the estimate is however not significant, but the magnitude is $66 \%$ of the estimated effect for native females.

Note that the magnitude of the effect is larger for native students as compared to migrants. One potential explanation of this is that migrants who claim to have successfully completed a higher school level before arriving to Colombia -but do not have the documentation to prove it-are allowed to be promoted just by taking a test that is administered by the local Secretary of Education of the municipality where their new school is located (Decree 1288 of 2018). However, as discussed next, the effect of the shock on dropout rates is also larger (and indeed the gap is much wider) for local students, and this could not be accounted by this or any other explanation about the institutional environment.

The fact that the Venezuelan migration shock decreases promotion rates is consistent with an interpretation of school congestion: if school inputs remain constant in the short run (our sample period cover 7 years), the documented large increase in enrollment is likely to harm the learning process of both migrant and native students. This interpretation finds further support in Column 3 of Table 3, where we study the effects of the Venezuelan migration shock on dropout rates. As mentioned in section 3, this outcome already accounts for school switchers, so it should be interpreted a schoolsystem dropout. We find that the Venezuelan migration shock increased dropout rates for all types of students. A one-standard-deviation increase in the predicted migration shock increases the dropout rate of foreign males (females) in 1.6 (1.4) percent of the group-specific standard deviation. It also increases the dropout rate of native males (females) in 3.6 (4.2) of the group-specific standard deviation.

While it is worrisome that the shock increases dropout rates and that it does so across
the board, notice that the magnitude of the effect is substantially larger for native students. This finding is important for the design of school retention policies.

Finally, we study the effect of the migration shock on the scores of the standardized end-of-school-test, a proxy of educational quality. We do so for the case of math scores (Column 4) and language scores (Column 5). The migration-driven increased school enrollment does not seem to affect school performance, as all the coefficients are close to zero. The only exception is a positive and significant effect on the performance of migrant male students in the language test. A one-standard-deviation increase in the predicted migration shock increases this outcome in 5 percent of a standard deviation. According to the education literature this is about $25 \%$ of a year worth of education.
5.2. Results by school types. We move to studying migration impacts on educational outcomes in different types of school. First, we distinguish between public and private schools, and report the results in Tables 4 and 5, respectively.

In both Tables, the results reported in Column 1 imply that the documented increase in the enrollment of foreign students of both genders occur both in public and private schools. Anecdotal evidence suggests that many Venezuelans seek private education, even if their economic conditions are precarious. Still, since enrolling in a public school is free, relative to the total average enrollment the effect is twice as large for public schools than for private schools.

On the other hand, the documented reduction in promotion rates, and the increase in dropout rates, are both entirely driven by public schools (Column 2 and 3 of both Tables, respectively). The estimated coefficients of the effect of the migration shock on promotion/dropout rates in private schools is not only statistically insignificant, but also much smaller in magnitude relative to the estimates for public schools. This heterogeneity is largely consistent with the different capacity of public and private schools to react to increases in enrollment by providing more or better school inputs, a mechanism that we test formally in the next section.

The effects of the migration shock on school performance of high school seniors is encouraging, and it is concentrated on foreign students. In public schools, the migration shock increases school performance of both foreign females (in math and language) and foreign males (in language only), but has no effect on natives (Columns 4 and 5 of Table 4). In private schools, only foreign males benefit from the Venezuelan migration flows, and they do so both in math and language.

The second dimension of heterogeneity is the focus on primary versus secondary school grades. Do the documented effects of the shock depend on the schooling cycle and therefore on age? We explore this on Tables 6 and 7, which report the estimated effects of the shock in primary school grades and in secondary grades respectively. ${ }^{16}$ Interestingly, the shock-induced enrollment increase of foreign students is present in both primary and secondary grades, suggesting that migrant kids cover a wide age spectrum (Column 1). Moreover, the negative effect of the shock on promotion rates seems to be driven by primary school grades in all sub-groups except that of foreign females, who seem to have their promotion rate affected in secondary school grades (Column 2). Finally, the estimates for dropout rates are rather imprecise, but the coefficients are positive in both cases and larger in magnitude fro primary school grades (Column 3). While inconclusive, this evidence is consistent with the migration shock affecting disproportionally primary school grades.

The third and final dimension of heterogeneity if whether the school is located in a relatively more urban or more rural areas. We implement this classification by identifying schools located in municipalities above and below the median of the ratio of rural to total municipal population. These data come for the Colombian Statistics Bureau. The descriptive statistics of this variable are reported in Panel B of Table 1. Table 8 reports the results for the subsample of schools located in urban areas, and Table 9 does so for the subsample of rural areas. Once again, it is reassuring to corroborate that larger migration cumulative inflows of Venezuelans increase school enrollment of both migrant men and women in both urban and rural areas (Column 1). Interestingly, however, in rural areas the migration shock seems to have positive spillovers on local children, as the enrollment of native males and females also increases significantly (Table 9). The other outcomes have imprecisely estimated effects, which prevent us from drawing strong conclusions about their heterogeneity across the urban/rural dimension.
5.3. Dynamics. Because of the cumulative nature of the migration shock (see Figure 1), we also study the yearly dynamics of the effect of the year-by-year cumulative migration inflows coming from Venezuela on the outcomes of interest. Figures 5 to 9 report the marginal effects of an event-study specification that interacts all the components of equation 4.1 with year dummies, together with their $95 \%$ confidence interval. ${ }^{17}$

[^10]As usual in this type of specifications, standard errors are somewhat large. However, interesting patterns do emerge. For instance, Figure 5 shows that the effect of the migration shock on the enrollment of both foreign men and women has virtually the same magnitude from 2014 to 2018, and it is consistently larger than the effect for natives (and always significantly different from zero). Moreover, the enrollment of both native males and females does increase with the migration shock, but only in the middle of the sample period, from 2014 to 2017. In fact, it follows an inverse U pattern.

Figure 6 corroborates the aforementioned findings for the case of promotion rates, and further highlights that promotion rates decrease with the shock for all students, but especially natives, almost every year of the sample period. In addition, Figure 7 suggests that the discussed increase in dropout rates -for native students only-following the migration shock, is driven by its behavior in 2013 to 2015. This is encouraging as it suggests that schools have adjusted in the later period (which incidentally is the one that has faced the largest migration flows), in ways that have allowed them to reduce the negative spillovers of increased enrollment. Finally, as reported in Figures 8 and 9, the shock has a precisely measured null effect on test scores of native students every year. For the case of foreigners the effect is rather volatile, but migrant males seem to have benefited the most from the migration shock in terms of school performance, especially in language tests. This gain is however not quite long lasting. The estimates of both outcomes for all the subgroups stabilize at zero starting in 2017 (2016 for the case of the math test).

## 6. Potential mechanisms

We find that the massive recent migration of Venezuelan children to Colombia increased school enrollment but also decreased promotion rates and increased dropout rates, especially so for native children in public schools. These findings are consistent with an interpretation in which exogenous enrollment surges generate school congestion and harm the learning environment of both native and foreign students. However, perhaps migrant students exert more effort to offset this threat, as suggested by their performance in standardized tests. In this section, we test this idea in several different, but complementary, ways.

First, we explore the extent to which the observed increases in the enrollment of migrant students differentially affect the outcomes that we study in this paper. To that, end we compute the school-specific capacity of absorbing new students. Unfortunately, however, there is no data on school-level vacancies. Moreover, by law, public schools
need to accommodate any new enrollment demand. We therefore compute an 'enrollment capacity gap' measure that is specific to 2016. This is the last sample year prior to the largest Venezuelan inflow shock (see Figure 1). In order to compute each school's enrollment gap, we calculate the largest historical observed enrollment of the school, and subtract from it the 2016 enrollment. Finally, we run our main specification (equation 4.1) in the subsample of schools located each of the four enrollment gap quartiles. In other words, we explore the heterogeneous effects of our main results by the extent to which school can absorbe new students, as suggested by the size of their historical enrollment.

The results are reported on Table 10. Clearly, the aforementioned decrease in promotion rates and increase in dropout rates is, by and large, explained by schools located in the first quartile of the enrollment capacity gap (Panel D) and to a lesser extent (in terms of the magnitude of the coefficients) by the schools located in the second quartile (Panel C). In other words, the schools at the bottom half of the enrollment capacity gap (i.e. those that have less ability to absorbe new students just prior to the large migration shock) are the ones negatively affected by the exogenous shift in the demand for school places.

We also examine the effect of the migration shock on key school inputs, specifically associated with the number and quality of teachers and class size. To that end we estimate the following simpler version of equation 4.1:

$$
\begin{equation*}
Y_{s m d t}=\theta\left[\text { Pr.Ven.Shock }{ }_{m d t}^{1993}\right]+\lambda_{s}+\gamma_{d \times t}+\sum_{c \in \mathbf{X}_{\mathbf{m d}}} \delta^{\prime}\left(c \times \phi_{t}\right)+\epsilon_{s m d t} \tag{6.1}
\end{equation*}
$$

where $Y_{\text {smdt }}$ is either the ( $\log$ of) the number of teachers in school $s$, the pupil-to- teacher ratio (class size) or the ratio of teachers with a temporary contract to total school teachers. On the last outcome, school teachers in Colombia that pass a qualification exam become tenured teachers, while those who do not receive temporary contracts. This is thus a measure of the quality of the teachers. It is also worth noting that, unfortunately, these data are only available for public schools and from 2014 onwards.

The results are reported on Tables 11 and 12. The first Table looks at the effect on all (public) schools (Panel A), the schools located in urban areas (Panel B) and those located in rural areas (Panel C). We find that the migration shock reduces the number of school teachers and increases class size (the ratio of students to teachers). However, it seems to have no effect on the quality of the teachers, as measured by their meritdetermined contract type. These are important findings as they suggest that (public)
school inputs deteriorate with the migration shock, which may explain at least in part why both foreign and native students are promoted less and also dropout more. In addition, Table 12 suggests that the reduction in the number of teachers is driven by secondary school grades and the increased ratio of pupils to teachers is driven by primary school grades.

## 7. Conclusion

For several years, Venezuela has faced a humanitarian crisis generated by economic and political turmoil. Public safety has deteriorated and the access to basic supplies and medications is largely restricted. This situation has pushed over 5 million Venezuelans to leave their country, and most of them have settled across South America. By mid 2020, the country that had received the vast majority of Venezuelan migrants is Colombia, where the official statistics approach the 2 million migrants, almost $5 \%$ of the its own native population. This constitutes a shock of unprecedented magnitud, that has affected most economic and social outcomes in receiving municipalities.

The extent to which the labor market, the housing market, the health and the education systems can absorbe such a large shock without causing large externalities to local communities (thus generating backlash and public outcry) depends on the policy response of the national and the local governments. These will shape the sectoral and geographical adaptation to the migration wave, and thus the capacity of local communities to offset potential negative externalities and boost the positive spillovers.

We find that plausibly exogenous predicted cumulative Venezuelan migration inflows have large effects on the enrollment of migrants, and even positive enrollment spillovers for local children in rural areas. However, we also find that, perhaps because the enrollment surge and the consequential congestion of resources (including but not limited to teachers) the migration shock negatively affects school promotion and increases dropout rates. While this occurs for both migrant and local students, these negative spillovers are substantially larger for natives. One potential reason is that migrant students exert more effort at school. This is consistent with out findings that, after the migration shock, both foreign men and women perform better in the national end-of-school exam, but the same is not true for natives.

Importantly, we also find that while the enrollment boost occurs in all types of schools (public and private, urban and rural, primary and secondary), the negative spillovers are mainly taking place in public schools, and especially in primary school grades. This
is likely driven by the differential capacity of public and private schools to react to the demand shock by increasing key inputs such as the number of teachers. Indeed, we find that the migration shock reduced the number of teachers in public schools, while at the same time increased class-size in detriment of more targeted learning experiences for both migrant and native students. The lack of short-term investments and response of public schools are perhaps what make these results contrast to a large literature that has found no effects of migration flows on the schooling outcomes of native students. ${ }^{18}$.

Understanding the effect of the recent surge in migration flows from Venezuela on selected outcomes such as those related with the capacity of children to accumulate human capital, and understanding the potential mitigating effects of different policy responses is of foremost policy importance. This will help achieve a smooth and beneficial absorption of the Venezuelan community into Colombia. This paper contributes to this policy agenda, perhaps the most important that Colombia will face in the next decade, as the crisis in Venezuela intensifies.

[^11]Figure 1. Evolution of Venezuelan migration to Colombia


Figure 2. Distribution of Venezuelans according to the 1993 census


Figure 3. Distribution of Venezuelans according to the 2018 census


Figure 4. Predicted Distribution of Cumulative Venezuelan Inflows for 2018


Figure 5. Marginal yearly effect on enrollment


Figure 6. Marginal yearly effect on promotion rate


Figure 7. Marginal yearly effect on dropout rate


Figure 8. Marginal yearly effect on math test scores


Figure 9. Marginal yearly effect on language test scores


Table 1. Descriptive statistics: main variables

| Variable | Obs | Mean | Std. Dev. | Min | Max |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Panel A: School Level |  |  |  |  |  |
| Enrollment | 119,061 | 470.661 | 651.445 | 1.000 | 10320.000 |
| Promotion Rate | 119,061 | 94.290 | 10.241 | 0.000 | 100.000 |
| Dropout Rate | 119,061 | 3.214 | 8.874 | 0.000 | 100.000 |
| Saber 11 Math STD. Scores | 60,348 | 0.097 | 1.003 | -3.946 | 7.803 |
| Saber 11 Language STD. Scores | 60,348 | 0.099 | 0.997 | -4.027 | 5.013 |
| Public Schools | 119,061 | 0.602 | 0.489 | 0.000 | 1.000 |
| N. of Teachers | 44,890 | 32.852 | 32.940 | 1.000 | 347.000 |
| Pupil/Teachers Ratio | 44,890 | 21.260 | 39.266 | 0.120 | 2332.000 |
| Temporal Teachers (\%) | 44,890 | 21.787 | 25.812 | 0.000 | 100.000 |
| Capacity Gap at 2016 | 16769 | 60.644 | 130.314 | 0.000 | 2875.000 |
| Panel B: Municipality Level |  |  |  |  |  |
| Predicted Cum. Venezuelans Inflow | 6,874 | 6.746 | 22.891 | 0 | 643.313 |
| Indicator for Urban Municipality | 6,874 | 0.494 | 0.500 | 0 | 1.000 |

Table 2. Descriptive Statistics: pre-determined municipal controls

| Variable | Year | Obs. | Mean | Standard Deviation | Category |
| :--- | :---: | :---: | :---: | :---: | :--- |
| Per capita GDP (Millions) | 2005 | 1,097 | 6.381 | 6.632 | Economic Growth |
| Night Light Density | 1995 | 1,048 | 3.968 | 7.466 | Economic Growth |
| GINI | 1993 | 1,043 | 0.456 | 0.0378 | Poverty and Inequality |
| Subsidized Health System Cov. (\%Pop.with UBN) | 1998 | 1,136 | 0.716 | 0.411 | Poverty and Inequality |
| Unsatisfied Basic Needs (UBN, \% Households ) | 1993 | 1,035 | 52.98 | 19.21 | Poverty and Inequality |
| Number of Financial Institutions | 1995 | 1,046 | 1.754 | 8.922 | Institutions |
| Number of Tax Collection Offices | 1995 | 1,046 | 36.05 | 182.4 | Institutions |
| Informal Labor* (\% Household) | 2005 | 1,114 | 0.949 | 0.0571 | Labor Market |
| Municipal Tax Income (Millions) | 1995 | 1,098 | 1,033 | 16,066 | Government Finance |
| Mun. Public Expenditure (Thousands) | 1995 | 1,098 | 2,909 | 28,866 | Government Finance |
| Central Gov.Transfers (Millions) | 1995 | 1,098 | 1,168 | 5,348 | Government Finance |
| Homicide Rate (per 100,000 Indv.) | 1995 | 1,048 | 52.92 | 66.89 | Conflict and Violence |
| Hectares of Coca Crops | 1999 | 1,124 | 142.5 | 960.2 | Conflict and Violence |
| N. of Terrorist Attacks | 1993 | 1,124 | 0.657 | 2.628 | Conflict and Violence |
| Notes: *Informal Labor is a dummy variable equal to one if less than $100 \%$ of the economically active population |  |  |  |  |  |
| within a household does not contribute to the pension system. |  |  |  |  |  |

Table 3. Average effect of the Venezuelan migration shock on educational outcomes - All schools (marginal effects)

| Dependent Var. | $\begin{gathered} \hline \hline 1) \\ \operatorname{Ln}(\text { Enrollment }) \end{gathered}$ | $\begin{gathered} \hline \hline(2) \\ \text { Promotion Rate } \end{gathered}$ | $(3)$ Dropout Rate | (4) <br> Math Std. <br> Score | $(5)$ $\substack{\text { Language Std. } \\ \text { Score }}$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | Panel A: Without | Controls |  |  |
| Foreign Males | $\begin{gathered} 0.0043^{* * *} \\ (0.0010) \end{gathered}$ | $\begin{gathered} -0.0244^{* * *} \\ (0.0090) \end{gathered}$ | $\begin{gathered} 0.0146^{*} * \\ (0.0067) \end{gathered}$ | $\begin{gathered} 0.0017 \\ (0.0012) \end{gathered}$ | $\begin{gathered} 0.0040^{* * *} \\ (0.0012) \end{gathered}$ |
| Native Males | $\begin{gathered} 0.0005 \\ (0.0009) \end{gathered}$ | $\begin{gathered} -0.0228^{* *} \\ (0.0091) \end{gathered}$ | $\begin{gathered} 0.0146^{* *} \\ (0.0069) \end{gathered}$ | $\begin{gathered} -0.0000 \\ (0.0006) \end{gathered}$ | $\begin{gathered} 0.0003 \\ (0.0005) \end{gathered}$ |
| Foreign Females | $\begin{gathered} 0.0040^{* * *} \\ (0.0010) \end{gathered}$ | $\begin{aligned} & -0.0135 \\ & (0.0095) \end{aligned}$ | $\begin{aligned} & 0.0122^{*} \\ & (0.0068) \end{aligned}$ | $\begin{gathered} 0.0014 \\ (0.0013) \end{gathered}$ | $\begin{aligned} & 0.0016^{*} \\ & (0.0009) \end{aligned}$ |
| Native Females | $\begin{gathered} 0.0004 \\ (0.0009) \end{gathered}$ | $\begin{gathered} -0.0199^{* *} \\ (0.0090) \end{gathered}$ | $\begin{gathered} 0.0162^{* *} \\ (0.0070) \end{gathered}$ | $\begin{gathered} 0.0003 \\ (0.0004) \end{gathered}$ | $\begin{gathered} 0.0005 \\ (0.0004) \end{gathered}$ |
| R-Squared | 0.8739 | 0.2568 | 0.2102 | 0.7949 | 0.7786 |
|  | Panel B: With Controls |  |  |  |  |
| Foreign Males | $\begin{gathered} 0.0041^{* * *} \\ (0.0010) \end{gathered}$ | $\begin{gathered} -0.0235^{* * *} \\ (0.0088) \end{gathered}$ | $\begin{gathered} 0.0135^{* *} \\ (0.0066) \end{gathered}$ | $\begin{gathered} 0.0016 \\ (0.0012) \end{gathered}$ | $\begin{gathered} 0.0039^{* * *} \\ (0.0012) \end{gathered}$ |
| Native Males | $\begin{aligned} & 0.0003 \\ & (0.0008) \end{aligned}$ | $\begin{gathered} -0.0219 * * \\ (0.0090) \end{gathered}$ | $\begin{aligned} & 0.0135^{*} \\ & (0.0069) \end{aligned}$ | $\begin{aligned} & -0.0001 \\ & (0.0006) \end{aligned}$ | $\begin{gathered} 0.0002 \\ (0.0005) \end{gathered}$ |
| Foreign Females | $\begin{gathered} 0.0037^{* * *} \\ (0.0010) \end{gathered}$ | $\begin{aligned} & -0.0126 \\ & (0.0094) \end{aligned}$ | $\begin{aligned} & 0.0111^{*} \\ & (0.0067) \end{aligned}$ | $\begin{gathered} 0.0013 \\ (0.0013) \end{gathered}$ | $\begin{gathered} 0.0015 \\ (0.0010) \end{gathered}$ |
| Native Females | $\begin{gathered} 0.0002 \\ (0.0008) \end{gathered}$ | $\begin{gathered} -0.0190^{* *} \\ (0.0088) \end{gathered}$ | $\begin{aligned} & 0.0150^{* *} \\ & (0.0070) \end{aligned}$ | $\begin{gathered} 0.0002 \\ (0.0003) \end{gathered}$ | $\begin{gathered} 0.0004 \\ (0.0004) \end{gathered}$ |
| R-Squared | 0.8740 | 0.2573 | 0.2106 | 0.7951 | 0.7788 |
| Native Males Mean | 4.431 | 93.64 | 3.334 | 0.268 | 0.0731 |
| Native Males SD | 1.671 | 10.71 | 8.673 | 1.004 | 0.977 |
| Native Females Mean | 4.354 | 95.25 | 2.800 | -0.102 | 0.0900 |
| Native Females SD | 1.707 | 9.383 | 8.178 | 0.907 | 0.964 |
| Foreign Males Mean | 1.101 | 90.79 | 6.241 | 0.811 | 0.511 |
| Foreign Males SD | 1.120 | 22.49 | 19.12 | 1.852 | 1.764 |
| Foreign Females Mean | 1.082 | 92.10 | 5.834 | 0.236 | 0.406 |
| Foreign Females SD | 1.104 | 21.18 | 18.71 | 1.697 | 1.736 |
| Observations | 334,160 | 334,160 | 334,160 | 120,478 | 120,478 |

All columns include School FE, Year FE and Department $\times$ Year FE
Selected controls include the following variables interacted with year dummies: N. of Terrorist Attacks $\times 2012,2014$ and 2016, Informal Labor $\times 2018$, UBN $\times 2013$.

Table 4. Average effect of the Venezuelan migration shock on educational outcomes - Public schools (marginal effects)

| Dependent Var. | $\begin{gathered} (1) \\ \operatorname{Ln}(\text { Enrollment }) \end{gathered}$ | $\frac{(2)}{\text { Promotion Rate }}$ | (3) <br> Dropout Rate | (4) <br> Math Std. <br> Score | (5) Language Std. Score |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  | Panel A: Without Controls |  |  |  |  |
| Foreign Males | $\begin{gathered} 0.0053^{* * *} \\ (0.0013) \end{gathered}$ | $\begin{gathered} -0.0294^{* * *} \\ (0.0096) \end{gathered}$ | $\begin{gathered} 0.0128^{* *} \\ (0.0064) \end{gathered}$ | $\begin{gathered} 0.0015 \\ (0.0013) \end{gathered}$ | $\begin{gathered} 0.0041^{* *} \\ (0.0020) \end{gathered}$ |
| Native Males | $\begin{gathered} 0.0013 \\ (0.0012) \end{gathered}$ | $\begin{gathered} -0.0312^{* * *} \\ (0.0090) \end{gathered}$ | $\begin{gathered} 0.0119 * * \\ (0.0059) \end{gathered}$ | $\begin{gathered} 0.0000 \\ (0.0006) \end{gathered}$ | $\begin{gathered} 0.0003 \\ (0.0005) \end{gathered}$ |
| Foreign Females | $\begin{gathered} 0.0051^{* * *} \\ (0.0013) \end{gathered}$ | $\begin{gathered} -0.0193^{*} \\ (0.0114) \end{gathered}$ | $\begin{aligned} & 0.0126^{*} \\ & (0.0068) \end{aligned}$ | $\begin{gathered} 0.0022^{* *} \\ (0.0009) \end{gathered}$ | $\begin{gathered} 0.0022^{* *} \\ (0.0010) \end{gathered}$ |
| Native Females | $\begin{gathered} 0.0018 \\ (0.0013) \end{gathered}$ | $\begin{gathered} -0.0176^{* *} \\ (0.0088) \end{gathered}$ | $\begin{gathered} 0.0102 \\ (0.0064) \end{gathered}$ | $\begin{gathered} 0.0004 \\ (0.0003) \end{gathered}$ | $\begin{aligned} & 0.0007^{*} \\ & (0.0004) \end{aligned}$ |
| R-Squared | 0.8980 | 0.2539 | 0.2167 | 0.6896 | 0.6729 |
|  | Panel B: With Controls |  |  |  |  |
| Foreign Males | $\begin{gathered} 0.0051^{* * *} \\ (0.0013) \end{gathered}$ | $\begin{gathered} -0.0286^{* * *} \\ (0.0093) \end{gathered}$ | $\begin{gathered} 0.0129^{* *} \\ (0.0064) \end{gathered}$ | $\begin{gathered} 0.0014 \\ (0.0012) \end{gathered}$ | $\begin{gathered} 0.0041^{* *} \\ (0.0020) \end{gathered}$ |
| Native Males | $\begin{gathered} 0.0011 \\ (0.0011) \end{gathered}$ | $\begin{gathered} -0.0305^{* * *} \\ (0.0089) \end{gathered}$ | $\begin{gathered} 0.0120^{* *} \\ (0.0059) \end{gathered}$ | $\begin{gathered} -0.0001 \\ (0.0006) \end{gathered}$ | $\begin{gathered} 0.0002 \\ (0.0004) \end{gathered}$ |
| Foreign Females | $\begin{gathered} 0.0049^{* * *} \\ (0.0013) \end{gathered}$ | $\begin{aligned} & -0.0185^{*} \\ & (0.0112) \end{aligned}$ | $\begin{aligned} & 0.0126^{*} \\ & (0.0067) \end{aligned}$ | $\begin{gathered} 0.0021^{* *} \\ (0.0009) \end{gathered}$ | $\begin{aligned} & 0.0021^{* *} \\ & (0.0010) \end{aligned}$ |
| Native Females | $\begin{gathered} 0.0016 \\ (0.0013) \end{gathered}$ | $\begin{aligned} & -0.0170^{*} \\ & (0.0088) \end{aligned}$ | $\begin{gathered} 0.0103 \\ (0.0064) \end{gathered}$ | $\begin{gathered} 0.0003 \\ (0.0003) \end{gathered}$ | $\begin{gathered} 0.0006 \\ (0.0004) \end{gathered}$ |
| R-Squared | 0.8982 | 0.2544 | 0.2169 | 0.6907 | 0.6735 |
| Native Males Mean | 4.706 | 91.76 | 3.961 | -0.0329 | -0.249 |
| Native Males SD | 1.787 | 11.32 | 8.874 | 0.743 | 0.751 |
| Native Females Mean | 4.648 | 94.07 | 3.176 | -0.400 | -0.262 |
| Native Females SD | 1.820 | 9.700 | 8.194 | 0.626 | 0.691 |
| Foreign Males Mean | 1.247 | 87.48 | 8.391 | -0.0445 | -0.231 |
| Foreign Males SD | 1.167 | 25.09 | 21.43 | 1.389 | 1.535 |
| Foreign Females Mean | 1.221 | 89.29 | 7.842 | -0.527 | -0.319 |
| Foreign Females SD | 1.147 | 23.81 | 21.09 | 1.319 | 1.475 |
| Observations | 203,326 | 203,326 | 203,326 | 81,082 | 81,082 |

All columns include School FE, Year FE and Department $\times$ Year FE.
Selected controls include the following variables interacted with year dummies: N. of Terrorist Attacks $\times 2012$, 2014 and 2016, Informal Labor $\times 2018$, UBN $\times 2013$.

Table 5. Average effect of the Venezuelan migration shock on educational outcomes - Private schools (marginal effects)

| Dependent Var. | $\begin{gathered} \hline \hline(1) \\ \operatorname{Ln}(\text { Enrollment }) \end{gathered}$ | $\begin{gathered} \hline \hline(2) \\ \text { Promotion Rate } \end{gathered}$ | $(3)$ Dropout Rate | (4) <br> Math Std. <br> Score | $\begin{gathered} \hline \hline(5) \\ \text { Language Std. } \\ \text { Score } \end{gathered}$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  | Panel A: Without Controls |  |  |  |  |
| Foreign Males | $\begin{gathered} 0.0027^{* *} \\ (0.0011) \end{gathered}$ | $\begin{gathered} -0.0111 \\ (0.0121) \end{gathered}$ | $\begin{gathered} 0.0045 \\ (0.0156) \end{gathered}$ | $\begin{gathered} 0.0031^{* *} \\ (0.0014) \end{gathered}$ | $\begin{gathered} 0.0034^{* * *} \\ (0.0009) \end{gathered}$ |
| Native Males | $\begin{gathered} 0.0000 \\ (0.0018) \end{gathered}$ | $\begin{aligned} & -0.0060 \\ & (0.0151) \end{aligned}$ | $\begin{gathered} 0.0008 \\ (0.0187) \end{gathered}$ | $\begin{gathered} 0.0003 \\ (0.0013) \end{gathered}$ | $\begin{aligned} & -0.0000 \\ & (0.0010) \end{aligned}$ |
| Foreign Females | $\begin{aligned} & 0.0022^{* *} \\ & (0.0010) \end{aligned}$ | $\begin{gathered} 0.0022 \\ (0.0149) \end{gathered}$ | $\begin{gathered} -0.0019 \\ (0.0173) \end{gathered}$ | $\begin{gathered} -0.0009 \\ (0.0025) \end{gathered}$ | $\begin{aligned} & -0.0010 \\ & (0.0012) \end{aligned}$ |
| Native Females | $\begin{gathered} -0.0006 \\ (0.0019) \end{gathered}$ | $\begin{gathered} -0.0067 \\ (0.0151) \end{gathered}$ | $\begin{gathered} 0.0032 \\ (0.0184) \end{gathered}$ | $\begin{gathered} 0.0003 \\ (0.0013) \end{gathered}$ | $\begin{aligned} & -0.0003 \\ & (0.0008) \end{aligned}$ |
| R-Squared | 0.8363 | 0.2059 | 0.2087 | 0.7915 | 0.7415 |
| Panel B: With Controls |  |  |  |  |  |
| Foreign Males | $\begin{gathered} 0.0025^{* *} \\ (0.0011) \end{gathered}$ | $\begin{gathered} -0.0110 \\ (0.0119) \end{gathered}$ | $\begin{gathered} 0.0046 \\ (0.0153) \end{gathered}$ | $\begin{gathered} 0.0032^{* *} \\ (0.0014) \end{gathered}$ | $\begin{gathered} 0.0035^{* * *} \\ (0.0008) \end{gathered}$ |
| Native Males | $\begin{gathered} -0.0002 \\ (0.0017) \end{gathered}$ | $\begin{gathered} -0.0059 \\ (0.0149) \end{gathered}$ | $\begin{gathered} 0.0009 \\ (0.0184) \end{gathered}$ | $\begin{gathered} 0.0005 \\ (0.0013) \end{gathered}$ | $\begin{gathered} 0.0001 \\ (0.0010) \end{gathered}$ |
| Foreign Females | $\begin{aligned} & 0.0020^{* *} \\ & (0.0010) \end{aligned}$ | $\begin{gathered} 0.0023 \\ (0.0148) \end{gathered}$ | $\begin{gathered} -0.0018 \\ (0.0169) \end{gathered}$ | $\begin{gathered} -0.0007 \\ (0.0025) \end{gathered}$ | $\begin{gathered} -0.0009 \\ (0.0012) \end{gathered}$ |
| Native Females | $\begin{gathered} -0.0008 \\ (0.0018) \end{gathered}$ | $\begin{gathered} -0.0066 \\ (0.0149) \end{gathered}$ | $\begin{gathered} 0.0032 \\ (0.0181) \end{gathered}$ | $\begin{gathered} 0.0005 \\ (0.0014) \end{gathered}$ | $\begin{gathered} -0.0002 \\ (0.0009) \end{gathered}$ |
| R-Squared | 0.8364 | 0.2063 | 0.2091 | 0.7916 | 0.7417 |
| Native Males Mean | 4.009 | 96.50 | 2.373 | 0.906 | 0.756 |
| Native Males SD | 1.373 | 8.971 | 8.263 | 1.174 | 1.046 |
| Native Females Mean | 3.905 | 97.06 | 2.225 | 0.510 | 0.813 |
| Native Females SD | 1.405 | 8.565 | 8.119 | 1.074 | 1.040 |
| Foreign Males Mean | 0.871 | 96.01 | 2.841 | 1.788 | 1.359 |
| Foreign Males SD | 0.999 | 16.30 | 14.10 | 1.833 | 1.621 |
| Foreign Females Mean | 0.853 | 96.75 | 2.519 | 1.125 | 1.251 |
| Foreign Females SD | 0.988 | 14.76 | 13.27 | 1.656 | 1.632 |
| Observations | 130,834 | 130,834 | 130,834 | 39,396 | 39,396 |

All columns include School FE, Year FE and Department $\times$ Year FE
Selected controls include the following variables interacted with year dummies: N. of Terrorist Attacks $\times 2012,2014$ and 2016, Informal Labor $\times 2018$, UBN $\times 2013$.

Table 6. Average effect of the Venezuelan migration shock on educational outcomes - Primary school grades (marginal effects)

| Dependent Var. | (1) | (2) | (3) |
| :---: | :---: | :---: | :---: |
|  | Ln(Enrollment) | Promotion Rate | Dropout Rate |
| Foreign Males | Panel A: With | ut Controls |  |
|  | $0.0038^{* * *}$ | $-0.0257^{* * *}$ | $0.0175^{* * *}$ |
|  | (0.0009) | (0.0080) | (0.0067) |
| Native Males | 0.0010 | -0.0187** | 0.0109 |
|  | (0.0008) | (0.0075) | (0.0070) |
| Foreign Females | 0.0036 *** | -0.0115 | 0.0085 |
|  | (0.0009) | (0.0088) | (0.0070) |
| Native Females | 0.0008 | -0.0167** | 0.0120* |
|  | (0.0008) | (0.0078) | (0.0072) |
| R-Squared | 0.8691 | 0.2449 | 0.2063 |
|  | Panel B: With | Controls |  |
| Foreign Males | $0.0036{ }^{* * *}$ | $-0.0247^{* * *}$ | $0.0162^{* *}$ |
|  | (0.0008) | (0.0077) | (0.0065) |
| Native Males | 0.0007 | $-0.0177^{* *}$ | 0.0095 |
|  | (0.0007) | (0.0074) | (0.0070) |
| Foreign Females | $0.0034^{* * *}$ | $-0.0105$ | 0.0071 |
|  | $(0.0009)$ | $(0.0087)$ | (0.0069) |
| Native Females | 0.0006 | -0.0157** | 0.0106 |
|  | (0.0008) | (0.0077) | (0.0072) |
| R-Squared | 0.8693 | 0.2453 | 0.2068 |
| Native Males Mean | 4.005 | 94.61 | 2.941 |
| Native Males SD | 1.442 | 10.24 | 8.492 |
| Native Females Mean | 3.892 | 95.91 | 2.470 |
| Native Females SD | 1.462 | 9.077 | 7.976 |
| Foreign Males Mean | 0.911 | 91.56 | 5.933 |
| Foreign Males SD | 1.017 | 22.45 | 19.27 |
| Foreign Females Mean | 0.884 | 92.70 | 5.529 |
| Foreign Females SD | 0.997 | 21.20 | 18.82 |
| Observations | 313,195 | 313,195 | 313,195 |
| Clustered standard errors by municipality in parentheses. ${ }^{* * *} \mathrm{p}<0.01$, ${ }^{* *} \mathrm{p}<0.05$, ${ }^{*} \mathrm{p}<0.1$. All columns include School FE, Year FE and Department $\times$ Year FE. |  |  |  |
|  |  |  |  |
| Selected controls include the following variables interacted with year dummies: |  |  |  |
| N. of Terrorist Attacks $\times 2012,2014$ and 2016, Informal Labor $\times 2018$, UBN $\times 2013$. |  |  |  |

Table 7. Average effect of the Venezuelan migration shock on educational outcomes - Secondary school grades (marginal effects)

| Dependent Var. | (1) | (2) | (3) |
| :---: | :---: | :---: | :---: |
|  | Ln(Enrollment) | Promotion Rate | Dropout Rate |
| Foreign Males | Panel A: Witho | ut Controls |  |
|  | $0.0023^{* * *}$ | -0.0152 | 0.0032 |
|  | (0.0007) | (0.0111) | (0.0075) |
| Native Males | 0.0005 | -0.0147 | 0.0066 |
|  | (0.0007) | (0.0116) | (0.0074) |
| Foreign Females | 0.0025*** | -0.0212* | 0.0190** |
|  | (0.0008) | (0.0118) | (0.0089) |
| Native Females | 0.0005 | -0.0104 | 0.0067 |
|  | (0.0007) | (0.0110) | (0.0077) |
| R-Squared | 0.8784 | 0.2680 | 0.2098 |
|  | Panel B: With Controls |  |  |
| Foreign Males | $0.0022^{* * *}$ | -0.0143 | 0.0027 |
|  | (0.0007) | (0.0110) | (0.0075) |
| Native Males | 0.0005 | -0.0139 | 0.0061 |
|  | (0.0007) | (0.0117) | (0.0075) |
| Foreign Females | 0.0024*** | -0.0203* | 0.0185** |
|  | (0.0008) | (0.0117) | (0.0088) |
| Native Females | 0.0004 | -0.0095 | 0.0062 |
|  | (0.0007) | (0.0110) | (0.0077) |
| R-Squared | 0.8784 | 0.2684 | 0.2099 |
| Native Males Mean | 4.611 | 91.17 | 4.077 |
| Native Males SD | 1.292 | 11.50 | 8.145 |
| Native Females Mean | 4.614 | 93.83 | 3.322 |
| Native Females SD | 1.291 | 9.446 | 7.659 |
| Foreign Males Mean | 0.880 | 88.99 | 6.790 |
| Foreign Males SD | 0.990 | 25.97 | 21.11 |
| Foreign Females MeanForeign Females SD | 0.861 | 90.95 | 6.290 |
|  | 0.980 | 23.91 | 20.44 |
| Observations | 203,560 | 203,560 | 203,560 |
| Clustered standard errors by municipality in parentheses. *** $\mathrm{p}<0.01$, ${ }^{* *} \mathrm{p}<0.05,{ }^{*} \mathrm{p}<0.1$ All columns include School FE, Year FE and Department $\times$ Year FE. <br> Selected controls include the following variables interacted with year dummies: <br> N. of Terrorist Attacks $\times 2012$, 2014 and 2016, Informal Labor $\times 2018$, UBN $\times 2013$. |  |  |  |
|  |  |  |  |
|  |  |  |  |
|  |  |  |  |

Table 8. Average effect of the Venezuelan migration shock on educational outcomes - Urban areas (marginal effects)

| Dependent Var. | $\begin{gathered} \hline \hline(1) \\ \operatorname{Ln}(\text { Enrollment }) \end{gathered}$ | $(2)$ Promotion Rate | $(3)$ Dropout Rate | (4) <br> Math Std. <br> Score | (5) Language Std. Score |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  | Panel A: Without Controls |  |  |  |  |
| Foreign Males | $\begin{gathered} 0.0041^{* * *} \\ (0.0010) \end{gathered}$ | $\begin{aligned} & -0.0205^{*} \\ & (0.0108) \end{aligned}$ | $\begin{gathered} 0.0112 \\ (0.0078) \end{gathered}$ | $\begin{gathered} 0.0014 \\ (0.0011) \end{gathered}$ | $\begin{gathered} 0.0036^{* * *} \\ (0.0011) \end{gathered}$ |
| Native Males | $\begin{aligned} & -0.0006 \\ & (0.0011) \end{aligned}$ | $\begin{aligned} & -0.0164 \\ & (0.0113) \end{aligned}$ | $\begin{gathered} 0.0079 \\ (0.0089) \end{gathered}$ | $\begin{aligned} & -0.0004 \\ & (0.0007) \end{aligned}$ | $\begin{gathered} -0.0000 \\ (0.0005) \end{gathered}$ |
| Foreign Females | $\begin{gathered} 0.0038^{* * *} \\ (0.0010) \end{gathered}$ | $\begin{gathered} -0.0103 \\ (0.0115) \end{gathered}$ | $\begin{gathered} 0.0079 \\ (0.0080) \end{gathered}$ | $\begin{gathered} 0.0008 \\ (0.0015) \end{gathered}$ | $\begin{gathered} 0.0013 \\ (0.0010) \end{gathered}$ |
| Native Females | $\begin{aligned} & -0.0008 \\ & (0.0012) \end{aligned}$ | $\begin{aligned} & -0.0130 \\ & (0.0113) \end{aligned}$ | $\begin{gathered} 0.0086 \\ (0.0089) \end{gathered}$ | $\begin{gathered} 0.0000 \\ (0.0004) \end{gathered}$ | $\begin{gathered} 0.0002 \\ (0.0004) \end{gathered}$ |
| R-Squared | 0.8683 | 0.2497 | 0.2033 | 0.8051 | 0.7836 |
|  | Panel B: With Controls |  |  |  |  |
| Foreign Males | $\begin{gathered} 0.0040^{* * *} \\ (0.0009) \end{gathered}$ | $\begin{aligned} & -0.0201^{*} \\ & (0.0105) \end{aligned}$ | $\begin{gathered} 0.0106 \\ (0.0077) \end{gathered}$ | $\begin{gathered} 0.0014 \\ (0.0011) \end{gathered}$ | $\begin{gathered} 0.0036^{* * *} \\ (0.0011) \end{gathered}$ |
| Native Males | $\begin{aligned} & -0.0007 \\ & (0.0011) \end{aligned}$ | $\begin{aligned} & -0.0160 \\ & (0.0112) \end{aligned}$ | $\begin{gathered} 0.0074 \\ (0.0089) \end{gathered}$ | $\begin{gathered} -0.0004 \\ (0.0007) \end{gathered}$ | $\begin{gathered} -0.0000 \\ (0.0005) \end{gathered}$ |
| Foreign Females | $\begin{gathered} 0.0037^{* * *} \\ (0.0009) \end{gathered}$ | $\begin{gathered} -0.0099 \\ (0.0114) \end{gathered}$ | $\begin{gathered} 0.0073 \\ (0.0080) \end{gathered}$ | $\begin{gathered} 0.0008 \\ (0.0015) \end{gathered}$ | $\begin{gathered} 0.0013 \\ (0.0010) \end{gathered}$ |
| Native Females | $\begin{gathered} -0.0010 \\ (0.0012) \end{gathered}$ | $\begin{gathered} -0.0126 \\ (0.0112) \end{gathered}$ | $\begin{gathered} 0.0080 \\ (0.0089) \end{gathered}$ | $\begin{gathered} -0.0000 \\ (0.0004) \end{gathered}$ | $\begin{gathered} 0.0002 \\ (0.0004) \end{gathered}$ |
| R-Squared | 0.8684 | 0.2502 | 0.2037 | 0.8052 | 0.7837 |
| Native Males Mean | 4.631 | 93.74 | 3.309 | 0.387 | 0.214 |
| Native Males SD | 1.627 | 10.50 | 8.572 | 1.024 | 0.981 |
| Native Females Mean | 4.561 | 95.24 | 2.847 | -0.00142 | 0.227 |
| Native Females SD | 1.660 | 9.275 | 8.158 | 0.934 | 0.974 |
| Foreign Males Mean | 1.138 | 91.13 | 5.880 | 0.897 | 0.603 |
| Foreign Males SD | 1.137 | 21.80 | 18.32 | 1.870 | 1.755 |
| Foreign Females Mean | 1.119 | 92.42 | 5.545 | 0.311 | 0.470 |
| Foreign Females SD | 1.120 | 20.45 | 18 | 1.694 | 1.747 |
| Observations | 253,107 | 253,107 | 253,107 | 95,866 | 95,866 |

All columns include School FE, Year FE and Department $\times$ Year FE
Selected controls include the following variables interacted with year dummies: N. of Terrorist Attacks $\times 2012,2014$ and 2016, Informal Labor $\times 2018$, UBN $\times 2013$.

Table 9. Average effect of the Venezuelan migration shock on educational outcomes - Rural areas (marginal effects)

| Dependent Var. | $\begin{gathered} \hline \hline 1) \\ \operatorname{Ln}(\text { Enrollment }) \end{gathered}$ | $(2)$ Promotion Rate | $(3)$ Dropout Rate | (4) <br> Math Std. Score | $(5)$ $\substack{\text { Language Std. } \\ \text { Score }}$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  | Panel A: Without Controls |  |  |  |  |
| Foreign Males | $\begin{gathered} 0.0077^{* * *} \\ (0.0020) \end{gathered}$ | $\begin{gathered} -0.0314 \\ (0.0239) \end{gathered}$ | $\begin{aligned} & -0.0051 \\ & (0.0184) \end{aligned}$ | $\begin{gathered} 0.0016 \\ (0.0036) \end{gathered}$ | $\begin{gathered} 0.0060 \\ (0.0064) \end{gathered}$ |
| Native Males | $\begin{gathered} 0.0110^{* * *} \\ (0.0019) \end{gathered}$ | $\begin{gathered} -0.0343 \\ (0.0220) \end{gathered}$ | $\begin{gathered} 0.0033 \\ (0.0153) \end{gathered}$ | $\begin{gathered} -0.0006 \\ (0.0010) \end{gathered}$ | $\begin{gathered} -0.0003 \\ (0.0011) \end{gathered}$ |
| Foreign Females | $\begin{gathered} 0.0073^{* * *} \\ (0.0018) \end{gathered}$ | $\begin{gathered} -0.0100 \\ (0.0239) \end{gathered}$ | $\begin{gathered} -0.0019 \\ (0.0181) \end{gathered}$ | $\begin{aligned} & 0.0046^{*} \\ & (0.0024) \end{aligned}$ | $\begin{gathered} 0.0014 \\ (0.0041) \end{gathered}$ |
| Native Females | $\begin{gathered} 0.0112^{* * *} \\ (0.0019) \end{gathered}$ | $\begin{aligned} & -0.0180 \\ & (0.0224) \end{aligned}$ | $\begin{gathered} 0.0043 \\ (0.0156) \end{gathered}$ | $\begin{gathered} 0.0005 \\ (0.0010) \end{gathered}$ | $\begin{gathered} 0.0007 \\ (0.0014) \end{gathered}$ |
| R-Squared |  | 0.2908 | 0.2464 | 0.6467 | 0.5996 |
|  | Panel B: With Controls |  |  |  |  |
| Foreign Males | $\begin{gathered} 0.0076^{* * *} \\ (0.0020) \end{gathered}$ | $\begin{gathered} -0.0302 \\ (0.0237) \end{gathered}$ | $\begin{aligned} & -0.0065 \\ & (0.0182) \end{aligned}$ | $\begin{gathered} 0.0015 \\ (0.0036) \end{gathered}$ | $\begin{gathered} 0.0059 \\ (0.0064) \end{gathered}$ |
| Native Males | $\begin{gathered} 0.0109^{* * *} \\ (0.0019) \end{gathered}$ | $\begin{gathered} -0.0331 \\ (0.0219) \end{gathered}$ | $\begin{gathered} 0.0018 \\ (0.0152) \end{gathered}$ | $\begin{gathered} -0.0008 \\ (0.0009) \end{gathered}$ | $\begin{gathered} -0.0005 \\ (0.0011) \end{gathered}$ |
| Foreign Females | $\begin{gathered} 0.0072^{* * *} \\ (0.0018) \end{gathered}$ | $\begin{gathered} -0.0088 \\ (0.0238) \end{gathered}$ | $\begin{gathered} -0.0033 \\ (0.0178) \end{gathered}$ | $\begin{aligned} & 0.0045^{*} \\ & (0.0023) \end{aligned}$ | $\begin{gathered} 0.0013 \\ (0.0041) \end{gathered}$ |
| Native Females | $\begin{gathered} 0.0111^{* * *} \\ (0.0018) \end{gathered}$ | $\begin{aligned} & -0.0168 \\ & (0.0223) \end{aligned}$ | $\begin{gathered} 0.0028 \\ (0.0154) \end{gathered}$ | $\begin{gathered} 0.0003 \\ (0.0010) \end{gathered}$ | $\begin{gathered} 0.0005 \\ (0.0014) \end{gathered}$ |
| R-Squared | 0.8979 | 0.2910 | 0.2467 | 0.6477 | 0.6003 |
| Native Males Mean | 3.888 | 93.34 | 3.400 | -0.180 | -0.459 |
| Native Males SD | 1.669 | 11.23 | 8.939 | 0.774 | 0.752 |
| Native Females Mean | 3.789 | 95.28 | 2.670 | -0.492 | -0.442 |
| Native Females SD | 1.708 | 9.671 | 8.230 | 0.667 | 0.704 |
| Foreign Males Mean | 0.934 | 89.25 | 7.876 | -0.339 | -0.713 |
| Foreign Males SD | 1.027 | 25.33 | 22.33 | 1.084 | 1.384 |
| Foreign Females Mean | 0.912 | 90.64 | 7.175 | -0.834 | -0.504 |
| Foreign Females SD | 1.007 | 24.20 | 21.67 | 1.353 | 1.248 |
| Observations | 81,049 | 81,049 | 81,049 | 24,612 | 24,612 |

All columns include School FE, Year FE and Department $\times$ Year FE
Selected controls include the following variables interacted with year dummies: N. of Terrorist Attacks $\times 2012,2014$ and 2016, Informal Labor $\times 2018$, UBN $\times 2013$.

Table 10. Effect of the Venezuelan migration shock on educational outcomes by quartile of enrollment capacity gap


Table 11. Average effect of the Venezuelan migration shock on school inputs

|  | $(1)$ | $(2)$ | $(3)$ |
| :---: | :---: | :---: | :---: |
| Dependent Var. | $\operatorname{Ln}(\#$ Teachers $)$ | Pupil/Teacher Ratio | Share Tem. Teachers |


| Panel A: All schools (with controls) |  |  |  |
| :--- | :---: | :---: | :---: |
| Predicted Ven. Shock | $-0.0021^{* * *}$ | $0.1899^{* * *}$ | $-0.0269^{*}$ |
|  | $(0.0007)$ | $(0.0691)$ | $(0.0158)$ |
| R-squared | 0.9826 | 0.6087 | 0.8187 |
|  |  |  |  |
| Observations | 42,765 | 42,765 | 42,765 |
| Dep. Var. Mean | 2.762 | 21.26 | 21.79 |
| Dep. Var. SD | 1.477 | 39.27 | 25.81 |


| Panel B: Urban schools (with controls) |  |  |  |
| :--- | :---: | :---: | :---: |
| Predicted Ven. Shock | $-0.0018^{* *}$ | $0.1370^{*}$ | -0.0233 |
|  | $(0.0008)$ | $(0.0704)$ | $(0.0184)$ |
| R-squared | 0.9724 | 0.5815 | 0.8198 |
|  |  |  |  |
| Observations | 25,135 | 25,135 | 25,135 |
| Dep. Var. Mean | 3.271 | 23.04 | 19.64 |
| Dep. Var. SD | 1.266 | 42.80 | 21.92 |


| Panel C: Rural schools (with controls) |  |  |  |
| :--- | :---: | :---: | :---: |
| Predicted Ven. Shock | $-0.0030^{* *}$ | $0.2952^{* * *}$ | -0.0542 |
|  | $(0.0013)$ | $(0.0951)$ | $(0.0330)$ |
| R-squared | 0.9853 | 0.6849 | 0.8230 |
|  |  |  |  |
| Observations | 17,555 | 17,555 | 17,555 |
| Dep. Var. Mean | 2.046 | 18.76 | 24.80 |
| Dep. Var. SD | 1.455 | 33.51 | 30.21 |
| Clustered standard errors by municipality in parentheses. ${ }^{* * *} \mathrm{p}<0.01,{ }^{* *} \mathrm{p}<0.05, * \mathrm{p}<0.1$. |  |  |  |
| All columns include School FE, Year FE and Department $\times$ Year FE. |  |  |  |
| Selected controls include the following variables interacted with year dummies: Hom. Rate $\times 2015$, |  |  |  |
| N. of Terrorist Attacks $\times 2015$, N. of Terrorist Attacks $\times 2018$, Informal Labor $\times 2014$, |  |  |  |
| Informal Labor $\times 2017$, Informal Labor $\times 2017$, Night Light Density $\times 2015$, UBN $\times 2018$. |  |  |  |

Table 12. Average effect of the Venezuelan migration shock on school inputs by teaching school grade (with controls)

|  | $(1)$ | $(2)$ | $(3)$ |
| :---: | :---: | :---: | :---: |
| Dependent Var. | $\operatorname{Ln}(\#$ Teachers $)$ | Pupil/Teacher Ratio | Share Temp. Teachers |



## APPENDIX

Table A.1. Average effect of the Venezuelan migration shock on educational outcomes - All schools (regression output)

|  | $(1)$ |  | $\begin{array}{c}(2) \\ \text { Ln(Enrollment) }\end{array}$ |  | $(3)$ |
| :--- | :---: | :---: | :---: | :---: | :---: |
| Promotion Rate |  |  |  |  |  |$)$

Table A.2. Average effect of the Venezuelan migration shock on educational outcomes - Public schools (regression output)

| Dependent Var. | (1) | (2) | (3) | (4) |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  | Ln(Enrollment) | Promotion Rate | Dropout Rate | Math Std. <br> Score | Language Std. Score |
| Predicted Ven. Shock | $0.0051^{* * *}$ | $-0.0286^{* * *}$ | 0.0129** | 0.0014 | $0.0041^{* *}$ |
|  | (0.0013) | (0.0093) | (0.0064) | (0.0012) | (0.0020) |
| Native | 4.4985*** | 4.3857*** | -4.7909*** | 0.1190*** | $0.1666^{* * *}$ |
|  | (0.1034) | (0.2851) | (0.2920) | (0.0460) | (0.0529) |
| Native $\times$ Pred. Ven. Shock | -0.0040** | -0.0019 | -0.0009 | -0.0015 | -0.0039** |
|  | (0.0017) | (0.0085) | (0.0064) | (0.0013) | (0.0018) |
| Female | $-0.0515^{* * *}$ | 1.7446*** | -0.5195** | $-0.4516^{* * *}$ | -0.0246 |
|  | (0.0085) | (0.2768) | (0.2016) | (0.0585) | (0.0746) |
| Female $\times$ Pred. Ven. Shock | -0.0002 | 0.0101 | -0.0003 | 0.0007 | -0.0019 |
|  | (0.0002) | (0.0066) | (0.0029) | (0.0015) | (0.0023) |
| Native $\times$ Female | $-0.0185^{* *}$ | 0.4666** | -0.2351 | 0.0688 | -0.0066 |
|  | (0.0094) | (0.2235) | (0.1909) | (0.0589) | (0.0745) |
| Native $\times$ Female | $0.0006^{* * *}$ | 0.0034 | -0.0014 | -0.0003 | 0.0024 |
| $\times$ Pred. Ven. Shock | (0.0002) | (0.0036) | (0.0032) | (0.0016) | (0.0023) |
| R-squared | 0.8982 | 0.2544 | 0.2169 | 0.6907 | 0.6735 |
| Native Males Mean | 4.706 | 91.76 | 3.961 | -0.0329 | -0.249 |
| Native Males SD | 1.787 | 11.32 | 8.874 | 0.743 | 0.751 |
| Native Females Mean | 4.648 | 94.07 | 3.176 | -0.400 | -0.262 |
| Native Females SD | 1.820 | 9.700 | 8.194 | 0.626 | 0.691 |
| Foreign Males Mean | 1.247 | 87.48 | 8.391 | -0.0445 | -0.231 |
| Foreign Males SD | 1.167 | 25.09 | 21.43 | 1.389 | 1.535 |
| Foreign Females Mean | 1.221 | 89.29 | 7.842 | -0.527 | -0.319 |
| Foreign Females SD | 1.147 | 23.81 | 21.09 | 1.319 | 1.475 |
| Observations | 203,326 | 203,326 | 203,326 | 81,082 | 81,082 |
| Clustered standard errors by municipality in parentheses. ${ }^{* * *} \mathrm{p}<0.01,{ }^{* *} \mathrm{p}<0.05,{ }^{*} \mathrm{p}<0.1$. <br> All columns include School FE, Year FE and Department $\times$ Year FE |  |  |  |  |  |
|  |  |  |  |  |  |
| Selected controls include the following variables interacted with year dummies: N. of Terrorist Attacks $\times$ 2012, 2014 and 2016, Informal Labor $\times 2018$, UBN $\times 2013$. |  |  |  |  |  |

Table A.3. Average effect of the Venezuelan migration shock on educational outcomes - Private schools (regression output)

| Dependent Var. | $\begin{gathered} (1) \\ \operatorname{Ln}(\text { Enrollment }) \end{gathered}$ | (2) <br> Promotion Rate | (3) <br> Dropout Rate | (4) <br> Math Std. <br> Score | (5) <br> Language Std. <br> Score |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Predicted Ven. Shock | $\begin{gathered} 0.0025^{* *} \\ (0.0011) \end{gathered}$ | $\begin{gathered} -0.0110 \\ (0.0119) \end{gathered}$ | $\begin{gathered} 0.0046 \\ (0.0153) \end{gathered}$ | $\begin{gathered} 0.0032^{* *} \\ (0.0014) \end{gathered}$ | $\begin{gathered} 0.0035^{* * *} \\ (0.0008) \end{gathered}$ |
| Native | $\begin{gathered} 3.6962^{* * *} \\ (0.1584) \end{gathered}$ | $\begin{gathered} 0.8736^{* * *} \\ (0.1909) \end{gathered}$ | $\begin{gathered} -0.9418^{* * *} \\ (0.1857) \end{gathered}$ | $\begin{gathered} -0.0599 \\ (0.0663) \end{gathered}$ | $\begin{gathered} 0.1195^{* * *} \\ (0.0428) \end{gathered}$ |
| Native $\times$ Pred. Ven. Shock | $\begin{gathered} -0.0027 \\ (0.0019) \end{gathered}$ | $\begin{gathered} 0.0051 \\ (0.0058) \end{gathered}$ | $\begin{gathered} -0.0037 \\ (0.0050) \end{gathered}$ | $\begin{gathered} -0.0028^{* * *} \\ (0.0008) \end{gathered}$ | $\begin{gathered} -0.0034^{* * *} \\ (0.0012) \end{gathered}$ |
| Female | $\begin{gathered} -0.0668^{* * *} \\ (0.0178) \end{gathered}$ | $\begin{gathered} 0.5288^{* * *} \\ (0.1424) \end{gathered}$ | $\begin{gathered} -0.1745 \\ (0.1262) \end{gathered}$ | $\begin{gathered} -0.6320^{* * *} \\ (0.0799) \end{gathered}$ | $\begin{gathered} -0.0796 \\ (0.0841) \end{gathered}$ |
| Female $\times$ Pred. Ven. Shock | $\begin{gathered} -0.0004 \\ (0.0004) \end{gathered}$ | $\begin{gathered} 0.0133^{* *} \\ (0.0054) \end{gathered}$ | $\begin{gathered} -0.0064^{* *} \\ (0.0032) \end{gathered}$ | $\begin{gathered} -0.0040 \\ (0.0028) \end{gathered}$ | $\begin{gathered} -0.0044^{* * *} \\ (0.0014) \end{gathered}$ |
| Native $\times$ Female | $\begin{gathered} -0.0456^{* * *} \\ (0.0127) \end{gathered}$ | $\begin{gathered} 0.0337 \\ (0.1401) \end{gathered}$ | $\begin{gathered} 0.0175 \\ (0.1352) \end{gathered}$ | $\begin{gathered} 0.1978^{* *} \\ (0.0823) \end{gathered}$ | $\begin{gathered} 0.0966 \\ (0.0792) \end{gathered}$ |
| Native $\times$ Female |  |  |  |  |  |
| $\times$ Pred. Ven. Shock | $(0.0004)$ | $(0.0050)$ | $(0.0035)$ | (0.0027) | $(0.0015)$ |
| R-squared | 0.8364 | 0.2063 | 0.2091 | 0.7916 | 0.7417 |
| Native Males Mean | 4.009 | 96.50 | 2.373 | 0.906 | 0.756 |
| Native Males SD | 1.373 | 8.971 | 8.263 | 1.174 | 1.046 |
| Native Females Mean | 3.905 | 97.06 | 2.225 | 0.510 | 0.813 |
| Native Females SD | 1.405 | 8.565 | 8.119 | 1.074 | 1.040 |
| Foreign Males Mean | 0.871 | 96.01 | 2.841 | 1.788 | 1.359 |
| Foreign Males SD | 0.999 | 16.30 | 14.10 | 1.833 | 1.621 |
| Foreign Females Mean | 0.853 | 96.75 | 2.519 | 1.125 | 1.251 |
| Foreign Females SD | 0.988 | 14.76 | 13.27 | 1.656 | 1.632 |
| Observations | 130,834 | 130,834 | 130,834 | 39,396 | 39,396 |
| Clustered standard errors by muni All columns include School FE, Y Selected controls include the follow Informal Labor $\times 2018$, UBN $\times 2$ | cipality in parenthe ar FE and Departm wing variables intera 013. | es. ${ }^{* * *} \mathrm{p}<0.01,{ }^{* *} \mathrm{p}$ ent $\times$ Year FE. <br> ted with year dumm | $<0.05,{ }^{*} \mathrm{p}<0.1 .$ <br> es: N. of Terrorist | $\text { Attacks } \times 20$ | 2014 and 2016, |

Table A.4. Average effect of the Venezuelan migration shock on educational outcomes - Primary school grades (regression output)

| Dependent Var. | (1) | (2) | (3) |
| :---: | :---: | :---: | :---: |
|  | Ln(Enrollment) | Promotion Rate | Dropout Rate |
| Predicted Ven. Shock | $0.0036{ }^{* * *}$ | $-0.0247^{* * *}$ | 0.0162** |
|  | (0.0008) | (0.0077) | (0.0065) |
| Native | $3.8177^{* * *}$ | 3.2320 *** | -3.2290*** |
|  | (0.0841) | (0.3415) | (0.3264) |
| Native $\times$ Pred. Ven. Shock | -0.0029** | 0.0070 | -0.0067 |
|  | (0.0012) | (0.0048) | (0.0046) |
| Female | -0.0674*** | 1.0542*** | -0.3126* |
|  | (0.0075) | (0.2419) | (0.1609) |
| Female $\times$ Pred. Ven. Shock | -0.0002 | $0.0142^{* * *}$ | -0.0091*** |
|  | (0.0002) | (0.0054) | (0.0029) |
| Native $\times$ Female | -0.0559*** | 0.2119 | -0.1423 |
|  | (0.0069) | (0.1740) | (0.1437) |
| Native $\times$ Female | 0.0001 | $-0.0121^{* * *}$ | 0.0102*** |
| $\times$ Pred. Ven. Shock | (0.0002) | (0.0035) | (0.0032) |
| R-squared | 0.8693 | 0.2453 | 0.2068 |
| Native Males Mean | 4.005 | 94.61 | 2.941 |
| Native Males SD | 1.442 | 10.24 | 8.492 |
| Native Females Mean | 3.892 | 95.91 | 2.470 |
| Native Females SD | 1.462 | 9.077 | 7.976 |
| Foreign Males Mean | 0.911 | 91.56 | 5.933 |
| Foreign Males SD | 1.017 | 22.45 | 19.27 |
| Foreign Females Mean | 0.884 | 92.70 | 5.529 |
| Foreign Females SD | 0.997 | 21.20 | 18.82 |
| Observations | 313,195 | 313,195 | 313,195 |
| Clustered standard errors by municipality in parentheses. ${ }^{* * *} \mathrm{p}<0.01,{ }^{* *} \mathrm{p}<0.05,{ }^{*} \mathrm{p}<0.1$. |  |  |  |
| All columns include School FE, Year FE and Department $\times$ Year FE. |  |  |  |
| Selected controls include the following variables interacted with year dummies: |  |  |  |
| N. of Terrorist Attacks $\times 2012$, 2014 and 2016, Informal Labor $\times 2018$, UBN $\times 2013$. |  |  |  |

Table A.5. Average effect of the Venezuelan migration shock on educational outcomes - Secondary school grades (regression output)

| Dependent Var. | (1) | (2) | (3) |
| :---: | :---: | :---: | :---: |
|  | Ln(Enrollment) | Promotion Rate | Dropout Rate |
| Predicted Ven. Shock | $0.0022^{* * *}$ | -0.0143 | 0.0027 |
|  | (0.0007) | (0.0110) | (0.0075) |
| Native | $4.1614^{* * *}$ | $3.1487^{* * *}$ | $-3.5184^{* * *}$ |
|  | (0.0985) | (0.3911) | (0.3705) |
| Native $\times$ Pred. Ven. Shock | -0.0018 | 0.0005 | 0.0034 |
|  | (0.0011) | (0.0070) | (0.0050) |
| Female | $-0.0426^{* * *}$ | $2.0774^{* * *}$ | $-0.6452^{* * *}$ |
|  | (0.0108) | (0.3082) | (0.1673) |
| Female $\times$ Pred. Ven. Shock | 0.0002 | -0.0060 | $0.0158^{* * *}$ |
|  | (0.0002) | (0.0060) | (0.0045) |
| Native $\times$ Female | $0.0406^{* * *}$ | 0.5387** | -0.0893 |
|  | (0.0107) | $(0.2164)$ | (0.1623) |
| Native $\times$ Female | -0.0002 | $0.0103^{* *}$ | $-0.0157^{* * *}$ |
| $\times$ Pred. Ven. Shock | (0.0003) | (0.0045) | (0.0043) |
| R-squared | 0.8784 | 0.2684 | 0.2099 |
| Native Males Mean | 4.611 | 91.17 | 4.077 |
| Native Males SD | 1.292 | 11.50 | 8.145 |
| Native Females Mean | 4.614 | 93.83 | 3.322 |
| Native Females SD | 1.291 | 9.446 | 7.659 |
| Foreign Males Mean | 0.880 | 88.99 | 6.790 |
| Foreign Males SD | 0.990 | 25.97 | 21.11 |
| Foreign Females Mean | 0.861 | 90.95 | 6.290 |
| Foreign Females SD | 0.980 | 23.91 | 20.44 |
| Observations | 203,560 | 203,560 | 203,560 |
| Clustered standard errors by municipality in parentheses. ${ }^{* * *} \mathrm{p}<0.01,{ }^{* *} \mathrm{p}<0.05,{ }^{*} \mathrm{p}<0.1$. |  |  |  |
| All columns include School FE, Year FE and Department $\times$ Year FE. |  |  |  |
| Selected controls include the following variables interacted with year dummies: |  |  |  |
| N. of Terrorist Attacks $\times 2012$, 2014 and 2016, Informal Labor $\times 2018$, UBN $\times 2013$. |  |  |  |

Table A.6. Average effect of the Venezuelan migration shock on educational outcomes - Urban areas (regression output)

| Dependent Var. | (1) | (2) | (3) |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  | Ln(Enrollment) | Promotion Rate | Dropout Rate | Math Std. Score | Language Std. Score |
| Predicted Ven. Shock | $0.0040^{* * *}$ | -0.0201* | 0.0106 | 0.0014 | $0.0036 * * *$ |
|  | (0.0009) | (0.0105) | (0.0077) | (0.0011) | (0.0011) |
| Native | 4.2357*** | 2.6759*** | $-2.9175^{* * *}$ | 0.0253 | 0.1340*** |
|  | (0.1154) | (0.3532) | (0.3625) | (0.0399) | (0.0359) |
| Native $\times$ Pred. Ven. Shock | $-0.0047^{* * *}$ | 0.0041 | -0.0032 | -0.0018* | $-0.0036 * * *$ |
|  | (0.0018) | (0.0066) | (0.0052) | (0.0009) | (0.0009) |
| Female | $-0.0632^{* * *}$ | 1.2371*** | -0.2763* | -0.5479*** | -0.0838 |
|  | (0.0112) | (0.2774) | (0.1614) | (0.0556) | (0.0605) |
| Female $\times$ Pred. Ven. Shock | -0.0003* | 0.0102* | -0.0033 | -0.0006 | -0.0023 |
| Cum. Ven. Inflows | (0.0002) | (0.0059) | (0.0026) | (0.0020) | (0.0017) |
| Native $\times$ Female | -0.0146 | 0.2210 | -0.1742 | 0.1260** | 0.0600 |
|  | (0.0091) | (0.1699) | (0.1399) | (0.0555) | (0.0591) |
| Native $\times$ Female | 0.0001 | -0.0069* | 0.0040 | 0.0010 | 0.0026 |
| $\times$ Pred. Ven. Shock | (0.0002) | (0.0036) | (0.0027) | (0.0019) | (0.0016) |
| R-squared | 0.8684 | 0.2502 | 0.2037 | 0.8052 | 0.7837 |
| Native Males Mean | 4.631 | 93.74 | 3.309 | 0.387 | 0.214 |
| Native Males SD | 1.627 | 10.50 | 8.572 | 1.024 | 0.981 |
| Native Females Mean | 4.561 | 95.24 | 2.847 | -0.00142 | 0.227 |
| Native Females SD | 1.660 | 9.275 | 8.158 | 0.934 | 0.974 |
| Foreign Males Mean | 1.138 | 91.13 | 5.880 | 0.897 | 0.603 |
| Foreign Males SD | 1.137 | 21.80 | 18.32 | 1.870 | 1.755 |
| Foreign Females Mean | 1.119 | 92.42 | 5.545 | 0.311 | 0.470 |
| Foreign Females SD | 1.120 | 20.45 | 18 | 1.694 | 1.747 |
| Observations | 253,107 | 253,107 | 253,107 | 95,866 | 95,866 |
| Clustered standard errors by municipality in parentheses. ${ }^{* * *} \mathrm{p}<0.01,{ }^{* *} \mathrm{p}<0.05,{ }^{*} \mathrm{p}<0.1$. All columns include School FE Year FE and Department $\times$ Year FE |  |  |  |  |  |
|  |  |  |  |  |  |
| Selected controls include the following variables interacted with year dummies: N. of Terrorist Attacks $\times 2012,2014$ and 2016 Informal Labor $\times 2018$, UBN $\times 2013$. |  |  |  |  |  |

Table A.7. Average effect of the Venezuelan migration shock on educational outcomes - Rural areas (regression output)

| Dependent Var. | $\begin{gathered} (1) \\ \operatorname{Ln}(\text { Enrollment }) \end{gathered}$ | (2) Promotion Rate | (3) <br> Dropout Rate | (4) <br> Math Std. <br> Score | (5) <br> Language Std. <br> Score |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Predicted Ven. Shock | $\begin{gathered} 0.0076^{* * *} \\ (0.0020) \end{gathered}$ | $\begin{gathered} -0.0302 \\ (0.0237) \end{gathered}$ | $\begin{gathered} -0.0065 \\ (0.0182) \end{gathered}$ | $\begin{gathered} 0.0015 \\ (0.0036) \end{gathered}$ | $\begin{gathered} 0.0059 \\ (0.0064) \end{gathered}$ |
| Native | $\begin{gathered} 3.9437^{* * *} \\ (0.1225) \end{gathered}$ | $\begin{gathered} 4.3602^{* * *} \\ (0.4471) \end{gathered}$ | $\begin{gathered} -4.7548^{* * *} \\ (0.4435) \end{gathered}$ | $\begin{aligned} & 0.2053^{*} \\ & (0.1245) \end{aligned}$ | $\begin{gathered} 0.3977^{* * *} \\ (0.1460) \end{gathered}$ |
| Native $\times$ Pred. Ven. Shock | $\begin{gathered} 0.0033 \\ (0.0029) \end{gathered}$ | $\begin{aligned} & -0.0029 \\ & (0.0141) \end{aligned}$ | $\begin{gathered} 0.0083 \\ (0.0122) \end{gathered}$ | $\begin{gathered} -0.0023 \\ (0.0034) \end{gathered}$ | $\begin{gathered} -0.0064 \\ (0.0063) \end{gathered}$ |
| Females | $\begin{gathered} -0.0540^{* * *} \\ (0.0163) \end{gathered}$ | $\begin{gathered} 1.3224^{* * *} \\ (0.3561) \end{gathered}$ | $\begin{gathered} -0.7132^{* *} \\ (0.2949) \end{gathered}$ | $\begin{gathered} -0.4696^{* * *} \\ (0.1743) \end{gathered}$ | $\begin{aligned} & 0.3454^{*} \\ & (0.1902) \end{aligned}$ |
| Female $\times$ Pred. Ven. Shock | $\begin{gathered} -0.0004 \\ (0.0007) \end{gathered}$ | $\begin{gathered} 0.0214 \\ (0.0154) \end{gathered}$ | $\begin{gathered} 0.0033 \\ (0.0105) \end{gathered}$ | $\begin{gathered} 0.0030 \\ (0.0041) \end{gathered}$ | $\begin{gathered} -0.0046 \\ (0.0063) \end{gathered}$ |
| Native $\times$ Female | $\begin{gathered} -0.0542^{* * *} \\ (0.0170) \end{gathered}$ | $\begin{gathered} 0.5544 \\ (0.3593) \end{gathered}$ | $\begin{gathered} 0.0009 \\ (0.2983) \end{gathered}$ | $\begin{gathered} 0.1484 \\ (0.1747) \end{gathered}$ | $\begin{gathered} -0.3369^{*} \\ (0.1901) \end{gathered}$ |
|  |  |  |  |  |  |
| $\times$ Pred. Ven. Shock | $(0.0007)$ | $(0.0155)$ | $(0.0110)$ | $(0.0042)$ | $(0.0064)$ |
| R-squared | 0.8979 | 0.2910 | 0.2467 | 0.6477 | 0.6003 |
| Native Males Mean | 3.888 | 93.34 | 3.400 | -0.180 | -0.459 |
| Native Males SD | 1.669 | 11.23 | 8.939 | 0.774 | 0.752 |
| Native Females Mean | 3.789 | 95.28 | 2.670 | -0.492 | -0.442 |
| Native Females SD | 1.708 | 9.671 | 8.230 | 0.667 | 0.704 |
| Foreign Males Mean | 0.934 | 89.25 | 7.876 | -0.339 | -0.713 |
| Foreign Males SD | 1.027 | 25.33 | 22.33 | 1.084 | 1.384 |
| Foreign Females Mean | 0.912 | 90.64 | 7.175 | -0.834 | -0.504 |
| Foreign Females SD | 1.007 | 24.20 | 21.67 | 1.353 | 1.248 |
| Observations | 81,049 | 81,049 | 81,049 | 24,612 | 24,612 |
| Clustered standard errors by municipality in parentheses. ${ }^{* * *} \mathrm{p}<0.01,{ }^{* *} \mathrm{p}<0.05,{ }^{*} \mathrm{p}<0.1$. <br> All columns include School FE, Year FE and Department $\times$ Year FE. |  |  |  |  |  |


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[^1]:    ${ }^{1}$ Source: United Nations' Regional Interagency Coordination Platform. See https://r4v.info/es/ situations/platform (last accessed July 31, 2020). The actual figure, however, is likely higher as registration is not enforced and a large share of migrants may actively avoid it and work in the informal sector.
    ${ }^{2}$ UNICEF estimated that at least 327 thousand Venezuelan children had arrived in Colombia by April, 2019, when the total number of registered Venezuelans was 1.2 million. See https://news.un.org/ en/story/2019/04/1037501 (last accessed February 5, 2020).
    ${ }^{3}$ Importantly, given the absence of longitudinal data on the places where Venezuelan migrants have settled over time, we use our predicted migration measure in a reduced-form specifications instead of

[^2]:    as an instrument for the endogenous actual settlement of Venezuelans. However, a visual comparison of Figures 3 and 4 suggests that the spatial distribution of the census-observed and the predicted number of Venezuelans in 2018 is very similar. Indeed, the correlation is 0.67 .
    ${ }^{4}$ Other studies do find non-zero effects. ? find that native kids obtain lower test scores in a crosscountry setting and ? confirm these findings for the case of Denmark. While ? finds that native children face a lower probability of finishing high-school in the long run in Israel, ? finds the opposite for native black students in the U.S.

[^3]:    ${ }^{5}$ Following the repression of protests by the Maduro administration, several countries led by the U.S. and the European Union established in 2017 sanctions to individuals associated with Maduro, including politicians, military personnel and private citizens. The sanctions were soon extended to include private companies and, in 2019, entire industries associated with mining and banking activities. The United Nations High Commissioner for Human Rights has warned that sanctions could have worsened the precarious situation of Venezuelans.
    ${ }^{6}$ Source: United Nations' Regional Interagency Coordination Platform. See https://r4v.info/es/ situations/platform (last accessed February 5, 2020).

[^4]:    ${ }^{7}$ To the extent that this figure is similar in the rest of the country, this may help explain why our average findings are generally explained by the observed impacts of the Venezuelan migration on primary school grades. See section 5 .

[^5]:    ${ }^{8}$ If we compute this share at the municipality level the average is 0.74 and the standard deviation 0.29 . This suggests that the biggest cities in population, such as Bogota, have a somewhat smaller share.
    ${ }^{9}$ The name of the dataset originated in the Ministry's Resolution 166 of 2004, which created the National Enrollment System (SIMAT, from the Spanish acronym) that mandated all education institutions to report to the Ministry individual-level enrollment each year as well as the condition of each student at the end of the academic year. Importantly, this registry excludes schools that have nontraditional education models. This is the case of some indigenous communities in rural areas. It also excludes public institutions for adult education and literacy, and training colleges.

[^6]:    ${ }^{10}$ See for example ? and ?. ? use a similar empirical strategy to estimate the effect of the Venezuelan migration shock on electoral outcomes in Colombia.

[^7]:    ${ }^{11}$ We use the 1993 census because by the time of the next census (2005) the Venezuelan political crises -and thus migration to Colombia- had started under the rule of Hugo Chavez. Our results are however largely unchanged if we use the 2005 census to compute the predicted migration flow of each municipality. Indeed, the correlation of the 1993 and the 2005 -based measures if 0.93 .
    ${ }^{12}$ In other words if we were to rely on a 2SLS strategy, the first stage would likely be strong.

[^8]:    ${ }^{13}$ The just over 1,100 Colombian municipalities are distributed across 32 departments.
    ${ }^{14}$ Even when the share of early migrants is not exogenous, ? show that identification can be achieved if the aggregate shocks are as good as random, a condition that is satisfied when: i) one controls by observable municipal characteristics weighted by shock exposure and ii) there is a large number of observed shocks per period and a large number of periods. We meet these criteria.

[^9]:    ${ }^{15}$ We multiply the interaction of the coefficient and the standard deviation of the predicted measure by 100 because of the log-level nature of the specification for the case of enrollment.

[^10]:    ${ }^{16}$ Note that these tables do not report effects on test scores since, for the entire sample period under study (2012-2018), these are available only for high-school seniors (their end-of-school test).
    ${ }^{17}$ Because they plot the marginal effects for each subgroup of interest, the figures show no omitted year of reference.

[^11]:    ${ }^{18}$ We discuss such papers in the introduction

