Immigrant children and optimal school choice: Evidence from the Venezuelan migration to Peru

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Abstract

In recent years, millions of children have been displaced, and evidence informing public policy for the welfare of migrants and recipient communities will be critical in the coming years. In this paper, we leverage cross-grade within-school variation on migrant share to understand the effect of the sudden influx of Venezuelan migrant children into the Peruvian school system. Our estimates show that as Venezuelan migrants enter Peruvian schools, parents of incumbent students react by transferring their children to higher-quality schools with fewer migrants. A ten-percentage-point increase in migrant exposure increases the probability of switching by 1.5 percentage points in primary and 1.1 percentage points in secondary schools. To understand the implications of this native flight on academic achievement, we employ a structural model that identifies students who switch schools because of migrants and compare their outcomes in the presence of migrants to a counterfactual scenario without migrants. Our findings reveal that switchers experience small gains (close to zero), albeit at a higher tuition cost, while students left behind are not negatively impacted. This suggests that native flight can serve as an adaptive strategy only for some students to mitigate the effects of the migrant influx, but generally brings no gains to students who switch schools. Moreover, it comes at a high cost.

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1 Introduction

Global migration and displacement have surged in the past two decades due to conflict, severe economic and political instability, and extreme weather events. By 2019, there were approximately 272 million international migrants, a figure that had already surpassed the United Nations' 2050 projections, estimated at around 230 million. In 2022, over 40% of the global refugee population comprised school-age children, and 76% was in low and middle-income countries[1]. While access to education for these migrant children is critical to ensure access to economic opportunities, their influx can stress the existing educational system, particularly in the developing countries that are more likely to host them. In this paper, we study the effect of an inflow of one million[2] Venezuelan school-age migrants[3] to Peru on their incumbent peers' academic performance and on the likelihood of *native flight*, a phenomenon in which parents relocate their children to schools with fewer or no migrants.[4]

Peer composition can have a significant influence on academic and behavioral outcomes (Sacerdote, 2014). Large inflows of immigrants can alter the composition of peers in schools in two ways: directly, due to differences between migrant and native students, and endogenously, as incumbent students may respond to immigrant exposure by opting for native flight. It is crucial to understand the overall effect of migration influxes on native academic achievement and how native flight impacts the academic performance of incumbent students because both factors can shape downstream outcomes related to inequality and segregation in education. Native flight is one case of a broader set of problems where the native population employs extensive margin responses to adapt to a migration shock. The labor markets and education literature studying the impact of migrant influxes has shown that extensive

[1]Global Trends. Forced Displacement in 2022 (UNHCR)

[2]UNHRC estimates from 2017 to 2019

[3]We will use the term 'migrants' throughout the paper. Given the Venezuelan situation, the term 'immigrant' or 'refugee' may more accurately capture some families' current situation. However, we do not have the necessary information to distinguish the various subcategories. We use the word 'migrants' to capture the migrant, immigrant, and refugee populations.

[4]While typically associated with the shift from public to private schools when exposed to migrants, we use the term 'native flight' in a broader sense to include any movement of native students to schools with less migrants.

margin choices can be adaptive strategies for natives to navigate migration shocks.[5] However, studying these extensive margin responses requires data that can capture the intricacies of school turnover. Moreover, identifying who moves because of native flight to isolate the effects of native flight on academic performance requires an empirical model that imposes structure on parental choices. We address these issues with unique administrative data and a structural model that complements our reduced-form strategy.

In the reduced form, we measure the average effects of exposure to migrants on native flight and the academic achievement of native students. Given the magnitude of native flight in this context, we proceed to study its implications of native flight on academic achievement. We estimate a structural model that allows us to identify specific native students induced to move due to migrant presence and study the academic achievement implications in the native population. In this second part of the paper, we model preferences to identify who moves because of migrants and analyze the academic achievement effects of native flight for two subgroups: native students who switch schools and native students left behind after the native flight.

We leverage time and cross-grade within-school variation to identify the effect of Venezuelan peers on incumbent students' academic performance and likelihood of switching schools. The cross-grade within-school design allows us to compare incumbent students exposed to a different proportion of migrants, fixing the observable and non-observable characteristics of the school. Ultimately, the variation we use comes from the age distribution of Venezuelans within schools, where we see that different grades have different shares of migrants. The effect we identify is the reduced form relative impact of the influx of Venezuelan migrants into Peruvian schools across grades, inclusive of the native children who leave and the ones who stay.

[5] Borjas (2006); Cadena and Kovak (2016); Card (2001); Dustmann and Glitz (2011); Lewis (2013) and others document how migration shocks can lead to adjustments in spatial mobility patterns and education choices among certain groups of natives. In the education literature, Betts and Fairlie (2003); Cascio and Lewis (2012); Farre et al. (2018); Tumen (2019) and others show that native students are more likely to switch schools as their exposure to migrants increases.

We find that the large influx of Venezuelan migrants into the Peruvian school system has effects on incumbent students' academic achievement and on the probability of transferring to a different school. Having a higher percentage of migrants as classmates decreases language and math grades. The magnitudes of our point estimates are comparable to those found in the literature (Figlio et al., 2021; Gould et al., 2009; Imberman et al., 2012). In contemporaneous work, Contreras and Gallardo (2022) use a difference-in-difference approach and find that the Venezuelan and Haitian migration decreased sixth-grade incumbent students' standardized test scores in math and language in Chile in 2018. The magnitude of the effects is in the same range as what we find. All these studies are estimated using cross-section data. Our paper improves on the literature using student-level panel data, making our estimates more precise. We also study a context with fewer school resources and a larger migration influx. Thus, our context represents the features of countries more likely to receive migrants. However, our most significant contribution is in the analysis of native flight.

We find that the effect of migration on native flight is large compared to similar studies.[6] In Peruvian schools, about 8 to 9% of students switch schools yearly before the migration influx. Our estimates suggest that an increase of 10 percentage points in the share of migrants –eight migrants in an average-size school grade– increases the probability of an incumbent student switching schools by 1.55 percentage points for primary and 1.17 percentage points for secondary. These effects are equivalent to a 10.4% and 10.5% increase in primary and secondary school student turnover, respectively. The effects are non-linear and increasing in the percentage of migrants. The tipping point where migrant concentration starts affecting incumbents' school switching is around 2.4% and 4.5% of migrants in their cohort for primary and secondary, respectively. In the native flight literature, the switching of local students to other schools is driven mainly by migrant children who do not speak the recipient country's language, arguing that language differences demand additional school resources (Betts and Fairlie, 2003; Cascio and Lewis, 2012; Farre et al., 2018; Tumen, 2019). Adding to this

[6] Figlio and Özek (2019); Tumen (2019)

literature, this paper explores migration and school choice in a context where incumbents and migrants speak the same language. Thus, our results are more likely to reflect the effects of the perceptions of natives, the resource constraints, and a deeper interaction between native children and migrants. Contreras and Gallardo (2022) explore school switching in the context of the Venezuelan and Haitian migration to Chile but do not find a native flight between public and private schools or cream skimming. The Venezuelans who migrated to Chile are more selected than the ones who arrived in Peru. According to the IOM (2020) [7], 74% of Venezuelan migrants who arrived in Chile have a college degree or more. This number is 20% of the Venezuelan migrants in Peru. Our context allows us to study a migration influx with less selection.

We characterize the schools to which these students are more likely to switch. We find migrant concentration increases the probability of students switching to higher-quality schools with fewer migrants in primary and secondary schools. Like the native flight widely studied in the US, migrant inflow generates student transfers from public to private schools. However, given the flexibility of the Peruvian school system (school enrollment is not restricted to the neighborhood of residence), we also observe student mobility within private and public schools. We can see whether students move to schools in different cities. We find that the effects of migration on student turnover are not explained by families moving to different locations.

We follow the reduced-form analysis with a structural model that allows us to isolate the effects of native flight on the academic achievement of the students who opt for native flight and the native students they leave behind. In the structural part of the paper, we follow the literature that models the preferences for schools to study effects in the demand for schools (Allende, 2019; Burgess et al., 2015; Hastings et al., 2009; Lavy et al., 2009; Neilson et al., 2013; Sanchez, 2018). The purpose of the model is to identify who moves because they were exposed to migrants, in order to understand who gains and who loses when there is

[7] Chaves-González and Echevarría Estrada (2020)

native flight. In addition to our panel administrative education data, we use household level data from the national census to study families' school choice decisions and how they are affected by exposure to migrants. Having estimated the preferences for schools, we can make comparisons between school choices made by native parents when they face the presence of migrants in their children's schools and a counterfactual scenario in which they do not. We estimate these counterfactuals for the children that switch schools and for those that are left behind by the native flight.

Before the migration influx, about 8 to 9% of students switch schools every year. In the reduced form, we observe that, on average, native students that are more exposed to migrants are more likely to switch schools. The structural model shows that, after the migration influx, about 9 to 16% of the total turnover is induced by the presence of migrants in Primary and Secondary schools, respectively. Among the students who switch schools because they are exposed to migrants, there are small academic performance gains from the migrant-induced movement. We see that these students experience an increase of 0.02 to 0.05 SD on their math academic performance when their school choice accounts for migrant presence, compared to a counterfactual in which there are no migrants. These gains are small. Due to the effect size, we consider the gains a precisely estimated zero for all groups except for some lower socioeconomic status students. Moreover, moving is costly. Many students move to private schools. We see that, on average, these families' tuition costs increase by 330 to 412 soles (around 89 to 111 USD) per month, which is above to the monthly equivalent of the cash transfer program *Juntos* (100 soles). On the other hand, the students who are left behind do not seem to be negatively affected by the native flight. The estimate for their loss in academic achievement ranges from -0.005 to 0.005 SD, which we interpret as a precisely estimated zero. The evidence from the model suggests that native flight can be viewed as a strategic adaptation strategy employed by some parents in response to the influx of migrants. However, it is costly and generally brings no gains to students who switch schools. This shows that native flight is driven by factors beyond academic achievement losses, which motivate parents to make costly decisions.

2 Background

2.1 Venezuelan Migration

The number of migrants leaving Venezuela has increased significantly in the last years, and 20% of the migrants are going to Peru. The UNHRC estimates that around 1.3 million Venezuelans were living in Peru by 2021. Figure A1 shows the exponential increase of Venezuelan immigrants in Peru after the Venezuelan Government opened the border with Colombia in 2016. The most common migration route is through Colombia and then Ecuador. The data from the Peruvian migration agency shows that around 95% of the migrants travel by bus, in a journey that takes at the very least four days and can last for months. Government records show that around 500,000 Venezuelans have applied for refugee status and that around 18% of them travel with children [8]. They are located mainly in Lima and in other cities along the Peruvian coast, as shown in Figure A3. They are either unemployed or working in informal jobs. Those migrants who join the formal sector report low wages [9].

In 2017, the Peruvian government passed a law to establish a temporary permanence permit (PTP for its acronym in Spanish). This permit allowed Venezuelan migrants to stay legally in Peru for a year and gave their children access to public health and education public services. Even if it expired, Venezuelan migrants could present their Venezuelan ID or passport to meet the requirements. These somewhat lenient requirements made Peru a more attractive destination for Venezuelan migrants [10].

The massive inflow came hand in hand with a change in the attitudes of Peruvian citizens. In 2018, the local newspaper *El Comercio* surveyed people in Lima about their attitudes

[8] Standard Operating Procedure for Venezuelan Migrants in Peru by the IOM.

[9] Standard Operating Procedure for Venezuelan Migrants in Peru by the IOM.

[10] See details on the Venezuelan migration to Peru on Appendix A

regarding Venezuelan migrants. Around 55% of them disagreed with allowing Venezuelan migrants into the country. In 2019, a new survey by the same newspaper resulted in 67%. In 2019, the Peruvian migration agency launched a campaign against xenophobia. However, the people's perceptions that Venezuelans are taking scarce jobs and services from Peruvians are pervasive. The Universidad Católica in Peru and the Panamerican Development Foundation report widespread concerns[11]. These organizations collected testimonies of education experts who report that finding schools to enroll Peruvian children is difficult and perceive that the inflow of immigrant students worsens this situation.

2.2 Peru's Education System

The Peruvian education system enrolls more than 6 million students in primary and secondary levels each year. In 2019, 74% were in public and 26% in private schools. Education is compulsory for primary and secondary levels. Public schools are free, and there is a wide variety of private schools in terms of tuition costs and quality levels. Unlike other systems, parents do not face restrictions in choosing a school depending on their neighborhood or residence. They can enroll their children in any school if there are slots. However, public schools prioritize enrollment first for children with disabilities and children whose siblings are already enrolled there and second for children who reside in the school area. Yearly enrollment is automatic for children that are already in a school. According to Peruvian law, the access and permanence of the students in public and private schools cannot be denied or conditioned by students' characteristics. Additionally, private schools can not perform evaluations or tests on students as part of their admission process. [12]

Regarding enrollment procedures, students need some form of identification to enroll, but an exception is made for Venezuelan students with no identification who can apply for enrollment and defer the document requirement. Last UNESCO's report about the situation of Venezuelan children in Peru documents that this procedure is subject to the discretion

[11] https://data2.unhcr.org/en/documents/download/70863

[12] Ministry of Education Decree N° 005-2021-MINEDU

of principals. Some reject Venezuelan migrants if they cannot provide evidence of the last grade they passed, while others let children enroll without any documents regarding this matter [13]. The report also mentions that costs to attend offices and lack of knowledge of the Peruvian school system are the main restrictions that Venezuelan parents face in enrolling their children in Peruvian schools. Despite this, enrollment grew; Figure A2 shows the evolution of enrollment of Venezuelan children in Peruvian primary and secondary schools. Between 2014 and 2019, 75.6% of Venezuelan students enrolled in public schools and 24.4% in private schools.

The Peruvian school system allows school switching at the end of the school year and within the same school year. Parents who want to transfer their children to a different private or public school need to find a spot in the new school and ask for the enrollment transfer between the origin and the new institution. To help parents search for schools for their children, the Ministry of Education developed a webpage with all the schools' characteristics, including quality measures, location, and the number of free slots by grade. As shown in Figure A4, turnover rates in Peru lie between 9.5 and 10.5 percent in primary and 8 and 8.5 percent in secondary.[14] These turnover rates are close to those of countries such as Chile, which has a turnover rate in primary of 11.5 percent (Zamora Poblete and Moforte Madsen, 2013). Furthermore, it is somewhat smaller but similar to Florida's 16 percent turnover rate during the Haitian immigration after the earthquake reported by Figlio and Özek (2019).

There are no guidelines about the expenditure per student in the Peruvian law regarding the budget and resource allocation for public education. Saavedra and Suárez (2002) document how the resources allocated to public schools depend on the bargaining power of school principals, who negotiate with local authorities that allocate budgets. Additionally, they are affected by the inertia in old budget structures that have not changed over time. Finally, schools with more complex infrastructure require more resources for upkeep and

[13] https://inee.org/node/9953

[14] Figure A5 shows that Venezuelan migrants have higher turnover rates than their incumbent peers, consistent with Venezuelan parents having informal and less stable jobs (Morales and Pierola, 2020)

operation. These elements have resulted in a high inequality in per-student expenditure in Peru's different regions, cities, and neighborhoods. In this same study, the authors mention that parental investments in education are crucial for the operation of schools, even in public schools. The expenditure per student reported by the Peruvian Statistics Institute (INEI) in 2018 is about 835 USD in primary school and 1,180 USD in secondary school. For reference, on average, countries in the OECD spend about 8,700 USD per primary school student and 10,200 per secondary school student (OECD). This disadvantage in resources goes hand in hand with lower education quality. Peru's average score on the PISA tests was about 401 in 2018, the US score was 505, and the average OECD score was 487 (OECD, 2019).

3 Data

We use data from four administrative sources: (i) SIAGIE (Sistema de Información de Apoyo a la Gestión Educativa), a student panel from the Ministry of Education; (ii) ECE (Evaluación Censal de Estudiantes) student-level data on Peru's standardized test; (iii) School Roaster (Padrón Escolar) and School Census (Censo Escolar) school characteristics panel that includes both private and public schools in Peru. (iv) SiseVe, a platform where schools report school violence cases. For all of them, we have data from 2014 to 2019.

SIAGIE is the system that keeps enrollment records for every student in the education system in Peru. This dataset is a student-level panel from 2014 to 2019 that includes students' school, grade, classroom, nationality, age, sex, and report cards. The student ID allows us to track students across schools and years and merge the information with other Ministry of Education datasets. The student tracking gives us information on student transfers between schools and dropouts.

The key outcomes we use from SIAGIE are report cards' grades, switching schools, dropout, and retention. We use school report cards' grades standardized at the grade level. For the school switching outcome, a student transfers schools in year t if the school in year

t differs from the school in $t-1$. Since the first year in our data is 2014, we cannot observe which school the students enrolled in the prior year. Hence, we can only construct this variable from 2015 onwards. [15] For dropout, a student drops out of school in year t if they are not present in the school system in $t+1$ and did not graduate in $t+1$. Finally, for retention, if we observe a student in the same grade in year t as in $t-1$, we classify them as they experience retention.

Our second data source is the ECE, the Student Census Evaluation (known as ECE by its Spanish acronym). The ECE is a mandatory test taken by all Peruvian students in the second and fourth grades of elementary school and the second grade of secondary school. The test evaluates two subjects: language and math, and the scores have no impact on students' GPAs or report cards. The ECE includes a short survey to the students or parents (depending on the grade) that provides data on parental education and the household's socioeconomic characteristics. This data includes a wealth index constructed by the MinEduc using principal components analysis over this household survey information. The Peruvian Ministry of Education uses this index as their primary indicator of the socioeconomic level of the school.

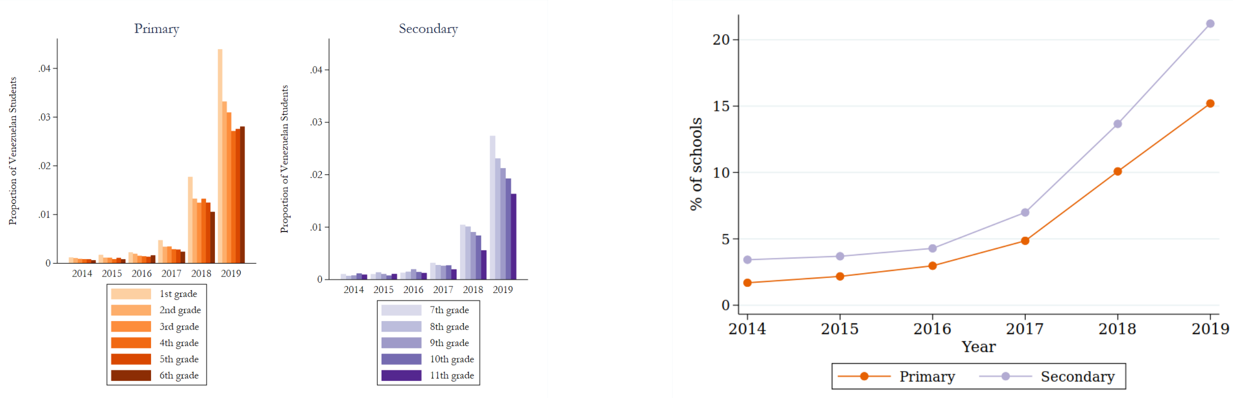
We have access to the ECE data from 2014 to 2019, but the data is somewhat sparse. Only the 2nd-grade tests are available starting in 2014. 4th-grade and 8th-grade tests are available starting in 2016 and 2015, respectively. Due to *El Niño* rainy season and the teacher's strike, the test was suspended in 2017 [16]. Initially, the universe of students in each grade did each test. However, the Ministry of Education modified who took the standardized test in later years. In 2018, only a sample of 2nd graders took the test, while the universe of all 4th and 8th graders took it. In 2019, the universe of 8th graders took the test, and 2nd and 4th graders' subsamples took it. We standardize the test scores at the grade level, as we do with report cards' grades.

[15] Some schools offer primary and secondary education, while others do not have continuity and only offer primary. Thus, we do not have information on school switching when students advance from primary to secondary in non-continuous schools. Hence, we cannot construct this variable for 7th graders.

[16] http://umc.minedu.gob.pe/evaluaciones-censales/sus-ece/

Our third data source is the Education Quality Statistics System ESCALE (by its Spanish acronym). This Ministry of Education tool contains information on all registered public and private educational institutions in Peru. We will use two primary datasets from ESCALE, the School Roaster and the School Census. The School Roaster has data on the type of school management (public, private, charter), ownership, whether it is coeducational, type of classrooms (single-teacher, multi-teacher, multi-grade, complete multi-teacher), and geocoded location. The School Census includes data on total enrollment (by grade, sex, age, native language), number of classrooms, teachers' experience, education, tenure, and school infrastructure (construction materials, public services, toilets, library, and computers). We use indicators for public and private schools, school location, the district IDs, the teacher-student ratio, and a school wealth index from the school-level data. We use a principal components analysis to construct the school wealth index, which contains school infrastructure (walls, floors, and roof), whether the school has access to essential services (clean water, electricity, trash, and sewage), the number of computers for pedagogical purposes that the school has, and whether the school has a library.

Figure 1: Venezuelan Migrants in the Peruvian Education System



(a) Average Migrant Share

(b) Schools with Migrants

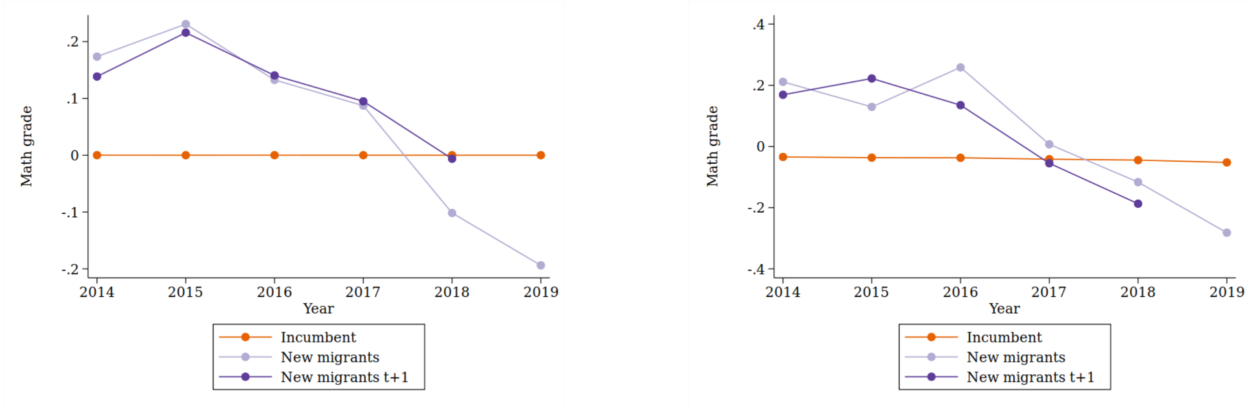
Our fourth data source is SiseVe, a Peruvian Ministry of Education platform where schools, students, and parents can file school violence reports. The list of reports is public, and each report has information on the year, school district, frequency, and motive of the aggression. From the motive, we can count the number of school violence reports related to discrimination in each school district [17]

Finally, our fifth data source is the microdata from the 2017 national census. We are able to match the national census and our enrollment administrative data. This match gives us two crucial pieces of information: the students' proximity to school and their household's socioeconomic status. There is a 73% match between the national census data and the enrollment administrative data in 2019, which accounts for 4,608,866 students. We choose 2019 because that is the year with the most prominent presence of Venezuelan migrants in the school system. The census data has the geolocation of students' residences for around 36% of the sample. This sample is on average more urban and of lower socio economic status than the rest of the sample, however it includes the students who are more affected by the migrant influx. The proximity of students to schools is a key component of model of school preferences. It is rare to find such detailed and comprehensive information in a developing country setting, hence this match between the census data and the enrollment data presents a unique opportunity to study school choice in the context of a migrant influx.

We proceed to provide some descriptive statistics of these data. In Figure 1a, we observe that the average migrant share increases exponentially over time. In 2014 it was lower than 1% in primary and secondary. In 2019, the average migrant share by grade was 4 to 5% in primary and 2 to 3% in secondary. These figures can be lower than expected, considering the magnitude of the Venezuelan migratory influx. However, Figure 1b shows that the number of schools with Venezuelan migrants is relatively high. In 2019, 15% of primary schools in the country had migrants, while 20% of secondary schools in the country had migrants. Figures 1a and 1b show that the Venezuelan children migration inflow was large and broadly spread among different schools.

[17] In 2019, the MinEduc included a question on the School Census of whether the school reported or not to the SiseVe and the number of reports. We have this information at the school level only for this year.

Figure 2: Venezuelan Migrants Performance in Math by Year



(a) Primary **(b)** Secondary

Figures 2a and 2b show the trends of performance in math for primary and secondary school, respectively. Both figures show the average by year, dividing the sample into two groups: Incumbent students and Venezuelans in the first year they appear on the panel (new migrants). For the second group, we also show the math grades after one year in the system (new migrants t+1) when their grades are more comparable to the ones of their peers. There is considerable heterogeneity in the academic performance of migrants over time, even after a year in the Peruvian school system. This heterogeneity in the performance of Venezuelan migrants is consistent with mixed migration —there are economic migrants, citizens returning to their countries of origin, and refugees. Besides, many highly educated Venezuelans migrated. With surveys, the Peruvian government estimates that 57.9% of the migrants have higher education studies [18].

Figures 2a and 2b show that the standardized grades of entering Venezuelan migrants decreased after the migration shock started in 2017. At the beginning of the migration episode, migrants were relatively high achievers, but this tendency reversed as the migration increased. Since most of our variation comes from later years, we expect that the impact of the relatively low-achieving migrants will dominate the effects. Figures A6a and A6b show the same pattern for language grades.

[18] Standard Operating Procedure for Venezuelan Migrants in Peru by the IOM.

Table 1: Summary Statistics Venezuelan-Receiving Schools 2014

	Primary		Secondary	
	Venezuelan Receiving Schools	Other Schools	Venezuelan Receiving Schools	Other Schools
Public schools = 1	1.000	0.741	0.880	0.569
Total student count	235.438	68.446	353.917	135.697
Proportion of female students	0.491	0.480	0.483	0.463
Student-Teacher ratio	21.941	17.916	15.581	12.461
% of teachers with professional education	0.826	0.722	0.955	0.907
Avg. math std. test score	-0.114	-0.305	-0.260	-0.170
Avg. language std. test score	-0.227	-0.322	-0.289	-0.210
SES index students	-0.433	-0.374	-0.373	-0.302
% of students high SES index	0.062	0.126	0.069	0.140
School violence reported = 1	0.179	0.049	0.338	0.139
Number of schools	5,510	37,494	2,942	13,583

All mean differences are statistically significant at 1% level. The std. errors for the differences are clustered at the district level and include district fixed effects. Math and language test scores are standardized at the grade level and from 2015, the earliest year available. Parents' SES is measured by the socioeconomic index of the ECE surveys on student household characteristics in 2016 (earliest year available). In our sample, the SES index goes from -2.9 to 1.8. The Peruvian MinEduc defines a high SES index as being at the 85th percentile or higher. The school wealth index was constructed using principal components and it includes school infrastructure, essential services, computers and library it ranges from -3.7 to 9.5. The school violence information comes from the school census, which asks the principal for the number of SiseVe reports made during 2019 (there is not school level data for earlier years).

Table 1 shows descriptive statistics in 2014 before the migrant influx for schools with and without Venezuelan migrants in 2019. In both primary and secondary, migrants tend to choose larger public schools with a higher proportion of teachers with professional education. However, schools chosen by migrant families were more strained regarding resources, having larger student-teacher ratios and poorer students before most migrants arrived. On average, these schools' 2015 standardized test scores for math and language were lower for both secondary and primary schools. In sum, Venezuelan receiving schools were systematically different from other schools even before the migrants' arrival. This is precisely why a simple difference between student outcomes in schools with and without migrants will not identify the effect of the Venezuelan migrants' inflow on incumbent students.

4 Reduced Form Empirical Strategy

Immigrants are more likely to settle in areas with more immigrants from their country (Card, 2001; Carrington et al., 1996; Stuart and Taylor, 2021). Then, there is an endogenous placement of immigrants in schools with specific characteristics. A model comparing schools with higher and lower proportions of Venezuelan students will probably generate biased estimates due to selection into schools. The differences between schools will account for all the schools' observable and non-observable characteristics and not only for the immigrant inflow effects. We rely on cross-grade within-school variation in the number of Venezuelan students entering the education system in Peru to address this problem. We implement a school-year fixed effects estimation to study the impact of contemporaneous exposure to Venezuelan migrants.

To identify the effect of a change in the concurrent number of immigrants on incumbent students' outcomes, we compare grades with different proportions of Venezuelan students within the same school and year. The identifying assumption is that the grade placement of Venezuelan students within schools is uncorrelated with what incumbent students' conditional outcomes would have been in the absence of the influx of Venezuelan migrants. In Figures A7 and A8 we can see the age distribution of migrants and incumbent students per grade. Grade placement by age is similar for incumbent students and migrants. Migrants are slightly older on average, but their age for grade coincides with the ages for the grade of incumbent students. Hence, our identifying assumption is closely related to the assumption that the age distribution of Venezuelan migrants within schools is uncorrelated to grade-specific educational inputs within a school. Principals can play a role in the selection of migrants into schools. We are assuming that principals will discourage all migrants equally. If they discourage migrants of a specific age, or prefer to enroll migrants into a specific grade, we have to assume that this selection is not correlated with grade pre-existing characteristics. Our empirical analysis follows this specification:

$$Y_{i,sg,t} = \alpha + \beta V_{sg,t} + \gamma X_i + \theta_{s,t} + \psi_g + \varepsilon_{i,sg,t} \tag{1}$$

Where, $Y_{i,sg,t}$ is the achievement measure of the incumbent student i of school-grade sg and year t. X_i is a vector of student characteristics, including sex, age, and the baseline math grade. This is the standardized math grade the first time we observe the incumbent student in the data set. $\theta_{s,t}$ and ψ_g are school by year and grade fixed-effects. Our treatment variable is $V_{sg,t}$, which is the percentage of Venezuelan students of the total student body in school-grade sg and year t. We observe all the outcomes at the end of the school year. The share of migrants, $V_{sg,t}$, corresponds to the peers that the incumbent children had in their grade during the school year. Thus, we calculate the effect of the concurrent share of migrants on the outcomes. This specification only includes incumbent students. Given that the migrant share is at the school-grade level, our standard errors are clustered at that same level.

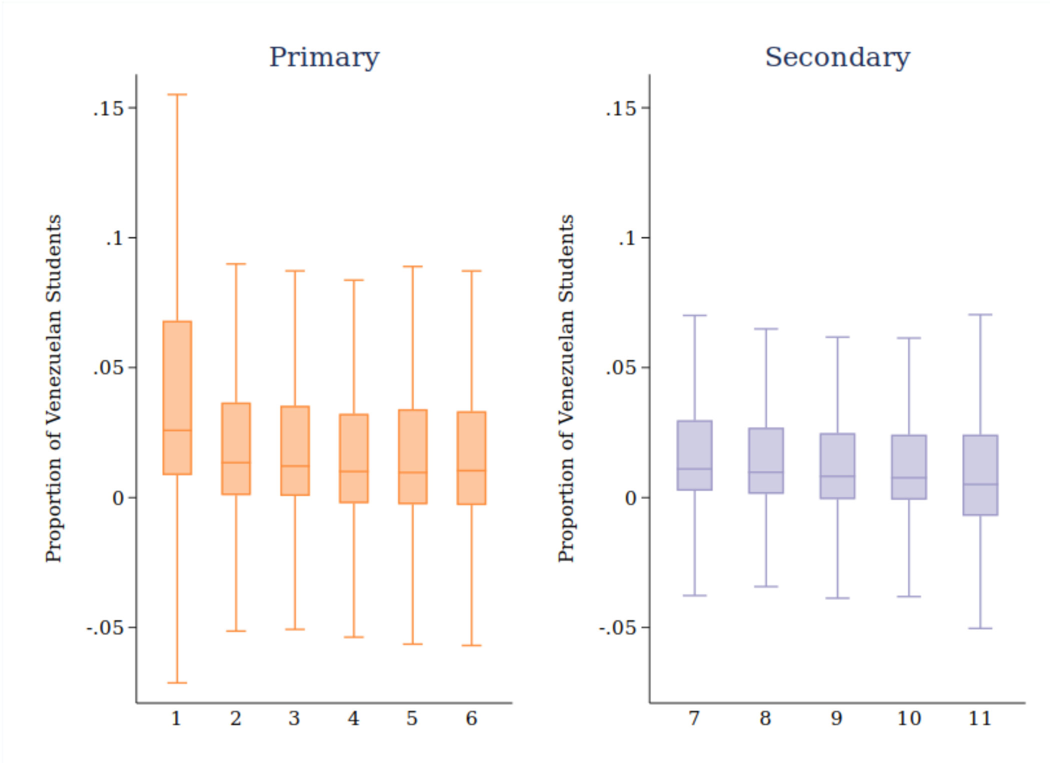
Incumbent students move to different schools over time. To avoid selection problems induced by parents of incumbent students who choose to move their children to another school (school switchers), we implement an estimation analogous to an intention to treat estimate (ITT). If children move, we assign them their previous school s – the one where they were enrolled before transferring schools after we observe the transfer. We also assign them the share of migrants they would have had if they had not switched to another school. Then, β accounts for the effect of being exposed to a larger share of migrants and the student turnover caused by the exposure.

Students' outcomes reflect the cumulative previous and current investments made to improve their human capital. Including baseline outcomes to control for the earlier investments allows us to focus on the effect of a contemporary input, the share of Venezuelan migrants in the cohort. Effects on test scores often fade out quickly (Bailey et al., 2020); hence, concurrent exposure is the key dimension we expect to impact schooling outcomes significantly.

As we mentioned in section 3, migrant students are relatively spread out in the education system. Figure A9 shows the distribution of $V_{sg,t}$. The share ranges from 0 to around 25% of children in primary and secondary schools and is right-skewed. However, we see considerable variability in the migrant share in each grade, even after controlling for school-year, grade, and district fixed effects. Figure 3 shows the distribution of the residualized migrant share per grade. The distribution is consistent across grades in both primary and secondary schools, although first grade has a slightly larger range than the other grades in primary schools.

The interpretation of our effect could be affected by the reallocation of resources between grades that receive more and fewer migrants within a school. Schools that receive more migrants in one grade likely reallocate resources from other grades to adjust to the changes. This reallocation would affect the outcomes we are using as counterfactuals negatively. If this is the case, our results are a lower bound of the effects of the migration.

Figure 3: Distribution of the Residualized Share of Venezuelan Migrants



5 Reduced Form Results

In this section, we first present estimates of the effect of migrant concentration on incumbents' schooling outcomes and the probability of switching schools. Then, we characterize the switching incumbent students and the difference between the origin and destination schools they are being transferred to. Finally, we dig into the mechanisms behind parents' re-optimizing and changing their children to different schools after the Venezuelan migrants' arrival.

5.1 Schooling Outcomes and School Switching

Table 2 presents the effects of Venezuelan immigrants' concentration on incumbent retention, dropout rates, and language and math grades, estimated using the cross-grade within-school variation on the share of migrants. Panels 1 and 2 present results for incumbent students in primary school grades (1-6) and secondary school grades (7-11), respectively. We find statistically significant results for primary school math and language grades. These results show that an increase of 1 percentage point in the share of Venezuelan migrants in a grade (approximately one migrant) decreases math and language grades by 0.0015 and 0.002 standard deviations, respectively. Similarly, the estimates for secondary school show positive effects on retention and dropout rates and negative effects on math and language grades, both statistically significant. In secondary, a 1 percentage point increase in the share of migrants increases the probability of retention and dropout by 0.009 and 0.023 percentage points, respectively, and reduces math and language grades by 0.007 standard deviations.

These effects are small and comparable with the magnitude of the evacuee effects on math standardized test scores measured by Imberman et al. (2012) (-0.01 standard deviations on math test scores), and the refugee effects measured by Figlio and Özek (2019), (0.003 and 0.006 standard deviations on math and language test scores respectively). A 5 percentage point is a shift in the distribution of the migrant share across school grades, which means going from the 25th to the 75th percentile of the distribution, representing, on average, three more migrant children in primary and five more migrant children in secondary. Going from the 25th to the 75th percentile of migrant share in primary school will decrease math and language grades by 0.007 and 0.008 standard deviations. In secondary, it will increase the likelihood of retention by 0.045 and the likelihood of dropping out by 0.1 percentage points and reduce math and language grades by 0.03 standard deviations. These effects are plausible and on the lower end of the peer effects range in the literature summarized by Sacerdote (2014).

Table 2: Effects of Migrant Exposure on Schooling Outcomes

Primary				
	Retention	Dropout	Math grades	Language grades
	(1)	(2)	(3)	(4)
Mig. Share ITT	0.00254	0.00834	-0.154***	-0.201***
	(0.00259)	(0.00554)	(0.0405)	(0.0385)
R-squared	0.032	0.107	0.182	0.184
Obs.	14,700,335	11,681,011	14,576,843	14,576,961
Mean	.005	.011	-.015	-.012

Secondary				
	Retention	Dropout	Math grades	Language grades
	(1)	(2)	(3)	(4)
Mig. Share ITT	0.00906**	0.0235*	-0.685***	-0.701***
	(0.00382)	(0.0138)	(0.0875)	(0.0921)
R-squared	0.020	0.105	0.270	0.281
Obs.	12,622,876	10,049,531	12,134,882	12,199,462
Mean	.005	.032	-.044	-.024

Standard errors clustered at school-grade level in parentheses. *** p<0.01 ** p<0.05 * p<0.1. Control variables: sex, age, baseline math grade, school by year, and grade fixed effects. The sample includes only incumbent students from 2015 to 2019 in primary and secondary schools.

Incumbents' parents might re-optimize and respond to the inflow of migrants to their children's schools. Student turnover is particularly important because children in Peru do not necessarily need to attend the schools in their neighborhoods. Also, parents have the legal right to change their children to a different school at any time during the academic year. This results in a turnover of about 8 to 9% each year, prior to the migrant influx. Table 3 examines the effects of Venezuelan immigrant concentration on the likelihood of school switching. Our estimates suggest that a 1 percentage point increase in the share of migrants increases the probability of an incumbent student switching schools by 0.275 percentage points for primary and 0.174 percentage points for secondary. Given that the average turnover rate for primary schools is 11.6% and for secondary schools is 8.1%. These effects are equivalent to a 2.4% and 2.1% increase in the student turnout for primary and secondary schools, respectively.

Table 3: Effects of Migrant Exposure in the Probability of Switching Schools

	Primary (1)	Secondary (2)
Mig. Share ITT	0.275***	0.174***
	(0.0122)	(0.0207)
R-squared	0.094	0.085
Obs.	14,700,336	12,622,876
Mean	.116	.081

Standard errors clustered at school-grade level in parentheses. *** p<0.01 ** p<0.05 * p<0.1. Control variables: sex, age, baseline math grade, school by year and grade. The sample includes only incumbent students from 2015 to 2019 in primary and secondary schools.

A 5 percentage point increase in the migrant share will increase the likelihood of switching schools by 1.37 percentage points for a primary student and 0.87 percentage points for a secondary student. In contrast to the effects on student achievement, these effects are larger than similar effects found in the literature. The point estimates are similar in magnitude if we compare them with Figlio and Özek (2019) point estimates of refugees on student mobility[19]. However, considering that in Peru in 2019, the student turnover rate was lower than the turnover rate in Florida in Figlio and Özek (2019) paper, which lies between 16% and 17%, effects are more extensive in the context of the influx of Venezuelan migrants to Peru.

As the peer-effects literature points out, the linear-in-means model might be insufficient to understand the mechanisms underlying peer effects (Sacerdote, 2011). We estimated a non-parametric, non-linear model of the effect of migration on schooling outcomes and school switching. We use the equation 1 specification, and instead of having the migrant share $V_{sg,t}$ as our primary explanatory variable, we add five dummy variables that take the value of 1 if the migrant share is on quintiles 1 to 5 of the migrant share distribution in grades where there is at least one migrant. In this way, we ensure that the comparison group is composed

[19] One percentage point increase in refugee concentration increases the probability of student movement by 0.2 percentage points (Figlio and Özek, 2019).

of grades with no migrants. Table A1 shows the range of the migrant share on each quintile. Figures A12 to A16 show the coefficient of each dummy and its confidence interval for each outcome. Figures A12 and A13 show null results for the incumbent's likelihood of retention and dropout on both primary and secondary schools. Figures A14 and A15 show significant negative results for math and language. In primary schools, moving from a zero migrant share to having at least 6 migrants (8.33%) in a school-grade decreases math and language grades by 0.03 standard deviations. There are no significant effects for lower quintiles. In Secondary, we see negative and significant effects that increase between the second and fifth quintiles. Larger effects occur in the fifth quintile, where an 8.33% increase in migrant share reduces incumbents' math and language grades by 0.07 and 0.06 standard deviations, respectively. The effects are between 0.02 and 0.03 standard deviations on the second to fourth quintiles. Figure A16 shows the point estimates of the non-linear specification on the probability of school switching. As the percentage of migrants increases, the likelihood of incumbents switching schools increases non-linearly. We find that primary incumbents start switching when the migrant share is higher than 2.44%, of their school grade (1.95 migrants), while in secondary, the tipping point is at 4.35% (3.5 migrants).

5.2 School Switching Characterization

Parents might re-optimize differently depending on their children's characteristics. We estimate heterogeneity analyses to characterize the students more prone to transfer schools after exposure to a higher share of migrants. Additionally, it generates an indirect change in peer composition that might reinforce or mitigate the migrant effects on schooling outcomes. If the school switchers are low achievers, the positive peer effects will mitigate the adverse effects on achievement. If the high achievers are the ones switching, the negative effect on achievement will be reinforced by the peer composition changes.

Our heterogeneity analyses follow the main specification in equation 1 and include the heterogeneity measure and the interaction between the heterogeneity measure and the migrant share. We explore heterogeneity in three dimensions: gender, baseline math grades, and baseline language grades, and the interaction between them. Table 4 shows the results for primary school. We see that boys and girls are equally likely to transfer schools as they are more exposed to migrants. For baseline performance in grades, we find that primary school students with lower grades are more likely to transfer schools when exposed to a higher share of migrants than students with higher grades exposed to the same share of migrants. Increasing 1 percentage point the migrant share in their school grade makes students with one standard deviation higher math grades less likely to move by 0.014 percentage points.

Table 4: Heterogeneity of Switching Schools in Primary

	Heterogeneity Measures		
	Girl	Baseline Math Grade	Baseline Lang Grade
	(1)	(2)	(3)
Mig. Share × Heterogeneity	-0.011	-0.014**	-0.005
	(0.013)	(0.006)	(0.006)
Het. Measure	0.000	-0.010***	-0.010***
	(0.000)	(0.000)	(0.000)
Mig. Share ITT	0.282***	0.275***	0.275***
	(0.014)	(0.012)	(0.012)
R-squared	0.093	0.094	0.094
Obs.	14,700,292	14,699,846	14,700,292

Standard errors clustered at school-grade level in parentheses. *** $p<0.01$ ** $p<0.05$ * $p<0.1$. Control variables: school by year and grade fixed effects. The specification includes the heterogeneity measure, the share of migrants per grade and the interaction between the migrant share and the heterogeneity measure. The baseline grades correspond to the first grade we observe for every student. The sample includes incumbent students from 2015 to 2019 in primary schools.

Table 5 shows the effects on students in secondary schools. Unlike what we found in primary schools, girls are more likely to switch schools when exposed to migrants. With a 1 percentage point increase in migrant share in the school-grade cohort, the likelihood that girls switch schools increases by 0.22 percentage points, while, for boys, it is 0.138 percentage points. The difference is significant at the 1% level. Additionally, higher-achieving students are more likely to switch secondary schools when exposed to more migrants. An increase of 1 percentage point on the migrant share increases the likelihood of switching by

0.041 percentage points for students with one standard deviation higher math grades and 0.047 percentage points for students with one standard deviation higher language grades. In secondary, girls and students who have higher grades are more likely to change schools as they are exposed to the same share of migrants.

Table 5: Heterogeneity of Switching Schools in Secondary

	Heterogeneity Measures		
	Girl	Baseline Math Grade	Baseline Lang Grade
	(1)	(2)	(3)
Mig. Share × Heterogeneity	0.082***	0.041***	0.047***
	(0.018)	(0.009)	(0.009)
Het. Measure	0.002***	-0.005***	-0.006***
	(0.000)	(0.000)	(0.000)
Mig. Share ITT	0.138***	0.175***	0.174***
	(0.022)	(0.021)	(0.021)
R-squared	0.085	0.085	0.085
Obs.	12,640,153	12,610,324	12,640,155

Standard errors clustered at school-grade level in parentheses. *** p<0.01 ** p<0.05 * p<0.1. Control variables: school by year and grade fixed effects. The specification includes the heterogeneity measure, the share of migrants per grade and the interaction between the migrant share and the heterogeneity measure. The baseline grades correspond to the first grade we observe for every student. The sample includes incumbent students from 2015 to 2019 in secondary schools.

We have characterized the students who are more likely to switch schools when exposed to migrants. Now, we describe the schools to which they move. We estimate our main specification from equation 1 on the changes of school time-invariant characteristics before and after students switch. First, we focus on whether the movement comes from public or private schools and whether the schools chosen are public or private. Tables 6 and 7 show the effect of migrants on the likelihood of moving from a public to a private school in column 1, from a private to a public school in column 2, from a public to a private school in column 3, and from a private to a private school in column 4.

Table 6: Switching Between Public and Private Schools in Primary

	Public to Public (1)	Private to Public (2)	Public to Private (3)	Private to Private (4)
Mig. Share ITT	0.087***	0.040***	0.049***	0.099***
	(0.006)	(0.007)	(0.004)	(0.009)
R-squared	0.065	0.126	0.029	0.165
Obs.	14,698,662	14,698,662	14,698,662	14,698,662
Mean	.051	.02	.013	.031

Standard errors clustered at school-grade level in parentheses. *** $p<0.01$ ** $p<0.05$ * $p<0.1$. Control variables: sex, age, baseline math grade, school by year, and grade fixed effects. By definition, the outcome variables take 0 value for all non-switchers. The sample includes only incumbent students from 2015 to 2019 in primary schools.

In Table 6, we see that primary school students who are exposed to a higher share of migrants are more likely to move to private schools from both public and private schools. The likelihood of switching from public to public schools increases by 0.087 percentage points as the share of migrants in the school grade increases by one percentage point. The likelihood of switching from private to public schools increases by 0.04 percentage points as the likelihood of switching from private to public schools. The higher effects are on the likelihood of switching from private to private schools, which increases by 0.1. The school mobility rates from public to public, private to public, public to private, and private to private primary schools are 5%, 2%, 1.3%, and 3.1%, respectively. Then, the effect of a one percentage point increase in migrant share increases the probability of switching within public schools by 1.7% and from private to public schools by 2%. In contrast, it increases the probability of switching from a public to a private school by 3.8% and 3.2% from private to private schools.

Table 7: Switching Between Public and Private Schools in Secondary

	Public to Public (1)	Private to Public (2)	Public to Private (3)	Private to Private (4)
Mig. Share ITT	0.024**	0.039***	0.024***	0.089***
	(0.010)	(0.011)	(0.006)	(0.015)
R-squared	0.046	0.094	0.024	0.127
Obs.	12,619,952	12,619,952	12,619,952	12,619,952
Mean	.034	.013	.012	.021

Standard errors clustered at the school-grade level in parentheses. *** $p<0.01$ ** $p<0.05$ * $p<0.1$. Control variables: sex, age, baseline math grade, school by year, and grade fixed effects. By definition, the outcome variables take 0 value for all non-switchers. The sample includes only incumbent students from 2015 to 2019 in secondary schools.

Table 7 shows that secondary school students are most likely to switch from public to public schools but also move to private schools. Increasing the migrant share by 1 percentage point increases the likelihood of switching from public to public schools by 0.024 percentage points, from private to public by 0.039, from public to private by 0.024 percentage points, and from private to private schools by 0.089 percentage points. The school mobility rates for secondary schools are 3.4% from public to public, 1.3% from private to public, 1.2% from public to private, and 2.1% from private to private. This last group of students incurs new costs to transfer schools after exposure to a higher share of migrants. A 1 percentage point on the migrant share increases the public-to-private and private-to-private switching rates by 2% and 4%, while it changes the public-to-public switching rate by 0.7%.

Second, we characterize schools in different dimensions: the proportion of migrants, test scores, student-teacher ratio, Parents' SES index, and teachers' education. We construct the historical average of these variables by school [20]. Then, we construct dummy variables that indicate if students are moving to schools that historically have had fewer migrants, higher test scores, lower student-teacher ratios, higher SES indexes in 2016, and a higher proportion of teachers with professional education. [21] Tables 8 and 9 show the results for primary and

[20] We use the 2016 Parent's SES index from the household survey made by the Ministry of Education as part of the ECE national standardized test

[21] By construction, these dummy variables equal 0 for all non-switchers

secondary schools, respectively.

Table 8: Switching Schools Profile in Primary

	Fewer Venezuelans (1)	Higher Math Scores (2)	Higher Lang. Scores (3)	Lower Stud/Teach (4)	Higher Parents' SES (5)	Higher Teach Educ (6)
Mig. Share	0.241***	0.152***	0.153***	0.111***	0.123***	0.131***
ITT	(0.012)	(0.011)	(0.010)	(0.008)	(0.009)	(0.010)
R-squared	0.112	0.113	0.104	0.062	0.042	0.138
Obs.	14,700,336	13,872,404	13,873,023	14,685,206	12,806,693	14,698,662
Mean	.039	.061	.06	.054	.05	.052

Standard errors clustered at school-grade level in parentheses. *** $p<0.01$ ** $p<0.05$ * $p<0.1$. Control variables: sex, age, baseline math grade, school by year and grade fixed effects. All the outcome variables are dummies defined by difference in school characteristics after switching. By definition is 0 for all non-switchers. School characteristics are historical averages from 2014 to 2019. Parents' SES is measured by the socioeconomic index of the ECE surveys on student household characteristics in 2016. The sample includes only incumbent students from 2015 to 2019 in primary schools.

The school destination characteristics are consistent with the incumbent's avoiding higher concentrations of migrants. In Table 8, we can observe that, as primary school students are more exposed to migrants, they tend to go to schools with fewer migrants, higher-income families, and higher quality in all our measures. A 1 percentage point increase in the share of migrants increases the probability of switching to a school with a lower native/migrant proportion by 0.241 percentage points. This same increase in the share of migrants increases the likelihood of switching to a higher-quality school. This effect ranges from 0.111 to 0.153 percentage points for the different quality measures. Table 9 shows the same pattern of results for secondary school. Increasing the migrant share by 1 percentage point increases the likelihood of switching to a school with fewer migrants by 0.093 percentage points. It also increases the likelihood of switching to higher-quality schools between 0.068 to 0.125 percentage points, depending on the quality measure we consider. Finally, as we expected from the high likelihood of switching to private schools, primary school and secondary school switchers have a higher probability of switching to schools with wealthier parents.

Table 9: Switching Schools Profile in Secondary

	Fewer Venezuelans (1)	Higher Math Scores (2)	Higher Lang. Scores (3)	Lower Stud/Teach (4)	Higher Parents' SES (5)	Higher Teach Educ (6)
Mig. Share ITT	0.093*** (0.022)	0.112*** (0.017)	0.112*** (0.017)	0.068*** (0.013)	0.102*** (0.012)	0.125*** (0.017)
R-squared	0.085	0.072	0.069	0.059	0.040	0.091
Obs.	12,622,876	12,413,962	12,414,030	12,617,787	12,004,923	12,619,952
Mean	.027	.04	.04	.039	.039	.038

Standard errors clustered at school-grade level in parentheses. *** p<0.01 ** p<0.05 * p<0.1. Control variables: sex, age, baseline math grade, school by year and grade fixed effects. All the outcome variables are dummies defined by difference in school characteristics after switching. By definition is 0 for all non-switchers. School characteristics are historical averages from 2014 to 2019. Parents' SES is measured by the socioeconomic index of the ECE surveys on student household characteristics in 2016. The sample includes only incumbent students from 2015 to 2019 in secondary schools.

School switching can result from households moving to neighborhoods with fewer migrants. White flight literature has shown that white households left cities and went to suburban areas in response to the black migration from the rural South (Boustan, 2010). A natural question in this context is whether the children are not only switching schools but families are also moving to different neighborhoods after the migrant's arrival. Given that we do not have data on the student's residence, we do not know if they are changing their neighborhood of residence, but we know the geolocation of the schools. Table A2 shows the main specification results for dummy variables that take the value of 1 if the incumbent student switches a school in a different region, province, district, and the distance in miles between the origin and the destiny schools [22]. We find minor significant effects of migrant share on switching school regions, provinces, and districts. Moreover, the effect of a 5 percentage point increase over the distance between the origin and destiny schools is 0.33 miles for primary and non-significantly different from zero in secondary. These estimates suggest that the effects of migration on student turnover are not explained by families moving to different locations.

[22]Peru territory is divided into regions that are subdivided by provinces and provinces are subdivided by districts. There are 25 regions, 196 provinces, and 1869 districts.

5.3 Mechanisms Behind School Switching

How does the inflow of immigrants into schools translate into higher student turnover rates? This section explores the mechanisms at play in primary and secondary schools. First, we discard this as a mechanical effect of class size changes. Second, we explore resources' role in the parent's decisions and check for evidence of binding resource constraints. Lastly, we examine the peer composition changes and whether this is a negative peer effect driven by low-achieving migrants or a disruption effect of having new, culturally different children at school. Although this evidence is descriptive, it shows that peer effects are one of the mechanisms at play and evidence of binding resource constraints, especially in low-resourced and public schools.

Class size: The significant influx of migrants may affect class sizes. Figure A10 shows that class sizes are relatively stable over time, even after the migration increased exponentially in 2017. On average, classrooms in primary schools are smaller and vary between 10 and 14 students; in secondary schools, classrooms range between 18 and 22 students. Although we do not see sharp increases in class size, there still may be a relationship between the number of migrants and class size. As a first approach to check for a correlation between migrant inflow and class size, we plot the residualized class size and number of migrants in the school grade after controlling for all our covariates and fixed effects. In Figure A11, the solid line shows the correlation between the residualized number of migrants and the residualized class size. The dashed line has a slope of 1 to compare the fitted values to the one-to-one relationship between the X and Y-axis variables. Figure A11 shows that the relationship between the residualized class size and the number of migrants is not one-to-one. Although class size is increasing and is one of the factors that can explain our effects, we do not find that the migrant influx has increased the probability of children being in classes that exceed the government recommended class size. Table A3 shows that the likelihood of exceeding the maximum class size is very close to zero, and even negative. When we split the effect by public and private schools, we see that the effect is zero in public schools and negative and small in private schools. This is consistent with private schools having more resources to adapt. Hence, although class sizes increase, we do not find evidence of them being crowded to the point of exceeding the maximum class size established by the Ministry of Education.

The role of school and parent resources: Considering that the Peruvian education system has high inequality in resource availability for students, if the inflow of migrants reduces school resources beyond having mechanical effects on class size, we should see different effects by resource availability. First, we split the sample between public and private schools. We expect tuition payment in private schools to mitigate resource constraints that the public sector might have experienced after the sudden inflow of Venezuelan migrants. More specifically, in private schools, the migrant inflow is not expected to change per-pupil expenditure. However, in Peru, between 2014 and 2019, 27% of schools were private and had very high variability in prices. Balarin (2015) shows that after its expansion in the late 90s and early 00s, Peruvian private education was no longer a privilege of the wealthy elites. There are low-fee private schools in poor settlements that do not necessarily offer higher quality than the public schools serving the same areas (Balarin, 2015).

For this reason, we added two more resource measures. First, we split the school sample by strictly parent resources using the average parent's socioeconomic index in 2016 before the migration pick. This socioeconomic index is calculated by the ministry of education at the school level using ECE's survey information on parents' education, income, assets, and household characteristics. Finally, we use a cleaner measure of resource availability at the school level: the student/teacher ratio in 2014 before our analysis period starts. Some primary schools in Peru have teachers that simultaneously teach one or more grades [23]. In secondary, there are different teachers for different assignments that might teach more than one classroom at a time. Class size does not capture the differences in resources for any of these modalities. In this context student-teacher ratio is a better resource availability

[23] In our sample, these represent 63% of the schools, most of which are in rural areas and 19% of the total primary student population

measure at the school level. Since there is selection because parents can enroll their children in high and low-resourced schools, this is a descriptive exercise.

Table A6 shows the resource splitting exercise for school switching. The first panel shows the results for public schools, schools below the 25th percentile of parents' SES index, and schools above the 75th percentile of the student-teacher ratio. The second panel shows the results for private schools, schools above the 75th percentile of parents' SES index, and schools below the 25th percentile of the student-teacher ratio. Column (1) shows that migrant effects on the likelihood of switching schools are higher in private schools. Given the wide market private schools cover in Peru is not clear if parents' income and willingness to pay or school resource constraints are behind these results. Column (2) shows that in primary, the effect of migrants on the probability of switching schools is higher for schools where the average parent is at the fourth SES index quantile, parents with more resources. However, tables A7 and A8 does not show evidence of statistically significant detrimental effects on achievement in this schools. Moreover, the negative effect on math and language in primary is driven by public schools. For high-income parents and private schools, evidence is inconsistent with a mitigating strategy. On the other hand, table A6 Column (3) shows higher effects of migrant concentration on lower-resourced schools where tables A7 and A8 show higher effects on achievement measures. This evidence is consistent with a parents' mitigation strategy and binding school resource constraints in low-resourced and public primary schools.

The results for secondary schools in Table A6 show a slightly different pattern. Column (4) shows that the effect of migrant concentration on the probability of school switching is positive and significant in private schools. At the same time, it is not statistically significant and is close to zero for public schools. Contrasted by the results shown in Column (4) in tables A7 and A8 where the negative effects of migration on achievement are significantly higher for public schools. Again private schools, evidence is inconsistent with a mitigating strategy. On the other hand, when we split the sample by parents' and school resources (Columns (5) and (6) respectively), we observe that the effects of migration on student turnover are higher for low-resourced parents and schools. Tables tables A7 and A8 the detrimental effects on grades are higher in low-resource schools. Hence, evidence is consistent with binding resource constraints and parents' using school switching as a mitigation strategy in low-resourced settings.

Changes on peer composition: Following the hypothesis of adverse peer effects driven by low-achieving migrant students, we analyze our main specification and outcomes breaking up the migrant share into two components: migrants that perform above and below the median performance level. This is a purely descriptive exercise. We construct migrant performance at baseline -the first year we observe the migrants in our data- and calculate the median performance for the baseline grade and year. Column 1 in Table A10 shows that, in secondary, predominantly low-achieving migrants cause incumbents to move, while in primary, both low and high-achieving migrants cause switching, and high-achieving migrants cause slightly more movements. Results Columns 3 to 5 on Table A10 show that both higher and lower-performing migrants adversely affect performance measures in primary and secondary schools. According to Hanushek et al. (2004), the disruption caused by new incoming students causes negative peer effects, which are larger in high-turnout schools. The negative point estimates for both types of migrants suggest this might be the mechanism behind our main results and not changes in the skill level peer composition.

6 Parental Preferences for Schools

As incumbent students are more exposed to migrants, we observe that there are minor negative effects on their academic performance. However, the likelihood that these students will switch schools is large. We cannot distinguish how much of the effects on academic performance come from the peer re-composition after incumbent students sort.

Our modeling approach allows us to identify which students change schools due to their exposure to migrants. We can then compare the school choices made by families when they face the presence of migrants to a counterfactual scenario in which there is an absence of migrants. We can then study the outcomes of the native students who switch schools and the students they leave behind under both counterfactuals to shed light on who benefits and who is adversely affected by native flight.

In our model, the determinants for school choice are the proximity to the school, the cost of tuition, school quality, school characteristics, and the proportion of migrants in the school. We measure school quality as the value added of the school. We allow preferences for these determinants to be heterogeneous by gender and baseline achievement of the student after observing that there is heterogeneity by these characteristics in the reduced form native flight results. Student i's preferences over school j are:

$$U_{ij} = \beta_1 d_{ij} + \beta_{2i} p_j + \beta_{3i} X_j + \beta_{4i} V_j + \beta_{5i} q_j + \xi_j + \varepsilon_{ij} \tag{2}$$

Where p_j is the school's price, d_{ij} is the distance to school, X_j is a vector of school characteristics, V_j is the proportion of Venezuelan students in school j, and q_j is the quality of school j. We allow heterogeneity in the preferences, so for $k \in [2,5]$, $\beta_{ki} = \beta_k + \sum_r z_{ir}\beta_{kr}$, with z_{ir} being the demographic characteristic r for student i. We use two demographic characteristics based on our findings from the reduced form: gender and whether they are lower or higher achieving. We let $W_{ij} = \beta_1 d_{ij} + \beta_{2i} p_j + \beta_{3i} X_j + \beta_{4i} V_j + \beta_{5i} q_j + \xi_j$, so that the indirect utility for schools is $U_{ij} = W_{ij} + \varepsilon_{ij}$. We assume ε_{ij} is EV type I. Hence the probability of student i choosing school j is:

$$P_{ij} = \frac{e^{W_{ij}}}{\sum_k e^{W_{ik}}} \tag{3}$$

We use a Maximum Likelihood to estimate preference for proximity, taste heterogeneity, and mean utilities or school popularity. The mean utilities absorb the preference components from the indirect utility function that vary only at the school level:

$$LL(\beta) = \sum_i \sum_j C_{ij} \ln \frac{\exp\left(\beta_1 d_{ij} + (\beta_{2i} - \beta_2)p_j + (\beta_{3i} - \beta_3)X_j + (\beta_{4i} - \beta_4)V_j + (\beta_{5i} - \beta_5)q_j + \delta_j\right)}{\sum_k \exp\left(\beta_1 d_{ik} + (\beta_{2i} - \beta_2)p_k + (\beta_{3i} - \beta_3)X_k + (\beta_{4i} - \beta_4)V_k + (\beta_{5i} - \beta_5)q_k + \delta_k\right)} \tag{4}$$

Where δ_j is the variation in preferences only at the school level

$$\delta_j = \beta_2 p_j + \beta_3 X_j + \beta_4 V_j + \beta_5 q_j + \xi_j \tag{5}$$

From this Maximum Likelihood estimation, we estimate $\hat{\delta}_j$. To estimate $\hat{q}_j$, we regress $Y_i = Z_i\gamma + q_j + \varepsilon_j$, with Z_i being observable characteristics, and Y_i being test scores. From this process, we obtain $\hat{q}_j$ and $\hat{\delta}_j$. Using a 2SLS estimation, we estimate:

$$\hat{\delta}_j = \beta_2 p_j + \beta_3 X_j + \beta_4 V_j + \beta_5 \hat{q}_j + \xi_j \tag{6}$$

Additionally, we recognize that price, quality of the school, and the presence of migrants in the school can be endogenous and we employ a W2SLS strategy to tackle this issue. To account for the endogeneity in price and quality, our first set includes instruments for the price and quality of the schools. Following Allende (2019), we leverage variation from a law reform in Peru that aimed to expand tenured contracts and raise wages for public school teachers. The implementation of the law spanned from 2013 to 2018. We use four instruments from 2018: a teacher wage index for teachers in public schools, teacher job openings in the school, the number of teachers with temporary contracts, and an indicator of whether the school hired teachers under the new regulation (for public schools only). The reform N-29944 regulated the selection process and career advancement of public school teachers in Peru. It established an entrance exam, which is mandated for all candidates to get a tenured teacher contract in a public school. It also established the pay grade scales for each level of experience. The goal of this law was to create better incentives to hire qualified teachers who can guarantee a better quality of education in public schools. Allende (2019) documents how the reform induced variation in the wages and types of contracts through time and space. The assumption behind the exclusion restriction of these instruments is that the variation that the reform introduces on our measures of changes in teacher contracts are unrelated to the unobserved school characteristics that drive parental preferences.

To account for the endogeneity of the presence of migrants in schools, our second set of instruments includes variables related to the geographic settlement of migrants in the previous years. We use the number of migrants by age group in the social security office closest to the school in 2018 and the proportion of migrant students in the three closest schools in 2018. The assumption behind the exclusion restriction of these instruments is that the spatial variation that explains the presence of Venezuelan migrants in 2018 is unrelated to the unobserved school characteristics that drive parental preferences in 2019. The idea behind this exclusion restriction is that the choice of residence happens before school enrollment, so adjusting to current unobservable shocks of school preferences takes a long time. All these elements allow us to construct the preferences of parents for schools.

Each student can choose any school within their market. In our context, each market is a city, except for Lima, which contains four markets (one for each subregion of the city). We use Lima and the following 6 largest cities in Peru, for a total of 10 markets. In secondary school, we estimate the model for grades 8 to 11, since some students attend schools that only offer Primary school up to grade 6, and have to enroll in a different school in grade 7. With these sample constraints, we have a sample of 132,401 students in Secondary.

7 Structural Model Results

The preference parameters we have estimated allow us to predict the choices of students. Our modeling approach allows us to identify which students change schools due to their exposure to migrants. We do this by comparing the choices made by families when they consider the presence of migrants in their school selection to a counterfactual scenario in which they do not account for such presence. We see that 9% to 16% of the switching we observe post-migration influx is due to the presence of migrants in the school. Since we can identify which students correspond to this proportion of the sample, we can also predict their outcomes under both counterfactuals. To do this, we follow

With this information, we can study the outcomes of the students who switch schools and the students that they leave behind under both counterfactuals to shed light on who benefits and who is adversely affected by native flight.

7.1 Demand Estimates

We start by presenting the first stage of the demand estimates to speak to the relevance of the instruments in Tables 10 and 11. For the cost and value added instruments in Primary school, we see that the F-statistics are 206.3 and 67.7, respectively. In Secondary, the F-statistics are 57.34 and 73.98, respectively. We see that our measures of vacancies, the teacher wage index, and temporary contracts and teacher test scores in 2018 are positively related to both cost and value-added. The relationship is strong enough to reassure us that we do not have a weak instrument problem. For the instruments of the presence of Venezuelan students in the school, we see that the F statistic is 36.69 in Primary school and 19.74 in Secondary school, supporting the relevance condition for this set of instruments. We see that the geographic location of Venezuelans in nearby schools in 2018 is related to the presence of Venezuelans in 2019.

We examine our estimates for the preference parameters for schools in Tables 12 and 13. The baseline parameters have the expected signs. Parents prefer schools closer to their residence, lower-cost schools, schools with better quality, and private schools. We see that the coefficient on the proportion of Venezuelan migrants is negative and large, albeit somewhat noisy. This is also the case for the cost parameters. However, large standard errors are expected, given the number of instrumented variables in the model that introduce

Table 10: First Stage - Primary

	(1) Cost	(2) Value Added	(3) Ven. Students (proportion)
Cost and Value Added Instruments			
Teacher Wage Index × vacancies	1.41e-07***	7.47e-08***	4.92e-09**
	(2.30e-08)	(2.22e-08)	(2.03e-09)
Teachers under temporary contract	0.0411***	0.0228***	-0.000966***
	(0.000972)	(0.000938)	(8.59e-05)
Teachers hired under new regulation	-0.0478*	-0.0342	0.00918***
	(0.0282)	(0.0272)	(0.00249)
Teacher test scores	0.0567*	0.00577	0.00627**
	(0.0303)	(0.0292)	(0.00267)
Proportion of Ven. Instruments			
Venezuelans in neighboring schools	-0.00891	-0.00989	0.00355*
	(0.0239)	(0.0231)	(0.00211)
Venezuelans in SS (18+)	-2.33e-05	-1.39e-05	-9.71e-07
	(1.82e-05)	(1.76e-05)	(1.61e-06)
Venezuelans in neighboring schools × Venezuelans in SS (18+)	-8.66e-05**	-1.90e-05	-9.32e-06***
	(3.53e-05)	(3.41e-05)	(3.12e-06)
Venezuelans in SS (13-17)	0.00113*	0.000325	0.000211***
	(0.000606)	(0.000585)	(5.36e-05)
Venezuelans in neighboring schools × Venezuelans in SS (13-17)	0.00237**	0.000552	0.000249***
	(0.000952)	(0.000919)	(8.42e-05)
School Characteristics			
School is gendered	0.213***	0.145***	-0.00272
	(0.0332)	(0.0320)	(0.00293)
School is public	-0.241***	0.422***	0.0265***
	(0.0141)	(0.0136)	(0.00125)
Constant	0.111***	-0.211***	0.00743***
	(0.0240)	(0.0232)	(0.00212)
Observations	5,223	5,223	5,223
F-statistic	206.3	67.70	36.69

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

noise to our estimates. Tables 14 and 15 show the taste heterogeneity parameters for girls and high achievers in Secondary schools. We define a high achiever student as a student whose baseline academic achievement is above the median academic achievement. We see that our Secondary school results are in line with what we find in the reduced form. We see that, in Secondary, girls and high-achieving students have a negative estimate for the preference of Venezuelan migrants in their schools. In primary school, the model predictions are different from the reduced form. We see that girls and high achieving students have a stronger disutility from being exposed to Venezuelan migrants in schools.

Table 11: First Stage - Secondary

	(1) Cost	(2) Value Added	(3) Ven. Students (proportion)
Cost and Value Added Instruments			
Teacher Wage Index × vacancies	2.43e-08**	1.61e-08**	-5.81e-10
	(9.55e-09)	(8.01e-09)	(4.31e-10)
Teachers under temporary contract	0.0204***	0.0195***	-0.000395***
	(0.00103)	(0.000865)	(4.65e-05)
Teachers hired under new regulation	-0.0660*	-0.0167	-0.000894
	(0.0356)	(0.0298)	(0.00160)
Teacher test scores	0.0292	0.00623	0.00376***
	(0.0274)	(0.0230)	(0.00124)
Proportion of Ven. Instruments			
Venezuelans in neighboring schools	0.0166	-0.00277	0.00275**
	(0.0290)	(0.0243)	(0.00131)
Venezuelans in SS (13-17)	-0.000850**	-0.000203	9.66e-05***
	(0.000340)	(0.000285)	(1.53e-05)
Venezuelans in neighboring schools × Venezuelans in SS (13-17)	5.81e-05	0.000252	-2.09e-05
	(0.000308)	(0.000258)	(1.39e-05)
School Characteristics			
School is gendered	0.125***	0.320***	-0.00357**
	(0.0309)	(0.0259)	(0.00139)
School is public	-0.441***	-0.0151	0.00921***
	(0.0178)	(0.0149)	(0.000802)
Constant	0.327***	0.120***	0.00671***
	(0.0284)	(0.0238)	(0.00128)
Observations	3,487	3,487	3,487
F-statistic	57.34	73.98	19.74

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

7.2 Simulations

With the estimates of the preference parameters of our demand model, we can identify which students change schools due to their exposure to migrants. We can do this by comparing the choices made by families when they consider the presence of migrants in their school selection to a counterfactual scenario in which they do not account for such presence. We observe that, in Secondary school, native flight accounts for 13% of the overall turnover in the education system. With this information, we can study the outcomes of the students who switch schools and the students that they leave behind under both counterfactuals to shed light on who benefits and who is adversely affected by native flight.

We estimate the outcomes under both counterfactuals following Dubin and McFadden (1984), who develop a control function approach for a discrete choice model. We can then compare both counterfactual outcomes for two subgroups: the students that produce the native flight, and the students who are left behind by those students who do the native

Table 12: Baseline Demand Parameters - Primary

	(1) Demand
Distance	-8.188***
	(0.021)
Cost	-2.805
	(5.497)
Value Added	8.296
	(10.63)
Proportion of Venezuelans in school	-2.188
	(18.04)
School is gendered	-0.376
	(0.437)
School is public	-2.434
	(6.255)
Constant	28.81***
	(2.740)
Observations	5,223
R-squared	0.441

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13: Baseline Demand Parameters - Secondary

	(1) Demand
Distance	-7.3737***
	(0.021)
Cost	-3.537
	(2.894)
Value Added	6.725**
	(2.764)
Proportion of Venezuelans in school	-7.337
	(23.65)
School is gendered	-1.490**
	(0.611)
School is public	-0.0106
	(1.140)
Constant	23.31***
	(0.780)
Observations	3,487
R-squared	0.649

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14: Taste Heterogeneity Demand Parameters - Primary

	Heterogeneity by	
	Girl (1)	Higher Achiever (2)
Cost	-0.020**	-0.087***
	(0.013)	(0.018)
Proportion of Venezuelan Students	-0.357***	-0.313
	(0.178)	(0.230)
School is gendered	0.640***	0.069***
	(0.028)	(0.035)
School is public	0.003	-0.028***
	(0.015)	(0.019)
$\hat{q}$	0.081***	0.178***
	(0.015)	(0.019)
Observations	114,490,007	114,490,007

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 15: Taste Heterogeneity Demand Parameters - Secondary

	Heterogeneity by	
	Girl	Higher Achiever
	(1)	(2)
Cost	-0.034***	0.028***
	(0.013)	(0.013)
Proportion of Venezuelan Students	-0.694***	-0.314
	(0.314)	(0.332)
School is gendered	0.773***	-0.002
	(0.021)	(0.021)
School is public	0.114***	0.048***
	(0.015)	(0.016)
$\hat{q}$	0.152***	0.116***
	(0.017)	(0.018)
Observations	54,388,691	54,388,691

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

flight.

First, we focus on the students who switch because migrants induce them. In Figures 4 and 5, the first estimate from the top down is the difference in switchers' achievement in the counterfactual with migrants minus their achievement in the counterfactual in which there are no migrants. In Primary schools, there appear to be no overall gains for the students who move. In Secondary schools, we see that native flight benefits students who move. The effect is close to 0.02 SD and statistically significant. The following four estimates in the figure break down the group of switchers into four subgroups: by academic achievement and by socioeconomic status. In Primary school, high achieving and low SES students show significant gains from movement of 0.05 SD. In Secondary school, we see that there is not any heterogeneity by academic achievement and SES. Overall, the results show that some students experience small benefits in academic achievement from switching schools, but that gain comes at a monetary cost. On average, when accounting for the presence for migrants, students who are induced to switch pay 330 more soles in Secondary and 412 more soles in

Figure 4: Academic Achievement Differences for Students who Switch - Primary

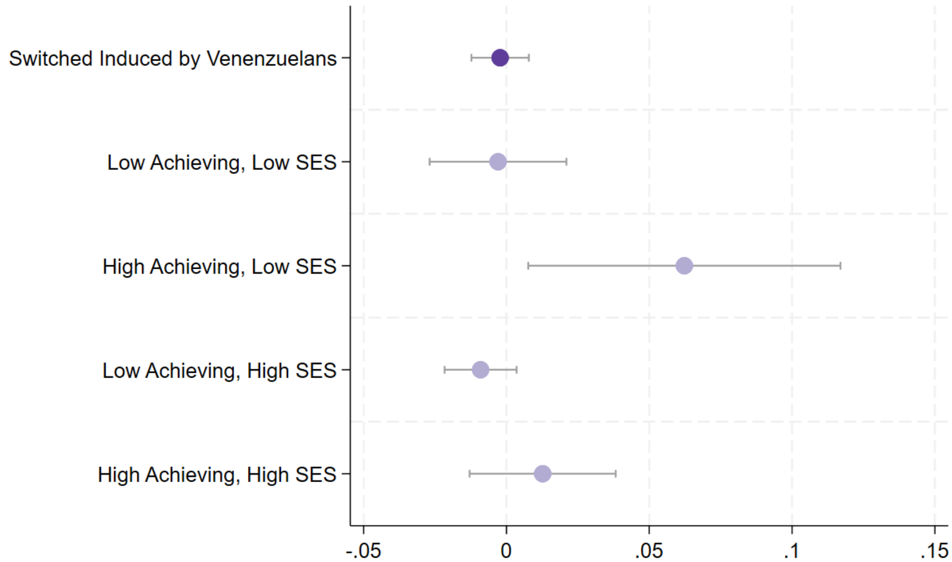


Figure 5: Academic Achievement Differences for Students who Switch - Secondary

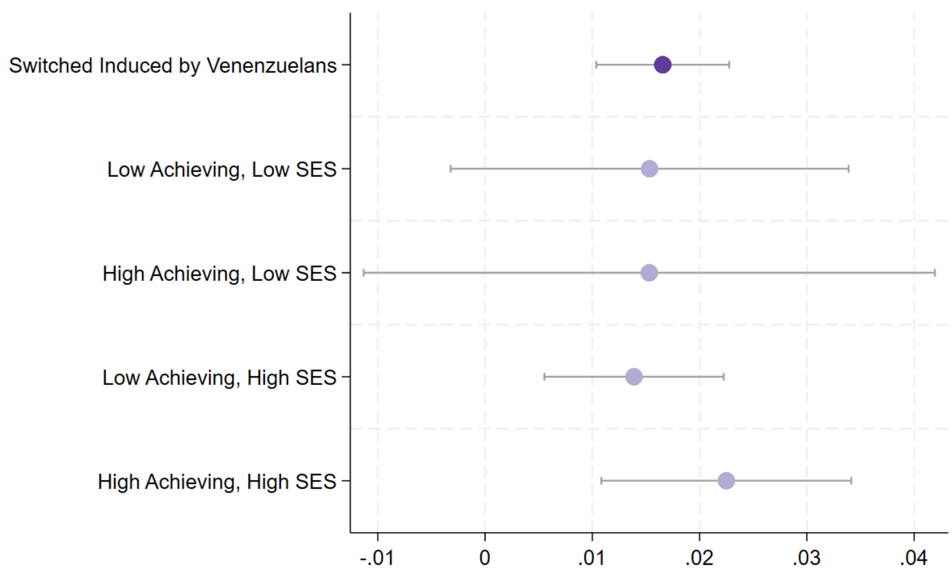
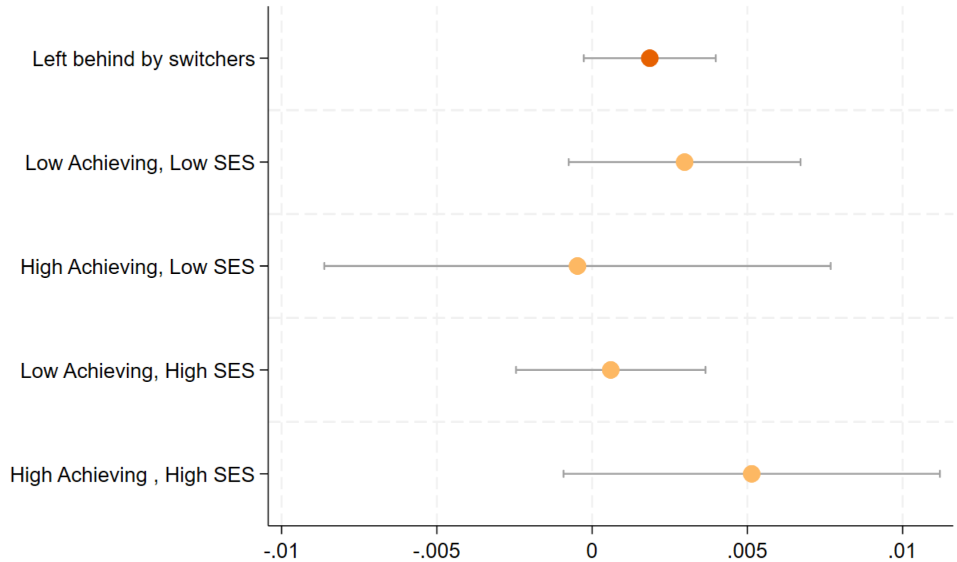


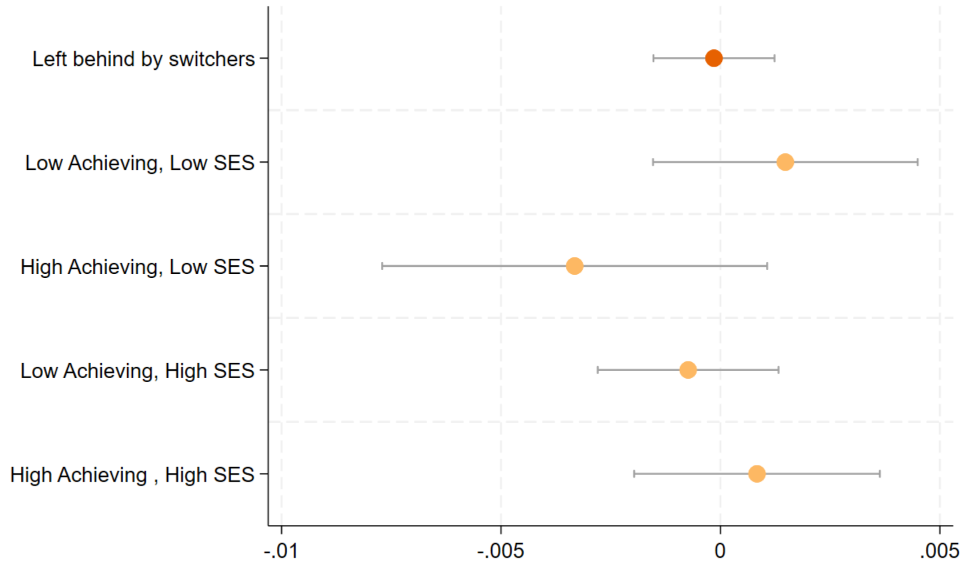
Figure 6: Academic Achievement Differences for Students Left Behind - Primary



Primary in tuition (89 and 111 USD) than in the counterfactual in which no migrants are present. For students who pay tuition, the median tuition payment is 255 soles in Secondary and 560 soles in Primary (69-151 USD) under the counterfactual where migrants are present, and 35 soles in Secondary and 60 soles in Primary (10-16 USD) under the counterfactual of no migrants. Although native flight can be an adaptive strategy for some students, it is costly for those who switch to private schools and overall brings no substantial gains in academic achievement to students who switch.

In Figures 6 and 7, the first estimate from the top down is the difference in achievement in the counterfactual with migrants minus their achievement in the counterfactual in which there are no migrants for the students who are left behind by the native flight. We see that the effect on academic achievement is a precisely estimated zero for both Primary and Secondary schools. As before, we look at the four subgroups given by achievement level and socioeconomic status to understand if there are gains or losses that average to zero. We see no distinct patterns for any particular group. Overall, we see that facilitating native flight is not detrimental to this population, but it is costly and not beneficial for the students who switch to private schools.

Figure 7: Academic Achievement Differences for Students Left Behind - Secondary



8 Conclusions

As Venezuelan migrants enter Peruvian schools, incumbent students experience detrimental effects on schooling outcomes. A higher share of migrants increases the likelihood of dropping out and decreases language and math achievement. The effects are small and comparable to those found in similar studies. However, our estimates are more precise because we use nationwide panel data. We also find that parents re-optimize when their children are more exposed to migrants by sending them to other schools. We characterize the students who move and the schools to which they move. In primary schools, students with lower grades are more likely to switch schools; in secondary schools, students with higher grades and girls are more likely to move. Students transfer predominantly from public schools to private and other public schools. Switching students move to higher-quality schools and schools with fewer migrants. However, we do not find evidence of students moving to schools far away from their original school, suggesting their families are not moving to different neighborhoods.

We discuss potential mechanisms behind the effects. Although larger classes play a role, they are not the main driver of the negative effects on achievement and the rise in school turnout. We find larger effects of migration on the probability of switching schools of high socioeconomic status families and private schools. We also find evidence consistent with binding resource constraints. Parents' are more likely to choose school switching in public and low-resourced schools where migrants have minor but adverse effects on incumbents' schooling outcomes. Nevertheless, we cannot disentangle the sorting effect from the peer effects migrants generate from their lone presence in the classroom unrelated to changes in incumbent composition.

The reduced form provides insights into average effects. we use a structural model to identify specific individuals induced to move due to migrant presence and shed light on the welfare implications. In the Peruvian school system, student turnover is about 8 to 9% per year. In the reduced form, we observe that, on average, native students that are more exposed to migrants are more likely to switch schools. The structural model shows that about 20% of the total turnover is induced by the presence of migrants in Secondary schools. Among the students who switch schools induced by migrants, there are small academic performance gains from the migrant-induced movement. Most of those gains come from the higher socioeconomic status students. However, moving is costly. Many students move to private schools. We see that on average, the monetary cost of tuition that these families face increases substantially. On the other hand, the students that are left behind do not seem to be negatively affected by the native flight. We interpret the estimate for their loss in academic achievement as a precisely estimated zero. The evidence from the model suggests that native flight can be viewed as a strategic adaptation strategy employed by a few parents in response to the influx of migrants. However, overall the gains are close to zero, and they come at a high cost for the families who switch their children to private school.

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Appendix

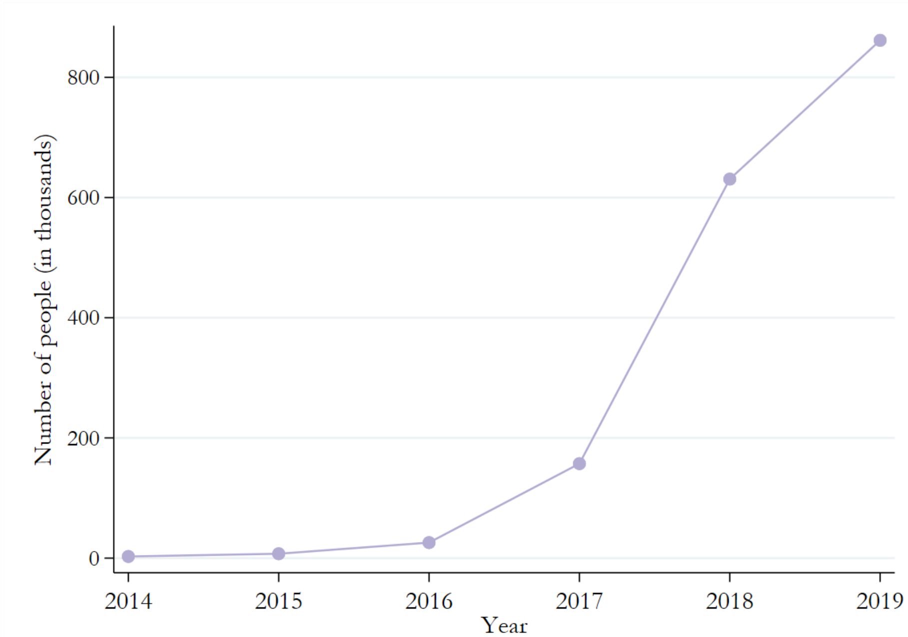
A Venezuelan crisis and migration timeline

For many years before Nicolás Maduro's presidency in Venezuela in 2013, South Americans migrated to Venezuela looking for better economic opportunities. This tendency has completely reversed, as Venezuela has fallen into one of the greatest economic crises of recent economic history. Hyperinflation and poverty were already concerning when, in May of 2017, Maduro called a Constitutional Assembly. The Venezuelan opposition and the international community rejected this. Regardless, in that Constitutional Assembly, Congress was dissolved. The opposition-held majority in Congress served as a check on Maduro's government, and they lost most of the power they held in 2017. The economic situation only worsened. The IMF reported that hyperinflation reached 65,000% in 2018, and poverty affected about 79% of the population (ENCOVI). Diseases like measles, diphtheria, tuberculosis, and malaria have spread rapidly. The shortage of food and goods for basic needs has been pervasive. Additionally, increasing crime and security issues have forced Venezuelans out of their country.

Corruption and precariousness in Venezuela made it almost impossible for Venezuelans to emigrate with updated documents. Migration offices in Venezuela could take years to issue a passport or charge large amounts of money to issue them in a reasonable time frame. Migrants also had to present a criminal record that Interpol offices can issue for about 25 USD and legally enter the country (tourists). At first, only migrants who arrived in Peru before December 2016 could apply, but, given the high demand, the Peruvian government expanded the PTP policy several times to allow migrants to legalize their stay even if they came later into the country. As more Venezuelans came, xenophobia proliferated, and the policies for Venezuelan migrants became unpopular. On August 25, 2018, only immigrants with unexpired passports could legally enter the country, increasing illegal immigration. However, after meeting all countries affected by Venezuelan migration in September of that same year, the Peruvian government reversed this change. They allowed Venezuelans with expired passports into the country. The government would reverse this again in June 2019 and allow only Venezuelan migrants with passports.

B Descriptive Statistics

Figure A1: Venezuelan Migration by Year [a]



[a]Data between 2014 to 2018 comes from the 2018 nationally representative survey of Venezuelan migrants in Peru ENCEVE. Data in 2019 from the Peruvian Migration authority

Figure A2: Venezuelan Migrants' Enrollment by Year

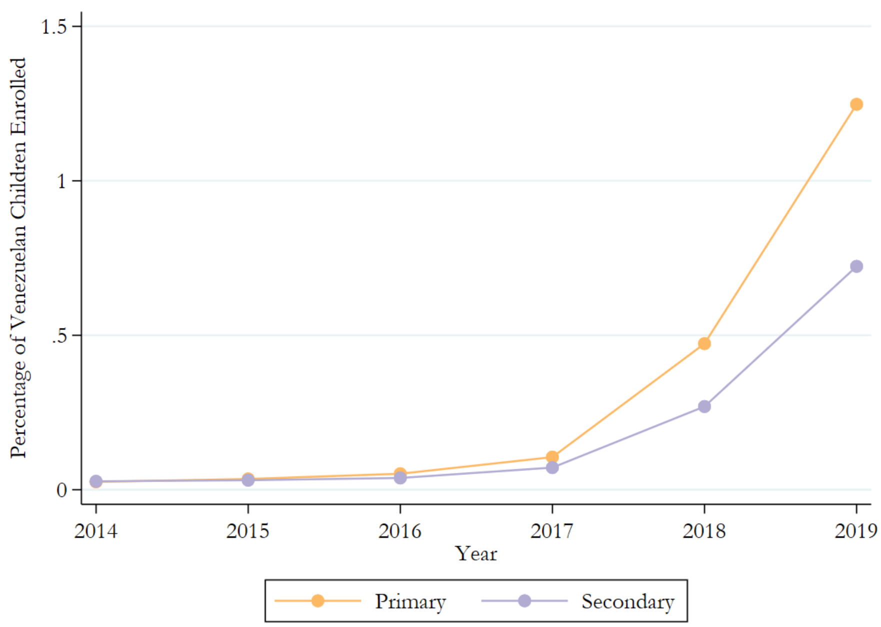


Figure A3: Venezuelan Migrant Children Enrolled in Schools by District in 2019

Figure A4: Student Turnover by level

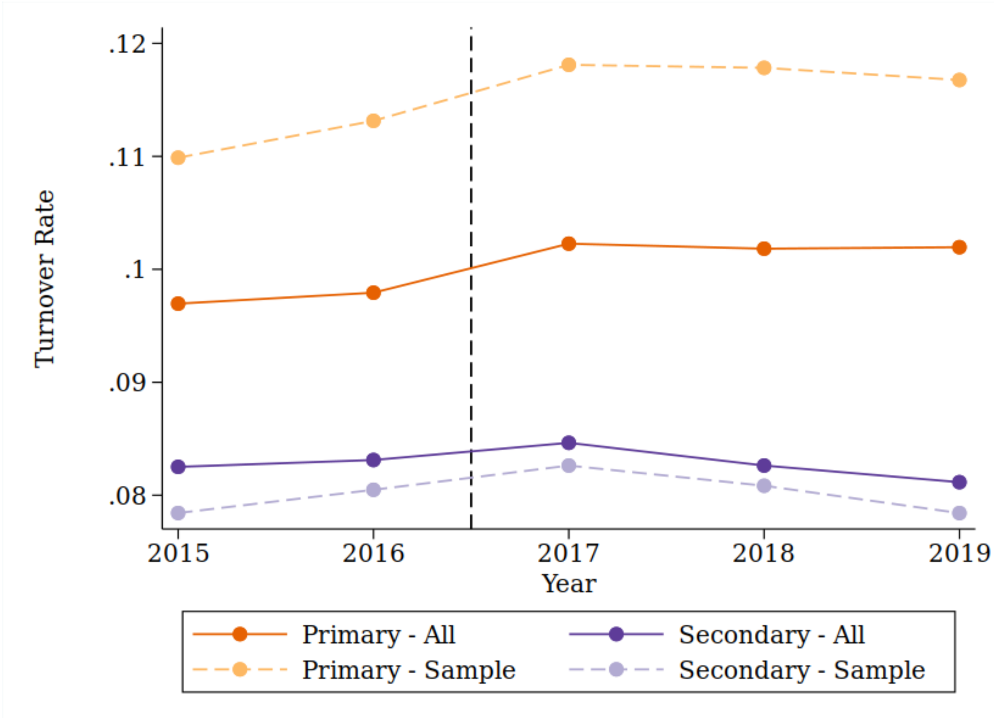


Figure A5: Student Turnover: Incumbents vs Migrants

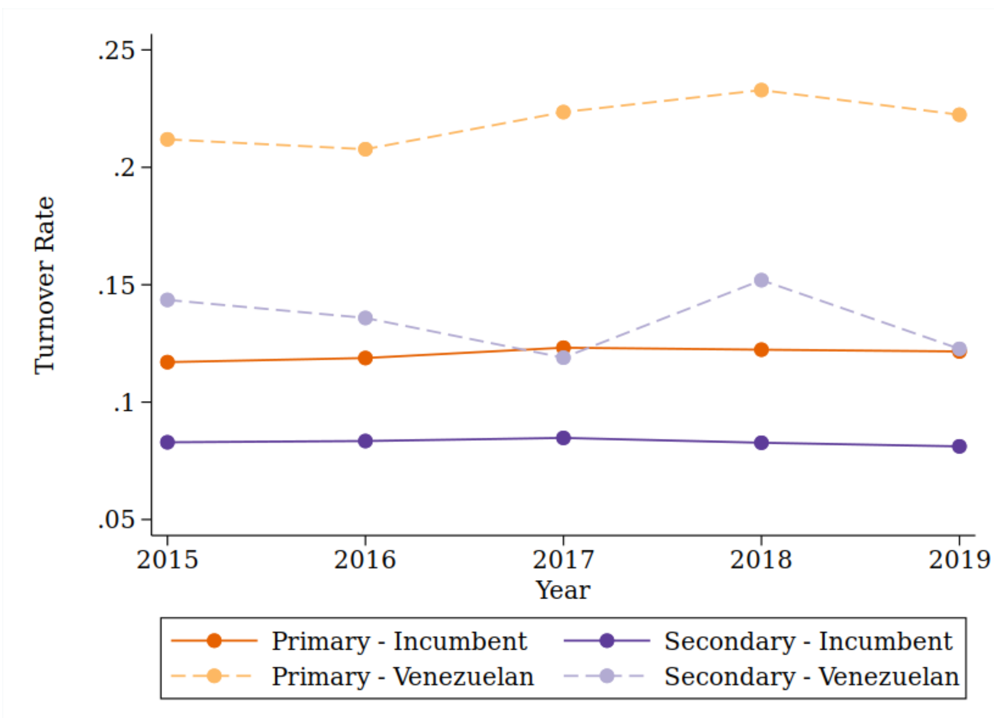
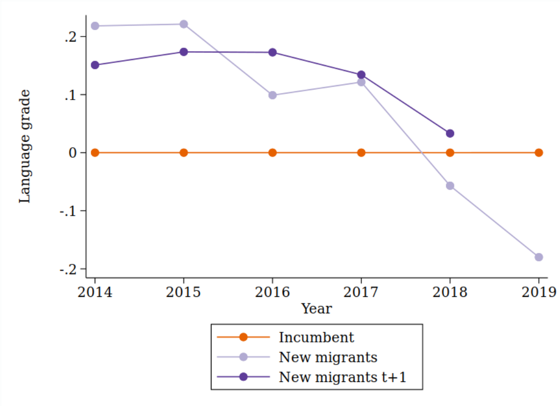
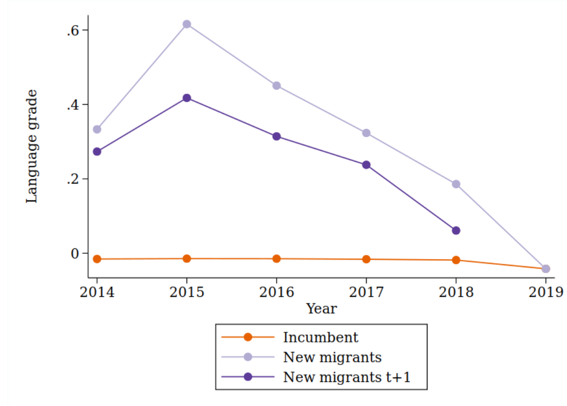


Figure A6: Venezuelan Migrants Performance in Language by Year



(a) Primary



(b) Secondary

Figure A7: Age Distribution by Grade in Primary

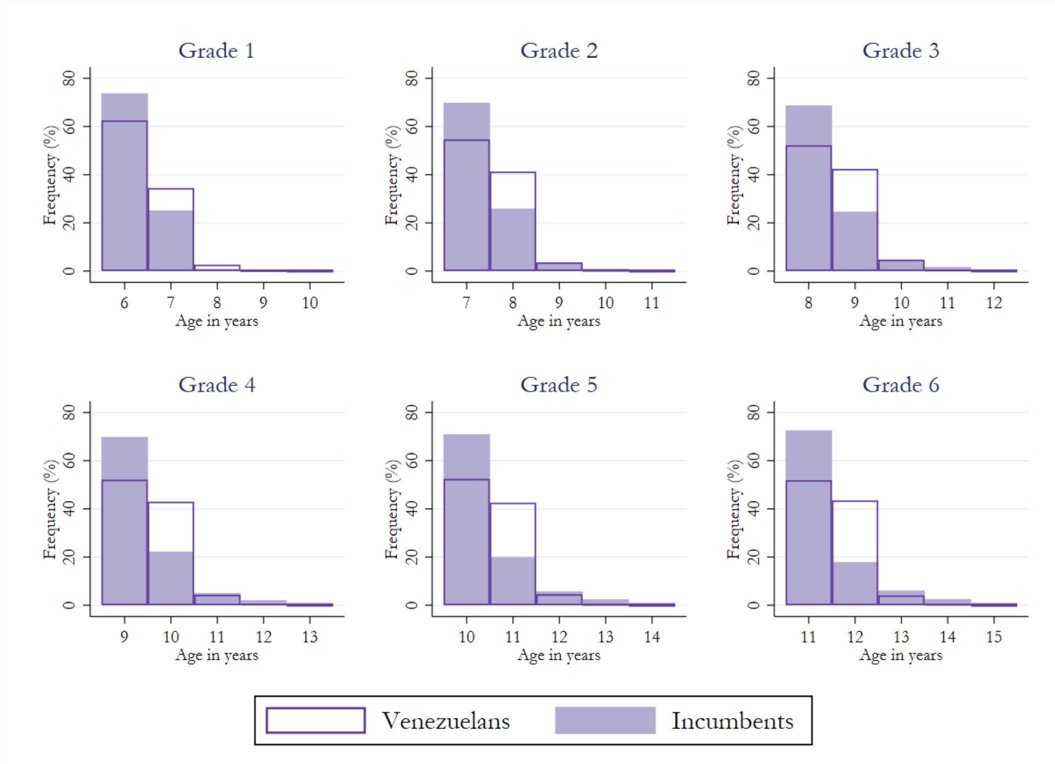


Figure A8: Age Distribution by Grade in Secondary

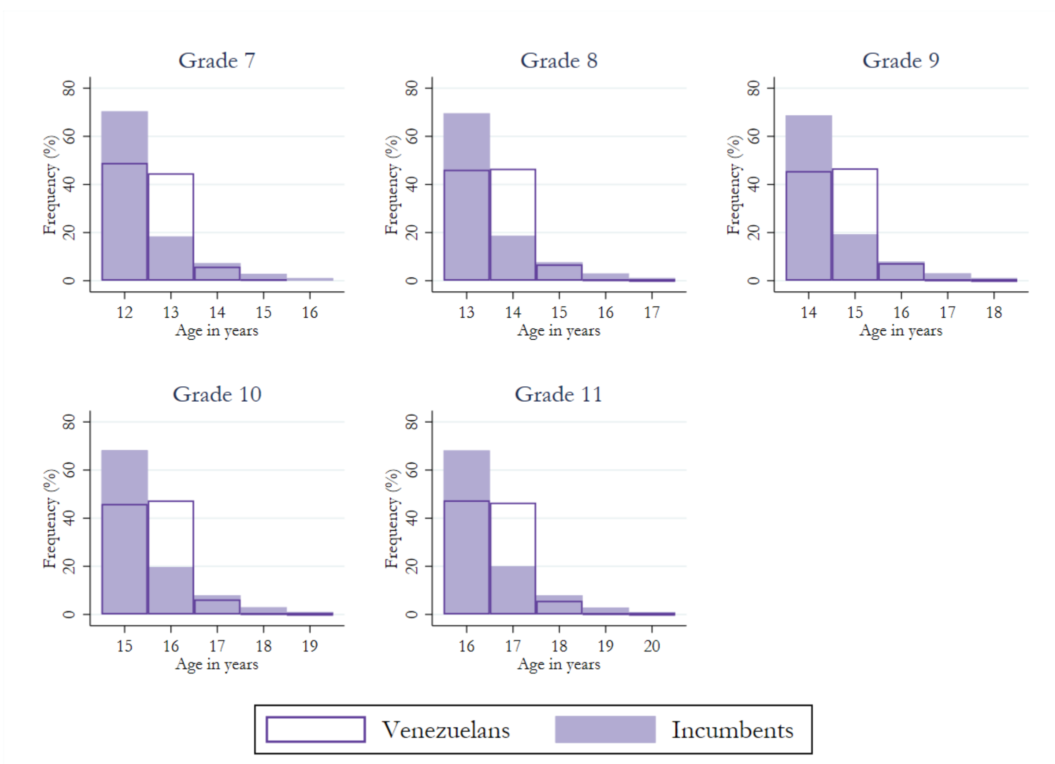


Figure A9: Treatment Distribution

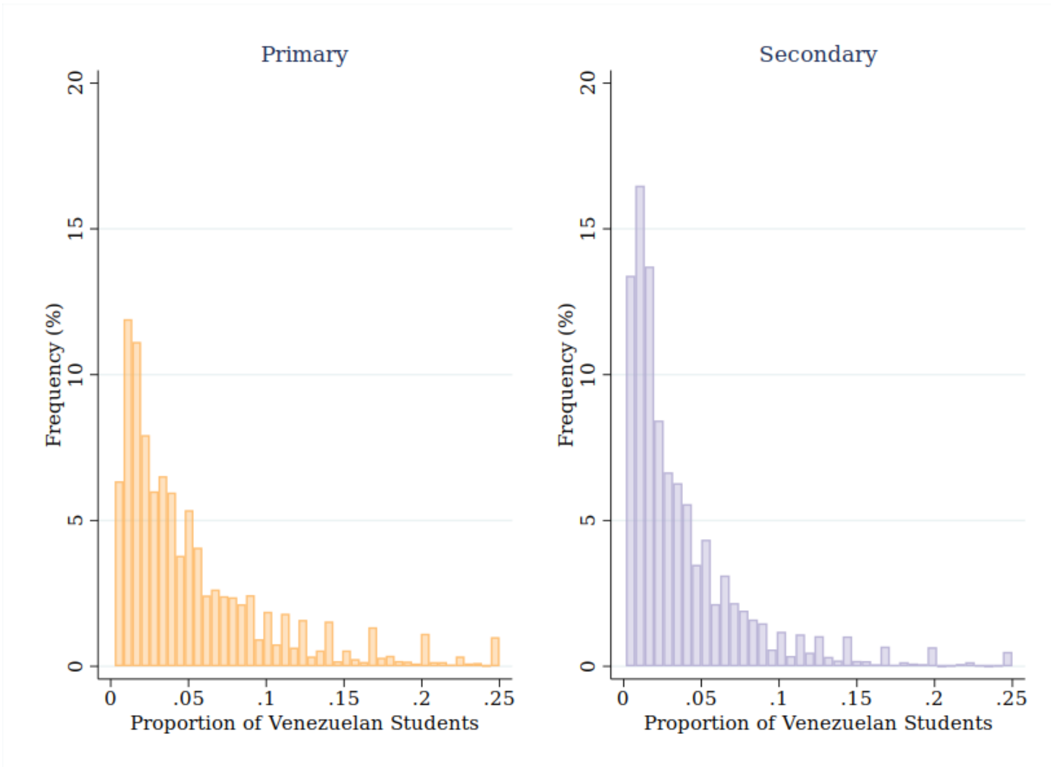


Figure A10: Class Size

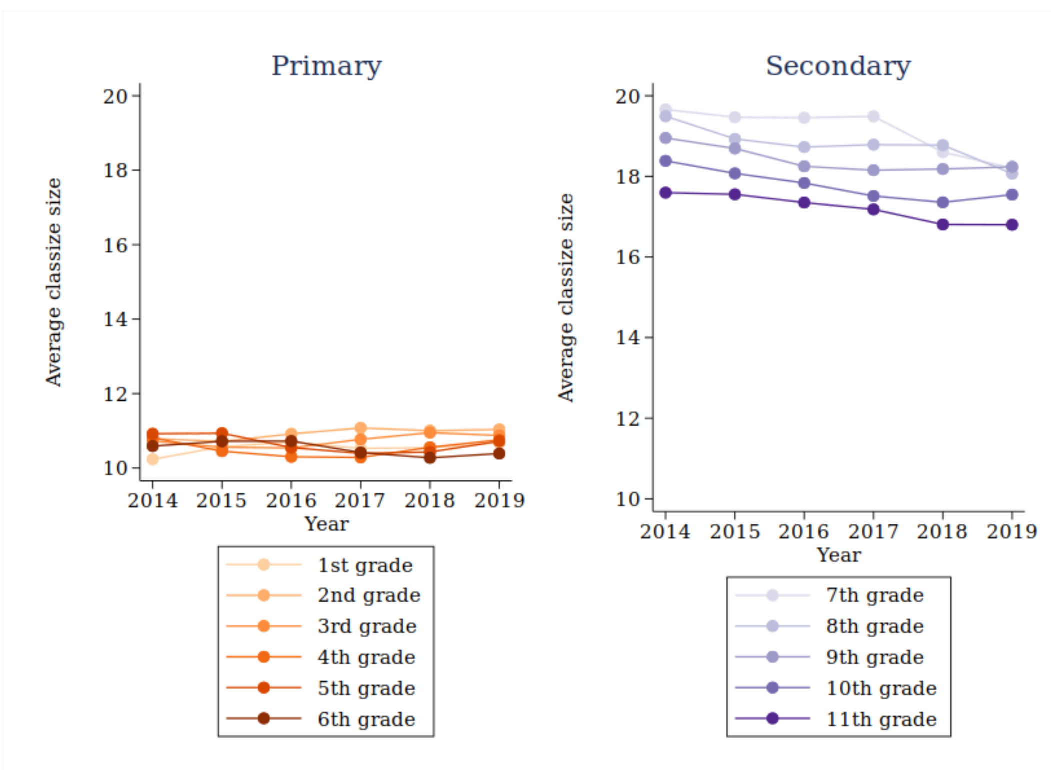
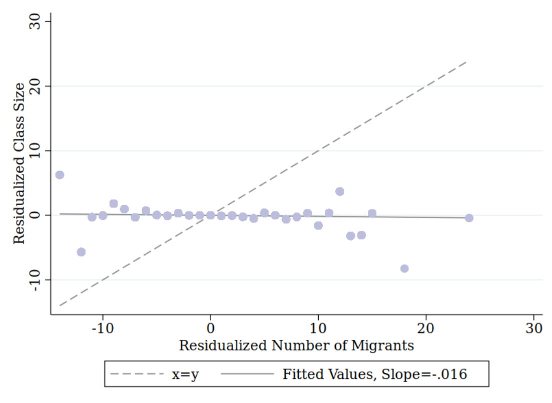


Figure A11: Residualized Share of Venezuelan Migrants and Residualized Class Size centering

(a) Primary



(b) Secondary

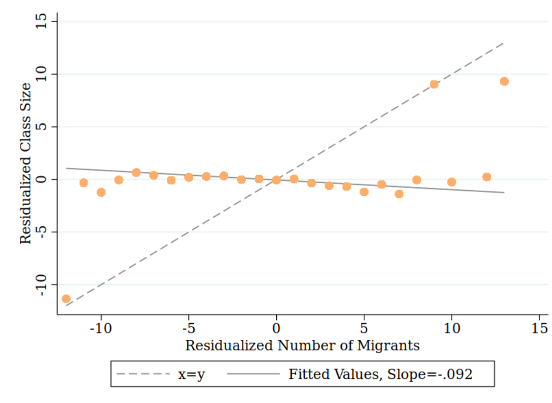
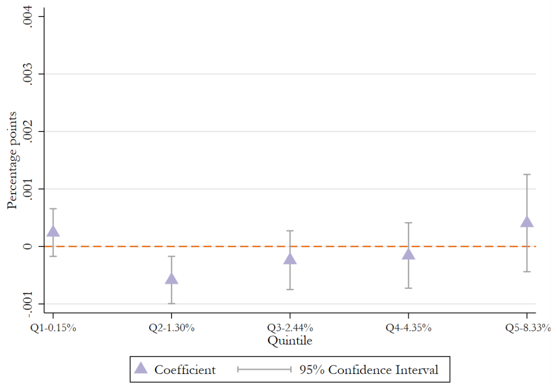


Figure A12: Non-linear Effects of Migrant Exposure on the Probability of Retention centering

(a) Primary



(b) Secondary

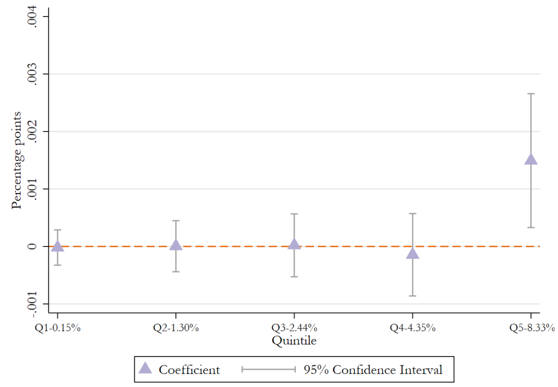
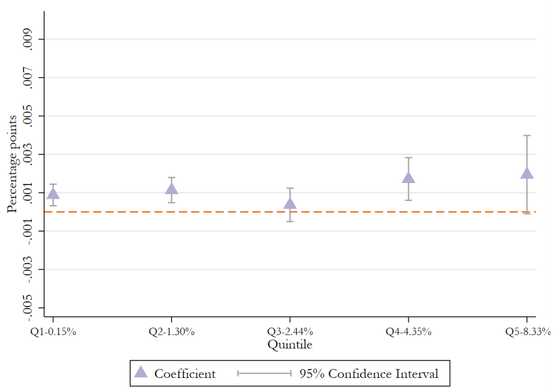


Figure A13: Non-linear Effects of Migrant Exposure on the Probability of Dropout centering

(a) Primary



(b) Secondary

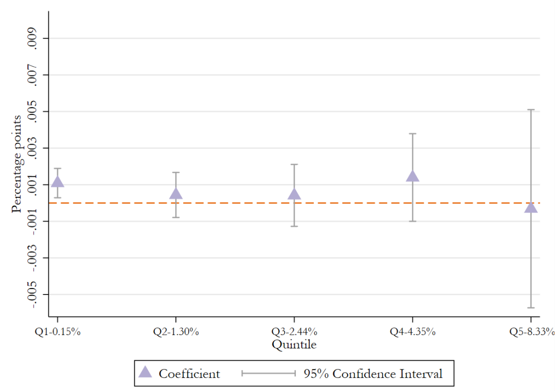
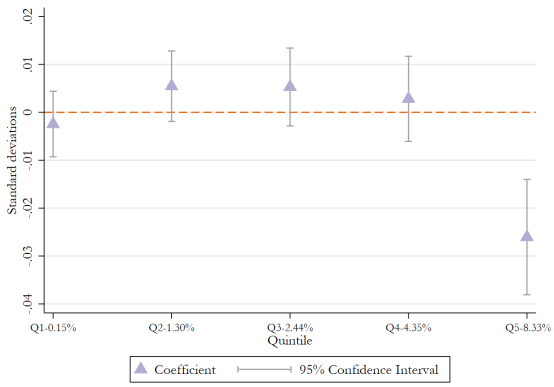


Figure A14: Non-linear Effects of Migrant Exposure on Math Grades

centering

(a) Primary



(b) Secondary

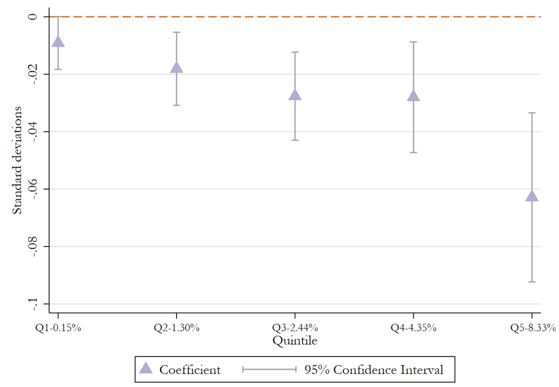
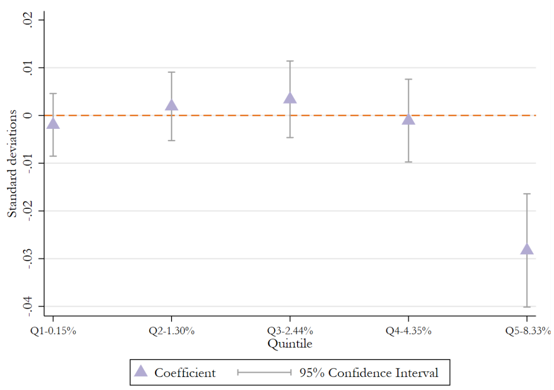


Figure A15: Non-linear Effects of Migrant Exposure on Language Grades

(a) Primary



(b) Secondary

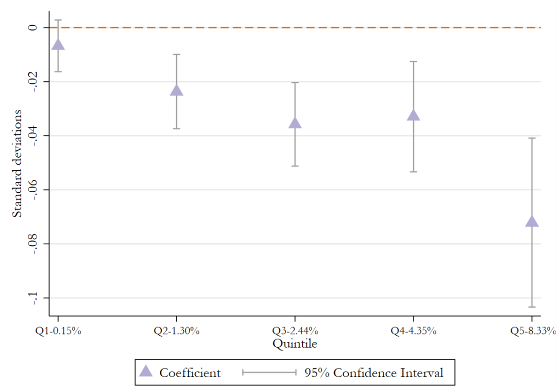
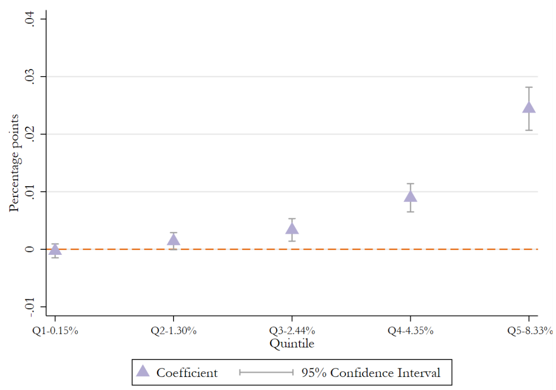


Figure A16: Non-linear Effects of Migrant Exposure on the Probability of Switching Schools

(a) Primary **(b)** Secondary



C Tables

Table A1: Mig. Share Quintiles Rage

Quintile	Range
1	$0 < V_{sg,t} \leq 0.013$
2	$0.13 < V_{sg,t} \leq 0.024$
3	$0.24 < V_{sg,t} \leq 0.043$
4	$0.43 < V_{sg,t} \leq 0.083$
5	$V_{sg,t} > 0.083$

Table A2: Switching Schools Location

Primary

	Region (1)	Province (2)	District (3)	Distance ml (4)
Mig. Share	0.018***	0.023***	0.081***	6.619***
	(0.005)	(0.005)	(0.009)	(1.581)
R-squared	0.045	0.053	0.062	0.042
Obs.	14,538,271	14,538,271	14,538,271	14,535,136
Mean	.023	.032	.061	6.204

Secondary

	Region (1)	Province (2)	District (3)	Distance ml (4)
Mig. Share	0.019***	0.021***	0.054***	-0.863
	(0.007)	(0.007)	(0.014)	(1.895)
R-squared	0.057	0.072	0.078	0.052
Obs.	12,510,851	12,510,851	12,510,851	12,509,229
Mean	.016	.024	.047	4.309

Standard errors clustered at school-grade level in parentheses. *** p<0.01 ** p<0.05 * p<0.1. Control variables: sex, age, baseline math grade, school by year fixed, grade, year, and district fixed effects. All the outcome variables are dummies defined by difference in school location after switching. By definition is 0 for all non-switchers. The geographical distance between schools is calculated using each school latitude and longitude. The sample includes only incumbent students from 2015 to 2019 in Peruvian schools.

Table A3: Effects of Migrant Enrollment in Class Size

	Primary	
	(1)	(2)
	Classize > Max	Classize > Max
Number of Mig.	-0.00469***	-0.0389***
	(0.00126)	(0.00155)
Number of Mig. × Public		0.0391***
		(0.00127)
R-squared	0.415	0.417
Obs.	3,300,746	3,296,905
Mean	.354	.354

	Secondary	
	(1)	(2)
	Classize > Max	Classize > Max
Number of Mig.	-0.00262**	-0.000364
	(0.00109)	(0.00151)
Number of Mig. × Public		-0.00251*
		(0.00137)
R-squared	0.406	0.406
Obs.	2,726,419	2,724,032
Mean	.147	.147

Standard errors clustered at school-grade level in parentheses. *** p<0.01 ** p<0.05 * p<0.1. This regressions are run at the classroom level. Class Size > Max is a dummy variable that takes the value of one is the classroom size is larger that 30 in primary and larger that 35 in secondary. Control variables: percentage of female students, mean age, school by year fixed, grade, year, and district fixed effects. The sample includes all classrooms from 2015 to 2019 in primary and secondary schools.

Table A4: Effects of Migrant Exposure on Schooling Outcomes Adding Class Size as a Control

	Primary			
	Retention	Dropout	Math Grade	Language Grade
	(1)	(2)	(3)	(4)
Mig. Share	0.00385	0.0193***	-0.141***	-0.171***
	(0.00246)	(0.00567)	(0.0343)	(0.0334)
R-squared	0.031	0.105	0.181	0.183
Obs.	14,543,841	11,568,653	14,423,528	14,423,649
Mean	.005	.013	-.014	-.011

	Secondary			
	Retention	Dropout	Math Grade	Language Grade
	(1)	(2)	(3)	(4)
Mig. Share	0.00858**	0.0179	-0.643***	-0.719***
	(0.00367)	(0.0125)	(0.0849)	(0.0884)
R-squared	0.019	0.102	0.267	0.275
Obs.	12,513,766	9,970,220	12,034,217	12,098,403
Mean	.005	.033	-.044	-.024

Standard errors clustered at school-grade level in parentheses. *** p<0.01 ** p<0.05 * p<0.1. Control variables: class size, sex, age, baseline math grade, school by year fixed, grade, year, and district fixed effects. The sample includes only incumbent students from 2015 to 2019 in primary and secondary schools.

Table A5: Effects of Migrant Exposure in the Probability of Switching Schools Adding Class Size as a Control

	Primary	Secondary
	(1)	(2)
Mig. Share	0.154***	0.111***
	(0.0126)	(0.0193)
R-squared	0.087	0.095
Obs.	14,543,842	12,513,766
Mean	.115	.08

Standard errors clustered at school-grade level in parentheses. *** p<0.01 ** p<0.05 * p<0.1. Control variables: class size, sex, age, baseline math grade, school by year, grade, year, and district fixed effects. The sample includes only incumbent students from 2015 to 2019 in primary and secondary schools.

Table A6: Effect of Migrant Exposure in the Probability of Switching Schools - Sample Split by Resource Level

	Low Resources					
	Primary			Secondary		
	Public	Q1 Parents SES	Q4 Stud/Teach	Public	Q1 Parents SES	Q4 Stud/Teach
	(1)	(2)	(3)	(4)	(5)	(6)
Mig, Share	0.101***	0.160***	0.158***	0.0278	0.185***	0.248***
	(0.0162)	(0.0244)	(0.0248)	(0.0232)	(0.0465)	(0.0529)
R-squared	0.186	0.236	0.332	0.198	0.216	0.484
Obs.	10,869,828	7,828,129	6,474,512	9,365,049	6,632,086	1,824,472
Mean	.094	.096	.102	.062	.054	.101

	High Resources					
	Primary			Secondary		
	Private	Q4 Parents SES	Q1 Stud/Teach	Private	Q4 Parents SES	Q1 Stud/Teach
	(1)	(2)	(3)	(4)	(5)	(6)
Mig, Share	0.175***	0.199***	0.132***	0.184***	0.108***	0.134***
	(0.0185)	(0.0232)	(0.0240)	(0.0252)	(0.0322)	(0.0254)
R-squared	0.200	0.356	0.483	0.249	0.358	0.435
Obs.	3,658,108	3,318,778	1,280,243	3,139,726	1,882,514	2,420,851
Mean	.174	.118	.168	.132	.116	.096

Standard errors clustered at school-grade level in parentheses. *** p<0.01 ** p<0.05 * p<0.1. Control variables: sex, age, baseline math grade, school by year, grade, year, and district fixed effects. The sample is split in 3 different ways using school-level characteristics. Column(1) splits the sample between private and public schools. Column (2) splits the sample between the first and fourth quintile of the parent's SES index in 2016. Column (3) splits the sample between the first and fourth quintile of the Student-Teacher ratio in 2014. For the Student-Teacher ratio, Q1 is in the high resources panel because this indicator reflects higher resources when it is lower. The sample includes only incumbent students from 2015 to 2019 in primary and secondary schools.

Table A7: Effect of Migrant Exposure in Standardized Math Std. Grades - Sample Split by Resource Level

	Low Resources					
	Primary			Secondary		
	Public	Q1 Parents SES	Q4 Stud/Teach	Public	Q1 Parents SES	Q4 Stud/Teach
	(1)	(2)	(3)	(4)	(5)	(6)
Mig, Share	-0.149***	0.00125	-0.0730	-0.938***	-0.573**	-0.524***
	(0.0506)	(0.0704)	(0.0647)	(0.146)	(0.254)	(0.187)
R-squared	0.172	0.168	0.185	0.240	0.246	0.312
Obs.	10,781,415	7,763,155	6,419,665	9,006,364	6,369,785	1,750,535
Mean	-.062	-.043	-.071	-.115	-.125	.028

	High Resources					
	Primary			Secondary		
	Private	Q4 Parents SES	Q1 Stud/Teach	Private	Q4 Parents SES	Q1 Stud/Teach
	(1)	(2)	(3)	(4)	(5)	(6)
Mig, Share	-0.0534	0.00493	-0.0338	-0.215***	-0.301***	-0.176*
	(0.0439)	(0.0599)	(0.0628)	(0.0791)	(0.113)	(0.106)
R-squared	0.236	0.236	0.245	0.330	0.350	0.325
Obs.	3,626,323	3,286,682	1,265,721	3,018,870	1,805,606	2,324,540
Mean	.127	-.007	.091	.167	.204	.037

Standard errors clustered at school-grade level in parentheses. *** $p<0.01$ ** $p<0.05$ * $p<0.1$. Control variables: sex, age, baseline math grade, school by year, grade, year, and district fixed effects. The sample is split in 3 different ways using school-level characteristics. Column(1) splits the sample between private and public schools. Column (2) splits the sample between the first and fourth quintile of the parent's SES index in 2016. Column (3) splits the sample between the first and fourth quintile of the Student-Teacher ratio in 2014. For the Student-Teacher ratio, Q1 is in the high resources panel because this indicator reflects higher resources when it is lower. The sample includes only incumbent students from 2015 to 2019 in primary and secondary schools.

Table A8: Effect of Migrant Exposure in Language Std. Grades - Sample Split by Resource Level

	Low Resources					
	Primary			Secondary		
	Public	Q1 Parents SES	Q4 Stud/Teach	Public	Q1 Parents SES	Q4 Stud/Teach
	(1)	(2)	(3)	(4)	(5)	(6)
Mig, Share	-0.185***	-0.0976	-0.0803	-1.101***	-1.163***	-0.438**
	(0.0499)	(0.0693)	(0.0635)	(0.154)	(0.264)	(0.194)
R-squared	0.172	0.168	0.188	0.249	0.257	0.327
Obs.	10,781,526	7,763,294	6,419,809	9,037,146	6,383,729	1,765,069
Mean	-.066	-.048	-.065	-.102	-.123	.056

	High Resources					
	Primary			Secondary		
	Private	Q4 Parents SES	Q1 Stud/Teach	Private	Q4 Parents SES	Q1 Stud/Teach
	(1)	(2)	(3)	(4)	(5)	(6)
Mig, Share	-0.0828**	0.00803	-0.0460	-0.170**	-0.226**	-0.112
	(0.0413)	(0.0559)	(0.0615)	(0.0756)	(0.110)	(0.101)
R-squared	0.231	0.244	0.245	0.336	0.352	0.342
Obs.	3,626,332	3,286,680	1,265,716	3,052,282	1,832,999	2,335,004
Mean	.152	-.006	.088	.209	.263	.048

Standard errors clustered at school-grade level in parentheses. *** $p<0.01$ ** $p<0.05$ * $p<0.1$. Control variables: sex, age, baseline math grade, school by year, grade, year, and district fixed effects. The sample is split in 3 different ways using school-level characteristics. Column(1) splits the sample between private and public schools. Column (2) splits the sample between the first and fourth quintile of the parent's SES index in 2016. Column (3) splits the sample between the first and fourth quintile of the Student-Teacher ratio in 2014. For the Student-Teacher ratio, Q1 is in the high resources panel because this indicator reflects higher resources when it is lower. The sample includes only incumbent students from 2015 to 2019 in primary and secondary schools.

Table A9: Effect of Migrant Exposure in Math and Language Std. Grades - Sample Split by Switching Status

	Primary					
	Non-Switchers		Switchers			
	Math grades (1)	Language grades (2)	Math grades (3)	Language grades (4)	Math grades (5)	Language grades (6)
Mig. Share	-0.218***	-0.263***	0.0251	-0.0473		
	(0.0595)	(0.0578)	(0.0435)	(0.0419)		
Mig. Share × Before Switch					-0.791***	-0.939***
					(0.149)	(0.145)
Mig. Share × After Switch					0.0623	-0.00660
					(0.0441)	(0.0424)
R-squared	0.211	0.212	0.166	0.169	0.166	0.169
Obs.	10,019,309	10,019,435	4,555,154	4,555,151	4,555,154	4,555,151
Mean	.004	.003	-.056	-.043	-.056	-.043

	Secondary					
	Non-Switchers		Switchers			
	Math grades (1)	Language grades (2)	Math grades (3)	Language grades (4)	Math grades (5)	Language grades (6)
Mig. Share	-0.607***	-0.799***	-0.646***	-1.301***		
	(0.110)	(0.114)	(0.0832)	(0.0921)		
Mig. Share × Before Switch					-0.458**	-0.355
					(0.221)	(0.220)
Mig. Share × After Switch					-0.655***	-1.344***
					(0.0847)	(0.0942)
R-squared	0.300	0.308	0.218	0.226	0.218	0.226
Obs.	8,744,722	8,787,929	3,346,142	3,367,426	3,346,142	3,367,426
Mean	-.04	-.017	-.053	-.038	-.053	-.038

Standard errors clustered at school-grade level in parentheses. *** p<0.01 ** p<0.05 * p<0.1. Control variables: sex, age, baseline math grade, school by year, grade, year, and district fixed effects. Columns (1) and (2) run the main specification for students who never switched schools between 2014 and 2019. Columns (3) to (6) for students who switched at least ones in the same period. On columns (5) and (6) the specification includes the concurrent share of migrants per grade (not the baseline as our main specification does) and the interaction between the migrant share and a dummy that indicates the years before and after the first time the student switched. The sample includes incumbent students from 2015 to 2019 in primary and schools.

Table A10: Effect of Migrant Exposure By Migrant Baseline Performance

Primary

	Switching (1)	Retention (2)	Dropout (3)	Math grades (4)	Language grades (5)
Mig. Share BL Achievement > Median	0.164***	-0.000238	0.0144**	-0.129***	-0.143***
	(0.0183)	(0.00350)	(0.00625)	(0.0482)	(0.0471)
Mig. Share BL Achievement < Median	0.145***	0.00757**	0.0349***	-0.141***	-0.188***
	(0.0170)	(0.00354)	(0.0126)	(0.0492)	(0.0472)
R-squared	0.087	0.031	0.104	0.180	0.182
Obs.	14,543,842	14,543,841	11,568,653	14,423,528	14,423,649
Mean	.115	.005	.013	-.014	-.011

Secondary

	Switching (1)	Retention (2)	Dropout (3)	Math grades (4)	Language grades (5)
Mig. Share BL Achievement > Median	0.0398	0.000775	0.0316*	-0.943***	-0.862***
	(0.0307)	(0.00526)	(0.0165)	(0.138)	(0.142)
Mig. Share BL Achievement < Median	0.160***	0.0127***	0.00239	-0.443***	-0.610***
	(0.0241)	(0.00490)	(0.0194)	(0.109)	(0.110)
R-squared	0.095	0.019	0.102	0.266	0.274
Obs.	12,513,766	12,513,766	9,970,220	12,034,217	12,098,403
Mean	.08	.005	.033	-.044	-.024

Standard errors clustered at school-grade level in parentheses. *** $p<0.01$ ** $p<0.05$ * $p<0.1$. Control variables: school by year fixed, grade, year, and district fixed effects. The specification includes the share of migrant students divided between the share of migrants with baseline math GPA above and below the median of their base line year. The sample includes incumbent students from 2015 to 2019 in primary and secondary schools.