Migration Opportunities and Human Capital Investments

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Abstract

We examine how shocks to migration affect schooling in origin communities. We focus on the migration between Mexico and the United States, and explore how the expansion of the Secure Communities program in the US – a federal data sharing program that substantially increased the risk of detainment and deportation for illegal migrants – affected attendance, enrollment, and grades in Mexico. Our results suggest that the Secure Communities program increased attendance and enrollment in municipalities that had stronger migration ties with counties in the US that adopted the program early-on, which is consistent with the interpretation that the Secure Communities program implicitly raised returns to education. We find no effect on grades (within the first year of Secure Communities exposure).

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1 Introduction

International migration has risen substantially over the last decades (Docquier and Rapoport, 2012), with strong implications for origin countries, and for family members and friends left behind. Early works have examined the extent to which the drain of qualified workforce hampers economic development in origin countries, casting a largely negative view on international migration (Bhagwati and Hamada 1974; McCulloch and Yellen 1977; Miyagiwa 1991, Haque and Kim 1995). More recent empirical evidence, in contrast, points to the beneficial effects of international migration: Migrants maintain networks with their friends and families (Docquier and Rapoport, 2012), and send a substantial fraction of their earnings home (Bollard et al.,2011).

Remittances – defined as household income received from abroad – have risen immensely over the last decades. In the decade preceding the 2007 financial crisis, the average real annual growth rate of remittances was 12.9% (Yang, 2011). In 2015, remittances to low and middle income countries amounted to 424.8 Billion US$ (World Bank, 2017b). This is almost three times the amount of Official Development Assistance received by these countries in the same time period (152.4 Billion US$), and more than half the net inflows of Foreign Direct Investment (641.2 Billion US$). And in contrast to private capital flows, remittances exhibit stability and even counter-cyclicality in the wake of economic crises, such as the global financial crisis in 2007-2009 (Yang, 2011).

The effects of international migration on educational investments remain much less well understood. The common expectation is that international migration is beneficial to education is origin countries through the income effects of remittances that are being sent back (CITE), yet, the incentives migration opportunities create to invest (or not) in education are unclear.

This paper investigates the effects of migration opportunities – more precisely a negative shock to those opportunities – on attendance, enrollment, and grades in Mexico. We explore the roll-out of the Secure Communities program throughout the US, which greatly increased the cost of illegal migration to the United States. It increased the risk of deportation, and created a climate of insecurity and fear among migrant communities (**?**).

The Secure Communities program is a federal data-sharing program, which implemented an automatic data sharing between local law enforcement and federal immigration enforcement agencies, and substantially increased the number of deportations from the US to Mexico in the time-period between 2008 and 2014. By substantially raising the risk of deportation, the Secure Communities program greatly increased the cost – and arguably reduced the return – of illegal migration to the United States.

We explore the effects of the Secure Communities program on schooling in Mexico by leveraging two crucial sources of variation. First, the roll-out of the Secure Communities program was staggered in the US, with some counties introducing the program relatively early and others following later. Second, migration from Mexico to the US tends to follow pre-existing networks, and these vary by region. In other words, migrants from specific municipalities in Mexico are more likely to migrate to certain US counties than to other counties, or than migrants from other municipalities. We explore these geographical patterns to predict which municipalities should be affected by the

Secure Communities program (given pre-existing networks) at a specific point in time.

Migration to the US (especially seasonal short-term migration) is a highly remunerative occupation that requires relatively few skills. Arguably such a lucrative outside option flattens the returns to education in Mexico, as the income of low-skill migrants is often more competitive than the income of skilled workers within Mexico. By making low-skill migration to the United States less attractive, then, the Secure Communities program implicitly increased the returns to education for young Mexicans.

Consistent with the notion that the Sc program implicitly increased the returns to education for adolescents in Mexico, we find find evidence that the roll-out of the Secure Communities Program increased school attendance and enrollment in Mexican municipalities that were more strongly exposed to the Secure Communities program (i.e. that had stronger migration networks with counties that adopted the program early-on).

The remainder of this paper proceeds as follows: In Section 2, we present some background information about the Secure Communities program. Section 3 introduces the conceptual framework, Section 4 the data and empirical appoach. Section 5 presents the results and Section 6 concludes.

2 Background: The Secure Communities Program

The Secure Communities program (henceforth SC program) is a federal data-sharing program, in which fingerprints that are collected by local law enforcement agencies are automatically shared with federal immigration enforcement agencies. These are then checked against immigration databases, and depending on the result, immigration officials decide whether to issue a detainer request (which is carried out by local law enforcement).

The program was in rolled-out throughout the United States between 2008 and 2014, discontinued in November 2014, and then reintroduced in January 2017. Up until 2017, participation in the program was decided at the county level, and entirely voluntary.

With the introduction of the SC program, any encounter with local law enforcement (be it in traffic, or because a person became victim of of a crime) could results in imminent deportation. Opponents of the SC program have argued that this program severely reduces trust in local law enforcement, creates a climate of fear, and reduces public safety (as victims with migrant background are less likely to seek support from local law enforcement). The SC program was also shown to reduce employment levels of low-skill non-citizens in the US (**?**), as well as to reduce the take-up of social benefits by legal migrants in the US (**?**).[1] The effects of the SC program on households in Mexico remain understudied.

[1] Interestingly the SC program also seems to have negatively impacted the employment of US citizens working in middle to high-skill occupations.

3 Conceptual Framework

To understand how the Secure Communities Program might affect schooling we conceptualize the schooling decision from the perspective of the student. We assume a Mincerian wage $w_{s,i,t}$ to be a function of time t, schooling s and the year-of-entry into the labor market i of each wage earner, as given by:

$$\ln(w_{s,i,t}) = a_0 + \gamma s + b(t - i) \tag{1}$$

with a_0 being the base wage, γ the return to an additional year of school, and b the return to experience. We further assume that the period utility of an individual is given by $u = \ln(y)$, with y being the individual's income, and that everyone works full-time. This allows us to rewrite utility to $u = \ln(w)$. In each period (here an entire academic year) the student can decide between dropping out of school and staying in school. The student expects to live forever, and discounts at rate ρ. The value of dropping out is reflected by the net present value of lifetime income with s years of education:

$$V_d = \sum_{t=1}^{\infty} \frac{1}{(1+\rho)^{t-1}} [a_0 + +\gamma s + b(t-1)]. \tag{2}$$

The value of staying in school for an additional year is given by the net present value of lifetime income with $s + 1$ years of education:

$$V_s = \ln(\bar{y}) + \sum_{t=2}^{\infty} \frac{1}{(1+\rho)^{t-1}} [a_0 + \gamma(s+1) + b(t-2)], \tag{3}$$

where $\bar{y}$ is the income while studying, *i.e.* support by parents.

A student will be exactly indifferent between continuing in school or dropping out when: $V_d = V_s$. Solving for ρ gives the expression:

$$\bar{\rho} = \frac{\gamma - b}{a_0 - \gamma s - \ln(\bar{y})} \equiv \frac{RetS}{OppC} \tag{4}$$

Eq. (4) illustrates how a decline in migration opportunities will affect schooling: Let b – the return to experience – be particularly high in the US, such that a decline in migration opportunities will reduce the expected value of b, and increase the implicit returns to education $RetS$. This will increase the number of individuals that are just patient enough to be willing to spend an extra year in school.

4 Data and Empirical Approach

4.1 Data

In order to analyze the research question outlined above, we put together a series of data sets that are merged at the level of the municipality in Mexico.

Secure communities data. From official records, we hand-code the roll-out of the Secure Communities program at the county level in the United States between 2008 and 2014. We also code the expansion of sanctuary cities in the US, a movement a the state and city level to stop cooperating with the ICE (Immigration and Customs Enforcement). For example, California enacted a state-law in January 2014 that prohibited local law enforcement in the entire state from cooperating with ICE.

Encuesta sobre Migración en la Frontera Norte de México (EMIF). The Survey on Migration at the Mexican Northern Border interviews visitors of several locations along the northern Mexican Border. Once an interviewee is identified as potential migrant, she is asked a number of questions, including the city of origin in Mexico (or beyond) and the place of destination (in the United States). This data provides one of the earliest systematic assessments of the flow of migrants crossing the terrestrial US-Mexico border, and allows us to create a map of geographic linkages between Mexico and the US at the municipality/county level. A limitation of this data is the relatively low sample size, and the geographic focus on the main transit cities along the border. We use data collected between 1998 and 2008 for the purpose of this analysis.

Encuesta Nacional de Ocupación y Empleo (ENOE). The Mexican labor force survey is conducted every three months and each round samples roughly 120,000 households from the entire country. The survey is a rotating panel, which means that each household is interviewed up to five times. This allows tracking individuals over time. We construct different variables from the ENOE. For children aged 5 and above we create an enrollment variable, i.e. whether the child is enrolled in school in a particular quarter. For every household member aged 12 and above, we have more detailed time-allocation data. We can look at actual attendance, labor supply, educational attainment, migration etc.

*Evaluación Nacional de Logros Académicos en Centros Escolares ENLACE).*The Mexican Evaluación Nacional de Logros Académicos en Centros Escolares (ENLACE) exams were administered throughout the country each June from 2006 to 2013. While ENLACE started out as a low stakes test, ENLACE results were broadly diffused, becoming one of the main metrics for school performance and eventually being linked to teacher salary bonuses (**?**, **?**). ENLACE was eventually discontinued because the growing performance incentives, combined with lack of implementation oversight, led to concerns about cheating. School level subject results for all tested grades in all schools in Mexico are publicly available. The data also includes the school's marginalization index (1 to 5) as defined by Mexico's National Population Council.[2]

[2]Mexico's National Population Council (CONAPO) calculates marginalization indices using a principal components method based on percentage indicators of social exclusion collected in the census. Indicators include illiteracy, incomplete primary education, lack of running water, sewage systems, and electricity, dirt floors,

We start with two panels of school performance: one for grades 3 thru 9 that includes 135,307 different schools administering the early ENLACE exams and a second that covers 14,524 schools administering the 12th grade ENLACE exam. To avoid results being confounded by possibly endogenous movement of students between schools, we aggregate outcome measures to the municipality level which is our unit of treatment. Thus we use the school panel to calculate the total number of students taking the exams at different grade levels in a municipality, and average performance of students in the municipality. We have data for years 2009-2013 for the early ENLACE exams and 2008-2014 for the 12th grade ENLACE.[3]

Censo General de Población y Vivienda. We use the 10.6% subsample of the 2000 Mexican population census, made available through IPUMS-International. The Mexican population census collects from every household the number of former household members that migrated internationally within the last 5 years. We construct the share of migrants in the total population by counting the number of reported migrants and dividing this number by the sample population in a particular municipality.

5 Empirical Approach

5.1 Measuring migration shocks

In order to link outcomes in Mexico to the expansion of the Secure Communities program in the US, the first step consists of identifying regional variation in migration networks between Mexico and the United States. The idea is to find out where people from certain regions predominantly migrate to, therewith obtaining variation between municipalities in Mexico with respect to the main destination regions (in the US) of Mexican migrants.

Historically, migration from Mexico to the US followed the three major railway lines that connected the two countries. Due to this process migrants from different Mexican communities have settled in different US destinations. In their destination, migrants established social networks which guide migration flows until today (**??**). As shown by **?**, the railway connections established in the late 19th century still predict migration patterns in the early 2000s. Similar evidence was produced for the Philippines, where the destination choice of early migrants is shown to strongly determine the subsequent migration decision (and destination choice) of migrants from the same village (**?**). Thus we can expect households from one region in Mexico to have migration networks

household overcrowding, geographic isolation, and low incomes in employment. Further details are available at http://www.conapo.gob.mx. Although the marginalization index does not change over time for most schools, there is some year on year variation. We opt to treat this index as time invariant, calculating the average for each school and rounding to the closest index category.

[3] In many schools, examinations were administered in several sessions throughout the day. Performance data is reported for each session. I construct a single school level subject result for each grade by calculating a weighted average of the performance in the different sessions using the number of tested students as weights. Though some data is available for the earlier years, the number of examined students is not included in the 2006 and 2007 data. Furthermore, the data in 2008 does not disaggregate performance by subject. Analysis is thus focused on the years 2009-2013. Finally, in 2011 two different test booklets were used for the 3rd and 4th grades in certain regions. As the data does not indicate which booklet was used, these observations are also dropped from the final dataset.

established predominantly with a specific region in the US. This gives us an important angle to causal identification, which I will come to below.

Based on the EMIF data, we calculate a migration intensity variable p_{jd} for each origin-destination pair. Migration intensity is defined as the number of migrants l_{jd} of municipality j that migrate to county d out of the total number of migrants of municipality j that migrate to the US (observed in the EMIF):

$$p_{jd} = \frac{l_{jd}}{\sum_{d=1}^{D} l_{jd}}. \tag{5}$$

We then combine the information on migration intensity with information on emigration rates from the Mexican census. From the Mexican population census of 2000, we calculate m_j, i.e. the share of migrants in the population of each municipality. While there is certainly variation over time in the share of migrants in the population (since migration responds to shocks at the origin as well as at the destination), we use this variable as time-invariant proxy of how important migration is as an economic strategy in a particular municipality in Mexico.

The estimated share of migrants n_{jd} from municipality j in county d would then be the product of migration intensity $p_j d$ in each municipality-county pair and the share of international migrants in the population m_j of municipality j. For each origin-destination pair, we compute:

$$n_{jd} = p_{jd} \times m_j. \tag{6}$$

In a second step, we combine county-level data on the roll-out of the Secure Communities program in the US with locality specific migration intensity, to construct a measure of how strongly each municipality in Mexico felt the effects of the Secure Communities program at a particular point in time. We define the Secure Communities shock for each municipality by:

$$SCshock_{jt} = \sum_{d=1}^{D} (n_{jd} \times SC_{dt}), \tag{7}$$

where SC_{dt} is an indicator equal to 1 if the Secure Communities program was active in county d at time t. As described previously, n_{jd} is the estimated share of the population of municipality j that migrated to a particular county/state d in the US, so that $\sum_{d=1}^{D} n_{jd}$ is the total share of US-migrants in the population of that municipality. The Secure Communities shock experienced in municipality j at time t is thus the weighted average of the Secure Communities experience of its current migrants, with the Secure Communities experience being weighted by the share of migrants to destination county d in the overall migrant population of municipality j. By multiplying SC_{dt} with n_{jd} rather than p_{jd}, we allow the effect of shocks to be stronger in municipalities with higher migration rate in the overall population. It is also important to see that the $SCshock_{jt}$ variable is defined solely on the basis of migration intensity and migrants' destinations prior to the shock in order to eliminate concerns about reverse causality.

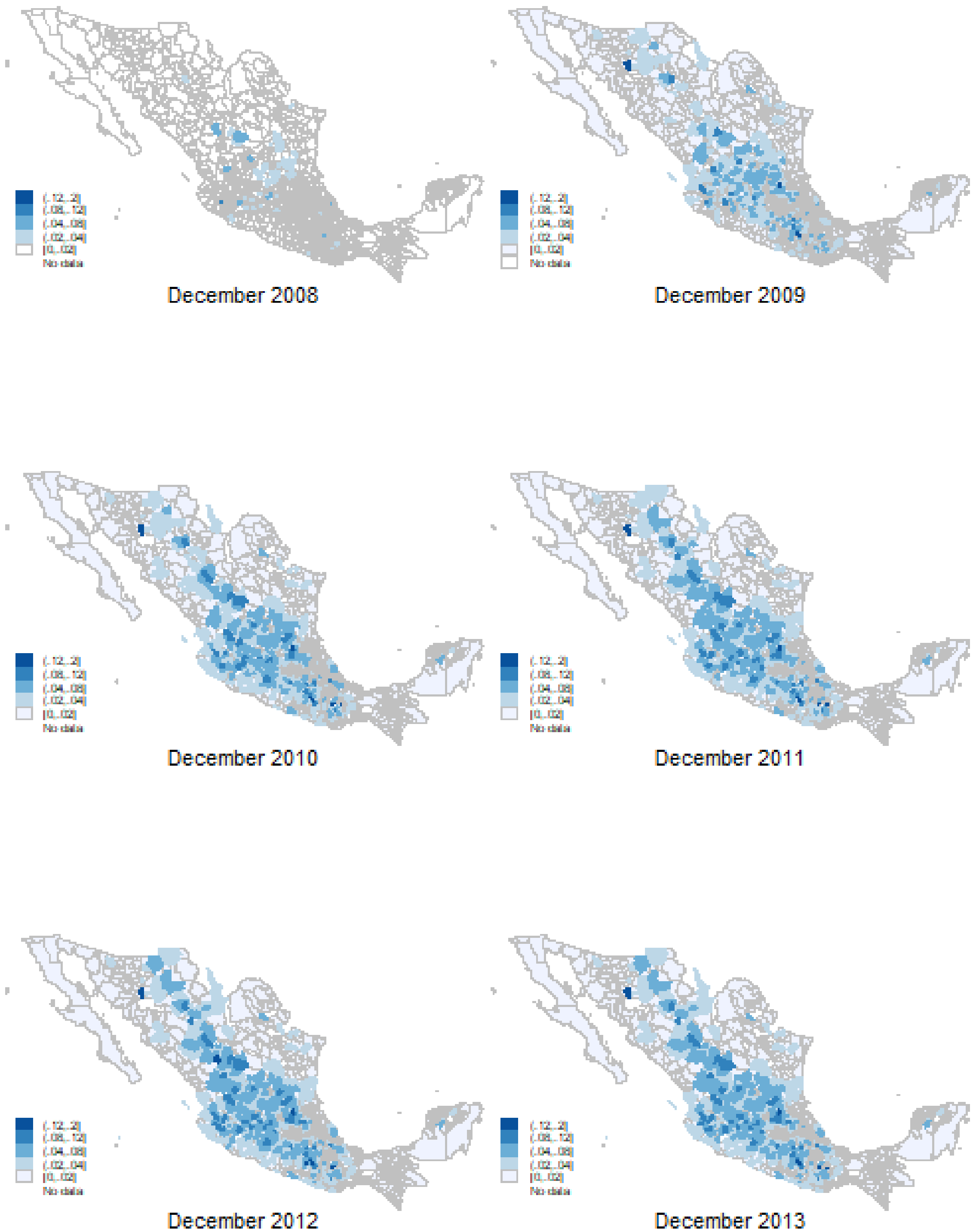

Figure 1: Secure Communities shocks in Mexico

Figure 1 depicts the temporal and geographical distribution of $SCshock_{jt}$ in Mexico. As can be seen, most variation in the variable occurs between 2008 and 2011. After December 2011 the effect seems to stabilize, which could be attributed to the fact that most states and counties with high migration rates had introduced Secure Communities by then.

5.2 Estimating the effect of migration shocks

Our empirical approach explores how shocks in destination regions (i.e. the Secure Communities program) affect outcomes in the regions of origin. In order to do this, we combine spatial variation in the typical destination of migrants from Mexico within the US with the time-variant roll-out of the Secure Communities program in the typical destinations of these migrants.

In a difference-in-differences setup, we explore how theses shocks affect the outcomes of interest. Differences in outcomes over time will then be compared between individuals (i.e. school-age children) in municipalities that were exposed to the SC shocks and individuals in municipalities that were not exposed to the shock. The identifying assumption is that in the absence of shocks to migration networks, changes over time – in attendance, enrollment and grades – would have been the same for individuals across municipalities (parallel trends). If this is true, the observed difference in changes over time can be entirely attributed to the exposure to the Secure Communities program.

We estimate:

$$Y_{ijt} = \alpha_0 + \alpha_1 SCshock_{jt} + X_{ijt} + \zeta_j + \gamma_{st} + \lambda_t + m_t + u_{ijt}, \tag{8}$$

where Y_{ijt} is any of the outcomes specified above, X_{ijt} is a vector of age and gender fixed effects, ζ_j is a vector of municipality fixed effects, γ_{st} are state-by-year fixed effects, λ_t are quarter-by-year fixed effects, m_t are survey month fixed effects, and u_{ijt} is an idiosyncratic error term. Standard errors are clustered at the level of the municipality throughout. To make the analysis more robust, we also allow for differential time trends between municipalities, based on the intensity of migration (as measured in the 2000 population census).

Although more robust than a simple comparison of means, this method is still prone to bias, if a) trends are not the same across municipalities, or b) time-varying factors influence migration networks and schooling outcomes. We conduct a number of robustness checks to address these concerns.

6 Results

Estimates of the effect of the Secure Communities program on attendance and enrollment in Mexico are presented in Table 1. We restrict the ENOE data to the time period 2006 to 2014. As can be seen, attendance and enrollment rates increase for children and young adults as response to the Secure Communities program. We focus on the age-groups 12-21, as there is near 100% enrollment at ages below 12. Columns (1) to (3) focus on school attendance. We add the lag of the Secure Communities shock in column (2). Column (3) additionally allows for differential time trends between municipalities with different initial migration rates (as of 2000). We find that the Secure Communities program increases attendance immediately. The effect seems to be sustained over time, but the contemporaneous effect is slightly muted when including the lag, and both point estimates are somewhat noisy. In columns (4) to (6), we explore the effect on enrollment in the same age group. Again, we find a positive and statistically significant effect of the expansion of the SC program on enrollment. The effect is more pronounced if lagged by one year, which is not surprising given that enrollment responds more slowly to economic changes than school attendance for example.

Table 1: Effect of Secure Communities on attendance and enrollment in Mexico

	Attendance			Enrollment		
	(1)	(2)	(3)	(4)	(5)	(6)
Secure communities in destination counties	0.627***	0.361	0.324	0.389**	-0.030	-0.006
	(0.183)	(0.232)	(0.244)	(0.197)	(0.235)	(0.250)
Secure communities (one year lag)		0.385	0.279		0.606**	0.674**
		(0.236)	(0.274)		(0.246)	(0.273)
Average share of migrants per capita $\times$ time			0.002			-0.001
			(0.004)			(0.004)
Observations	2700711	2700711	2700711	2700676	2700676	2700676
Adjusted R^2	0.271	0.271	0.271	0.286	0.286	0.286

Standard errors (clustered at the level of the municipality) in parentheses

Each regression controls for municipality, state-by-year, quarter-by-year, month, age and gender fixed effects.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In Figure 2, we explore the effects of the Secure Communities program on enrollment in an event study setup (with the one-year lead being normalized to zero). The results confirm our previous findings: we find no effect on enrollment leading up to the migration shock, but the one-year and two-year lag show pronounced positive effects of the SC program on enrollment, again suggesting that the effects are persistent over time.

We investigate the heterogeneity in treatment effects by age and find the strongest effects in the age group 12-14 and 15-17 (see Table 2)

In Table 3, we explore the effect of the SC program on test performance. The ENLACE data are reported at the school by grade by year level, and we aggregate the data to the level of the municipality by grade by year. The results reported here explore the share of students performing at different levels (insufficient, elementary, good, excellent) in the math exam of grade 12. As can be seen we find no detectable effect on school performance. What we cannot determine yet, is whether this null effect is driven by a selection effect, i.e. some students are performing better, while bad performers are more likely to remain in school and take the test, thereby driving overall test performance down.

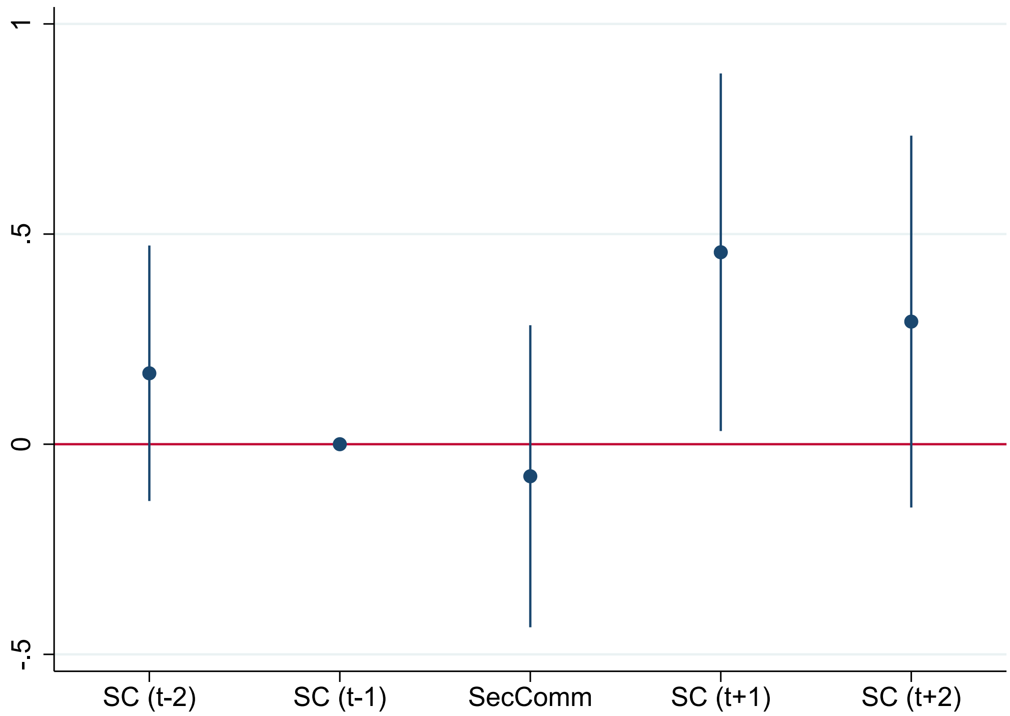

Figure 2: Effect of SC on Enrollment - Event Study

Table 2: Effect of Secure Communities on enrollment in Mexico

Age	12-14		15-17		18-21	
	(1)	(2)	(3)	(4)	(5)	(6)
Secure communities in destination counties	0.345**	-0.007	0.815**	-0.096	0.363	0.163
	(0.166)	(0.206)	(0.368)	(0.257)	(0.293)	(0.357)
Secure communities (one year lag)		0.508**		0.922***		0.293
		(0.215)		(0.266)		(0.343)
Observations	818288	818288	827998	1646290	772212	772212
Adjusted R^2	0.068	0.068	0.108	0.156	0.102	0.102

Standard errors in parentheses

Each regression controls for municipality, state-by-year, quarter-by-year, month, age and gender fixed effects.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Effect of Secure Communities on on student performance on ENLACE exams: 12th Grade

	(1) Insufficient	(2) Elementary	(3) Good	(4) Excellent
Secure Communities in destination counties	89.04	-111.0	-49.21	107.7
	(99.87)	(60.66)	(56.06)	(111.1)
Secure communities (one year lag)	32.58	31.94	19.34	-6.810
	(137.8)	(83.70)	(77.36)	(153.3)
Average share of migrants per capita by time	167.3***	26.57	-99.35***	-226.3***
	(30.65)	(18.62)	(17.21)	(34.09)
State by Year FE	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes
Observations	11458	11458	11458	11458
Mean of Dep. Variable	147.9	161.1	74.78	45.41

Standard errors (clustered at the level of the municipality) in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

7 Discussion and next steps

While the results presented above are indeed suggestive of a positive effect of the Secure Communities program on schooling in Mexico, several open questions remain.

First, we would like to show that the SC program indeed reduces migration to the United States (of cohorts that are no longer in school), and thus excluded from our analysis. We are in the process of cleaning and merging data form the March supplement of the Current Population Survey (CPS) in order to look at the effect of the SC program on migration (by age-group and legal status) with US data.

Second, we would like to shed more light on the mechanisms by exploring parental time allocation, child time use, remittances, and return migration with Mexican data.

Third, we are still trying to get better data to establish migration network strength between Mexico and the US. Other researchers have been able to get access to the confidential version of the Mexican government's Matrícula Consular (Consular ID card) database. This database would allow us to construct networks with a lot more precision.

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