Migration Opportunities and Human Capital Investments

Esther Gehrke *

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Abstract

We examine how shocks to migration opportunities affect schooling outcomes in origin communities. We focus on the migration between Mexico and the United States, and exploit 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— as exogenous shock to the attractiveness of illegal migration. Our results suggest that the Secure Communities program increased attendance, enrollment and educational attainment in municipalities that had stronger migration-network links with counties in the US that adopted the program early-on relative to municipalities that had ties with US counties that introduced the policy somewhat later. These results are consistent with the interpretation that the Secure Communities program implicitly raised the returns to education by making low-skill migration to the US less attractive.

Keywords: Migration; Human capital; Mexico
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*Wageningen University and Research, Agricultural Economics and Rural Policy, Hollandseweg 1, 6706KN Wageningen, The Netherlands. E-mail: *esther.gehrke@wur.nl.*

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, by 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).[1]

Casting doubt on the brain drain hypothesis, recent empirical evidence has shown that international migration can be beneficial to education outcomes in origin countries because of the income effects of incoming remittances flows, or because migration is itself high-skill, and individuals are incentivized to invest in education as migration prospects improve (Yang, 2008; Batista et al., 2012; Theoharides, 2017). However, when migration is low-skill, the positive income effects of remittances inflows may be counteracted by the negative wage-incentive effect of improved migration opportunities on educational investments (McKenzie and Rapoport, 2011). Whether migration opportunities are welfare enhancing, then, depends to substantial degree on which of these two effects dominates with respect to educational attainment, and is largely an empirical question.

This paper investigates the effects of migration opportunities —more precisely a negative shock to those opportunities— on educational outcomes in a context in which migration is typically low-skill and highly seasonal. To be specific, 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, on educational outcomes in Mexico. The Secure Communities program is a federal 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 raising the risk of deportation, the Secure Com-

[1] 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 alone, remittances to low and middle income countries amounted to 424.8 Billion US$. This is almost three times the amount of Official Development Assistance received by these countries in the same time period (152.4 Billion US$), 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 of 2007-2009 (Yang, 2011).

munities program greatly increased the cost of —and arguably reduced the return to— illegal migration to the United States.

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, and could thus incentivize higher investments in education. On the other side, an increase in the number of deportations from the US may also weaken existing migration links, lead to reduced remittance inflows and more competition on local labor markets.

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 (see e.g. East et al., 2023). Second, migration from Mexico to the US tends to follow pre-existing networks, and these vary by region (Munshi, 2003; Woodruff and Zenteno, 2007; McKenzie and Rapoport, 2010; Allen et al., 2018). 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.

We construct our main outcomes from the ENOE data, Mexico's quarterly labor-force survey, for the time period 2005 to 2012. From this data, we can construct not only enrollment and attainment figures, but also weekly attendance data and other labor-market related outcomes at the individual and household level. Our main analysis restricts the sample to the municipalities with the highest migration rates as observed in the 2000 Population census, arguing that shocks to migration should be felt most strongly in places that have higher reliance on international migration to begin with.

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, enrollment an educational attainment 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). This effect in concentrated among youths aged 15 to 17, which also display the highest drop-out rates of all age-groups, and thus are most susceptible to changes in the wage-returns to education structure. Conversely, we find no negative effects on attendance, enrollment, or attainment among youths aged 12-14 or 18-20, suggesting that the flow of remittances may not have been as negatively affected as feared.

This paper contributes to two strands of literature. First, to the literature that links human capital investments and migration (Yang, 2008; McKenzie and Rapoport, 2011; Gibson and McKenzie, 2011; Batista et al., 2012; Theoharides, 2017), we contribute novel evidence showing that a negative shock to migration opportunities can indeed incentivize investments in education in contexts in which international migration is low-skill and highly seasonal.[2] Most closely related to our work is McKenzie and Rapoport (2011), who show that Mexican provinces that are relatively more dependent on US migration also display lower educational attainment using historical migration rates as an instrument. Our paper, in turn, focuses on high-migration localities, and examines the effect of a policy-shift that alters the future attractiveness of migration as an income-generating activity.

Second, we contribute to a literature that investigates the effects of the Secure Communities program. Most of this literature has focused on outcomes in the US, and has highlighted negative labor market effects (East et al., 2023), reduced care availability (Almuhaisen et al., 2024; Ali et al., 2024), as well as reduced the take up of social benefits among legal migrants (Alsan and Yang, 2018). A growing number of papers investigate the spillover effects of the Secure Communities program (and the resulting rise in deportations) in Mexico (Caballero, 2022; Pearson, 2023; Medina-Cortina, 2023; Gomez and Medina-Cortina, 2024). Interestingly these papers come to varying conclusions about the effects on the secure communities program. As I show in this paper, a lot of these differences can be attributed to variations in the estimation strategy, in particular the role of non-random measurement error in the network data.

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 approach. Section 5 presents the results and Section 6 concludes.

[2] In work simultaneous to ours, Caballero (2022) uses the same shock to identify the extent to which investments in child human capital respond to reduced remittance inflows. However, in contrast to this paper, her outcome variable is collected from administrative sources, and does not allow distinguishing between increased grade progression (as retention rates are very high in lower-secondary school in Mexico) and dropouts. She finds negative effects on the enrollment of children in lower-secondary school, which she largely attributes to a decline in remittances incomes.

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 Immigration and Customs Enforcement (ICE), the federal agency responsible for immigration enforcement. The fingerprints are then checked against immigration databases in real-time, and depending on the result, immigration officials decide whether to issue a detainer request (which is carried out by local law enforcement). With the introduction of the SC program, any encounter by an undocumented migrant with local law enforcement (be it in traffic, or because a person was victim of a crime) could thus result in imminent deportation.

The program was in rolled-out throughout the United States between 2008 and 2014, replaced by the more narrowly focused Priority Enforcement Program (PEP) in July 2015, and then reintroduced in January 2017.[3] Participation in the SC program was decided at the county level, and entirely voluntary. Over the time period 2008 to 2014, almost 400,000 deportations have been made in connection to the SC program, the vast majority of those (74%) concerned Mexican citizens (Transactional Records Access Clearinghouse, 2024).

Critics 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 (East et al., 2023), as well as to reduce the take-up of social benefits by legal migrants in the US (Alsan and Yang, 2018).

3 Conceptual Framework

To understand how the Secure Communities Program might affect schooling we conceptualize the schooling decision from the perspective of the student who is at the end of compulsory schooling.[4] At that point in time, the student needs to decide whether to stay in school to obtain the next higher level of schooling ($s = 1$) or drop out after completing compulsory schooling ($s = 0$).

[3]While similar in nature to the SC, the PEP focused detainer requests on convicted criminals and other individuals who were perceived as posing a danger to public safety (Immigration and Customs Enforcement, 2024).

[4]The framework is sufficiently general to capture the trade-offs faced at any point in time while the student is still in school.

The students earnings are governed by a (simplified) Mincerian wage w_s^d, which depends on the location of employment d and the level of schooling s as given by:

$$\ln(w_{s,t}^d) = a^d + \gamma^d s \tag{1}$$

with a^d being the base wage in location $d \in [US, MX]$, γ^d the (location-specific) wage-return to completing an additional level of schooling. Upon labor-market entry, the student has to decide every period whether to migrate or not. We assume all migration is seasonal for the sake of simplicity. The probability of migrating p is governed by the cost of migrating c and the probability of being deported ζ, with $\partial p(c,\zeta)/\partial c < 0$ and $\partial p(c,\zeta)/\partial \zeta < 0$. Factoring in the risk of deportation, the expected annual income of the low-skilled individual is: $p[(1-\zeta)a^{US} + \zeta a^{MX} - c] + (1-p)a^{MX}$.

We assume that high-educated individuals always migrate legally ($\zeta|_{s=1} = 0$), but that $\gamma^{MX} > a^{US} - a^{MX} + \gamma^{US} - c$, such that the high-educated individual always finds it optimal to stay in Mexico, even if they would not face the risk of deportation. 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 $u = \ln(w)$. The student expects to live forever, and discounts at rate ρ.

The value of dropping out is reflected by the net present value of expected lifetime income for the low-educated individual ($s = 0$). We assume that the low-skill individual remains in Mexico in the first period (as they are of working-age, but not yet legally of age), and migrate from then onwards with migration propensity p:

$$V^l = a^{MX} + \sum_{t=2}^{\infty} \frac{1}{(1+\rho)^{t-1}} \left[p[(1-\zeta)a^{US} + \zeta a^{MX} - c] + (1-p)a^{MX} \right]. \tag{2}$$

The value of staying in school and completing an additional level is given by the net present value of lifetime income with $s = 1$, and $d = MX$.

$$V^h = \ln(\bar{y}) + \sum_{t=2}^{\infty} \frac{1}{(1+\rho)^{t-1}} [a^{MX} + \gamma^{MX}], \tag{3}$$

where $\bar{y}$ is the income received while studying, such as the support by parents.

A student will be exactly indifferent between continuing in school or dropping out when: $V^l = V^h$. Solving for $\bar{\rho}$, the threshold level of ρ that makes the student exactly indifferent between staying in school and dropping out, gives the expression:

$$\bar{\rho} = \frac{\gamma^{MX} - p[(1-\zeta)a^{US} + (\zeta - 1)a^{MX} - c]}{a^{MX} - \ln(\bar{y})} \equiv \frac{RetS}{OppC}. \tag{4}$$

The student draws their discount rate ρ from a distribution with density $f(\rho)$. They will invest in more education if $\rho \leq \bar{\rho}$, and not otherwise. Eq. (4) illustrates the trade offs involved in deciding on an extra level of education: As the implicit returns to education $RetS$ to schooling increase, the threshold $\bar{\rho}$ increases, such that more students find it optimal to stay in school for an extra period. As the opportunity cost of schooling increase (for example because the base wage in Mexico a^{MX} increases, or because support while studying declines), more students find it optimal to drop out. Taking the first order differential of $\bar{\rho}$ with respect to ζ illustrates the effect of an increase in deportation risk (e.g. through the introduction of Secure Communities) on schooling:

$$\frac{\partial \bar{\rho}}{\partial \zeta} = \frac{-1}{a^{MX} - \ln(\bar{y})} \left[\frac{\partial p}{\partial \zeta}[(1-\zeta)a^{US} + (\zeta - 1)a^{MX} - c] + p(\zeta)(a^{MX} - a^{US}) \right]. \tag{5}$$

Eq. (5) shows that $\bar{\rho}$ is increasing in ζ. To see this, note that $a^{MX} - \ln(\bar{y}) > 0$, $(1 - \zeta)a^{US} + (\zeta - 1)a^{MX} - c > 0$, and $p(\zeta) > 0$ by assumption, while $\partial p / \partial \zeta < 0$ and $a^{MX} - a^{US} < 0$. This implies that second part of the right hand side of eq. (5), $\frac{\partial p}{\partial \zeta}[(1-\zeta)a^{US} + (\zeta - 1)a^{MX} - c] + p(\zeta)(a^{MX} - a^{US})$, is negative. An increase in the deportation risk will therefore increase the number of individuals that are just patient enough to complete an extra level of schooling.

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.

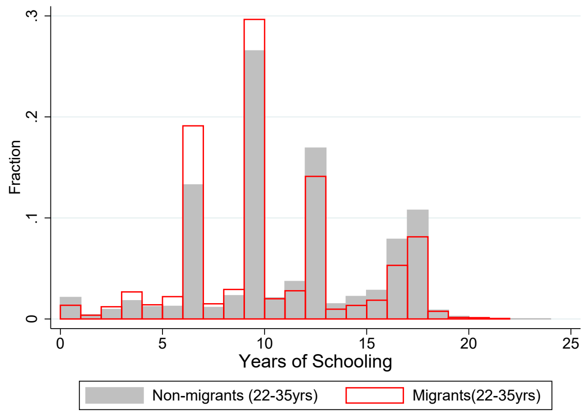
Secure communities data. From official records, we hand-code the roll-out of the Secure Communities program at the county level in the United States between 2008 and 2014. We also code the expansion of sanctuary cities in the US, a movement a the state and city level to stop any law enforcement cooperation with the ICE. For example, California enacted a state-law in January 2014 that prohibited local law enforcement in the entire state from cooperating with ICE. We code any county in the US as having revoked their SC program participation, as soon as at least one city becomes a sanctuary city.

Matrícula Consular de Alta Seguridad. We construct pre-existing migrations networks between the US and Mexico from the Matrícula Consular de Alta Seguridad (MCAS) data for 2005-2008. The MCAS cards serve as identity card and are issued by the Mexican consulates across the United States to all Mexican-born individuals who reside in the US. The cards are accepted by a wide range of institutions making this an attractive document for registered as well as unregistered migrants. The data contain the total count of all individuals who have been issued an MCAS card between 2005 and 2008, more than 3.6 million individuals, including their place of birth and county of residence. We use this data to establish the location-specific network linkages between all pairs of Mexican municipalities and US counties. The average municipality in Mexico has about 1500 recorded migrants in this database, with a substantial amount of variation: While the median municipality has about 419 migrants registered in the database, this number can be as high as 89,000.[5]

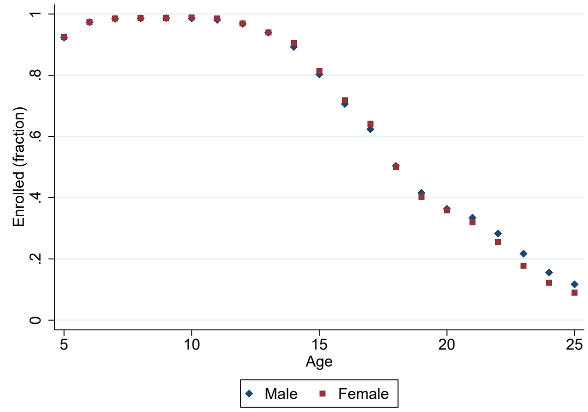
Encuesta Nacional de Ocupación y Empleo (ENOE). The Mexican labor force survey is conducted every three months and each round samples roughly 120,000 households from the entire country. The survey is a rotating panel, which means that each household is interviewed up to five times. This allows tracking individuals over time. We construct different variables from the ENOE. For children aged 5 and above we obtain information about enrollment, i.e. whether the child is enrolled in school in a particular quarter, and educational attainment, i.e. the highest grade that the child completed. For every household member aged 12 and above, we have more detailed time-allocation data (reference period is the 7 days prior to the interview). From this, we construct school attendance, labor supply, and migration variables. We use the household roster to construct information about household income, parental education, whether the household received remittances. We also use the ENOE data to corroborate one of the fundamental assumptions of our conceptual framework, namely that migration to the US is relatively low-skill. Exploiting the fact that the ENOE is a rotating panel, we split the sample of adults aged 22-35 into migrants (any individual household member who was reported to have migrated to the US by their family members in any interview round) and non-migrants. In Figure 1a, we plot educational attainment for migrants and non-migrants, and confirm that migrants have on average lower educational attainment than non-migrants.

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

[5] There is a strong correlation between the number of individuals from a particular municipality observed in the MCAS database and the fraction of migrants in the population, as collected from the Mexican Population Census, see below.



(a) Educational Attainment of Migrants and Non-Migrants



(b) Enrollment by age and gender

Figure 1: Migrant Characteristics and Enrollment in Mexico

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.

All these datasets are merged at the level of the Mexican municipality in borders of 2000 (2,443 municipalities). We restrict our attention to youths aged 12 to 20 in the main analysis, as this is the age-group in which enrollment varies the most (c.f Figure 1b). We also construct more general household level outcomes, where necessary. Summary statistics for this sample are presented in Table A1 in the Appendix.

4.2 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 (Munshi, 2003; McKenzie and Rapoport, 2010; Allen et al., 2018). As shown by Woodruff and Zenteno (2007), 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 (Yang, 2008). Thus we can expect households from one region in Mexico to have migration networks established predominantly with a specific region in the US. This gives us an important angle to causal identification, which we return to below.

Based on the MCAS data, we calculate a migration-network intensity variable p_{jd} for each origin-destination pair. Network 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 MCAS data):

$$p_{jd} = \frac{l_{jd}}{\sum_{d=1}^{D} l_{jd}}. \tag{6}$$

We then combine the information on network intensity with county-level data on the roll-out of the Secure Communities program in the US 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:

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

where SC_{dt} is an indicator equal to 1 if the Secure Communities program was active in county d at time t. 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. It is important to note 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.

The SC shock is zero for all municipalities prior to the rollout of Secure Communities in December 2008, and takes the value of one as soon as all observed destinations introduce the SC program. The average time trend in the SC shock is depicted in Figure 2. As can be seen the transmission of the SC shock is most pronounced between the years 2009 and 2011, and decelerates thereafter. In 2014, California retracted from the SC program, which reduced the intensity of the SC shock dramatically. The expansion of sanctuary cities explains the continued decline in the SC shock over the course of 2014 before the program was eventually discontinued at the end of 2014.

Figure 3 depicts the temporal and geographical distribution of $SCshock_{jt}$ in Mexico.

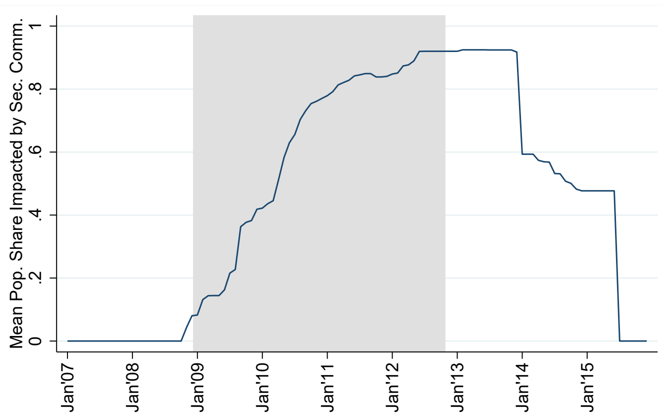


Figure 2: Secure Communities Shock

As can be seen, most variation in the variable occurs between 2008 and 2012. After December 2012 the effect seems to stabilize, as most US counties had introduced Secure Communities by then.

One major concern with this approach of tracing shocks through existing migration-networks is potential measurement error in the predicted network intensity for any given origin-destination pair. By design, not all migrants can be observed in the MCAS data, such that the network-intensity is always subject to (at least some) measurement error. However, this measurement error is likely non-random, as places that tend to have less migrants also appear in lower numbers in the MCAS data implying that outliers will affect the predicted network intensity more in places with lower migration rates than in places with higher migration rates. This measurement error may then systematically bias estimates of the treatment effect in case the treatment effect varies with migration intensity, which is almost certain to be the case.[6]

To address this concern, we employ a number of strategies. *First*, in our main analysis we restrict our attention to the 610 municipalities in the highest quartile of migration propensity (as observed in the 2000 population census, and computed as the fraction of any municipality's population that is reported to have migrated internationally in the last five years), as these municipalities should have the most reliable network data. Of these 610 municipalities, 290 were covered by the ENOE in the time period 2005 to 2012. *Second*,

[6]To see this, consider an individual living in a low migration-propensity municipality in Mexico. For this individual, any given SC shock should matter less than for a similar individual living in a high migration-propensity municipality. For one, remittances income is less likely to change, if less people were relying on migrant networks to begin with. In addition, the change in migration prospects is less likely to affect their own migration decision, if migration is generally less commonly chosen as a income generating strategy.

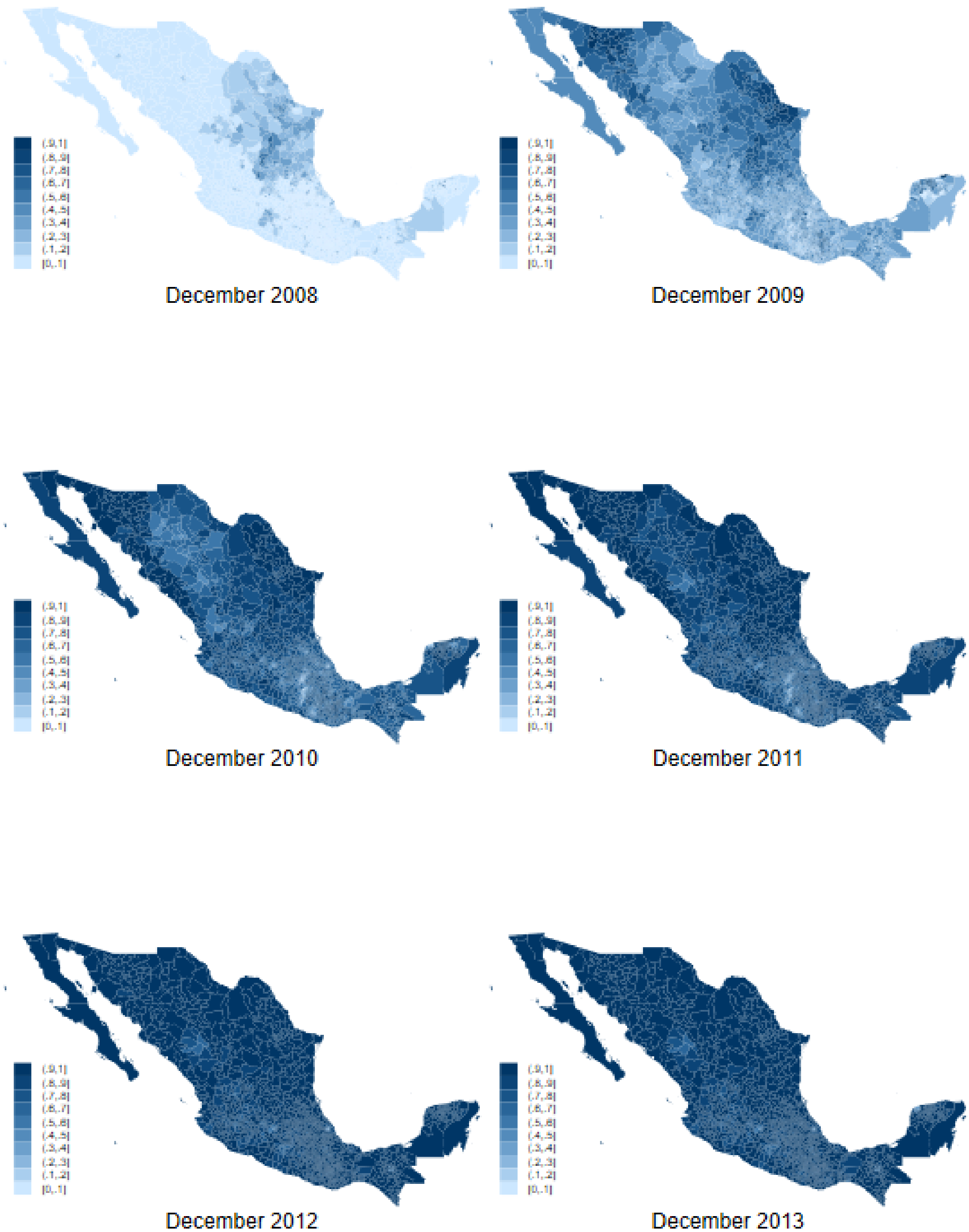


Figure 3: Secure Communities Shock in Mexico

we take a more structured approach and estimate the effect of Secure Communities separately for the municipalities in the remaining quartiles of migration propensity, and test if the effects vary systematically across municipalities with different rates of migration (and potentially measurement error in the network links).

4.3 Estimating the Effect of Migration Shocks

Our empirical approach explores how shocks in destination regions (i.e. the Secure Communities program) affect schooling 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 staggered roll-out of the Secure Communities program in the potential destinations of prospective migrants.

Our most basic specification is a simple difference-in-difference design, in which we regress the outcome of interest on the Secure Communities shock $SCshock_{jt}$, which varies between communities and over time, while controlling for time and municipality fixed effects, as given by:

$$y_{ijt} = \beta\, SCshock_{jt} + \delta_1' X_{ijt} + \delta_2' Z_{j,0} \times t + \zeta_j + \lambda_t + \varepsilon_{ijt}, \tag{8}$$

where y_{ijt} is the schooling outcome (*i.e.* attendance, enrollment and completed years of schooling) observed at the level of the individual, X_{ijt} is a vector of individual (and family) characteristics, which we capture by age-by-gender fixed effects initially, and extend subsequently. $Z_{j,0} \times t$ is the baseline migration share (computed from the 2000 Population Census) in municipality j (and its square) interacted with time fixed effects, ζ_j is a vector of municipality fixed effects, and λ_t are quarter-by-year fixed effects, and ε_{ijt} is an idiosyncratic error term. Standard errors are clustered at the level of the municipality throughout.

For β to have a causal interpretation, a number of identifying assumptions need to be satisfied. The first identifying assumption is that, in the absence of shocks to migration networks, changes over time in schooling outcomes would have been the same for individuals in treated and untreated municipalities (parallel trends and no correlated time-varying shocks). Given the staggered roll-out of the SC program, the second and third identifying assumptions relate to the absence of heterogeneity in treatment effects between early- and late-treated municipalities, and over time, respectively (as discussed e.g. in Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021; de Chaisemartin and D'Haultfœuille, 2020). As the SC shock variable is continuous, the fourth identifying assumption concerns the absence of treatment effect heterogeneity by dosage (Callaway et al., 2024).

To test the first identifying assumption, we augment our empirical strategy by an event-study design. Given the continuous nature of our treatment, we follow Schmidheiny and Siegloch (2023) and recover dynamic treatment effects from a distributed lag model that takes the form:

$$y_{ijt} = \sum_{p=-7}^{10} \gamma_p \; SCshock_{ij,t-p} + \delta_1' \, X_{ijt} + \delta_2' \, Z_{j,0} \times t + \zeta_j + \lambda_t + \varepsilon_{ijt}, \tag{9}$$

where p is the period (in quarters) since treatment, and all remaining variables are defined as in eq. (8). We cumulate the post-treatment and pre-treatment coefficients away from zero to recover dynamic treatment effects. To be specific, we construct $\beta_p = -\sum_{k=p+1}^{-1} \gamma_k$ if $p \leq -2$, $\beta_p = 0$ if $p = -1$ and $\beta_p = \sum_{k=0}^{p} \gamma_k$ if $p \geq 0$. As outlined in Schmidheiny and Siegloch (2023), this procedure delivers consistent estimates of dynamic treatment effects as long as the treatment effect is proportional to the observed treatment intensity (no treatment effect heterogeneity by dosage). In Section 5.3 we explore strategies that allow relaxing the assumptions regarding treatment effect heterogeneities, and find that our findings are robust.

5 Results

5.1 Main Results

Difference-in-Difference estimates of the effect of the Secure Communities program on school attendance, enrollment and attainment in Mexico are presented in Table 1. We restrict the ENOE data to the time period 2005 to 2012, such as to focus the analysis on the main roll-out period of the SC program plus a four year lead.[7] We focus on the age-group 12-20, as there is near 100% enrollment at ages below 12. For each outcome we present the effect on all youth aged 12-20, as well as disaggregated by three-year age-groups: 12-14, 15-17, and 18-20.

The first panel explores effects of the SC shock on school attendance. The point estimate in the full sample is positive but not statistically significant (col. 1). Disaggregating further by three-year age-groups shows a small positive effect among 12-14 year old youths which is not significant (col. 2), a positive and statistically significant effect (0.098) among individuals aged 15 to 17 (col. 3), and a small negative effect among individuals

[7] Given that we estimate dynamic effects for 8 quarters before treatment (2 years) in the event-study, the *de facto* time period we consider in terms of SC roll-out extends to December 2014 (a month after the SC program was discontinued).

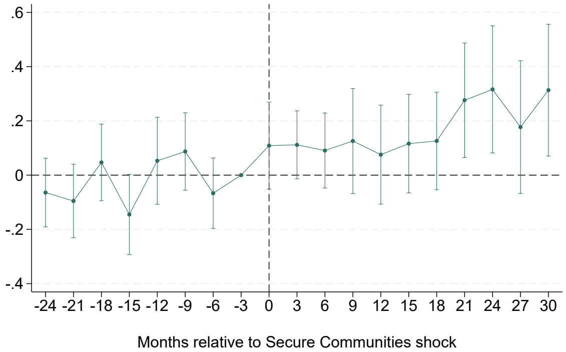
aged 18 to 20 (col. 4). The point estimate in column 3 suggests that the school attendance rate among individuals aged 15-17 increases by about 10pp (21% over the mean) as they move from having zero network-linked counties with SC activated to all. The second panel reveals that the effect on enrollment follows the same pattern: A small and positive overall effect masks a sizeable and statistically significant effect of about 10pp (17%) in the age group 15-17, and null-effects in the other age groups. The third panel, finally, shows the effects on completed years of schooling (at the time of interview). Again the effect pattern is similar: We observe small positive effects for the entire group, which are statistically significant only in the age group 15-17. The magnitude of the coefficient suggests that moving all linked US counties from not participating in the SC program to participating, increases educational attainment in this age group by 0.45 years (a bit under half a year and a 5.5% increase). Its important to note that this estimate should not be interpreted as the effect of SC on final years of schooling: As part of these adolescents are still in school, the coefficient likely captures improved grade progression (which could imply that overall attainment in the long-run is unchanged if students simply complete their aspired years of schooling earlier) as well as increased enrollment (and thus long-run improvements in attainment). We return to this point when discussing the event-study estimates. Overall our findings suggest that the SC program led to improved schooling outcomes in Mexico among youths aged 15-17, with no effects on other age groups.

Figure 4 shows event-study estimates for the age-group 15-17.[8] As can be seen, there in no evidence of pre-trends in any of the outcome variables considered. From these graphs we can identify a number of important differences between the effect timing for the three outcome variables considered. While exposure to the Secure Communities program seems to increase school attendance in this age-group immediately, these effects on the other outcomes take about 12 months to materialize. A potential explanation for this could be that enrollment and attainment are quite sticky, i.e. once a student started a given grade they may not dis-enroll even if they effectively stop attending school.

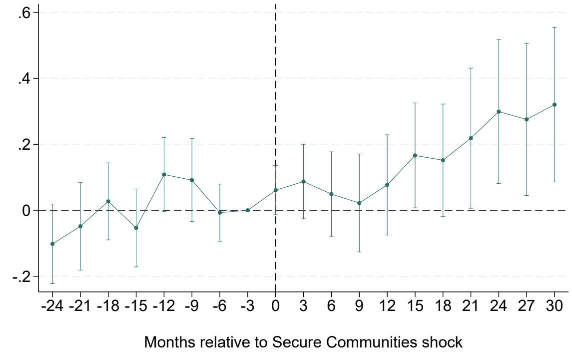
5.2 External Validity

In light of the differences between our results and those in other works (in particular Caballero, 2022), the question arises whether the positive effects we observe are generalizeable to the Mexican population as a whole. As mentioned previously, one of the challenges in identifying the effect of SC communities on outcomes in Mexico, is that

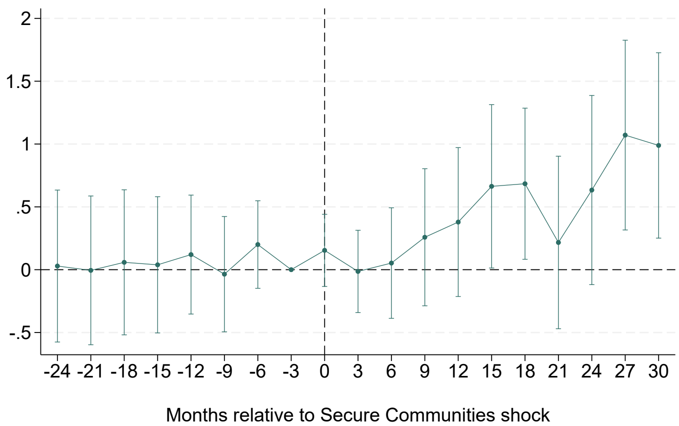
[8] We only show this age-group here for brevity, the full results (for all youth aged 12-20, as well as disaggregated by three-year age-groups) are available in the Appendix, Figures A1 to A3.



(a) Attendance



(b) Enrollment



(c) Years Schooling

Figure 4: Event-Study Estimates of SC on Schooling Outcomes - Youths 15-17

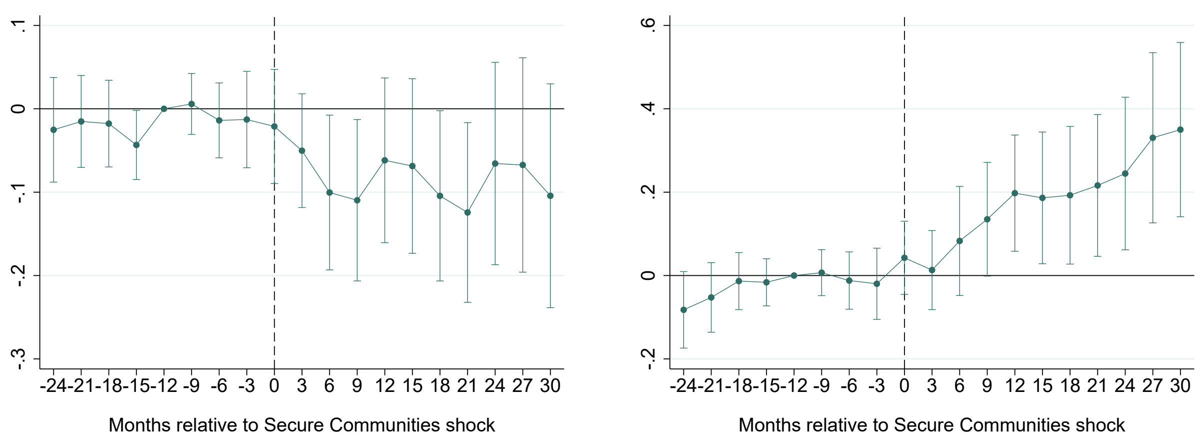
the effect should vary with migration intensities. It seems plausible to assume that the effect of the Secure Communities program would only be felt in places in which a reasonable share of the population actually migrates to the US. If there is a low-migration propensity to start with, why would a shock to migration opportunities affect outcomes? To understand whether treatment effects indeed vary with migration intensity, we separately estimate the effect of the SC shock in each of the remaining quartiles of migration intensity.

In Table 2, we report the effect of the SC shock in the remaining three subsamples of Mexican municipalities (split by migration share quartiles).[9] We find little evidence of any consistent effects. Out of the 36 estimated coefficients only two are statistically significant, suggesting marginal declines in school attendance among 12-14 years old adolescents

[9]We split the sample rather than interacting the $SCshock_{jt}$ variable with migration share, in order to avoid comparing municipalities that are on different time trends. Figures A4 to A6 show dynamic treatment effects from eq. (9).

in municipalities in the second quartile of migration intensity (which is not translating into declines in enrollment or educational attainment), and small increases in enrollment among 18-20 year old individuals in municipalities in the lowest quartile of migration intensity (again without any detectable effects on any of the other schooling outcomes). Evidence from the event-study estimates (Figures A4 to A6) underscores that there seems to be no systematic association between schooling outcomes and the SC shock in any of the municipalities but those that have large migrant populations.

Though indicative of the caveats involved with estimating the effect of migration shocks in low-migration populations, the effects in the remaining municipalities still fall short of the large negative effects on middle-school enrollment reported by Caballero (2022). We test if our results are consistent with theirs once we compute grade-specific enrollment, rather that age-specific enrollment.[10] As shown in Figure 5, panel (a) we find indeed find negative enrollment effects when focusing on middle-school enrollment although our effects are somewhat noisier (which is not surprising given that we compute enrollment from survey data). In panel (b), we compute high school enrollment, and find an overall positive effect of Secure Communities, which is consistent with our results presented above.



(a) Middle-school (b) High-school

Figure 5: Event-Study Estimates of SC on Enrollment (log) - municipality Aggregates

Taken together these results highlight that the focus on enrollment as outcome variable may lead to misleading conclusions about the true schooling effect of policies in popula-

[10]We construct grade-specific enrollment from the ENOE data, by coding every individual as being enrolled in a particular grade, if they are currently enrolled and their highest level of education reported is that grade minus one. In these regressions, we use the full sample of ENOE municipalities in the time period 2005-2014 (1,465), and estimate eq. (9) with the (log) population in middle school/ high school age instead of age-by-gender fixed effects in X_{ijt}.

tions with high retention rates (in our sample, about 25% of the individuals enrolled in grade 9 are 16 or older, while the correct age-for-grade would be 15). They also highlight the importance of accounting for treatment effect heterogeneities in populations that are exposed to migration shocks to very different extent.

5.3 Robustness

There are two main concerns with the results presented thus far: *First*, the extent to which the results are sensitive to selective attrition or survey response. *Second*, whether treatment effects heterogeneities (by treatment intensity or by treatment timing) may lead to bias in our estimated effects given the staggered roll-out of the Secure Communities.

To address the first concern, i.e. that our results may simply reflect compositional changes in the population due to internal or international migration responses, we exploit the panel structure of the data, and compute for every individual that was ever sampled and for each of the five survey rounds that the individual should be in the sample: whether the individual has been interviewed, whether the individual is reported by family members to be a domestic migrant, an international migrant, or whether the individual attrited (this can be either because the whole household could not be interviewed, because the individual was away for unexplained reasons or because of death).[11] We then investigate whether any of these outcomes vary systematically with the Secure Communities shock. As can be seen in Table 3 there are no statistically significant effects in any of the relevant age-groups on the probability of being interviewed, except for the age-group 15 to 17. When narrowing down on any of the reasons for non-interview, it becomes apparent that individuals in the age-group 15 to 17 are somewhat less likely to report as internal migrant, while individuals in the age-group 18-20 are somewhat less likely to attrit. This increased propensity of remaining at home (and in school) rather than migrating domestically may reflect exactly the mechanisms we have in mind: individuals in this age-group are not generally migrating internationally yet, so after dropping out of school many would choose to migrate for work. The important question is whether this would bias our results on schooling outcomes. In principle it seems hard to imagine that the positive effects can be explained by an increased propensity of observing an individual: in this group, years of schooling among individuals who are ever domestic migrants is lower than among individuals who are never reported as domestic migrants (8.2 vs 8.4

[11]Note that we can only calculate these outcomes in households that were scheduled to be interviewerd at least twice. For the year 2005, we therefore loose about 5% of the sample in this analysis (these are households who appeared in the first quarter of 2005 but had already completed four rounds on interviews in 2004)

years of schooling). In contrast, the small (and insignificant) negative effect on completed years of schooling in the age-group 18-20 could be partly driven by fewer low-skilled individuals attriting from the sample: individuals in this age-group who ever are reported to attrit have lower educational attainment than individuals who are never found to have attrited (9.1 vs 9.2 years of schooling, respectively).

To address concerns regarding bias in the OLS estimator, we dichotomize the treatment at the median shock intensity (0.11), and estimate treatment effects using the approach discussed in Borusyak et al. (2024).[12] As shown in Figure A7, the results (shown for enrollment and educational attainment among 15 to 17 year-old individuals) are robust.

5.4 Mechanisms

In the results presented above, we find that the roll-out of the SC program throughout the US increased schooling investments in the age-group 15 to 17, while leaving youths of other age-groups largely unaffected. While these results are consistent with a decline in the perceived attractiveness of seasonal migration, and an increased focus on the Mexican labor market where returns to education are steeper, other mechanisms may explain the observed effects.

Potentially, the roll-out of the SC program may have led to more return migration, which could increase the number of adults in the household, and reduce pressure on adolescents to contribute to family incomes. However, we do not find any evidence that the household composition (measured by the dependency ratio) changes in any meaningful way in affected municipalities, nor do we observe an increase in the number of households with return migrants (c.f Figure A8).

Alternatively, we may be simply capturing a compositional effect, if more motivated youths decide to stay at home in response to the SC roll-out, and these would have been more likely to be in school (rather than working) in the absence of migration. Given that we do not find any direct migration effects in this age group (c.f. Table 3), and migrants to the US tend to be of lower education overall, this seems unlikely to explain our findings.

[12] de Chaisemartin and D'Haultfœuille (2024) propose and estimator that can handle multi-valued treatment and incremental treatment. Unfortunately, their estimator is not able to handle the data-structure of this paper (unbalanced panel with many gaps) very well.

6 Conclusion

The results presented in this paper, suggest the a decline in the perceived attractiveness of migration from Mexico to the US increased educational investments among Mexican adolescents. These results are consistent with adolescents reassessing their labor markets opportunities in Mexico, and an implicit increase in the returns to education.

While the SC program has been associated with substantial costs for migrant populations in the US, this papers suggests that it may also have led to improved educational outcomes in Mexico, with the potential to improve incomes and economic development in the medium-run. This paper also provides important empirical evidence for the potential of migration opportunities to deter educational investments in origin communities, at least if the migration is low-skill and highly seasonal.

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Tables

Table 1: Effect of Secure Communities on Schooling Outcomes

Age group	All	12-14	15-17	18-20
	(1)	(2)	(3)	(4)
Dep.var.: School Attendance				
SC shock	0.034	0.028	0.098*	-0.018
	(0.033)	(0.044)	(0.052)	(0.036)
Observations	194909	70276	68791	55839
Dep. var. mean	0.484	0.720	0.462	0.216
Dep.var.: Enrollment				
SC shock	0.027	0.002	0.098*	-0.015
	(0.031)	(0.037)	(0.050)	(0.045)
Observations	194908	70276	68791	55838
Dep. var. mean	0.611	0.897	0.589	0.276
Dep.var.: Years of Schooling				
SC shock	0.083	-0.073	0.448**	-0.158
	(0.160)	(0.134)	(0.197)	(0.327)
Observations	194760	70266	68715	55776
Dep. var. mean	7.606	5.858	8.123	9.173
Clusters	290	289	290	288
Municipality, Time FE	✓	✓	✓	✓
Age-by-gender FE	✓	✓	✓	✓
Migration Share(^{2}) $\times$ Time FE	✓	✓	✓	✓

Note: Standard errors are clustered at the municipality level and reported in parentheses. Significance at or below 1% (***), 5% (**) and 10% (*).

Table 2: Effect of Secure Communities on Schooling Outcomes in Non-Migrant Commnunities

	Q1 of Migr Share				Q2 of Migr Share				Q3 of Migr Share			
Age group	All	12-14	15-17	18-20	All	12-14	15-17	18-20	All	12-14	15-17	18-20
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dep.var.: School Attendance												
SC shock	0.007	0.017	-0.040	0.044	-0.012	-0.042*	0.009	-0.000	0.021	0.004	0.025	0.031
	(0.029)	(0.036)	(0.042)	(0.034)	(0.021)	(0.022)	(0.030)	(0.026)	(0.033)	(0.041)	(0.044)	(0.031)
Observations	398389	135401	134588	128400	866925	288678	292576	285671	891475	297289	302244	291941
Dep. var. mean	0.580	0.758	0.596	0.375	0.586	0.772	0.605	0.378	0.559	0.746	0.564	0.364
Dep.var.: Enrollment												
SC shock	0.031	0.013	0.004	0.076**	0.003	-0.013	0.019	0.007	0.020	0.020	0.013	0.023
	(0.022)	(0.028)	(0.033)	(0.034)	(0.018)	(0.012)	(0.026)	(0.030)	(0.019)	(0.014)	(0.030)	(0.032)
Observations	398379	135400	134586	128393	866911	288676	292572	285663	891459	297288	302239	291931
Dep. var. mean	0.715	0.934	0.736	0.463	0.725	0.952	0.752	0.470	0.714	0.940	0.725	0.472
Dep.var.: Years of Schooling												
SC shock	0.045	0.010	0.080	-0.042	-0.088	-0.073	-0.071	-0.120	-0.045	-0.063	-0.053	-0.079
	(0.127)	(0.169)	(0.169)	(0.218)	(0.085)	(0.076)	(0.103)	(0.159)	(0.077)	(0.074)	(0.096)	(0.191)
Observations	397930	135359	134382	128189	866549	288661	292443	285445	890960	297230	302020	291709
Dep. var. mean	0.715	0.934	0.736	0.463	8.239	5.986	8.548	10.199	8.221	5.984	8.515	10.195
Clusters	262	262	262	262	373	373	373	373	357	357	357	355
Municipality, Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Age-by-gender FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Migration Share$(^2)$ $\times$ Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Note: Standard errors are clustered at the municipality level and reported in parentheses. Significance at or below 1% (***), 5% (**) and 10% (*).

Table 3: Effect of Secure Communities on Attrition

Age group	All	12-14	15-17	18-20
	(1)	(2)	(3)	(4)
Dep.var.: Individual was interviewed				
SC shock	0.035	0.012	0.060*	0.039
	(0.024)	(0.024)	(0.034)	(0.036)
Observations	225303	76599	79129	69572
Dep. var. mean	0.865	0.917	0.869	0.803
Dep.var.: Individual is abroad				
SC shock	0.002	0.002	-0.001	0.002
	(0.006)	(0.004)	(0.007)	(0.014)
Observations	225303	76599	79129	69572
Dep. var. mean	0.012	0.003	0.010	0.024
Dep.var.: Individual is away domestically				
SC shock	-0.022	-0.011	-0.053*	0.002
	(0.017)	(0.015)	(0.028)	(0.030)
Observations	225303	76599	79129	69572
Dep. var. mean	0.070	0.029	0.072	0.114
Dep.var.: Individual attrited				
SC shock	-0.015	-0.003	-0.006	-0.043*
	(0.016)	(0.020)	(0.020)	(0.022)
Observations	225303	76599	79129	69572
Dep. var. mean	0.053	0.051	0.049	0.059
Clusters	290	289	290	288
Municipality, Time FE	✓	✓	✓	✓
Age-by-gender FE	✓	✓	✓	✓
Migration Share$(^2)$ × Time FE	✓	✓	✓	✓

Note: Standard errors are clustered at the municipality level and reported in parentheses. Significance at or below 1% (***), 5% (**) and 10% (*).

A Online Appendix

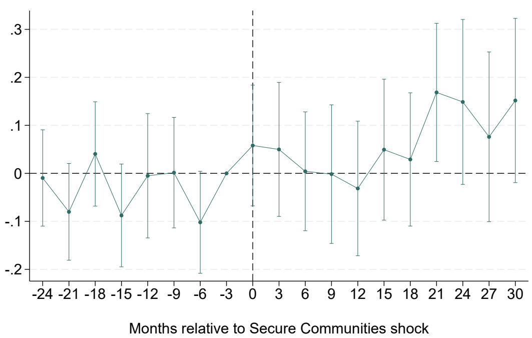
A.1 Additional Tables

Table A1: Summary Statistics

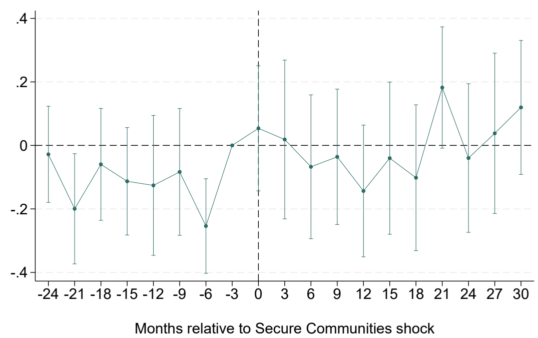
	All			2005			2012		
	Mean	SD	N	Mean	SD	N	Mean	SD	N
Full Sample									
MCAS and Pop. census variables:									
Secure Communities Shock	0.31	0.38	2,351,698	0.00	0.00	312,020	0.90	0.07	271,699
Migration rate (5 years)	0.02	0.02	2,351,698	0.02	0.01	312,020	0.02	0.02	271,699
ENOE variables:									
Age	15.95	2.56	2,351,698	15.86	2.57	312,020	16.03	2.58	271,699
Female	0.50	0.50	2,351,698	0.50	0.50	312,020	0.49	0.50	271,699
Currently enrolled	0.71	0.45	2,351,657	0.70	0.46	312,007	0.72	0.45	271,697
Went to school in past 7days	0.57	0.50	2,351,698	0.56	0.50	312,020	0.58	0.49	271,699
Completed years of schooling	8.13	2.61	2,350,199	8.00	2.64	311,839	8.30	2.56	271,456
High-Migration Sample									
MCAS and Pop. census variables:									
Secure Communities Shock	0.30	0.37	194,909	0.00	0.00	25,032	0.88	0.11	23,211
Migration rate (5 years)	0.06	0.02	194,909	0.05	0.02	25,032	0.05	0.02	23,211
ENOE variables:									
Age	15.74	2.51	194,909	15.56	2.50	25,032	15.90	2.55	23,211
Female	0.51	0.50	194,909	0.52	0.50	25,032	0.49	0.50	23,211
Currently enrolled	0.61	0.49	194,908	0.60	0.49	25,031	0.64	0.48	23,211
Went to school in past 7days	0.48	0.50	194,909	0.48	0.50	25,032	0.52	0.50	23,211
Completed years of schooling	7.61	2.48	194,760	7.35	2.48	25,013	7.93	2.41	23,179

Note: notes.

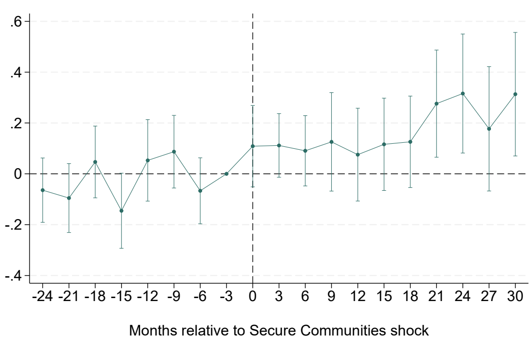
A.2 Additional Figures



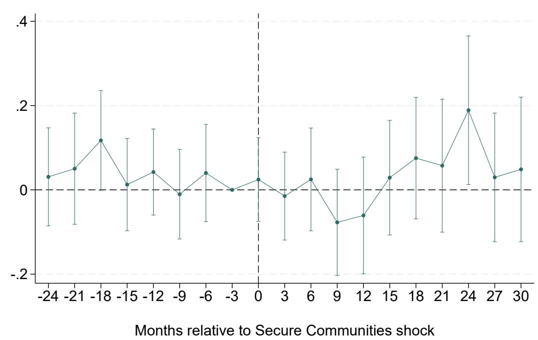
(a) All



(b) 12 to 14

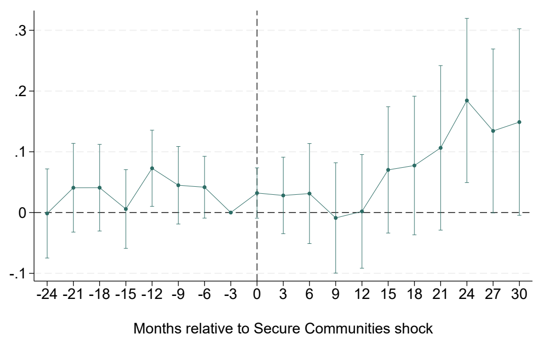


(c) 15 to 17

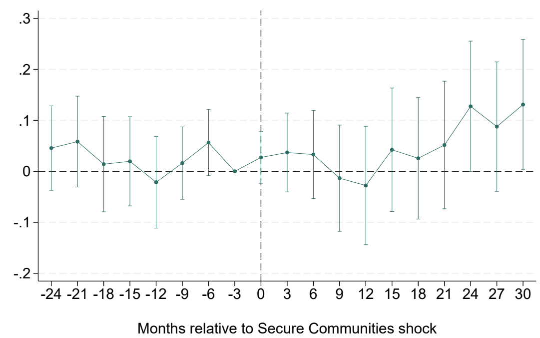


(d) 18 to 20

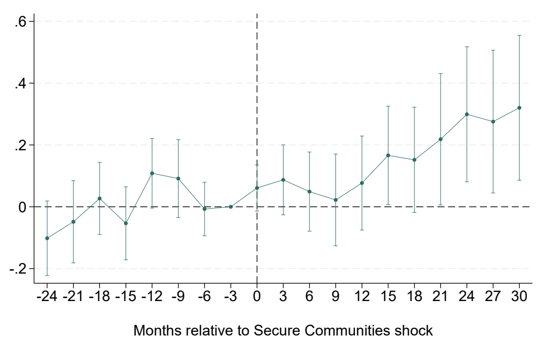
Figure A1: Effect of SC on School Attendance - Event Study Results



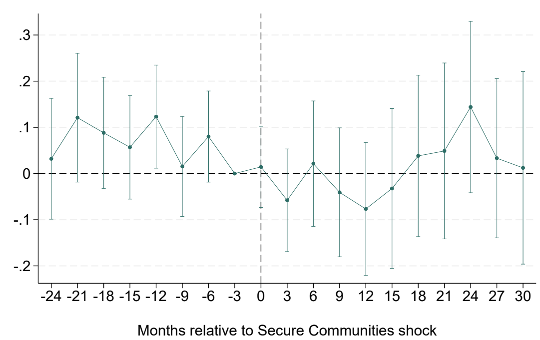
(a) All



(b) 12 to 14

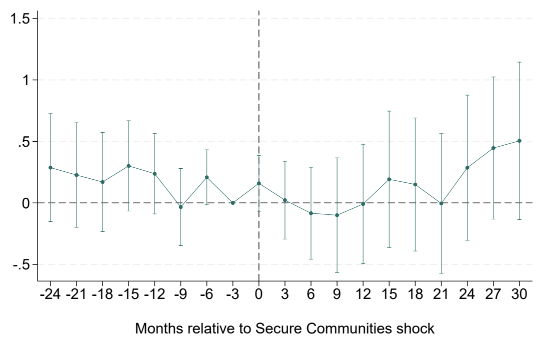


(c) 15 to 17

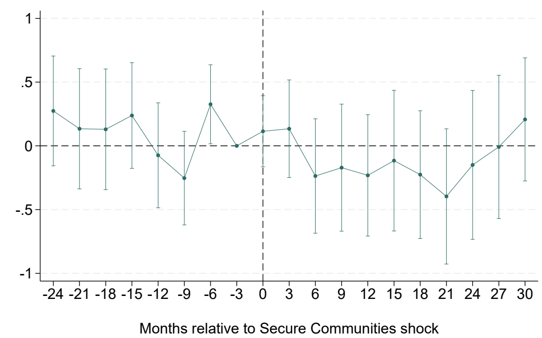


(d) 18 to 20

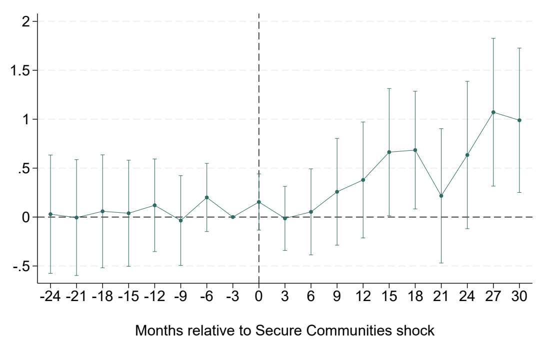
Figure A2: Effect of SC on Enrollment - Event Study Results



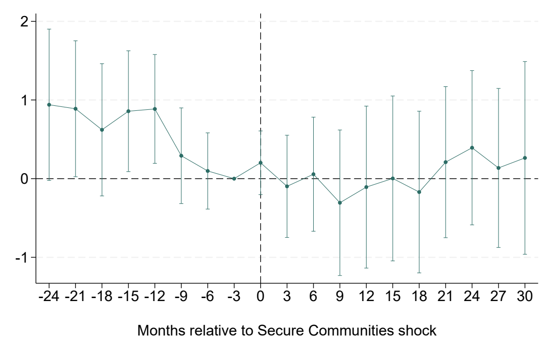
(a) All



(b) 12 to 14

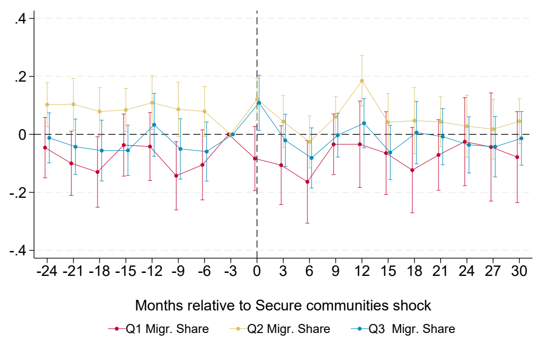


(c) 15 to 17

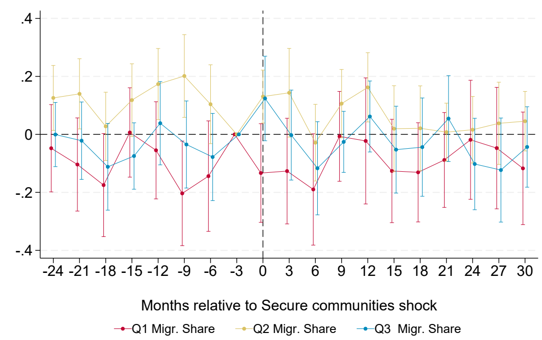


(d) 18 to 20

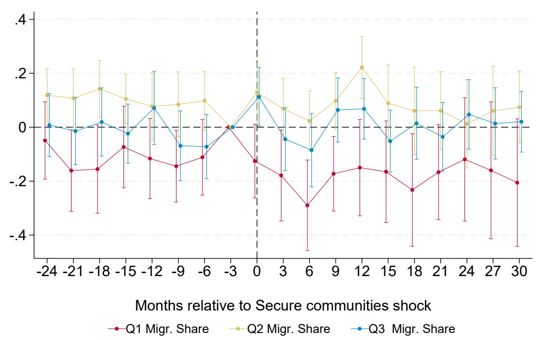
Figure A3: Effect of SC on Completed Years of Schooling - Event Study Results



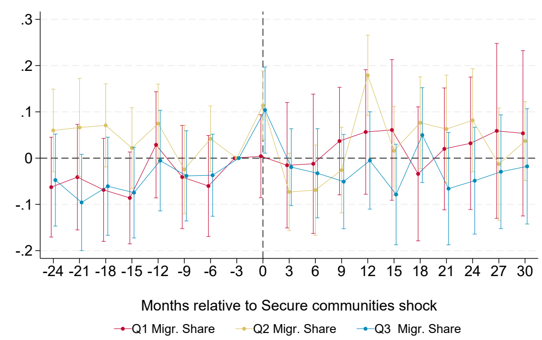
(a) All



(b) 12 to 14

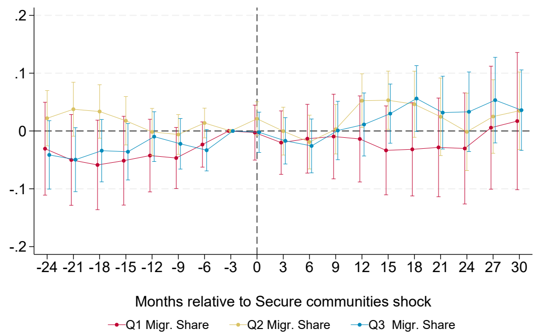


(c) 15 to 17

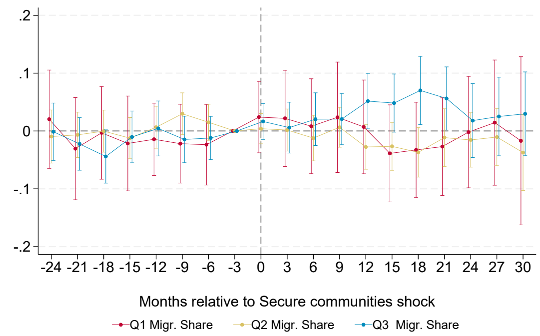


(d) 18 to 20

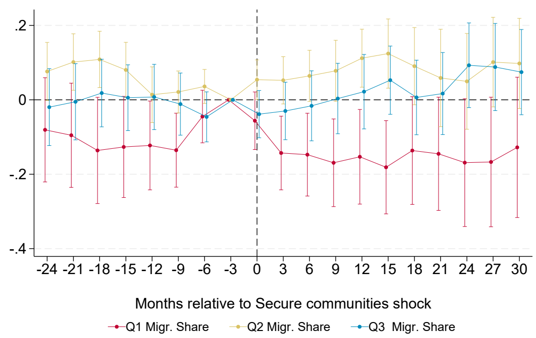
Figure A4: Effect of SC shock (at different levels of migrant share) on School Attendance



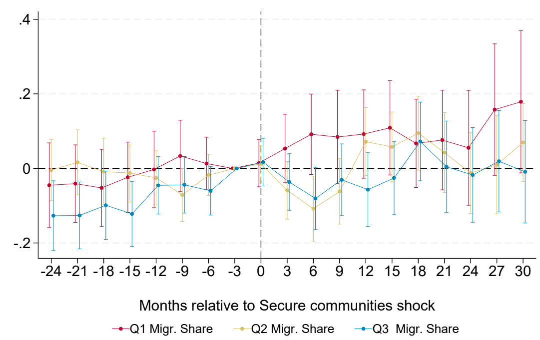
(a) All



(b) 12 to 14

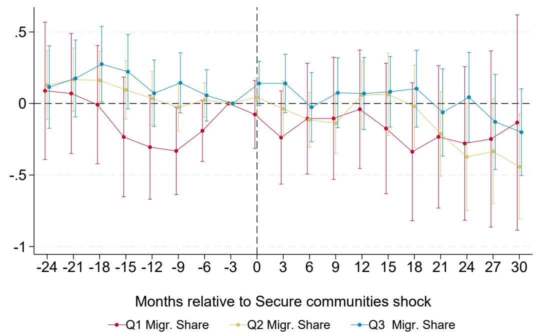


(c) 15 to 17

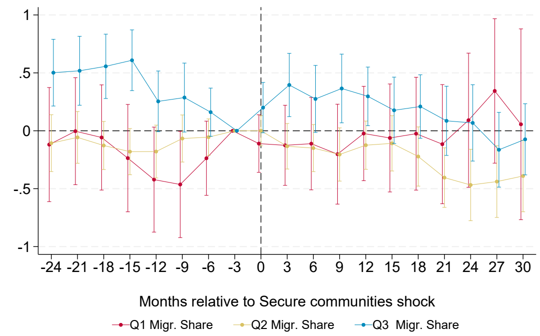


(d) 18 to 20

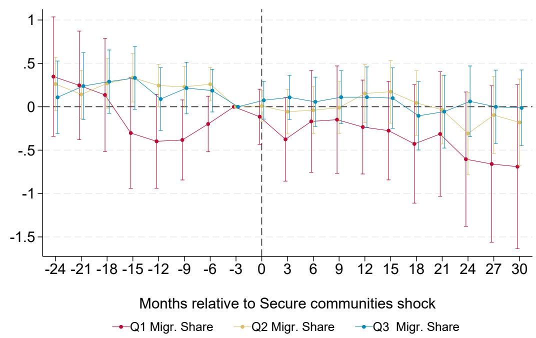
Figure A5: Effect of SC shock (at different levels of migrant share) on Enrollment



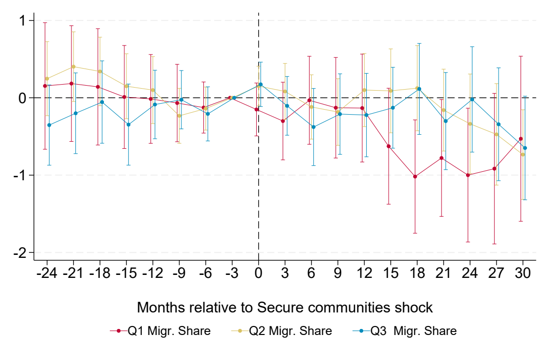
(a) All



(b) 12 to 14

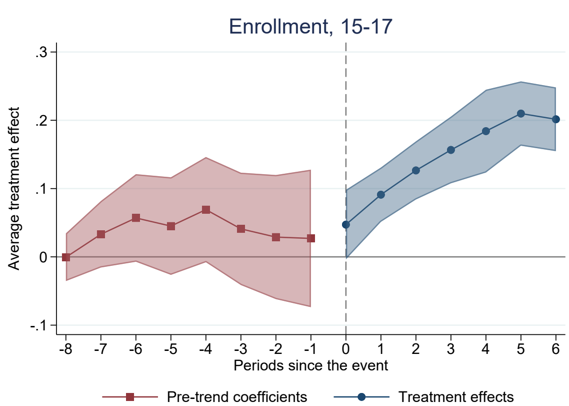


(c) 15 to 17

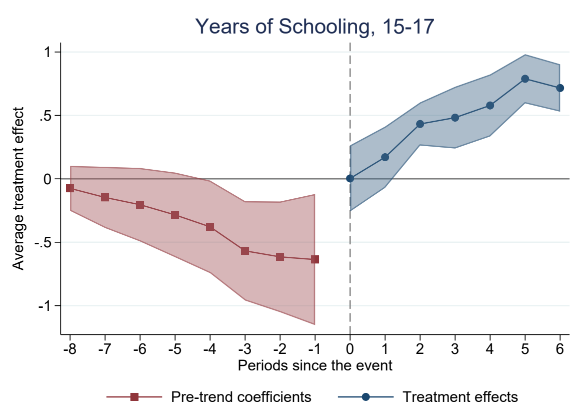


(d) 18 to 20

Figure A6: Effect of SC shock (at different levels of migrant share) on Completed Years of Schooling

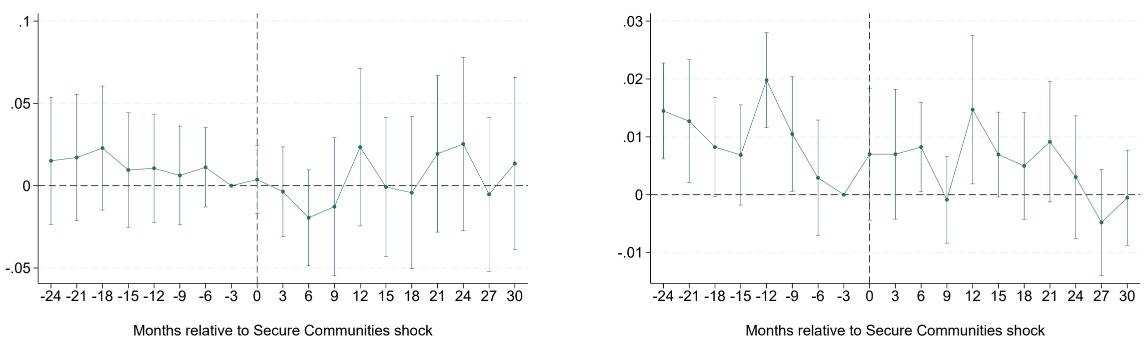


(a) Enrollment



(b) Years of Schooling

Figure A7: Effect of dichotomized SC Shock, Borusyak et al. (2014) imputation estimator



(a) Dependency ratio

(b) Any return migrant

Figure A8: Effect of SC on Household Composition