Immigration in Schools

Foreign-born students and the performance of natives

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Motivation:

- Never-ending debate in policy and academia on the impact of immigration on natives' welfare.
- This paper focuses on native public school students: arguably a first-order impact.

Why is this a relevant economic question?

- Role of class composition (not only size) in the education production function
- Evaluating the economic effects of immigrant shock entails taking into account the whole moving household
- Estimating the payoffs from immigration policies

Contribution

- The overwhelming majority of the literature focused on labor market impact on native adults. Still far from consensus on the sign (Card, 2001; Borjas, 2013; Ottaviano and Peri (2005))
  - We focus on a different effect: the exposure to immigrant peers on natives' educational achievement
- Papers studying the effects of foreign-born peers on natives' outcomes in school:
  - European context: negative [Jensen and Rasmusses (2011), Brunello and Rocco (2013), Ballatore et al. (2015), Tornello (2016)] or no effect [(Ohinata et al. (2013), Geay et al. (2013) and Schneeweis (2015)].
  - Israel: negative effect of immigrants on native Israeli students' likelihood of passing high school matriculation exam (Gould, Lavy and Paserman, (2009)).
  - United States: negative relationship between natives' test scores and immigrant share at the school level (Schwartz and Stiefel (2001)), but positive effect on the high school completion of natives (Hunt, (2016)).

Contribution

- Papers usually cannot take into account sorting of immigrants and natives. They use 'exogenous' inflows (e.g., Gould, Lavy, Paserman, 2009, FSU migration to Israel in 1990s). Problems: (i) natives' sorting; (ii) natural experiments are *local* by definition.
  - We exploit within-family variation and plausibly exogenous school-to-school transition.
  - We estimate a global parameter, while taking into account sorting of natives.

This paper in a nutshell

- Data
  - administrative
  - longitudinal
  - family identifiers

- Identification strategy exploits:
  - Siblings comparison
  - Holding fixed time-varying family characteristics (as well as time-varying school and grade characteristics), compare different cumulative exposures to first generation immigrants
  - Instrumental variable approach: use aggregate transition school-to-school probabilities to build predicted exposures for each kid at each subsequent grade, starting from the first at which she is first observed
  - Two siblings will therefore have the same transition matrix but a different exposure to immigrants, which depends on the specific cohort they are in

- Results:
  - Positive relationship (larger in math)
  - Coefficient mainly driven by disadvantaged groups
  - Potential channel: reduced disruption

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Data

Empirical Analysis

Instrument

Heterogeneity

Mechanisms

Data

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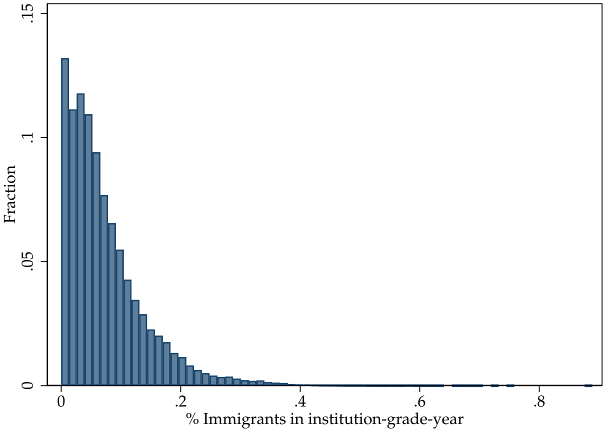
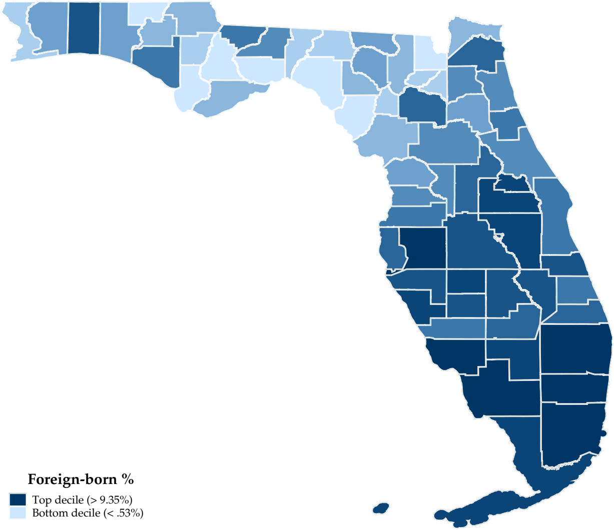
Data

- Individual-level administrative data from the Florida Department of Education Data Warehouse:
  - K-12 students who attended FLPS born between 1994-2002
  - longitudinal data
- Matched birth records for those born in Florida (using SSN, names, DOB)
- Florida is the 4th state with the highest share of immigrants.

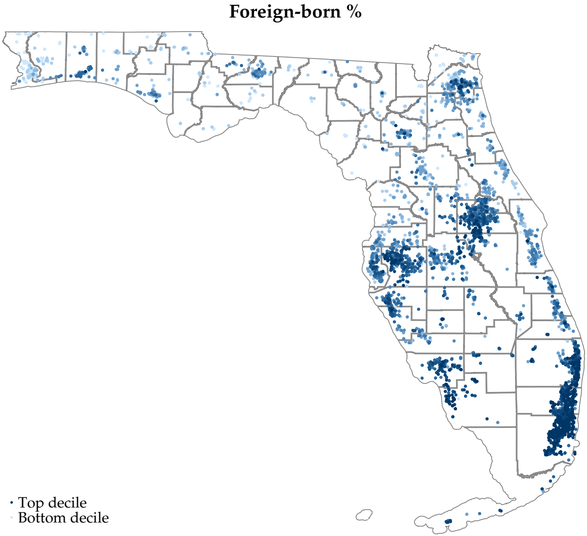
Exposure of US-born students to foreign-born peers



Distribution of foreign born students by district



Distribution of foreign-born students: within district



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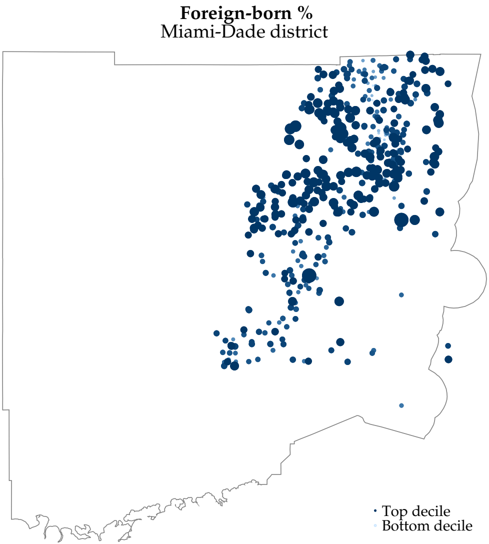

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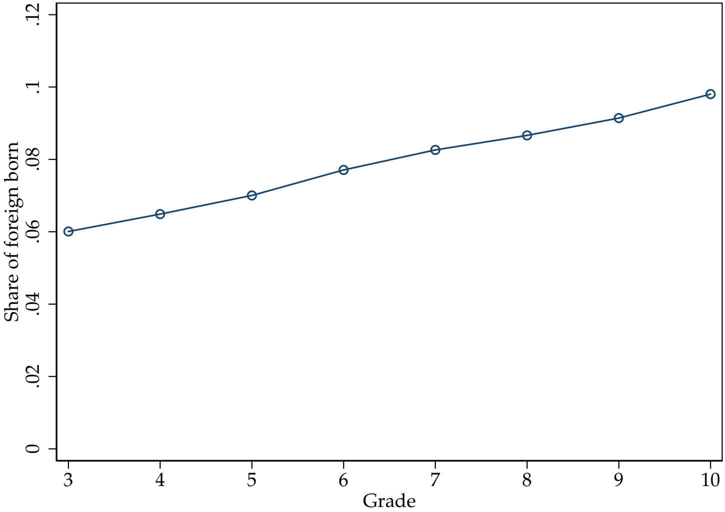

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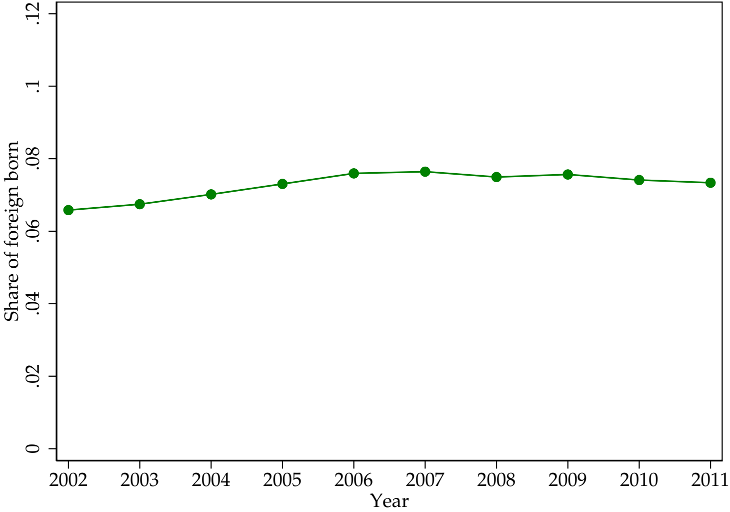

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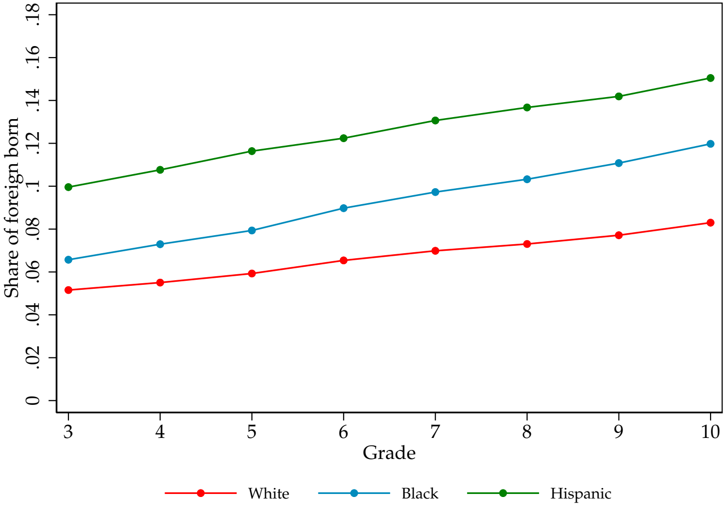
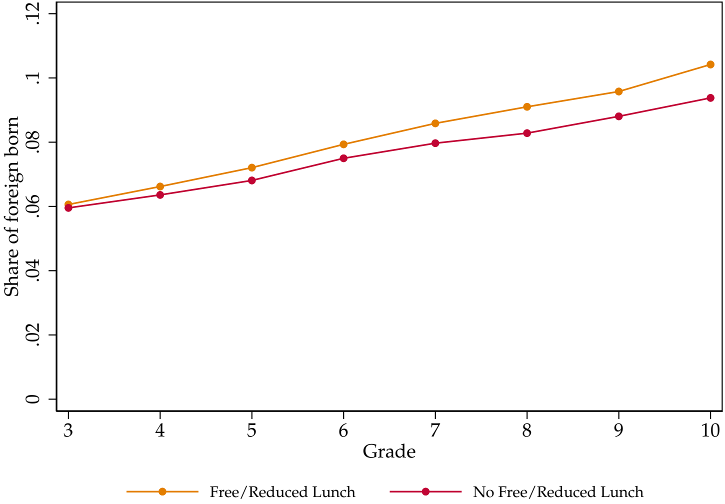


Exposure of US-born students to foreign born peers



Countries of origin

	Overall	Nat. White Majority*	Nat. Hisp. Majority	Nat. Black Majority
	Top 10 Immigrants' countries of origin			
1.	Cuba (16%)	Mexico (13%)	Cuba (45%)	Haiti (41%)
2.	Mexico (10%)	Puerto Rico (7%)	Colombia (9%)	Jamaica (13%)
3.	Haiti (10%)	Colombia (6%)	Mexico (7%)	Mexico (5%)
4.	Colombia (8%)	Germany (5%)	Venezuela (5%)	Puerto Rico (4%)
5.	Puerto Rico (6%)	Cuba (4%)	Puerto Rico (4%)	Cuba (3%)
6.	Venezuela (5%)	Haiti (4%)	Honduras (3%)	Honduras (3%)
7.	Jamaica (3%)	Canada (3%)	Dominican Rep. (3%)	Dominican Rep. (3%)
8.	Peru (3%)	Venezuela (3%)	Peru (3%)	Bahamas (2%)
9.	Honduras (2%)	Brazil (3%)	Nicaragua (3%)	Colombia (2%)
10.	Dominican Rep. (2%)	Japan (3%)	Argentina (2%)	Japan (1%)
Top-10 Cumul.	64%	50%	84%	78%

* Native white majority indicates that only school-specific cohorts with more than 50% white U.S.-born are selected. The third and fourth column are analogously constructed.

Ethnic groups

	Overall	Nat. White Majority	Nat. Hisp. Majority	Nat. Black Majority
		Top 3 Immigrants' ethnic groups		
1.	Hispanic (60%)	Hispanic (45%)	Hispanic (91%)	Black (64%)
2.	Black (16%)	White (30%)	Black (3%)	Hispanic (27%)
3.	White (7%)	Asian (13%)	White (3%)	Asian (5%)
Top-3 Cumul.	83%	88%	97%	96%

Data

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Mechanisms

Cumulative exposure

What is the impact of being exposed to a larger share of immigrants during a student's school career?

Right-hand-side variable:

$$\bar{X}_{ig} = \frac{1}{N_g} \sum_{g' \leq g} X_{stg'}$$

Left-hand-side: Standardized test scores in mathematics and reading (Y_{istg}).

A cumulative exposure measure has the advantages of

- smoothing out abrupt changes in class composition
- accounting for lagged effects

Main specification

$$Y_{istg} = \alpha_{st} + \alpha_{gt} + \lambda_{f(i),t} + \beta \bar{X}_{ig} + \boldsymbol{\delta}' \boldsymbol{W}_{istg} + \boldsymbol{\gamma}' \bar{\boldsymbol{Q}}_{ig} + \varepsilon_{istg} \tag{1}$$

- school by year FEs
- grade by year FEs
- family by year FEs
- $\boldsymbol{W}_{istg}$ individual and family controls (e.g., gender, age in months, birth order, free lunch, race)
- $\bar{\boldsymbol{Q}}_{ig}$ other cumulative exposures (e.g., exposure to free lunch students, to different ehtnic groups, to LEP students)

The regressions are run on a subset of observations such that there are at least 2 siblings in each family, each year.

Estimates: Math

	Math standardized scores (3-10 grades)					
Foreign-born exp.	-0.108**	0.026	0.080*	0.249***	0.231***	0.357***
	(0.055)	(0.043)	(0.041)	(0.056)	(0.079)	(0.085)
Individual Controls	Y	Y	Y	Y	Y	Y
School × Year FEs	Y	Y	Y	Y	Y	Y
Grade × Year FEs	Y	Y	Y	Y	Y	Y
Race FEs	N	Y	Y			
Lunch Status	N	Y	Y			
Mother's Educ. FEs	N	N	Y			
Family FE				Y		
Family × Year FE					Y	Y
Exposure controls	N	N	N	N	N	Y
Observations	1,269,935	1,269,935	1,267,394	1,269,935	1,269,935	1,269,935
Students	401,170	401,170	400,302	401,170	401,170	401,170
R^2	0.303	0.361	0.382	0.692	0.778	0.778
Mean RHS	0.06	0.06	0.06	0.06	0.06	0.06
SD RHS	0.05	0.05	0.05	0.05	0.05	0.05
β	-0.006	0.001	0.004	0.013	0.012	0.019

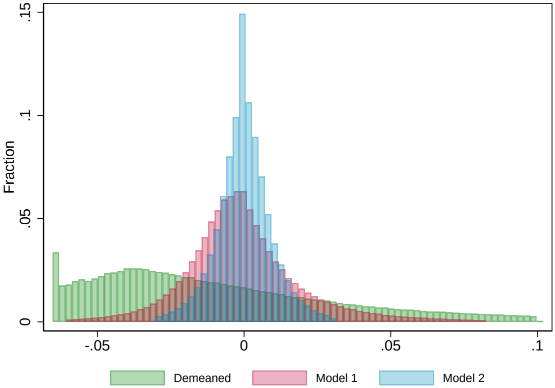
Exposure controls include cumulative exposures to black peers, asian, hispanic, LEP students, free or reduced price lunch students. Individual controls include gender, age in months, special education, birth order FEs. Standard errors are clustered at the cohort-school level. Summary statistics.

Estimates: Reading

	Reading standardized scores (3-10 grades)					
Foreign-born exp.	-0.179***	-0.015	0.050	0.167***	0.143**	0.240***
	(0.051)	(0.041)	(0.038)	(0.051)	(0.067)	(0.073)
Individual Controls	Y	Y	Y	Y	Y	Y
School × Year FEs	Y	Y	Y	Y	Y	Y
Grade × Year FEs	Y	Y	Y	Y	Y	Y
Race FEs	N	Y	Y			
Lunch Status	N	Y	Y			
Mother's Educ. FEs	N	N	Y			
Family FE				Y		
Family × Year FE					Y	Y
Exposure controls	N	N	N	N	N	Y
Observations	1,397,433	1,397,433	1,394,740	1,397,433	1,397,433	1,397,433
Students	408,785	408,785	407,907	408,785	408,785	408,785
R^2	0.299	0.353	0.375	0.673	0.754	0.754
Mean RHS	0.06	0.06	0.06	0.06	0.06	0.06
SD RHS	0.05	0.05	0.05	0.05	0.05	0.05
β	-0.010	-0.001	0.003	0.009	0.008	0.013

Exposure controls include cumulative exposures to black peers, asian, hispanic, LEP students, free or reduced price lunch students. Individual controls include gender, age in months, special education, birth order FEs. Standard errors are clustered at the cohort-school level.

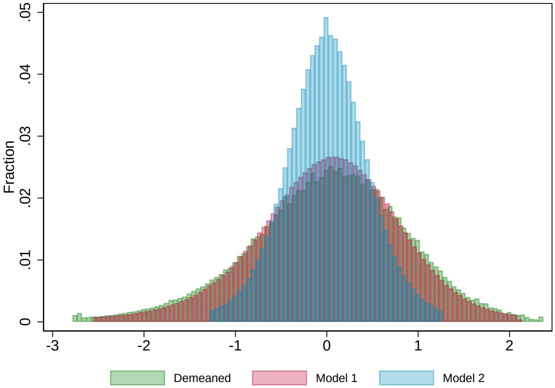
Identifying variation: Exposure



Demeaned: $\mathbb{P}(X - \bar{X})$
Model 1: $\mathbb{P}(X\,|\text{institution} \times \text{year, year} \times \text{grade})$.

Model 2: $\mathbb{P}(X\,|\text{institution} \times \text{year, year} \times \text{grade, family} \times \text{year})$.

Identifying variation: Math scores



Demeaned: $\mathbb{P}(Y - \bar{Y})$
Model 1: $\mathbb{P}(Y|\text{institution} \times \text{year, year} \times \text{grade})$.
Model 2: $\mathbb{P}(Y|\text{institution} \times \text{year, year} \times \text{grade, family} \times \text{year})$.

Predicted Exposure: Intuition

Variation within the family is large.

There is still scope for choices *within* the family, based on kid-specific unobserved characteristics, which might still bias our results.

Proposed solution:

1. Fix the initial school
2. Build aggregate school-to-school transition matrices
3. Predict exposures at each subsequent grade starting from the first observed
4. Compare siblings who started in the same school (in possibly different years/grades)

Predicted Exposure: Construction

- For each pair of consecutive grades g and $g+1$, π_{kj} is the probability that a student in school k at grade g ends up in school j at grade $g+1$.
- For each grade g and time t, $\boldsymbol{W}(g,t)$ is a vector of school characteristics.
- N_s is the total number of schools in the sample.

Transition matrix from grade g to grade $g+1$

$$\mathbb{P}(g+1|g) = \begin{bmatrix} \pi_{11} & \pi_{12} & \pi_{13} & \dots & \pi_{1N_s} \\ \pi_{21} & x_{22} & \pi_{23} & \dots & \pi_{2N_s} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \pi_{N_s1} & \pi_{N_s2} & \pi_{N_s3} & \dots & \pi_{N_sN_s} \end{bmatrix}$$

$$\boldsymbol{W}(g,t) = \begin{bmatrix} w_1(g,t) & w_2(g,t) & w_3(g,t) & \dots & w_{N_s}(g,t) \end{bmatrix}'$$

Predicted Exposure: Construction

Relevant objects:

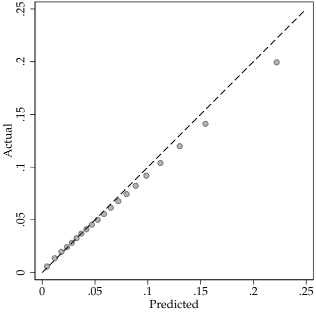
$$\left\{ \underset{(N_s \times N_s)}{\mathbb{P}(g+1|g)} \right\}_{g=0}^{11} \qquad 12\ (N_s \times N_s)\text{-transition matrices}$$

$$\left\{ \left\{ \underset{(N_s \times 1)}{\boldsymbol{W}(g,t)} \right\}_{g=0}^{12} \right\}_{t=2002}^{2011} \qquad 130\ (N_s \times 1)\text{-vectors}$$

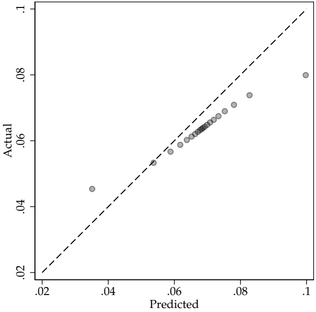
Building the predicted exposure at $(\tilde{g}, \tilde{t})$ based on Markov chains for given (g_0, t_0):

$$\underset{(N_s \times 1)}{\boldsymbol{Z}(\tilde{g}, \tilde{t})} = \mathbb{E}\left[\boldsymbol{W}(\tilde{g}, \tilde{t}) | (g_0, t_0)\right] = \underset{(N_s \times N_s)}{\left(\prod_{g=g_0}^{\overset{\curvearrowright}{\tilde{g}-1}} \mathbb{P}(g+1|g) \right)} \underset{(N_s \times 1)}{\boldsymbol{W}(\tilde{g}, \tilde{t})}$$

First stage



Unconditional



Conditional on family × initial school FEs

Deviation histogram

IV Estimates

	RF	OLS	IV
		Math	
Foreign-born exposure	0.287***	0.386***	0.335**
	(0.096)	(0.092)	(0.155)
N	1,347,619	1,392,971	1,347,581
Within R^2	0.053	0.052	0.053
		Reading	
Foreign-born exposure	0.172*	0.183**	0.228
	(0.094)	(0.089)	(0.158)
N	1,414,352	1,460,465	1,414,314
Within R^2	0.070	0.069	0.071
Individual Controls	Y	Y	Y
Exposure Controls	Y	Y	Y (IV)
Family × Initial School	Y	Y	Y
Family × Grade	Y	Y	Y

Individual controls include gender, age in months, special education. Standard errors are clustered at the cohort-initial-school level.

Heterogeneity

We expect selection of natives into schools based on immigrant exposures. Previous research has documented the existence of a ”native flight” (e.g., Cascio and Lewis, 2012).

We know from the first table that selection is likely negative: low achieving native students are associated with larger shares of immigrants.

But, what sub-populations are responsible for the flight? Let’s split the sample by ethnicity and socioeconomic status.

Heterogeneity: Ethnic group

	Math standardized scores (3-10 grades)					
	African American sub-population					
Foreign-born exp.	0.486***	0.464***	0.439***	0.384***	0.391***	0.439***
	(0.071)	(0.070)	(0.069)	(0.103)	(0.149)	(0.165)
N	364,047	364,047	362,861	364,047	364,047	364,047
R^2	0.279	0.286	0.296	0.614	0.731	0.732
	White sub-population					
Foreign-born exp.	-0.567***	-0.356***	-0.225***	0.197**	0.140	0.275**
	(0.067)	(0.063)	(0.060)	(0.079)	(0.113)	(0.120)
N	776,564	776,564	775,396	776,564	776,564	776,564
R^2	0.261	0.282	0.310	0.677	0.771	0.771
Individual Controls	Y	Y	Y	Y	Y	Y
School × Year FEs	Y	Y	Y	Y	Y	Y
Grade × Year FEs	Y	Y	Y	Y	Y	Y
Race FEs	N	Y	Y			
Lunch Status	N	Y	Y			
Mother's Educ. FEs	N	N	Y			
Family FE				Y		
Family × Year FE					Y	Y
Exposure controls	N	N	N	N	N	Y

Heterogeneity: SES

	Math standardized scores (3-10 grades)					
	Free or Reduced price lunch sub-population					
Foreign-born exp.	0.346***	0.250***	0.262***	0.368***	0.362***	0.509***
	(0.056)	(0.052)	(0.051)	(0.079)	(0.110)	(0.120)
N	680,665	680,665	678,879	680,665	680,665	680,665
R^2	0.256	0.287	0.301	0.637	0.740	0.740
	No reduced price sub-population					
Foreign-born exp.	-0.396***	-0.362***	-0.233***	-0.006	0.015	0.095
	(0.069)	(0.067)	(0.063)	(0.083)	(0.118)	(0.125)
N	589,270	589,270	588,515	589,270	589,270	589,270
R^2	0.215	0.232	0.267	0.675	0.769	0.769
Individual Controls	Y	Y	Y	Y	Y	Y
School × Year FEs	Y	Y	Y	Y	Y	Y
Grade × Year FEs	Y	Y	Y	Y	Y	Y
Race FEs	N	Y	Y			
Lunch Status	N	Y	Y			
Mother's Educ. FEs	N	N	Y			
Family FE				Y		
Family × Year FE					Y	Y
Exposure controls	N	N	N	N	N	Y

Data

Empirical Analysis

Instrument

Heterogeneity

Mechanisms

Potential mechanisms

Does the ”quality” of immigrants matter?

Homophyly

Disruption

Diversity: racial and by country of origin, potential non-linear effect

Does the socio-economic status of immigrants matter?

	Math standardized scores (3-10 grades)					
Foreign-born exp.	0.236***	0.195***	0.194***	0.268***	0.247***	0.361***
	(0.053)	(0.043)	(0.041)	(0.057)	(0.080)	(0.086)
Cumulative share of low-SES among foreign-born peers	-0.431***	-0.210***	-0.141***	-0.031***	-0.031***	0.001
	(0.009)	(0.007)	(0.006)	(0.007)	(0.009)	(0.009)
Individual Controls	Y	Y	Y	Y	Y	Y
School × Year FEs	Y	Y	Y	Y	Y	Y
Grade × Year FEs	Y	Y	Y	Y	Y	Y
Race FEs	N	Y	Y			
Lunch Status	N	Y	Y			
Mother's Educ. FEs	N	N	Y			
Family FE				Y		
Family × Year FE					Y	Y
Exposure controls	N	N	N	N	N	Y
Observations	1,246,982	1,246,982	1,244,510	1,246,982	1,246,982	1,246,982
R^2	0.309	0.363	0.383	0.694	0.781	0.781

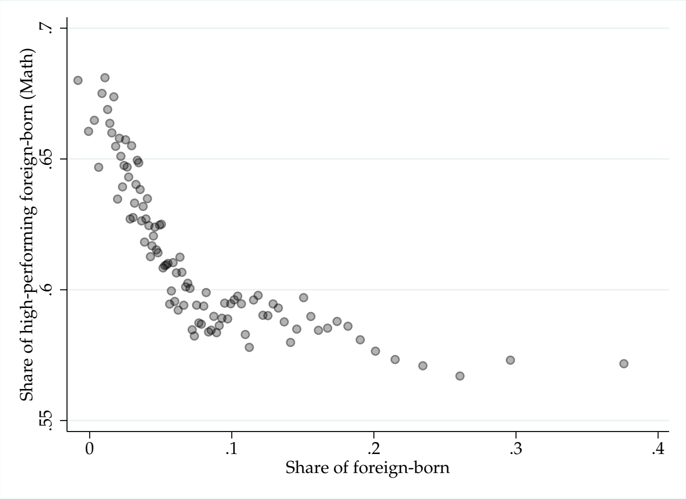
Exposure controls include cumulative exposures to black peers, asian, hispanic, LEP students, free or reduced price lunch students. Individual controls include gender, age in months, special education, birth order FEs. Standard errors are clustered at the cohort-school level. Free lunch split

Does the socio-economic status of immigrants matter?

	Math standardized scores (3-10 grades)					
Foreign-born exp. (High-SES)	5.048***	2.495***	1.649***	0.757***	0.708***	0.299**
	(0.130)	(0.094)	(0.087)	(0.101)	(0.140)	(0.146)
Foreign-born exp. (Low-SES)	-2.233***	-1.002***	-0.574***	-0.006	-0.021	0.392***
	(0.066)	(0.053)	(0.050)	(0.072)	(0.102)	(0.113)
Individual Controls	Y	Y	Y	Y	Y	Y
School × Year FEs	Y	Y	Y	Y	Y	Y
Grade × Year FEs	Y	Y	Y	Y	Y	Y
Race FEs	N	Y	Y			
Lunch Status	N	Y	Y			
Mother's Educ. FEs	N	N	Y			
Family FE				Y		
Family × Year FE					Y	Y
Exposure controls	N	N	N	N	N	Y
Observations	1,269,935	1,269,935	1,267,394	1,269,935	1,269,935	1,269,935
R^2	0.309	0.362	0.382	0.692	0.778	0.778

Exposure controls include cumulative exposures to black peers, asian, hispanic, LEP students, free or reduced price lunch students. Individual controls include gender, age in months, special education, birth order FEs. Standard errors are clustered at the cohort-school level.

Mechanisms: Does the "quality" of immigrants matter?



Mechanisms: Homophyly?

	Math standardized scores (3-10 grades)					
	African American sub-population					
Foreign-born exp.	0.483***	0.465***	0.437***	0.394***	0.396***	0.455***
	(0.071)	(0.070)	(0.070)	(0.105)	(0.152)	(0.168)
White share exp.	0.060***	0.058***	0.049***	-0.028	-0.015	-0.021
	(0.019)	(0.019)	(0.019)	(0.020)	(0.028)	(0.029)
Black share exp.	-0.206***	-0.164***	-0.129***	-0.078***	-0.078***	-0.054*
	(0.017)	(0.017)	(0.016)	(0.019)	(0.026)	(0.028)
Hispanic share exp.	-0.122***	-0.098***	-0.073***	-0.046**	-0.036	-0.012
	(0.016)	(0.016)	(0.016)	(0.018)	(0.025)	(0.026)
	White sub-population					
Foreign-born exp.	-0.375***	-0.215***	-0.130**	0.210***	0.143	0.271**
	(0.067)	(0.064)	(0.061)	(0.080)	(0.115)	(0.122)
White share exp.	0.010	0.010	0.015	0.006	0.003	0.013
	(0.011)	(0.011)	(0.010)	(0.009)	(0.013)	(0.013)
Black share exp.	-0.180***	-0.135***	-0.081***	-0.032**	-0.038*	-0.010
	(0.016)	(0.016)	(0.015)	(0.015)	(0.020)	(0.021)
Hispanic share exp.	-0.151***	-0.110***	-0.066***	-0.018*	-0.018	0.005
	(0.011)	(0.011)	(0.010)	(0.010)	(0.014)	(0.014)
Individual contr., S-Y, G-Y	Y	Y	Y	Y	Y	Y
Lunch Status	N	Y	Y			
Mother's Educ. FEs	N	N	Y			
Family FE				Y		
Family $\times$ Year FE					Y	Y
Exposure controls	N	N	N	N	N	Y

Mechanism: Disruption

Disruptive behavior is thought to impair the production of education (e.g, Lazear, 2001).

We analyze data on absence rates and disciplinary incidents as proxies for disruptive behavior and show that:

- Foreign-born students are significantly less likely to be involved in incidents (20 to 30%)
- Immigrant kids have significantly lower absence rates (14 to 20%)
- Students exposed to a larger share of peers involved in disciplinary incidents or with larger absenteeism show lower test scores.
  Consistent with $\uparrow$ Disruption $\rightarrow \downarrow$ Educational Outcomes

Mechanism: Disruption

	Rate of absence (mean = 0.051)			
$\mathbb{1}$[Foreign-born]	-0.009***	-0.010***	-0.008***	-0.007***
	(0.000)	(0.000)	(0.000)	(0.000)
N	9,367,040	9,367,040	9,367,040	9,364,639
R^2	0.002	0.009	0.110	0.130
	Incident binary (mean = 0.137)			
$\mathbb{1}$[Foreign-born]	-0.028***	-0.041***	-0.035***	-0.031***
	(0.001)	(0.001)	(0.000)	(0.000)
N	9,420,259	9,420,259	9,420,259	9,417,848
R^2	0.001	0.060	0.151	0.196
Individual Controls	N	N	N	Y
Grade × Year FEs	Y	Y		
School × Grade × Year FEs			Y	Y

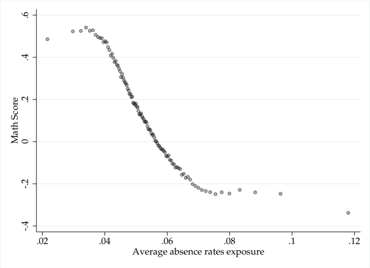
Individual controls include gender, age in months, special education. Standard errors are clustered at the cohort-school level.

Mechanism: Disruption

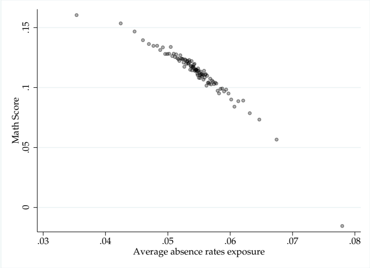
	Cumulative exposure to absence rates					
Foreign-born exp.	-0.001	-0.002**	-0.002***	-0.007***	-0.008***	-0.015***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Individual Controls	Y	Y	Y	Y	Y	Y
School × Year FEs	Y	Y	Y	Y	Y	Y
Grade × Year FEs	Y	Y	Y	Y	Y	Y
Race FEs	N	Y	Y			
Lunch Status	N	Y	Y			
Mother's Educ. FEs	N	N	Y			
Family FE				Y		
Family × Year FE					Y	Y
Exposure controls	N	N	N	N	N	Y
Observations	1,397,410	1,397,410	1,394,717	1,397,410	1,397,410	1,397,410
R^2	0.715	0.721	0.724	0.896	0.920	0.925
β	-0.004	-0.007	-0.008	-0.026	-0.028	-0.055

Exposure controls include cumulative exposures to black peers, asian, hispanic, LEP students, free or reduced price lunch students. Individual controls include gender, age in months, special education, birth order FEs. Standard errors are clustered at the cohort-school level.

Mechanism: Disruption

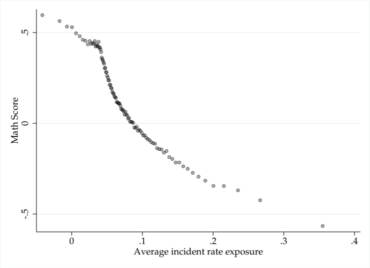


Conditional on year × grade

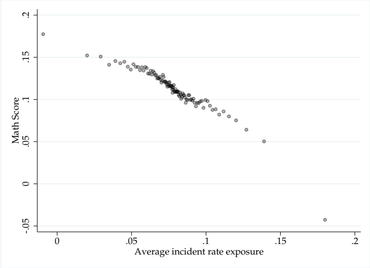


Conditional on year × grade and family

Mechanism: Disruption



Conditional on year × grade



Conditional on year × grade and family

Additional mechanisms to be explored

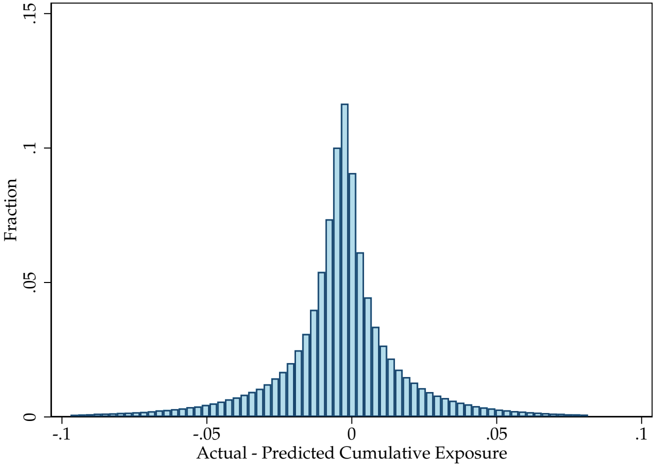
Does diversity also matter?

- Calculate measures of diversity, by race and country of origin
- Test whether they matter, in addition to the share, perhaps in a non-linear way

Conclusion

- We use within-family variation and a novel identification strategy to identify the impact of foreign-born exposure to native students' outcomes.
- We find that the effect is positive albeit somewhat small
- We provide evidence that the coefficient is mostly driven by low-SES and African-American students.
- Suggestive evidence of lower disruption as channel – positive shift to educational production function (à la Lazear, 2001)

Deviations



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Natives SES vs foreign-born SES

	Math standardized scores (3-10 grades)					
	Free or Reduced price lunch sub-population					
Foreign-born exp.	0.539***	0.382***	0.360***	0.385***	0.371***	0.501***
	(0.056)	(0.052)	(0.051)	(0.079)	(0.112)	(0.122)
Cumulative share of low-SES among foreign-born peers	-0.271***	-0.178***	-0.133***	-0.033***	-0.035***	-0.005
	(0.009)	(0.008)	(0.008)	(0.009)	(0.012)	(0.013)
N	667,360	667,360	665,613	667,360	667,360	667,360
R^2	0.259	0.288	0.302	0.639	0.744	0.744
	No reduced price sub-population					
Foreign-born exp.	-0.165**	-0.167**	-0.109*	-0.002	0.021	0.096
	(0.068)	(0.066)	(0.063)	(0.084)	(0.120)	(0.127)
Cumulative share of low-SES among foreign-born peers	-0.250***	-0.209***	-0.131***	-0.016*	-0.018	0.003
	(0.010)	(0.009)	(0.009)	(0.009)	(0.013)	(0.013)
N	579,622	579,622	578,897	579,622	579,622	579,622
R^2	0.218	0.234	0.269	0.677	0.771	0.772
Individual contr., S-Y, G-Y	Y	Y	Y	Y	Y	Y
Race FEs	N	Y	Y			
Mother's Educ. FEs	N	N	Y			
Family FE				Y		
Family × Year FE					Y	Y
Exposure controls	N	N	N	N	N	Y

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Summary Statistics

	Mean	Median	SD
Free/Reduced price lunch	0.54	–	–
Female	0.50	–	–
Special Education	0.14	–	–
White	0.60	–	–
Black	0.28	–	–
Hispanic	0.07	–	–
Mother's years of schooling	–	12	–
Age in months	138.59	137	25.23
% Black exposure	0.24	0.16	0.24
% Hispanic exposure	0.19	0.14	0.18
% Asian exposure	0.02	0.02	0.02
% LEP exposure	0.05	0.03	0.07
% Free/Red. p. lunch exposure	0.55	0.56	0.24

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