Immigration, Innovation, and Growth

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Motivation

- Immigration may cause innovation, economic dynamism, and income growth through theoretical channels including new ideas, more effort, or rising demand.
- Immigration is also the focus of major political controversies in many countries.
- Does immigration in fact cause local innovation, dynamism, and income growth?

A key challenge for identification:
Omitted factors jointly determine immigration, innovation, dynamism, and growth.

Our approach:

- Isolate plausibly exogenous **immigration shocks** using 130 years of data from the U.S. census.

Main Findings

1. Plausibly exogenous immigration causes an increase in local innovation, local economic dynamism, and local wage growth.
2. The impact of immigration on innovation increases significantly with immigrants' schooling level.
3. The impact of immigration spills over positively across local areas but weakens with distance.

Literature

Outline

Data

Identification and Historical Background

The Impact of Immigration

Education and Spillovers

Data

- **Immigration and Ancestry**
  - IPUMS datasets from US Census, 1880-2010:

$$I^t_{o,d} = \# \text{ individuals in US county } d \text{ born in foreign country } o \text{ who immigrated between } t \text{ and } t-1.$$
$$A^t_{o,d} = \# \text{ of individuals in } d \text{ with } o \text{ ancestry at time } t$$

- **Innovation**
  - USPTO Patent Microdata 1975-2010: number of successful patent applications in county d between time $t-1$ and t
- **Dynamism**
  - Census Business Dynamics Statistics, 1977-2015: employment reallocation, destruction, creation, & growth rates
  - Census County Business Patterns, 1985-2015: skewness of employment growth rates across industries
- **Wages**
  - BLS Quarterly Census of Empl. and Wages, 1975-2010: wages per worker in county d at time t

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Identification: The Problem

Equation of interest:

$$Y_d^t - Y_d^{t-1} = \delta_t + \delta_s + \beta Immigration_d^t + \epsilon_d^t$$

- Migrants are likely drawn to places that are innovative.
  $\rightarrow$ OLS biased: $cov(Immigration_d^t, \epsilon_d^t) \neq 0$. Need instrument!

- Could use Altonji and Card (1991)-type instrument.

$$Immigration_{o,d}^t = \alpha + \gamma Ancestry_{o,d}^{t-1} \times Immigration_o^t + \nu_{o,d}^t$$

- But: Ancestry patterns likely correlated with unobserved factors linked to innovation (e.g.: Indian engineers in Silicon Valley).

$\Rightarrow$ Combine Altonji-Card-type instrument with an instrument for ancestry composition of US counties (Burchardi, Chaney, Hassan, 2018).

Construct an Instrument for I_d^t in 3 steps

$$\hat{A}_{o,d}^{t}$$

Step 1 **Construct an instrument for ancestry o in US county d at time t exclusively using historical push-pull factors**.

Step 2 Use this exogenous variation in Ancestry to fit a recursive model of migration (similar to Altonji-Card shift-share).

Step 3 Sum predicted immigration across origins to isolate an exogenous immigration shock to county d at time t.

Construct an Instrument for I_d^t in 3 steps

$$I_{o,d}^t = X_{o,d}'\xi + \gamma \hat{A}_{o,d}^{t-1} \times I_o^t + \nu_{o,d}^t$$

Step 1 Construct an instrument for ancestry o in US county d at time t exclusively using historical push-pull factors.

Step 2 **Use this exogenous variation in Ancestry to fit a recursive model of migration** (similar to Altonji-Card shift-share).

Step 3 Sum predicted immigration across origins to isolate an exogenous immigration shock to county d at time t.

Construct an Instrument for I_d^t in 3 steps

$$\hat{I}_d^t = \sum_o [\hat{\gamma} \hat{A}_{o,d}^{t-1} \times I_o^t]$$

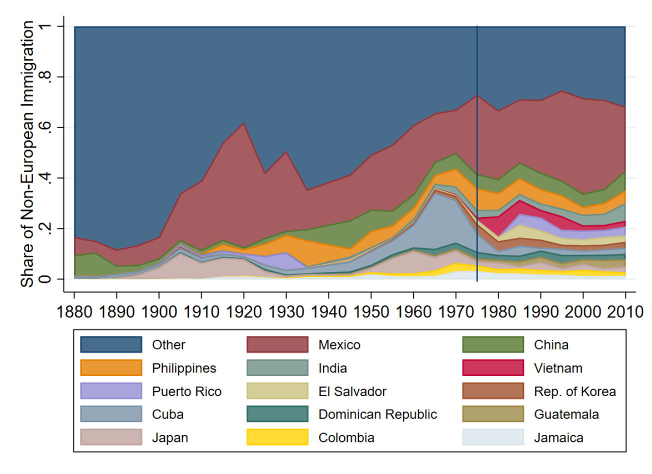
Step 1 Construct an instrument for ancestry o in US county d at time t exclusively using historical push-pull factors.

Step 2 Use this exogenous variation in Ancestry to fit a recursive model of migration (similar to Altonji-Card shift-share).

Step 3 **Sum predicted immigration across origins to isolate an exogenous immigration shock to county d at time t.**

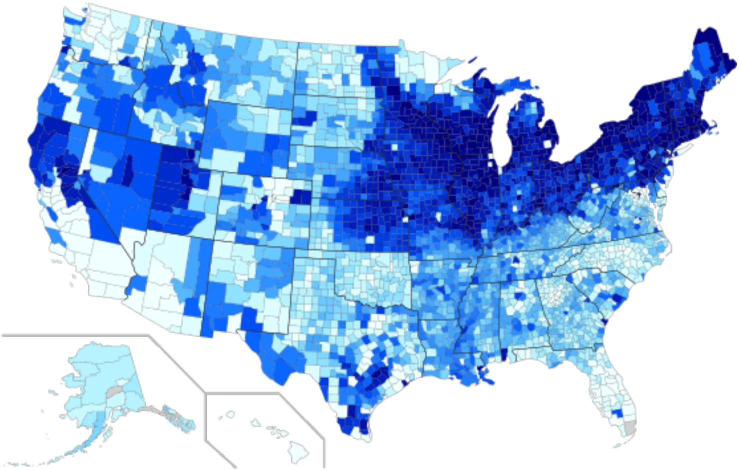
Step 1 Push: Origins of Immigrants to the U.S.

Top non-European origin countries

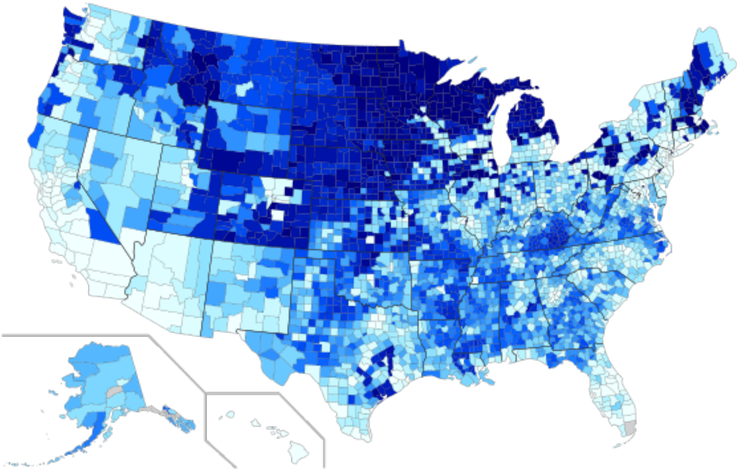


Notes: The figure shows the share of non-European immigration by origin country, breaking out migrants from the largest senders of migrants to the U.S. overall.

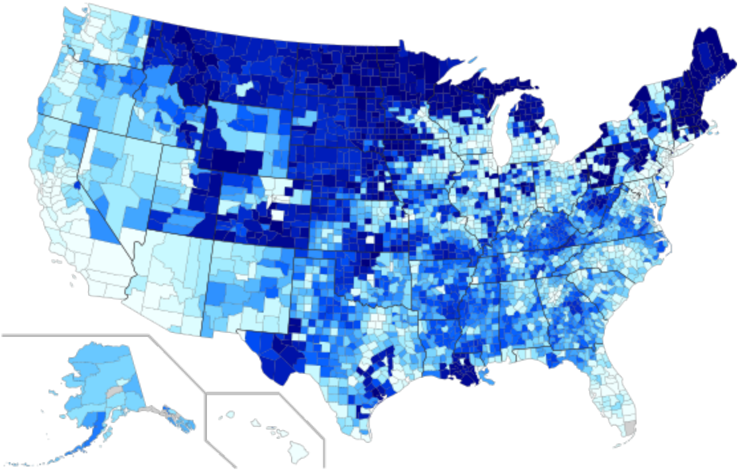
Step 1 Pull: Destinations of Immigrants Pre 1880



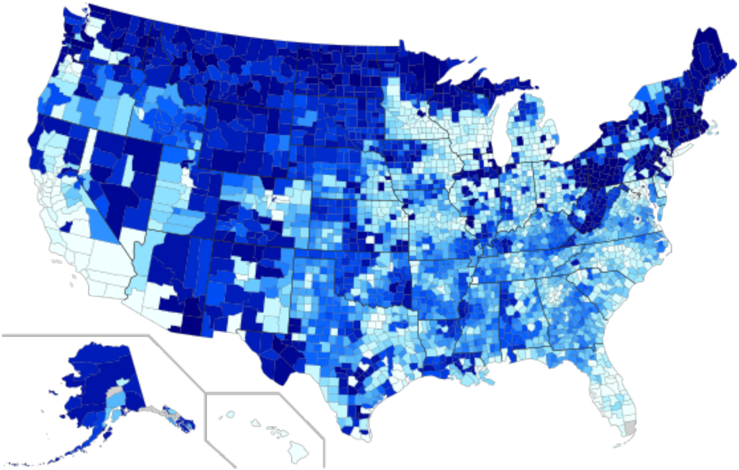
Step 1 Pull: Destinations of Immigrants 1880-1890



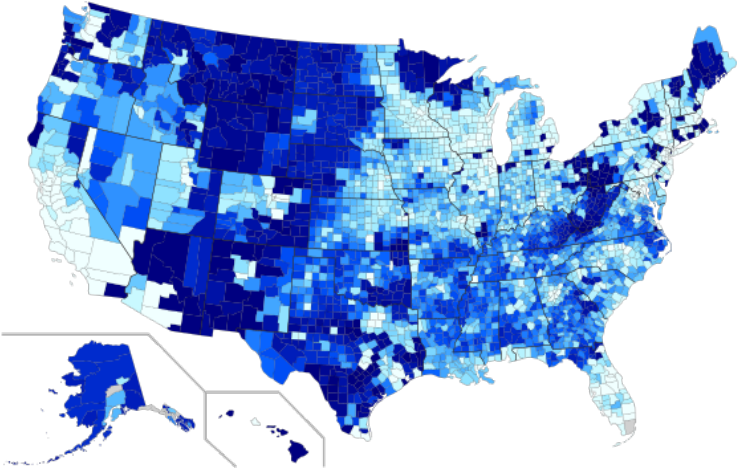
Step 1 Pull: Destinations of Immigrants 1890-1900



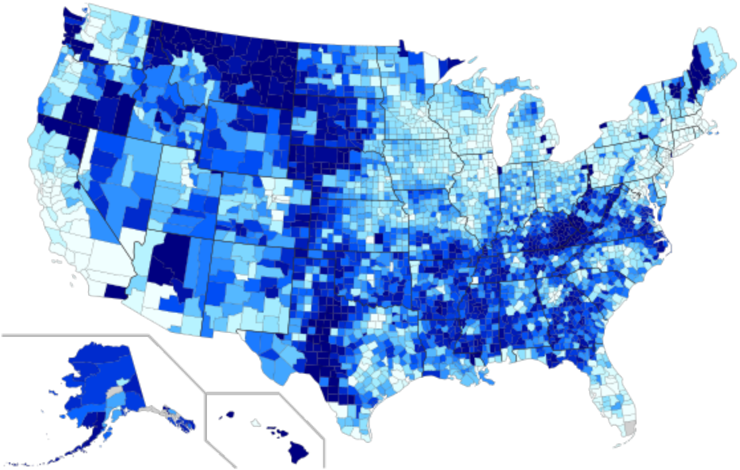
Step 1 Pull: Destinations of Immigrants 1900-1910



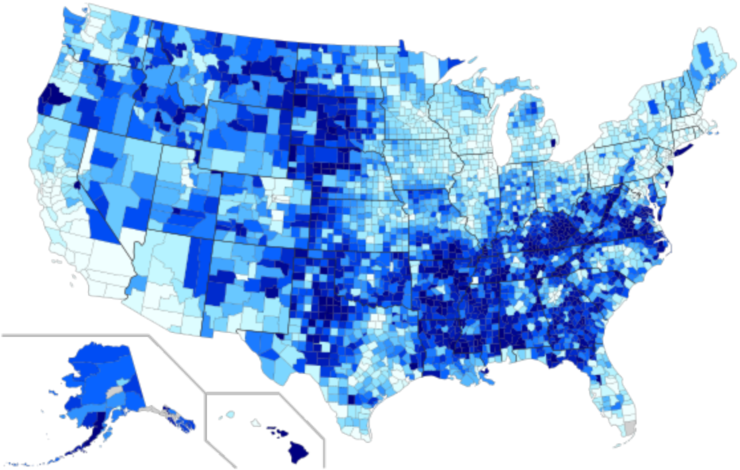
Step 1 Pull: Destinations of Immigrants 1910-1920



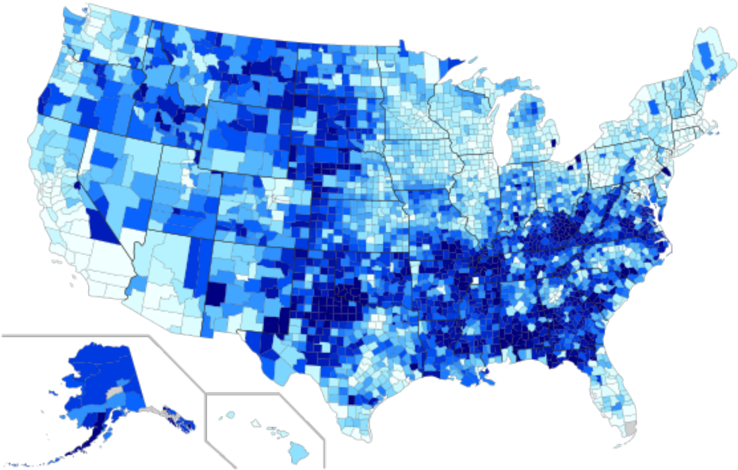
Step 1 Pull: Destinations of Immigrants 1920-1930



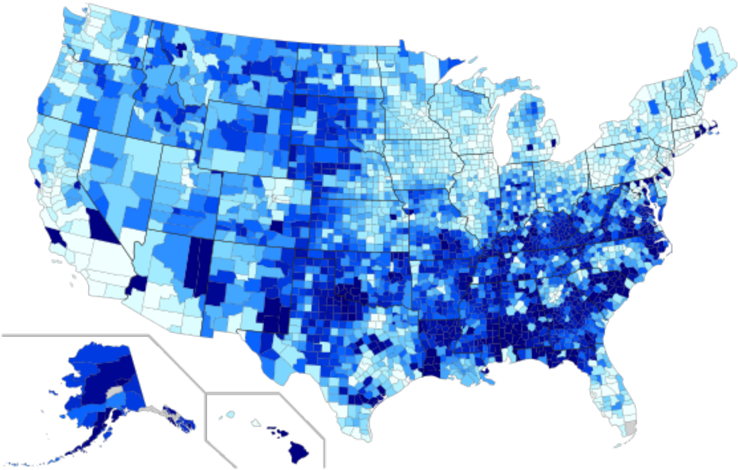
Step 1 Pull: Destinations of Immigrants 1930-1950



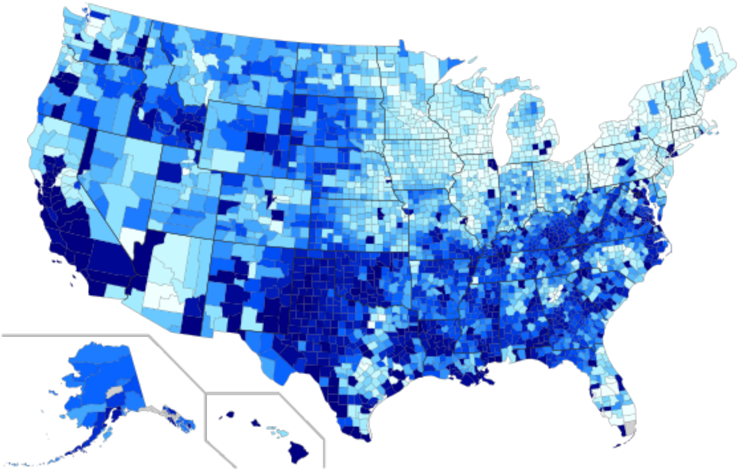
Step 1 Pull: Destinations of Immigrants 1950-1960



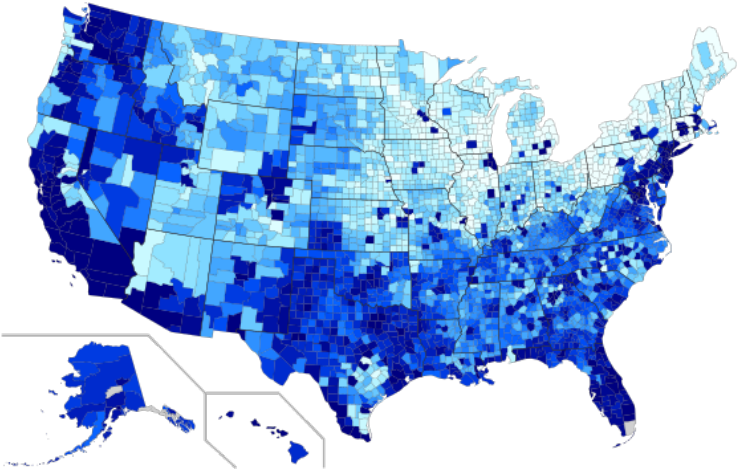
Step 1 Pull: Destinations of Immigrants 1960-1970



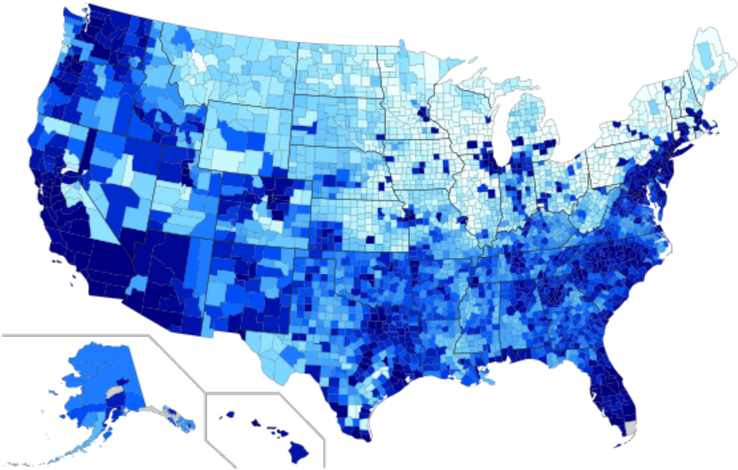
Step 1 Pull: Destinations of Immigrants 1970-1980



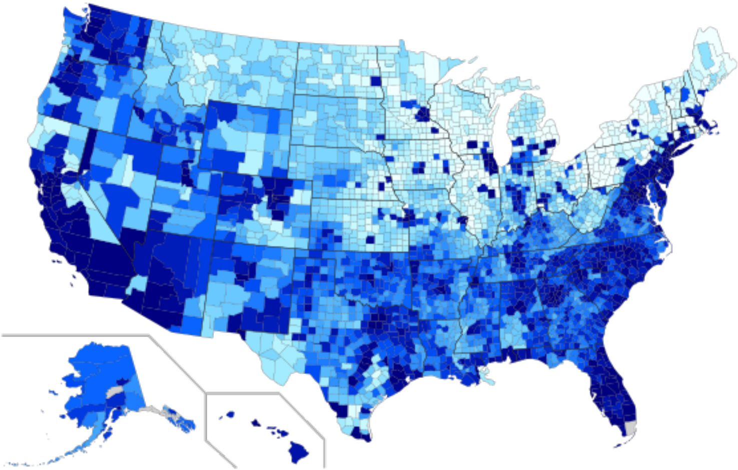
Step 1 Pull: Destinations of Immigrants 1980-1990



Step 1 Pull: Destinations of Immigrants 1990-2000



Step 1 Pull: Destinations of Immigrants 2000-2010



Estimation + Results

First Stage:

$$Immigration_d^t = \delta_s + \delta_t + \kappa \hat{I}_d^t + \eta_d^t$$

where δ_s and δ_t are state and time fixed effects, respectively.

Second Stage:

$$Y_d^t - Y_d^t = \delta_s + \delta_t + \beta \widehat{Immigration}_d^t + \epsilon_d^t$$

where Y_d^t is a measure of innovation or dynamism.

Details

Identifying Assumption

Any confounding factors that correlate with increases in a given county's innovation or dynamism post-1975 do not also correlate systematically with past instances of the interaction of the settlement of European migrants with the total number of migrants arriving from a set of non-European origins who settle in other US census regions and modern immigration from those non-European origins to other US census regions.

So a confounding factor causing, say, Indian migration to Silicon Valley (Santa Clara County) in 2010 **must also systematically correlate with**

- historical Indian migration to **other** Census divisions
- historical **European** migration to Silicon Valley, repeatedly across decades and in large-enough numbers to sway averages
- 2010 Indian migration to **other** Census divisions.

It could also **not reflect**

- **Silicon Valley-specific** average innovation or immigration levels,
- **Silicon Valley-specific** trends in innovation or immigration,
- or **any common** shifts across counties in 2010.

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Immigration's Effect on Innovation

	(1)	(2)	(3)
	5-Year Difference in Patenting per 100,000 People		
Immigration_d^t	0.167**	0.101***	0.108***
	(0.080)	(0.031)	(0.033)
N	18,846	18,846	18,846
First Stage			
$\widehat{Immigration}_d^t$		2.100***	1.580***
		(0.061)	(0.196)
N		21,987	21,987
F-Stat		1,202	65
R^2		0.777	0.947
Specification	OLS	IV	IV
Geography FE	State	State	County
Time FE	Yes	Yes	Yes

Standard errors clustered by state and *,**, and *** denote statistical significance of 10%, 5%, and 1%, respectively.

- 12K more migrants, about 1 SD, leads to 27% rise in innovation relative to mean growth

Alt. Robustness Controls Step 1, Time Step 1, County Step 2, O-D Step 3, Map

Immigration's Effect on Dynamism & Wage Growth

5-Year Difference in:	*Job Creation Rate*	*Job Destruction Rate*	*Job Growth Rate Skewness*	*Average Annual Wage*
	(1)	(2)	(3)	(4)
Immigration_d^t	0.176***	0.152***	0.019***	0.008***
	(0.033)	(0.035)	(0.004)	(0.002)
N	6,600	6,600	12,564	21,976
First Stage F-Stat	951	951	151	1,202
Controls:				
Geography FE	State	State	State	State
Time FE	Yes	Yes	Yes	Yes

Notes: Standard errors are clustered by state and *,**, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

- 12K more migrants, 1 SD, causes rise relative to mean change of: 7% in job creation, 11% in job destruction, 3% in job growth skewness, and 5% in wages

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Education and Spillovers

Spillovers

	5-Year Difference in Patenting per 100,000 People			
	(1)	(2)	(3)	(4)
Immigration^t_d	0.130***	0.107***	0.072**	0.080**
	(0.039)	(0.035)	(0.032)	(0.037)
$\text{Immigration}^t_{State}$		0.001***		
		(0.000)		
Neighbors' Immigration^t_d (Inverse Distance Weight)			6.600***	
			(1.593)	
$\text{Immigration}^t_{100km}$				0.056***
				(0.018)
$\text{Immigration}^t_{250km}$				0.014***
				(0.005)
$\text{Immigration}^t_{500km}$				0.006
				(0.005)
N	18,846	18,846	18,846	18,846
First Stage F-Stat d	876	1,792	2,175	6,065
First Stage F-Stat Spillover		470	162	383
First Stage F-Stat Spillover				150
First Stage F-Stat Spillover				66
Controls: Division, Year FE				

Standard errors clustered by state and *,**, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

1 SD more migrants increase innovation relative to mean by:

- 29% for local migrants (within county)
- 31% for nearby migrants (in other counties in the same state)

Education & Immigration's Effect on Innovation

	5-year Difference in Patenting per 100,000 People			
	(1)	(2)	(3)	(4)
Immigration_d^t	0.165***	0.200***	0.415***	
	(0.002)	(0.070)	(0.076)	
$\text{Average Years Education}_d^t \times \text{Immigration}_d^t$		0.221***		
		(0.068)		
$\text{Average Years College}_d^t \times \text{Immigration}_d^t$			0.887***	
			(0.166)	
$\mathbf{1}\{\text{Low Avg. Years Education}\} \times \text{Immigration}_d^t$				1.863
				(4.539)
$\mathbf{1}\{\text{Medium Avg. Years Education}\} \times \text{Immigration}_d^t$				0.084*
				(0.044)
$\mathbf{1}\{\text{High Avg. Years Education}\} \times \text{Immigration}_d^t$				1.401*
				(0.792)
N	18,846	18,846	18,846	18,846
First Stage F-Stat	1,000,642	871,892	154,901	1,041
First Stage F-Stat		49,425	4,563	1,242,524
First Stage F-Stat				3,242
Controls: State, Year FE				

Standard errors clustered by state and *,**, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

10K more migrants increase patenting per person by

- 2 patents per 100K people if mean education (11 yrs)
- 9 patents per 100K people if 1-SD higher education (14.5 yrs)

Details

Conclusion

- We study the impact of immigration on innovation, dynamism, and growth at the local level.
- Plausibly exogenous shocks to immigration at the county level in the US over 1975-2010 provide substantial power for examining overall immigration flows during this period.
- We find that more immigration leads to
  - More innovation or patents per person
  - More dynamism or creative destruction
  - Higher wages per person
- More highly educated immigrants boost innovation by more.
- Immigration causes positive spillovers to other nearby areas.

BACKUP SLIDES

Contribution

- Endogenous growth & innovation mechanisms
  Aghion & Howitt 1992, Romer 1990, Peretto 1998, Young 1998, Jones 1995, Jones, et al. 2017

  → Test short-term reduced-form predictions at county level

- Empirical work on declining dynamism in the US economy
  Decker, et al. 2014, Hathaway and Litan 2014, Alon, et al. 2018, Hopenhayn, et al. 2018, Karahan, et al. 2016

  → Bring an identification strategy and a link to immigration

- Empirical work on the effects of immigration
  Altonji & Card 1991, Borjas 1999, Sequeira, Nunn, & Qian 2018, Akcigit, et al. 2017, Peters 2017

  → Identify effects on local innovation, dynamism, and income growth.

Return

Step 1: An Instrument for Ancestry

Regress ancestry on interacted push and pull factors

$$A^t_{o,d} = \delta_{o-r(d)} + \delta_{c(o)-d} + X'_{o,d}\xi + \sum_{s=1880}^{t} \beta^s_{r(d)} \tilde{I}^s_{o,-r(d)} \frac{I^s_{Euro,d}}{I^s_{Euro}} + u^t_{o,d}$$

To make sure all $o-d$ specific variation is purged:

- Broad leave-out categories:
  - Measure pull factor to d at time t with the share of migrants arriving at the same time from Europe in d.
  - Measure push factor from o at time t with the number of migrants leaving at the same time from o to other census regions $(-r(d))$.
- Interacted fixed effects.
- Orthogonalize predicted ancestry with respect to controls.

Construct an Instrument for I_d^t in 3 steps

Step 1 Construct Instrumented Ancestry as

$$\hat{A}_{o,d}^{t-1} = \sum_{\tau=1880}^{t-1} \hat{\beta}_{r(d)}^{\tau} \left(\tilde{I}_{o,-r(d)}^{\tau} \frac{I_{Euro,d}^{\tau}}{I_{Euro}^{\tau}} \right)^{\perp}$$

Step 2 Use this exogenous variation in Ancestry to fit a recursive model of migration (similar to Altonji-Card shift-share).

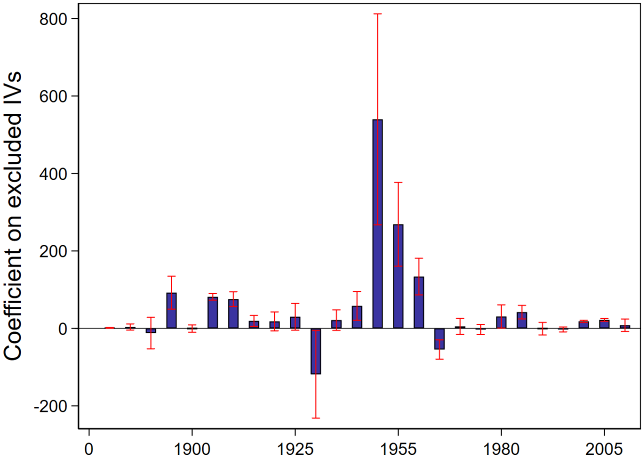
$$I_{o,d}^{t} = X'_{o,d}\beta + \gamma[\hat{A}_{o,d}^{t-1} \times \tilde{I}_{o,-r(d)}^{t}] + \nu_{o,d}^{t}$$

Step 3 Sum predicted immigration across origins to isolate an exogenous immigration shock to county d at time t.

$$\hat{I}_{d}^{t} = \sum_{o} \hat{\gamma}[\hat{A}_{o,d}^{t-1} \times \tilde{I}_{o,-r(d)}^{t}].$$

Return

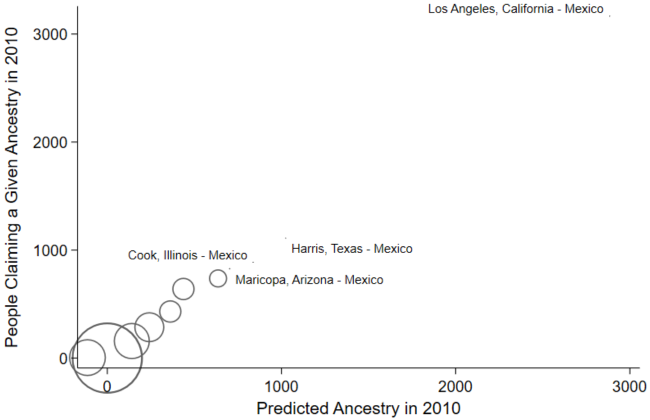
Step 1: Effect of historical push-pull on Ancestry today



Notes: Red lines give 95% confidence intervals. Standard errors are clustered at the origin country level. (F-stat 32,645.9)

Return

Step 1: Fit of Predicted Ancestry



Notes: This figure plots actual ancestry in 2010 against predicted ancestry, with the size of each circle indicating the log number of observations in a given bin of predicted ancestry. The labeled counties are those with the highest number of individuals declaring a given ancestry in 2010.

Return

Step 2: Predicting Origin-by-Destination Immigration

	$Immigration^{t}_{o,d}$				
	(1)	(2)	(3)	(4)	(5)
$\hat{A}^{1975}_{o,d} \times \tilde{I}^{1980}_{o,-r(d)}$	0.0036***	0.0036***	0.0035***	0.0035***	0.0035***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\hat{A}^{1980}_{o,d} \times \tilde{I}^{1985}_{o,-r(d)}$	0.0016***	0.0016***	0.0016***	0.0016***	0.0016***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\hat{A}^{1985}_{o,d} \times \tilde{I}^{1990}_{o,-r(d)}$	0.0018***	0.0018***	0.0018***	0.0018***	0.0018***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\hat{A}^{1990}_{o,d} \times \tilde{I}^{1995}_{o,-r(d)}$	0.0005***	0.0005***	0.0005***	0.0005***	0.0005***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\hat{A}^{1995}_{o,d} \times \tilde{I}^{2000}_{o,-r(d)}$	0.0004***	0.0004***	0.0004***	0.0004***	0.0004***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\hat{A}^{2000}_{o,d} \times \tilde{I}^{2005}_{o,-r(d)}$	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\hat{A}^{2005}_{o,d} \times \tilde{I}^{2010}_{o,-r(d)}$	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$I^{t}_{Euro,d}$					0.0109***
					(0.0031)
N	3,583,881	3,583,881	3,583,881	3,583,881	3,583,881
F-Stat	1.35e+06	1.36e+06	3.55e+05	3.55e+05	3.39e+05
R^2	0.656	0.657	0.709	0.709	0.709
Controls:					
Distance	no	yes	yes	yes	yes
Latitude Dis.	no	yes	yes	yes	yes
Region-Country FE	no	no	yes	yes	yes
County-Continent FE	no	no	yes	yes	yes
Time FE	no	no	no	yes	yes
Concurrent European Immigration	no	no	no	no	yes

Notes: Standard errors are clustered by country and *,**, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Return

Alternatives: Immigration's Effect on Innovation

Specification:	*OLS Specification*	*Card Instrument*	*Baseline Instrument*	*Ancestry in 1975 Only*	*Leave-Out Correlated Counties*	*Leave-Out Own Continent*
	(1)	(2)	(3)	(4)	(5)	(6)
	5-year Difference in Patenting per 100,000 People Post-1980					
Immigration$_d^t$	0.167**	0.132**	0.101***	0.093***	0.098***	0.094***
	(0.080)	(0.055)	(0.031)	(0.027)	(0.033)	(0.027)
N	18,846	18,846	18,846	18,846	18,846	18,846
Geography FE	state	state	state	state	state	state
Time FE	yes	yes	yes	yes	yes	yes

Notes: Standard errors are clustered by state and *,**, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Return

Robustness: Immigration's Effect on Innovation

	5-year Difference in Patenting per 100,000 People Post-1980				
	(1)	(2)	(3)	(4)	(5)
Excluding:	*Mexico*	*China*	*India*	*Philippines*	*Vietnam*
Immigration$_d^t$	0.080***	0.102***	0.101***	0.100***	0.101***
	(0.025)	(0.032)	(0.031)	(0.031)	(0.031)
N	18,846	18,846	18,846	18,846	18,846
First Stage F-Stat	666	1,576	1,267	1,261	1,179
Controls:					
Geography FE	state	state	state	state	state
Time FE	yes	yes	yes	yes	yes

Notes: Standard errors are clustered by state and *,**, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Return

Bad Controls: Immigration's Effect on Innovation

	5-year Difference in Patents per 100,000 People for 1980 to 2010					
	(1)	(2)	(3)	(4)	(5)	(6)
Immigration$_d^t$	0.101***	0.102***	0.100***	0.092***	0.082***	0.108***
	(0.031)	(0.032)	(0.031)	(0.029)	(0.027)	(0.033)
Population Density (1970)		-0.001				
		(0.004)				
Patents per 1,000 People (1975)			0.089**			
			(0.042)			
Share High School Education (1970)				27.821**		
				(11.059)		
Share 4+ Years College (1970)					103.990***	
					(29.961)	
N	18,846	18,846	18,846	18,846	18,846	18,846
First Stage F-Stat	911	1,658	911	945	1,017	85
Controls:						
Geography FE	state	state	state	state	state	county
Time FE	yes	yes	yes	yes	yes	yes

Notes: Standard errors are clustered by state and *,**, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Return

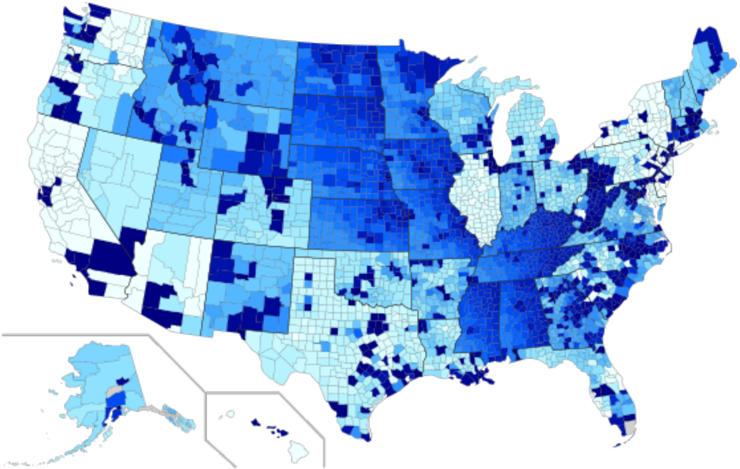
Education & Immigration's Effect on Innovation

Generalize IV to instrument separately for effect of education.

- Use the fact that education levels vary dramatically across origins and over time.
  - Use as instruments country-county migration shocks ($\hat{I}^{t}_{o,d}$) generated in Step 2.
- Run a regression with two endogenous variables:
  1. **Immigration**: number of adult migrants to county d in t
  2. **Education**: total number of years of education of adult migrants to d in t

Results

Step 3: Immigration Shock $\hat{I}_d^{1980}$



Later Years Return

First-stage: County-Level Population Growth

	5-Year Population Growth			
	(1)	(2)	(3)	(4)
$\widehat{Immigration}_d^t$	1.890***	1.890***	1.818***	1.767***
	(0.168)	(0.190)	(0.180)	(0.157)
N	21,986	21,986	21,986	6,600
F-Stat	127	99	102	126
R^2	0.233	0.272	0.314	0.370
Controls:				
Geography FE	no	division	state	state
Time FE	no	yes	yes	yes
MSA Counties	no	no	no	yes

Notes: Standard errors are clustered by state and *,**, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Second Stage: Effect of Immigration and Population Growth on Innovation

	5-year Difference in Patenting per 100,000 People Post-1980			
	(1)	(2)	(3)	(4)
Immigration_d^t	0.167**	0.101***		
	(0.080)	(0.031)		
Δ Population_d^t			0.223***	0.113***
			(0.066)	(0.030)
N	18,846	18,846	18,846	18,846
Controls:				
Specification	OLS	IV	OLS	IV
Geography FE	state	state	state	state
Time FE	yes	yes	yes	yes

Notes: Standard errors are clustered by state and *,**, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Education & Immigration's Effect on Wage Growth

	5-year Difference in Average Annual Wage ($1,000) Post-1975			
	(1)	(2)	(3)	(4)
Immigration_d^t	0.028**	0.034***	0.053***	
	(0.011)	(0.007)	(0.013)	
$\text{Average Years Education}_d^t \times \text{Immigration}_d^t$		0.029***		
		(0.006)		
$\text{Average Years College}_d^t \times \text{Immigration}_d^t$			0.089***	
			(0.020)	
$\mathbf{1}\{\text{Low Avg. Years Education}\} \times \text{Immigration}_d^t$				-0.013
				(0.015)
$\mathbf{1}\{\text{Medium Avg. Years Education}\} \times \text{Immigration}_d^t$				0.019**
				(0.008)
$\mathbf{1}\{\text{High Avg. Years Education}\} \times \text{Immigration}_d^t$				0.200***
				(0.066)
N	21,976	21,976	21,976	21,976
First Stage F-Stat	284,264	209,169	42,824	100,244
First Stage F-Stat		31,561	7,266	192,212
First Stage F-Stat				2,734
Geography FE	state	state	state	state
Time FE	yes	yes	yes	yes

Notes: Standard errors are clustered by state and *,**, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Spillovers in Immigration's Effect on Wage Growth

	5-year Difference in Patenting per 1,000 People Post-1980			
	(1)	(2)	(3)	(4)
Immigration_d^t	0.010***	0.009***	0.005***	0.005***
	(0.002)	(0.003)	(0.001)	(0.002)
$\text{Immigration}_{State}^t$		0.000		
		(0.000)		
Neighbors' Immigration_d^t (Inverse Distance Weight)			0.560***	
			(0.191)	
$\text{Immigration}_{100km}^t$				0.006***
				(0.002)
$\text{Immigration}_{250km}^t$				-0.001
				(0.001)
$\text{Immigration}_{500km}^t$				-0.000
				(0.001)
N	21,976	21,976	21,976	21,976
First Stage F-Stat d	1,166	2,289	3,482	7,967
First Stage F-Stat Spillover		434	165	395
First Stage F-Stat Spillover				157
First Stage F-Stat Spillover				67
Geography FE	division	division	division	division
Time FE	yes	yes	yes	yes

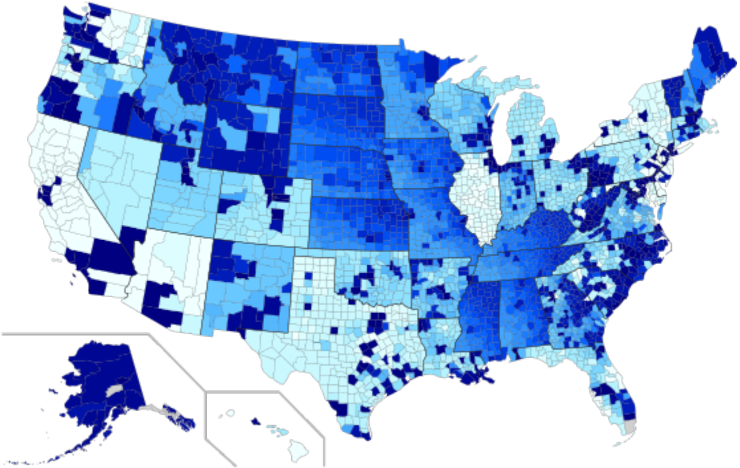
Notes: Standard errors are clustered by state and *,**, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Growth Models and Population Change

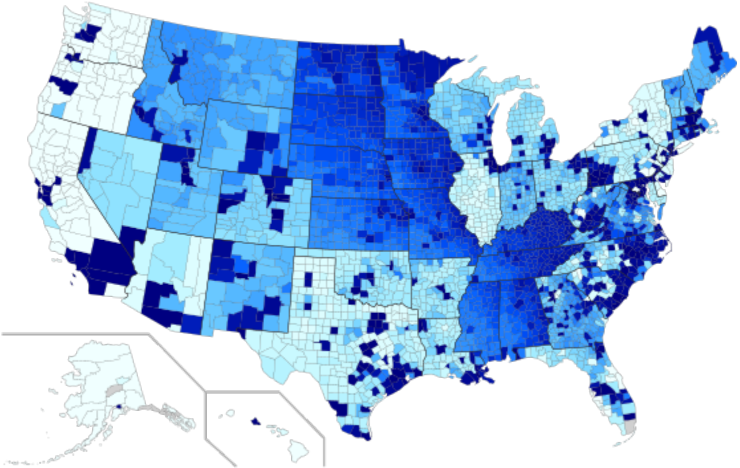
	Difference in Patenting per 100,000 People Post-1980		Patenting per 100,000 People Post-1975		IHS of Patents Post-1975			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Immigration_d^t	0.101***	0.509***	0.501**	2.505***	0.028***			
	(0.031)	(0.090)	(0.190)	(0.268)	(0.011)			
$\text{sq}(\text{Immigration}_d^t)$		-0.001***		-0.004***				
		(0.000)		(0.000)				
$\Delta\ \text{Population}_d^t$						0.033***		
						(0.012)		
$\text{IHS}(\text{Immigration}_d^t)$							1.723***	
							(0.111)	
$\text{IHS}(\Delta\ \text{Population}_d^t)$								2.471***
								(0.510)
N	18,846	18,846	21,987	21,987	21,987	21,986	21,987	21,986
First Stage F-Stat	911	95	1,202	102	1,202	102	94	16
First Stage F-Stat		11,231		11,879				
Controls:								
Geography FE	state	state	state	state	state	state	state	state
Time FE	yes	yes	yes	yes	yes	yes	yes	yes

Notes: Standard errors are clustered by state and *,**, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

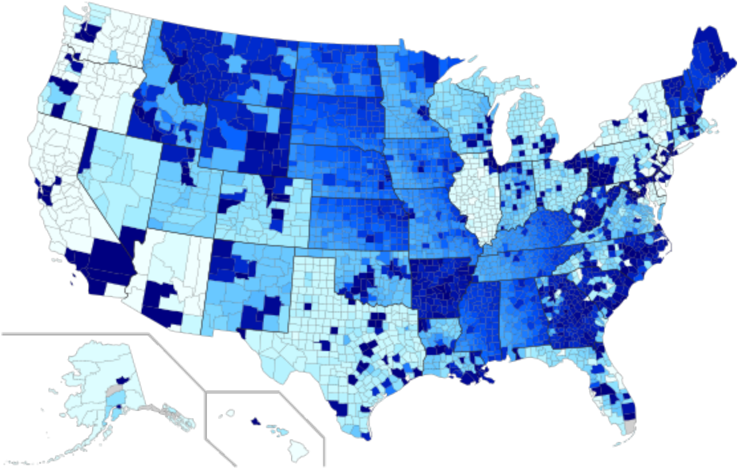
Immigration Shock for the 5-year Period Ending in 1985



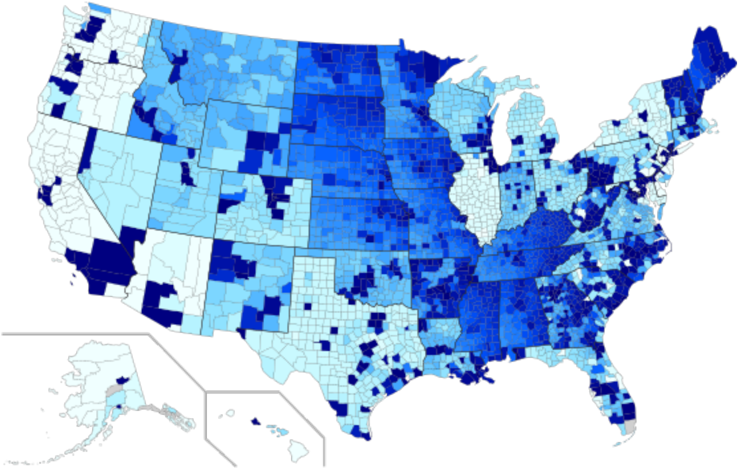
Immigration Shock for the 5-year Period Ending in 1990



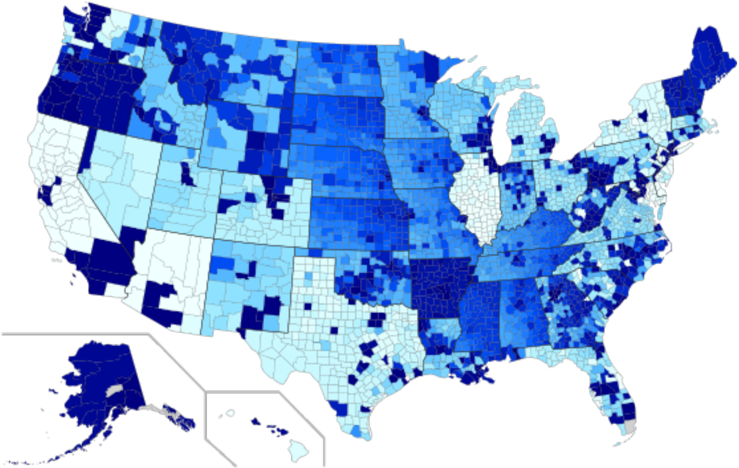
Immigration Shock for the 5-year Period Ending in 1995



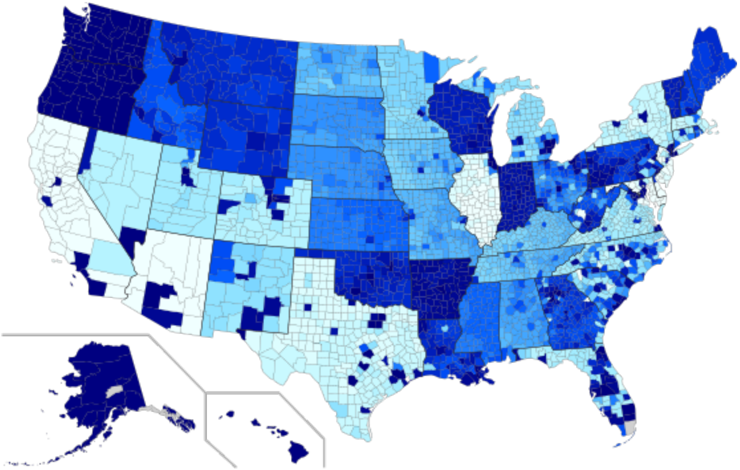
Immigration Shock for the 5-year Period Ending in 2000



Immigration Shock for the 5-year Period Ending in 2005



Immigration Shock for the 5-year Period Ending in 2010



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