Immigration, Innovation, and Growth

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Motivation

- Canonical models suggest immigration (and population growth) should cause innovation, economic dynamism, and growth through new ideas, more effort, higher demand.
- Immigration is also the focus of major political controversies.
- Does immigration cause local economic dynamism, innovation, and growth?

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

Our approach:

 Isolate plausibly exogenous immigration shocks to US counties using 130 years of census data.



Identification: The Problem

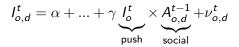
Equation of interest:

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

- ▶ But: Migrants are likely drawn to places that are innovative.
- \rightarrow OLS biased: $cov(I_d^t, \epsilon_d^t) \neq 0$. Need instrument.
 - Conventional Card (2001)-type instrument: interaction of 'push factor' with 'social pull' factor in migration

$$I_{o,d}^{t} = \alpha + \ldots + \gamma \underbrace{I_{o}^{t}}_{\text{push}} \times \underbrace{A_{o,d}^{t-1}}_{\text{social}} + \nu_{o,d}^{t}$$

- But: Ancestry patterns likely correlated with unobserved factors linked to innovation (e.g.: Indian engineers in Silicon Valley).
- ⇒ Instrument Ancestry with historical interactions of push and economic pull factors. (Burchardi-Chaney-Hassan'19)



- Add economic pull factor: Migrants choose destinations that are attractive to the average migrant arriving at the time.
- The stock of ancestry cumulates as a function of historical immigration flows. Iterate to solve.
- ⇒ Instrument Ancestry with historical interactions of push and economic pull factors.
- ▶ To be extra safe, use broad leave-out categories, e.g.
- Push: all migrants leaving o but settling in another region
- Pull: fraction of European migrants settling in d

$$I_{o,d}^{t} = \alpha + \underbrace{I_{o}^{t}}_{\text{push}} \times (\theta \underbrace{I_{d}^{t}/I^{t}}_{\text{economic}} + \gamma \underbrace{A_{o,d}^{t-1}}_{\text{social}}) + \nu_{o,d}^{t}$$

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$$A_{o,d}^{t} = \dots + \sum_{\tau=1880}^{t} \beta^{\tau} \underbrace{I_{o}^{\tau}}_{\text{push economic}} \underbrace{I_{d}^{\tau}/I^{\tau}}_{\text{economic}} + u_{o,d}^{t}$$

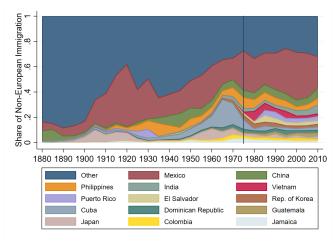
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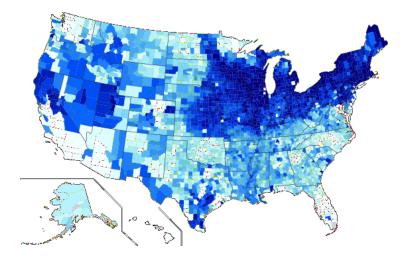
Push Factor

Top non-European origin countries

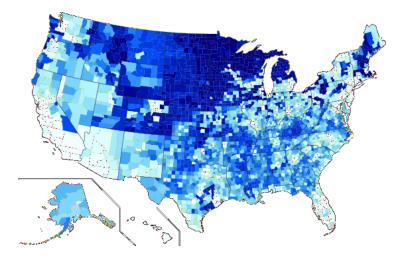


Notes: The figure shows the share of non-European immigration by origin country, breaking out migrants from the largest senders of migrants to the U.S. overall.

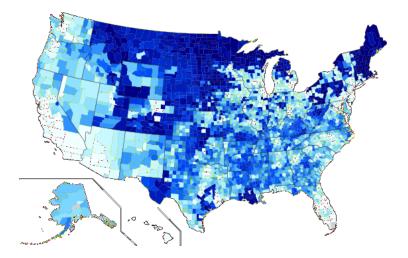
Destinations of Immigrants Pre 1880



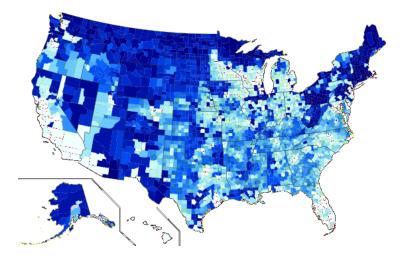
Destinations of Immigrants 1880-1890



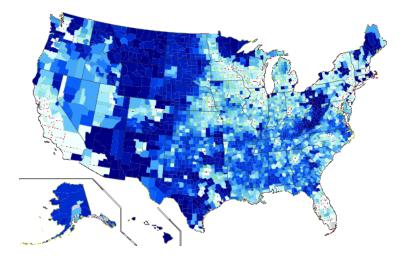
Destinations of Immigrants 1890-1900



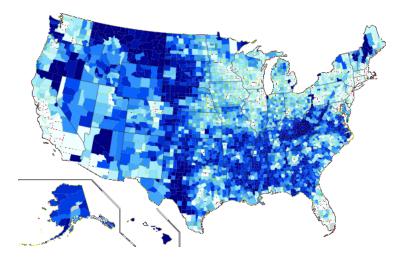
Destinations of Immigrants 1900-1910



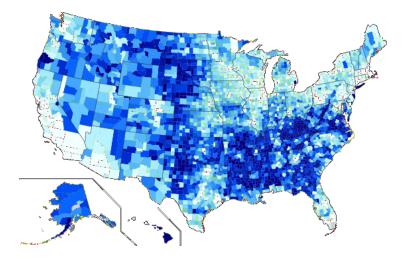
Destinations of Immigrants 1910-1920



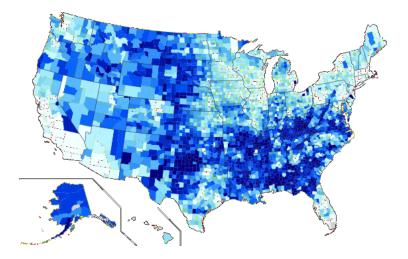
Destinations of Immigrants 1920-1930



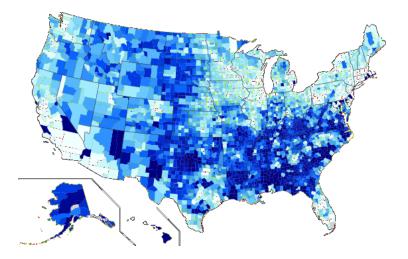
Destinations of Immigrants 1930-1950



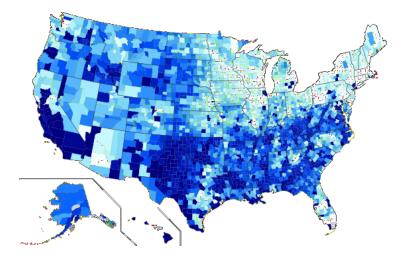
Destinations of Immigrants 1950-1960



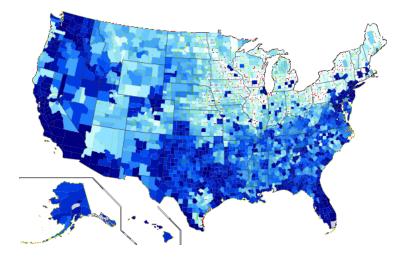
Destinations of Immigrants 1960-1970



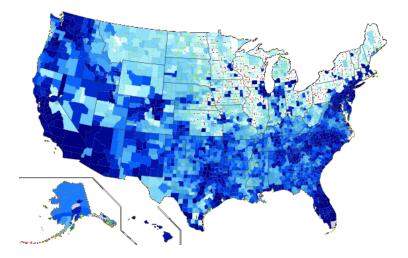
Destinations of Immigrants 1970-1980



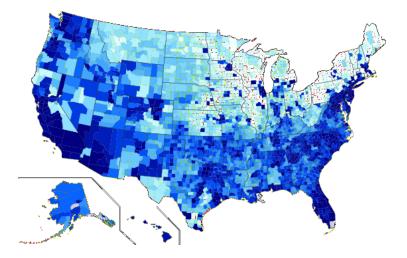
Destinations of Immigrants 1980-1990



Destinations of Immigrants 1990-2000



Destinations of Immigrants 2000-2010



Construct an Instrument for I_d^t in 3 steps

Step 1 Construct instrumented ancestry as

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

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

$$I_{o,d}^{t} = X_{o,d}^{\prime}\beta + \gamma [\hat{A}_{o,d}^{t-1} \times \tilde{I}_{o,-r(d)}^{t}] + \nu_{o,d}^{t}$$

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

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

Instrument Construction: Step 2

	Immigration ^t _{o,d}				
	(1)	(2)	(3)	(4)	(5)
$\hat{A}_{o,d}^{1975} imes \tilde{l}_{o,-r(d)}^{1980}$	0.0036***	0.0036***	0.0035***	0.0035***	0.0035***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\hat{A}_{o,d}^{1980} imes \tilde{l}_{o,-r(d)}^{1985}$	0.0016***	0.0016***	0.0016***	0.0016***	0.0016***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\hat{A}_{o,d}^{1985} imes \tilde{I}_{o,-r(d)}^{1990}$	0.0018***	0.0018***	0.0018***	0.0018***	0.0018***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\hat{A}_{o,d}^{1990} imes \tilde{l}_{o,-r(d)}^{1995}$	0.0005***	0.0005***	0.0005***	0.0005***	0.0005***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\hat{A}_{o,d}^{1995} imes \tilde{I}_{o,-r(d)}^{2000}$	0.0004***	0.0004***	0.0004***	0.0004***	0.0004***
-, -(-)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\hat{A}_{o,d}^{2000} imes \tilde{l}_{o,-r(d)}^{2005}$	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\hat{A}_{o,d}^{2005} imes \tilde{I}_{o,-r(d)}^{2010}$	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)	
$I_{o,-r(d)}^t \frac{I_{Euro,d}^t}{I_{Euro}^t}$					0.3913**
o, (a) Euro					(0.1558)
Ν	3,583,881	3,583,881	3,583,881	3,583,881	3,583,881
R ²	0.656	0.657	0.709	0.709	0.709
Distance, Latitude Diff.	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	yes	yes	yes

Notes: Standard errors are clustered by country.

Immigration and Innovation

	OLS	IV	IV		
	5-year Difference in Patenting Rate post-1970				
$Immigration_d^t$	0.167** (0.080)	0.101*** (0.031)	0.108*** (0.033)		
Ν	18,846	18,846	18,846		
F-Stat		1,202	65		
Geography FE Time FE	State Y	State Y	County Y		

Notes: Standard errors are clustered by state.

▶ +12k migrants (1 s.d.) \rightarrow +27% innovation (rel. to mean).

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.

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 (push factor)
- historical European migration to Silicon Valley (repeatedly across decades and in large-enough numbers to sway averages) (pull factor)
- > 2010 Indian migration to **other** Census divisions.

It could also not reflect

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

Robustness

- Obtain almost identical results when we use other reasonable leave-out categories or hold constant A¹⁹⁷⁵_{o.d}.
- ▶ Do not suffer from issues relating to correlation between pre-existing shares and the error term (Adao & al., 2018).
- Results not driven by specific origins, destinations.
- Results hold with county FE, "bad" controls.
- Use population growth as endogenous variable.
- Alternative functional forms.
- Timing placebo, dynamics.

Dynamism & Income Growth

	5-Year Difference in:			10-year Diff. Wages of		
	Job Creation Rate	Job Destruction Rate	Job Growth Rate Skewness	Average Annual Wage	Natives	Native Non-Movers
	(1)	(2)	(3)	(4)	(5)	(6)
$Immigration_d^t$	0.176*** (0.033)	0.152*** (0.035)	0.019*** (0.004)	0.083*** (0.019)	0.049*** (0.016)	0.056*** (0.020)
Ν	6,600	6,600	12,564	21,976	9,411	6,274
First Stage F-Stat	951	951	151	1,202	750	1,178
<i>Controls:</i> Geography FE Time FE	state yes	state yes	state yes	state yes	state yes	state yes

Notes: Standard errors are clustered by state.

 ▶ 12k more migrants (1 s.d.) → +7% more job creation (relative to mean), +11% job destruction, +3% job growth skewness, 5% higher per capita wage growth.

Education & Immigration's Effect on Innovation

- ► Generalize IV to instrument separately for effect of education.
- Leverage dramatic differences in education across origins and over time.
- Run a separate first stage

Education^t_d =
$$\delta_s + \delta_t + \sum_{o=1}^{20} \kappa_o \hat{l}_{o,d}^t + \nu_d^t$$

where $Education_d^t$ is the total number of years of education of adult immigrants to d at t

to then disentangle in the second stage

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

Education & Innovation

	5-year Difference in:			
	Patenting Avg. Annual			nual Wage
	(1)	(2)	(3)	(4)
Immigration $_d^t$	0.200***		0.290***	
	(0.070)		(0.058)	
Average Years Education $_{d}^{t}$ × Immigration $_{d}^{t}$	0.221***		0.231***	
5 5	(0.068)		(0.051)	
1 {Low Avg. Education} $ imes$ Immigration $_d^t$		1.863		-0.296
		(4.539)		(0.249)
1 {Medium Avg. Education} \times Immigration ^t _d		0.084*		0.189***
		(0.044)		(0.069)
1 {High Avg. Education} $ imes$ Immigration $_d^t$		1.401*		1.514***
		(0.792)		(0.473)
Ν	18,846	18,846	21,976	21,976

 $\it Notes:$ All specifications include state and time fixed effects. Standard errors are clustered by state.

 Reduced-form effects of highly educated migrants approx 8× and 6× larger than (local) average effect.

Regional Spillovers

	5-year Difference in:			
	Patenting		Avg. Ann	nual Wage
	(1)	(2)	(3)	(4)
$Immigration_d^t$	0.107***	0.080**	0.093***	0.054***
-	(0.035)	(0.037)	(0.026)	(0.018)
$Immigration_{State}^t$	0.001***		0.000	
	(0.000)		(0.001)	
Immigration ^t within 100km		0.056***		0.061***
		(0.018)		(0.022)
Immigration ^t within 250km		0.014***		-0.006
		(0.005)		(0.011)
Immigration ^t within 500km		0.006		-0.001
		(0.005)		(0.008)
Ν	18,846	18,846	21,976	21,976
First Stage F-Stat d	1,792	6,065	2,289	7,967
First Stage F-Stat Spillover	470	383	434	395
First Stage F-Stat Spillover		150		157
First Stage F-Stat Spillover		66		67

Notes: All specifications include census division and time fixed effects. Standard errors are clustered by state.

Conclusion

- We study the short-term impact of immigration on innovation, dynamism, and growth at the local level.
- Identify plausibly exogenous shocks to immigration shocks at the county level 1975-2010.
- Find that more immigration causes
- more innovation (patents per person)
- more dynamism and creative destruction
- higher wages for native non-movers.
- More highly educated immigrants boost innovation by more.
- Immigration causes positive spillovers to nearby areas.

THANK YOU

Table: First Stage Regressions Varying Sample of Counties based on 1970 Population

Sample:	All	<95%	>5% and $<95%$	<95%	>5% and $<$ 95%
	(1)	(2)	(3)	(4)	(5)
			Immigration ^t	: 1	
$\widehat{Immigration}_{d}^{t}$	2.100*** (0.061)	0.615*** (0.105)	0.619*** (0.105)		
$\widehat{Immigration}_{d}^{t,mid90}$					2.066*** (0.390)
$\widehat{Immigration}_{d}^{t,bot95}$				2.064*** (0.378)	
Ν	21,987	20,881	19,775	20,881	19,775
F-Stat	1,202	34	35	30	28
R^2	0.777	0.190	0.195	0.336	0.336
<i>Controls:</i> State FE	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes

Notes: Standard errors are clustered by state.

BACKUP SLIDES



Main Contributions

- 1. Isolate plausibly exogenous shocks to immigration 1975-2010.
- 2. Immigration causes a significant increase in local innovation, economic dynamism, and income growth.
- 3. The impact of immigration on innovation increases significantly with immigrants' schooling level.
- 4. The impact of immigration diffuses over space, with a fast spatial decay.

Return

Related Literature

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

 $\rightarrow~$ Test short-term reduced-form predictions at county level

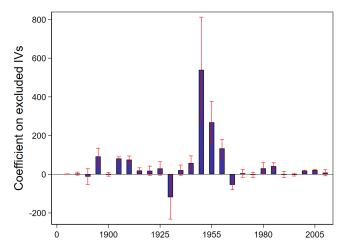
Empirical work on declining dynamism in the US economy Decker, et al. 2014, Hathaway and Litan 2014, Alon, et al. 2018, Hopenhayn, et al. 2018, Karahan, et al. 2016

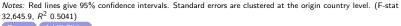
 $\rightarrow\,$ Bring an identification strategy and a link to immigration

- Empirical work on the effects of immigration Altonji & Card 1991, Borjas 1999, Sequeira, Nunn, & Qian 2018, Akcigit, et al. 2017, Peters 2017
 - $\rightarrow\,$ Identify effects on local innovation, dynamism, and income growth.

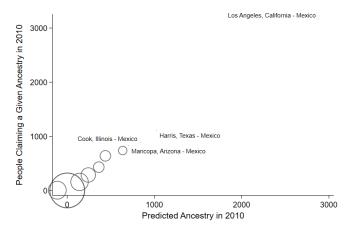


Step 1: Effect of historical push-pull on Ancestry today





Step 1: Fit of Predicted Ancestry



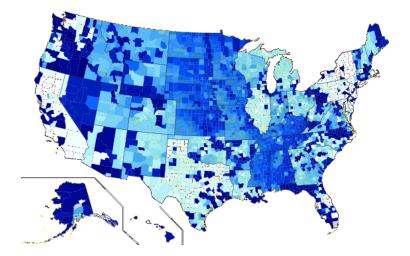
Notes: This figure plots actual ancestry in 2010 against predicted ancestry, with the size of each circle indicating the log number of observations in a given bin of predicted ancestry. The labeled counties are those with the highest number of individuals declaring a given ancestry in 2010.

Step 2: Predicting Origin-by-Destination Immigration

	Immigration ^t _{o,d}					
	(1)	(2)	(3)	(4)	(5)	
$\hat{A}_{o,d}^{1975} \times \tilde{l}_{o,-r(d)}^{1980}$	0.0036***	0.0036***	0.0035***	0.0035***	0.0035*	
0,0 0, 1(0)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.000	
$\hat{A}_{o,d}^{1980} \times \tilde{I}_{o,-r(d)}^{1985}$	0.0016***	0.0016***	0.0016***	0.0016***	0.0016*	
-,, -(-)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.000	
$\hat{A}_{o,d}^{1985} \times \tilde{I}_{o,-r(d)}^{1990}$	0.0018***	0.0018***	0.0018***	0.0018***	0.0018*	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.000	
$\hat{A}_{o,d}^{1990} \times \tilde{I}_{o,-r(d)}^{1995}$	0.0005***	0.0005***	0.0005***	0.0005***	0.0005*	
0,0 0,-7(0)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.000	
$\hat{A}_{o,d}^{1995} \times \tilde{I}_{o,-r(d)}^{2000}$	0.0004***	0.0004***	0.0004***	0.0004***	0.0004*	
,	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.000	
$\hat{A}^{2000}_{o,d} imes \tilde{I}^{2005}_{o,-r(d)}$	0.0002***	0.0002***	0.0002***	0.0002***	0.0002	
0,0 0,-7(0)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.000	
$\hat{A}_{o,d}^{2005} \times \tilde{I}_{o,-r(d)}^{2010}$	0.0002***	0.0002***	0.0002***	0.0002***	0.0002	
0,0 0,-r(a)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.000	
I ^t Euro.d	· /	. ,	` '	0.0109***		
				(0.0031)		
$I_{o,-r(d)}^t \frac{I_{Euro,d}^t}{I_{Euro}^t}$					0.3913	
o,-r(a) I _{Euro}					(0.155	
N	3,583,881	3,583,881	3,583,881	3,583,881	3,583,8	
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	

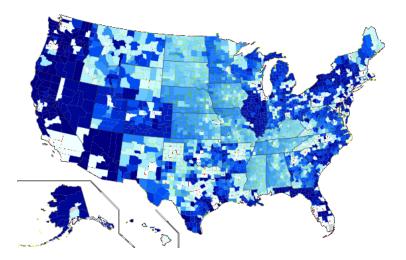
Notes: Standard errors are clustered by country and *,**, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Step 3: Immigration Shock \hat{l}_d^{1980} Conditional on County and State-Time Fixed Effects

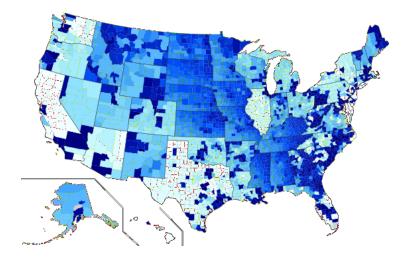




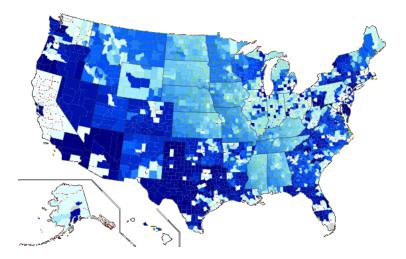
Immigration Shock \hat{I}_d^{1985}



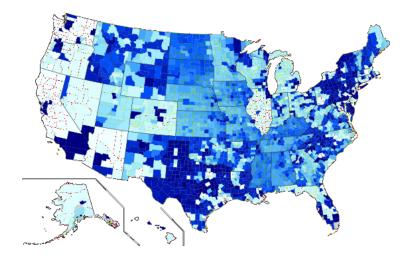
Immigration Shock \hat{I}_d^{1990}



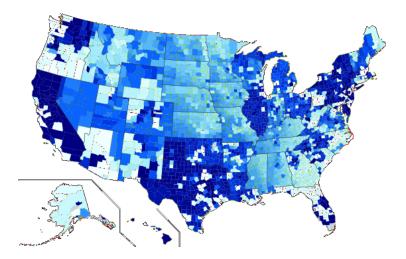
Immigration Shock \hat{I}_d^{1995}



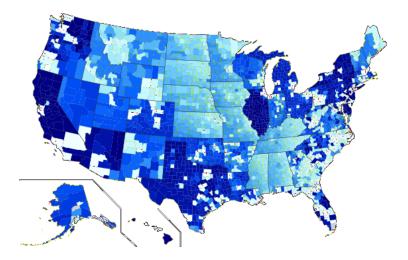
Immigration Shock \hat{I}_d^{2000}



Immigration Shock \hat{I}_d^{2005}



Immigration Shock \hat{I}_d^{2010}





First-stage: County-Level Population Change

	(1)	(2)	(3)	(4)	(5)			
	5-Year Population Growth							
Immigration ^t _d	1.890*** (0.168)	1.890*** (0.190)	1.818*** (0.180)	1.767*** (0.157)	1.921*** (0.323)			
Ν	21,986	21,986	21,986	6,600	21,986			
F-Stat	127	99	102	126	35			
R^2	0.233	0.272	0.314	0.370	0.795			
Controls:								
Geography FE	None	Division	State	State	County			
Time FE	no	yes	yes	yes	yes			
MSA Counties	no	no	no	yes	no			

Robustness: Alternative Instruments

Specification:	Ancestry in 1975 Only	Leave-Out Correlated Counties	Leave-Out Own Continent				
	(1)	(2)	(3)				
	5-year Difference in Patenting						
Immigration $_d^t$	0.093*** (0.027)	0.098*** (0.033)	0.094*** (0.027)				
N	18,846	18,846	18,846				
First Stage F-Stat	1,171	127	830				
<i>Controls:</i> Geography FE	state	state	state				
Time FE	yes	yes	yes				

Notes: Standard errors are clustered by state.

Robustness: Instrument Construction

	5-year Difference in Patenting per 100,000 People Post-1980					
Specification:	Predicted Ancestry Shares	Realized Ancestry Shares	Realized Ancestry No Leave-Out			
	(1)	(2)	(3)			
$Immigration_d^t$	0.195** (0.090)	0.106*** (0.035)	0.132** (0.055)			
Ν	18,846	18,846	18,846			
First Stage F-Stat	656	265	361			
Adão et al (2019) First Stage False Rejection Rate:	4.5	28.2	28.2			
Instrument Functional Form:						
Instrumented Ancestry	yes	no	no			
Shift Leave-Out	yes	yes	no			
Controls:						
Geography FE	state	state	state			
Time FE	yes	yes	yes			

Robustness: Specific Countries

	Difference in Patenting per 100,000 People Post-1980						
	Mexico	China	India	Philippines	Vietnam		
	(1)	(2)	(3)	(4)	(5)		
Panel A: Excluding Given Country							
$Immigration_d^t$	0.080*** (0.025)	0.102*** (0.032)	0.101*** (0.031)	0.100*** (0.031)	0.101*** (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		
Panel B: Including	Only Given	Country					
$Immigration_d^t$	0.103*** (0.032)	0.068** (0.032)	0.129*** (0.032)	0.133** (0.051)	0.123** (0.060)		
N	18,846	18,846	18,846	18,846	18,846		
First Stage F-Stat	2,094	535	318	22	2		
<i>Controls:</i> Geography FE Time FE	ST yes	ST yes	ST yes	ST yes	ST yes		

Robustness: Bad Controls

	Difference in Patenting per 100,000 People Post-1980					
	(1)	(2)	(3)	(4)	(5)	(6)
$Immigration_d^t$	0.101*** (0.031)	0.102*** (0.032)	0.100*** (0.031)	0.092*** (0.029)	0.082*** (0.027)	0.108*** (0.033)
Population Density (1970)	(0.001)	-0.001 (0.004)	(0.001)	(0.023)	(0.021)	(0.000)
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)	
Ν	18,846	18,846	18,846	18,846	18,846	18,846
First Stage F-Stat	911	1,658	911	945	1,017	85
Geography FE Time FE	ST yes	ST yes	ST yes	ST yes	ST yes	CTY yes



Education & Wages

	(1)	(2)	(3)	(4)	(5)
5-year l	Difference i	n Average A	Annual Wa	ge (\$1,000)	Post-1975
$Immigration_d^t$	0.239** (0.091)	0.290*** (0.058)	0.770* (0.419)	0.400*** (0.078)	
Average Years $Education_d^t \times Immigration_d^t$. ,	0.231*** (0.051)	0.221** (0.096)		
Average Years $College_d^t \times Immigration_d^t$				0.569*** (0.084)	
$1\{Low \; Avg. \; Years \; Education\} imes Immigration_d^t$					-0.296
$1\{Medium Avg. Years Education\} \times Immigration_d^t$					(0.249) 0.189*** (0.069)
$1\{High \; Avg. \; Years \; Education\} \times Immigration_d^t$					(0.003) 1.514*** (0.473)
Ν	21,976	21,976	21,976	21,976	21,976
Controls:					
Geogrpahy FE	State	State	County	State	State
Time FE	yes	yes	yes	yes	yes

Notes: The Montiel-Pflueger Effective F-statistic in Column 1 is 42 (critical value 32 for τ of 5%). Standard errors are clustered by state.

Add'l Slides

Wage Spillovers

	(1)	(2)	(3)	(4)
5-Year Difference in Average Annua	al Wage (\$1	,000) Post-	1975	
Immigration $_d^t$	0.010***	0.009***	0.005***	0.005***
$Immigration_{State}^{t}$	(0.002)	(0.003) 0.000 (0.000)	(0.001)	(0.002)
Neighbors' Immigration $_d^t$ (Inverse Distance Weight)			0.560***	
Immigration ^t _{100km}			(0.191)	0.006*** (0.002)
Immigration ^t _{250km}				-0.001
				(0.001)
Immigration ^t _{500km}				-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	1,100	434	165	395
		454	105	
First Stage F-Stat Spillover				157
First Stage F-Stat Spillover				67
Controls:				
Geogrpahy FE	DIV	DIV	DIV	DIV
Time FE	yes	yes	yes	yes

Dynamic Effect of Immigration

	Difference in Patenting per 100,000 People					
	ΔPat_{t-2}^{t-1}	ΔPat_{t-1}^t	$\Delta \textit{Pat}_{t-1}^{t+1}$	ΔPat_{t-1}^{t+2}		
	(1)	(2)	(3)	(4)		
Immigration ^t	-0.099	0.108***	0.369***	0.332**		
	(0.069)	(0.033)	(0.098)	(0.137)		
Ν	15,705	18,846	15,705	12,564		
First Stage F-Stat	80	85	11	7		
Controls:						
Geogrpahy FE	county	county	county	county		
Time FE	yes	yes	yes	yes		

Notes: Standard errors are clustered by state.

Second Stage: Population Growth and Innovation

	5-year Difference in Patenting per 100,000 People Post-1980							
	(1)	(1) (2) (3) (4)						
Δ Population ^t _d	0.223*** (0.066)	0.113*** (0.030)	0.113*** (0.031)	0.087*** (0.027)				
Ν	18,846	18,846	18,840	18,846				
First-Stage F Stat.		112	105	53				
Controls:								
Specification	OLS	IV	IV	IV				
Geography FE	State	State	State	County				
Time FE	yes	yes	yes	yes				
State-Time FE	no	no	yes	no				

Notes: Standard errors are clustered by state.

Growth Model Parameters

	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*** (0.031)	0.509*** (0.090)	0.501**	2.505*** (0.268)	0.028*** (0.011)			
$sq(Immigration_d^t)$	()	-0.001*** (0.000)		-0.004*** (0.000)				
Δ Population ^t _d		· · ·		()		0.033*** (0.012)		
$IHS(Immigration_d^t)$						()	1.723*** (0.111)	
$IHS(\Delta \operatorname{Population}_d^t)$							()	2.471*** (0.510)
Ν	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