The Economics of International Migrations: Brains, Innovation and Knowledge Diffusion

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Lecture 5

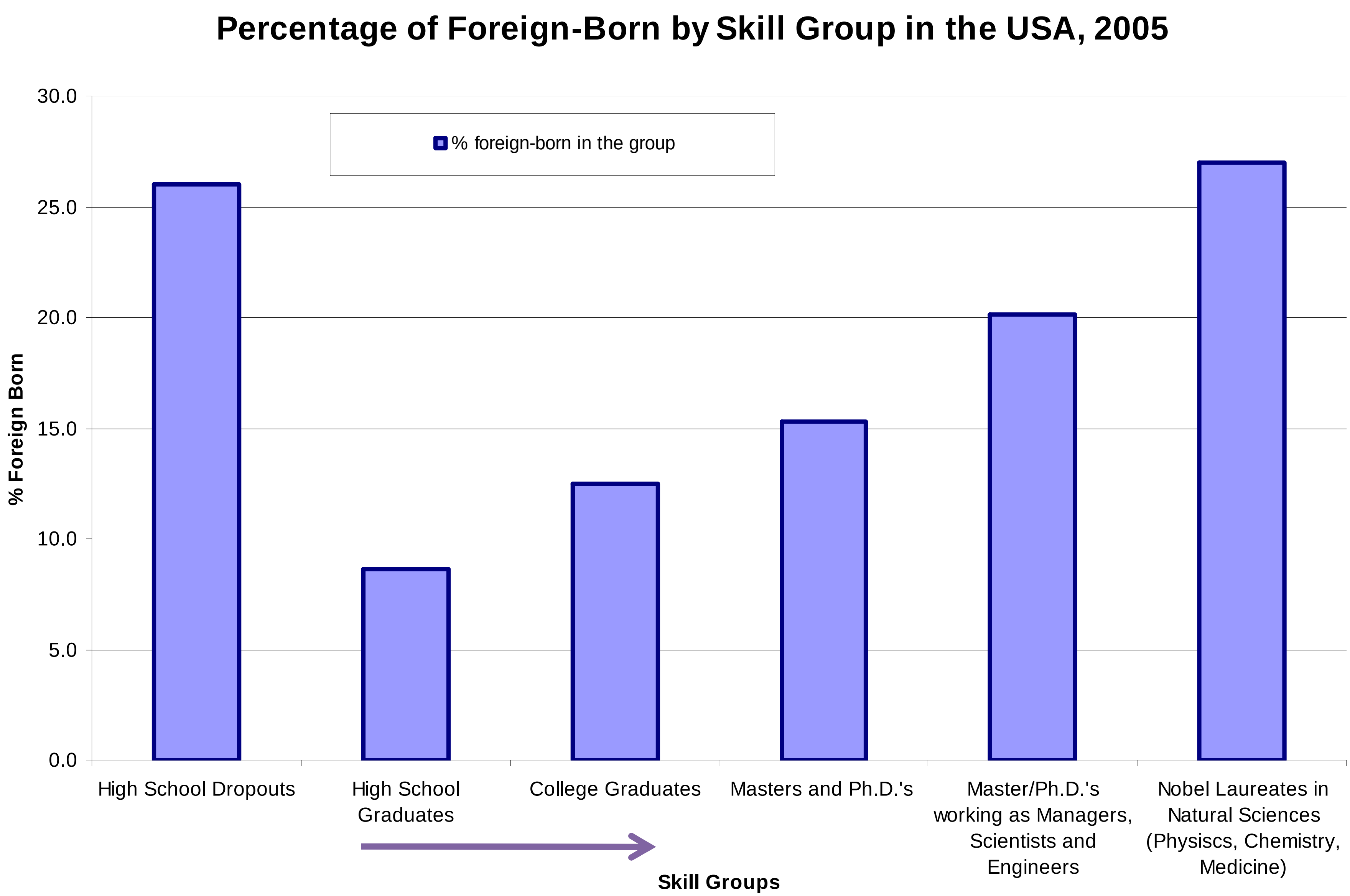
Shift the Focus to highly educated

- The most important skills are analytical, innovation
- The immigration to the US has a very high concentration of less educated doing manual jobs and also a very high concentration of very highly scientists and engineers
- Today we specifically analyze the impact of immigrant Scientists and Engineers on innovation
- Then we consider the role of migrant networks in reducing knowledge barriers in trade.

How important has been the inflow of Brains?

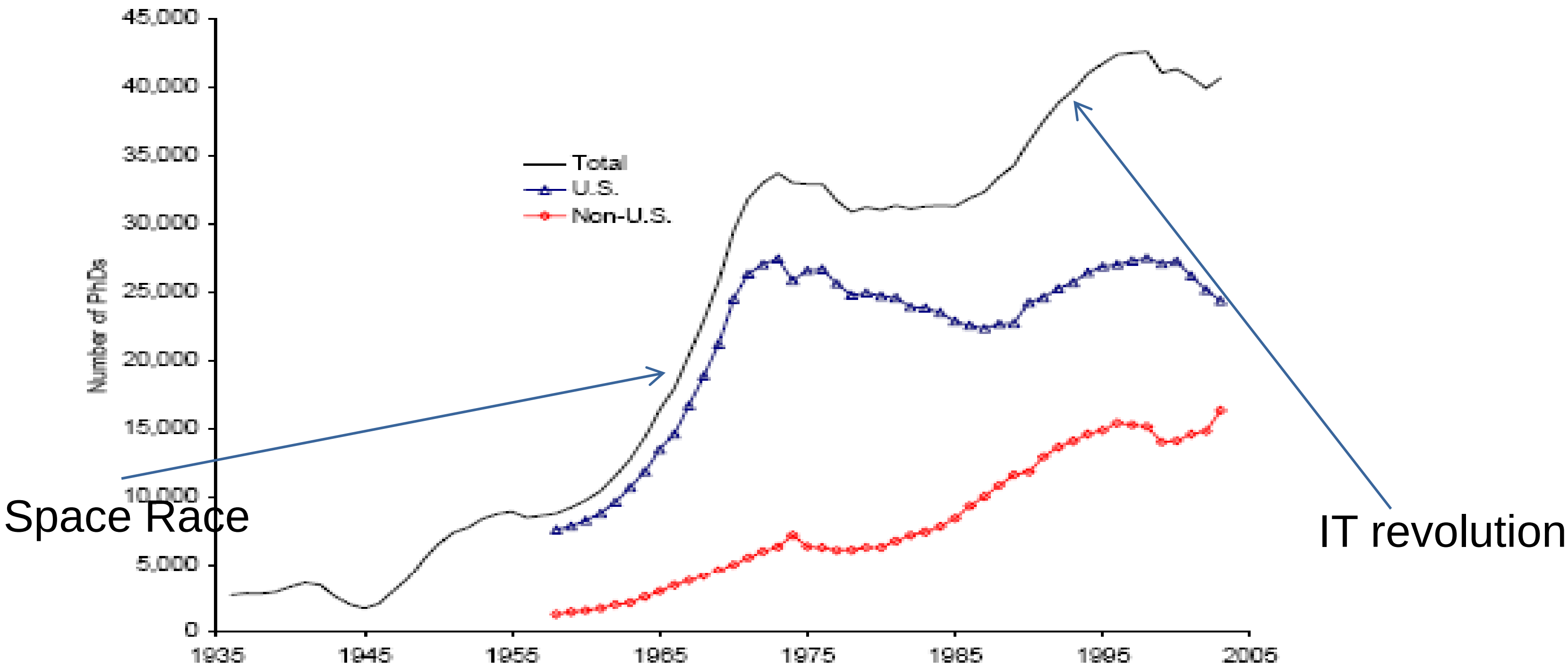
- Is the international mobility of brains an important input in the creation and diffusion of technological knowledge?
- Some countries (Canada, Australia) are adopting ever more skill-biased immigration policies
- Immigration policies, plus wages are very important in attracting talents (Grogger and Hanson 2008).
- Focus on the skilled immigration in the US

Globalization of talent is not new: Roman Emperors 100-300 AD


Percentage of Foreign-Born by Skill Group in the USA, 2005
30.0
25.0
20.0
15.0
10.0
5.0
0.0
% Foreign Born
% foreign-born in the group
High School Dropouts
High School Graduates
College Graduates
Masters and Ph.D.'s
Master/Ph.D.'s working as Managers, Scientists and Engineers
Nobel Laureates in Natural Sciences (Physiscs, Chemistry, Medicine)
Skill Groups

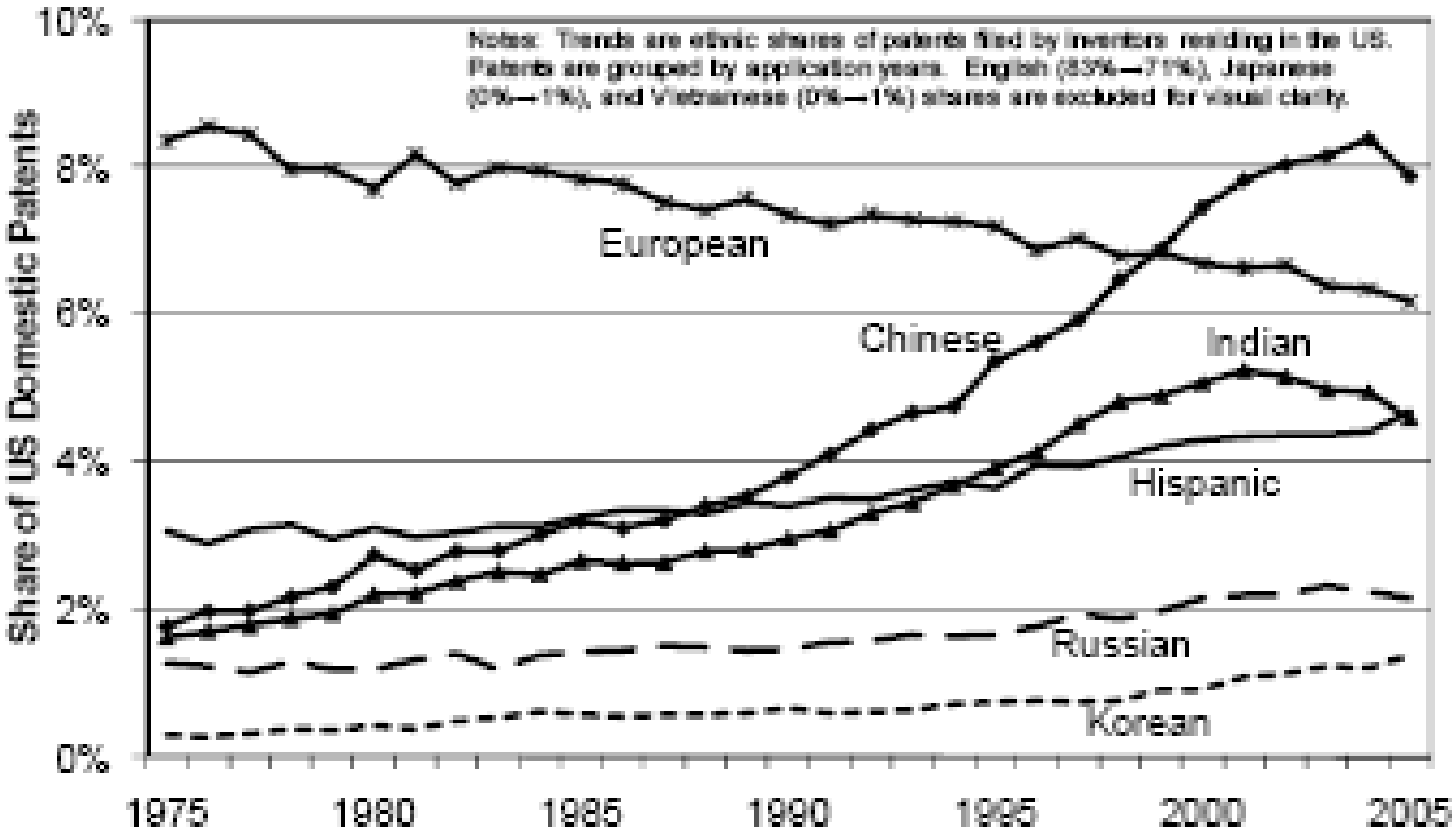
Native and Foreign PhD's in the US

Figure 1. PhD Degrees Awarded by US Universities and National Origin, 1958-2003



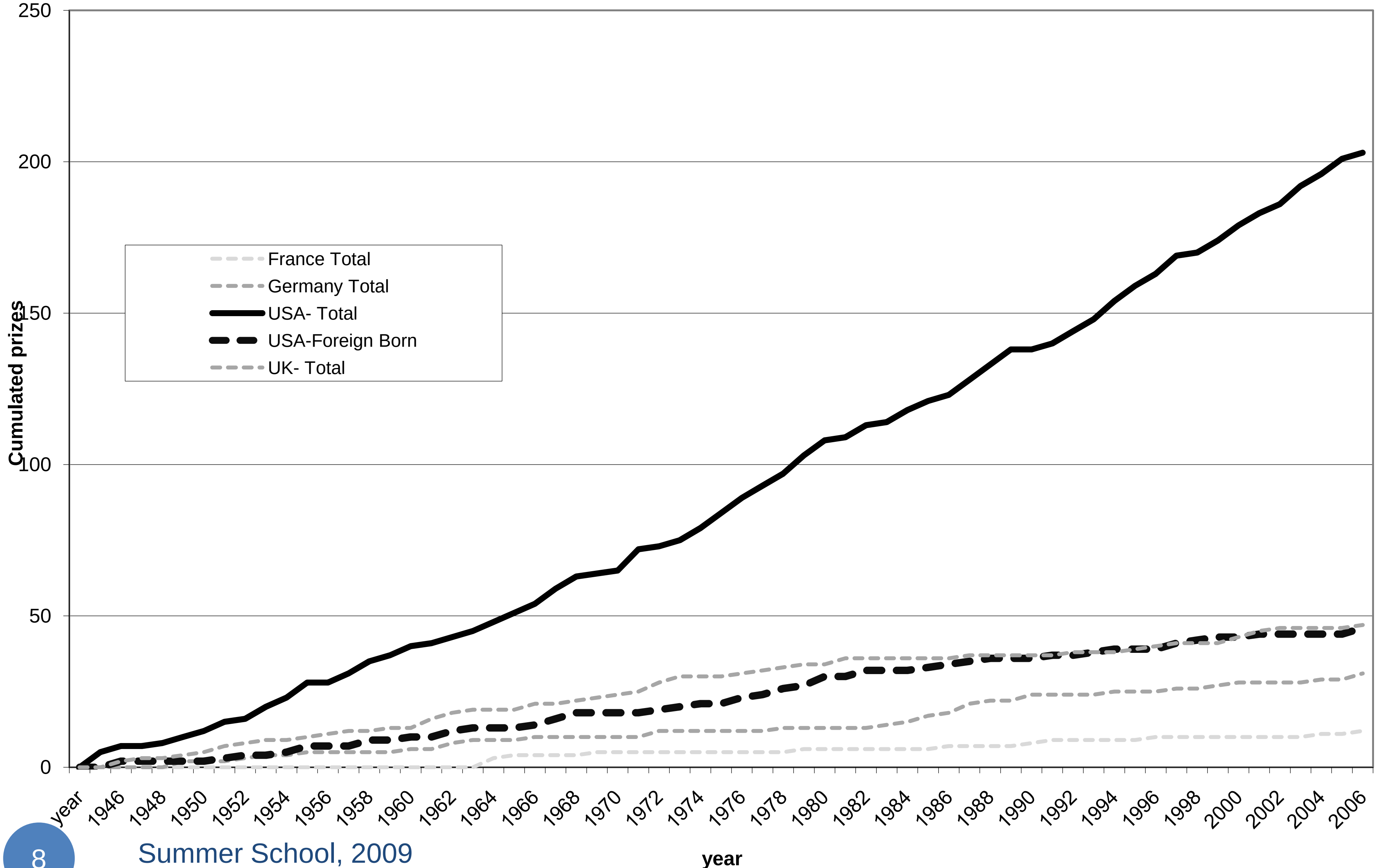
Source: NSF, *Survey of Earned Doctorates* microdata and, before 1958, National Academy of Sciences (1958). National origin is defined by the country in which an individual went to high school.

Share of Patented Innovation by Foreign-Born, in US, 1975-2005, percentage of the total



Source: Kerr and Lincoln (2008)

Cumulated Nobel Prize in Physics, Chemistry and Medicine



Other Facts and a key question

- In year 2000 47% of the PHD's working in Science and technology were foreign-born.

- Between 1995 and 2006, 67% of the net increase of scientists and engineers in the US (almost half a million workers) was due to foreign-born.

- However: there can be crowding out. Do foreign-born scientists affect the innovation-rate of US economy?
  - State-level approach (using location preference of immigrants) Hunt and Gauthier 2008
  - City-level approach, using H1B policy differences, Kerr and Lincoln (2008)

Analysis of the effects of highly educated immigrants on Innovation

- Use Patents as measure of innovation
  - New product/Process that can be produced commercially
  - Application date: time when the idea is first invented
  - Weight patents by their importance (citations received)

- First identify whether immigrants crowd out or not native scientists and engineers

- The analyze the direct and indirect effect (or the total effect) on innovation

Analyze state-level data over long time period (Hunt and Gauthier-Loiselle 2008)

- Crowding-Out or Crowding in

$$\Delta S_{it} = \delta_o + \delta_1 \Delta I_{it}^S + \delta_2 X_{it} + \mu_t + \Delta \nu_{it}$$

S_{it} are total skilled workers in state s and year t

  - I^s_{it} are the skilled immigrants
  - X_{it} are other controls

- Effects on Patenting

$$\Delta \ln \left(\frac{P_{i,t+1}}{POP_{i,t+1}} \right) = \gamma_0 + \gamma_1 \Delta I_{it}^S + \gamma_2 \Delta N_{it}^S + \gamma_3 X_{it} + \mu_t + \Delta \nu_{it}$$

  - N^s_{it} are the skilled natives
  - P_{it} : Patents in state I year t.

Coefficient of 1 implies no crowding out
Some Evidence of Crowding in: Complementarities in Innovation?

Table 5: Crowd-out - effect of change in immigrant skilled share on change in total skilled share

	(1)	(2)	(3)	(4)	(5)	(6)
		Basic specification			Control for less skilled immigration	
Difference:	10 year	30 year	50 year	10 year	30 year	50 year
Panel A: Immigrant college+ as share of population						
Δ % Immigrant	0.51	**0.75**	**0.95**	**0.79**	**1.22**	**1.23**
	(0.32)	**(0.38)**	**(0.35)**	**(0.24)**	**(0.27)**	**(0.29)**
	[0.13]	[0.52]	[0.88]	[0.39]	[0.42]	[0.44]
R-squared	0.69	0.52	0.33	0.72	0.63	0.50
Panel B: Immigrant post-college as share of population						
Δ % Immigrant	**1.42**	**1.50**	**1.88**	**1.74**	**2.02**	**2.08**
	(0.25)	**(0.48)**	**(0.33)**	**(0.16)**	**(0.23)**	**(0.23)**
	[0.11]	[0.30]	[0.01]	[0.00]	[0.00]	[0.00]
R-squared	0.80	0.38	0.58	0.84	0.60	0.75
Panel C: Immigrant scientists and engineers as share of workers						
Δ % Immigrant	**1.01**	**0.79**	**1.37**	**1.13**	**1.10**	**1.51**
	(0.29)	**(0.35)**	**(0.34)**	**(0.25)**	**(0.33)**	**(0.38)**
	[0.98]	[0.56]	[0.27]	[0.61]	[0.76]	[0.19]
R-squared	0.74	0.42	0.45	0.74	0.46	0.48
Observations	253	151	49	253	151	49

Observations: 49 US states, 1950-60-70-80-90-2000

Endogeneity/omitted variables

- Native and immigrant scientists are attracted to states with pro-innovation technology. This would bias the estimate up.

- Use the share of low educated immigrants (less than high school) from Europe, India and China 10 years earlier
  - If preferences for location and local amenities are affected by presence of other immigrants of the same ethnicity this proxies a taste, supply factor
  - It should not be correlated with productivity-technological factors

Total Effect on Patenting: 1% increase of skilled immigrants (SE) as share of population implies 48 to 59% increase in patent per capita

Table 7: Effect of immigrant post-college and scientist and engineer shares on patents per capita

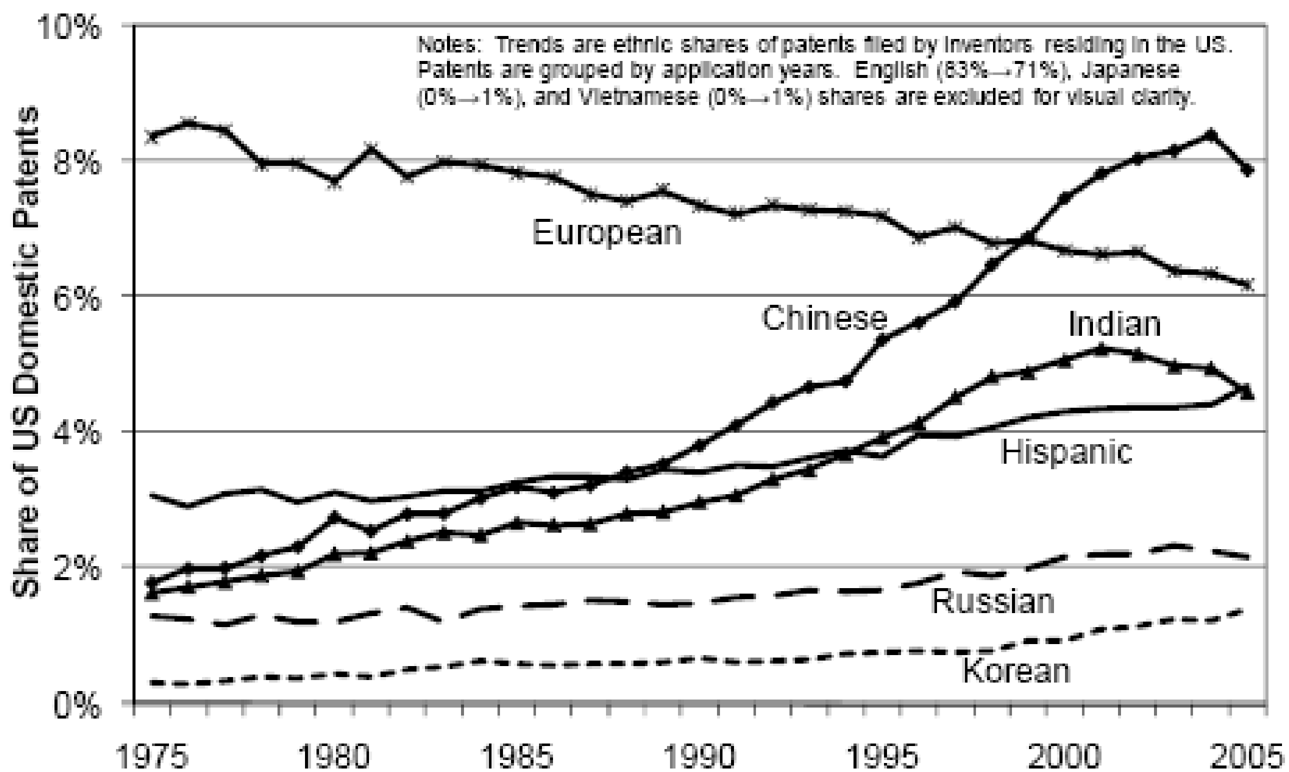
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Δ Log patents per capita				Δ Patents per capita		
	Weighted least squares			IV	Weighted LS		IV
Difference:	10 year	30 year	50 year	10 year	10 year	50 year	10 year
Panel A: Immigrant post-college as share of population							
Δ % Immigrant	17.7	**21.4**	**27.4**	38.1	0.756	0.657	1.733
	(11.1)	**(8.2)**	**(11.5)**	(21.9)	(0.526)	(0.481)	(1.160)
				[16]			[16]
Δ % Native	-1.2	1.3	9.9	-2.2	-0.079	0.197	-0.125
	(3.3)	(4.4)	(6.8)	(3.6)	(0.148)	(0.289)	(0.172)
R-squared	0.63	0.52	0.52	--	0.46	0.29	--
Panel B: Immigrant scientists and engineers as share of workers							
Δ % Immigrant	**48.7**	**48.6**	**59.2**	**53.6**	**2.393**	**1.934**	**2.263**
	(20.7)	**(16.1)**	**(15.8)**	**(25.1)**	**(1.017)**	**(0.717)**	**(1.188)**
				[6]			[6]
Δ % Native	**11.8**	**20.8**	**29.5**	**11.7**	0.231	**0.866**	0.233
	(5.3)	**(6.9)**	**(7.8)**	**(5.3)**	(0.237)	**(0.287)**	(0.241)
R-squared	0.68	0.59	0.67	--	0.55	0.48	--
Observations	253	151	49	253	253	49	253

Alternative approach (Kerr and Lincoln 2008)

- They Collect data on “Ethnic Innovation” i.e. patents invented by Indian-Chinese and inflow of H1B visa workers (highly skilled)

  - Use the yearly variation of H1B visa (capped by the government) and interact it with the dependence of cities on foreign Scientist-Engineers for innovation.
    - Measured as share of foreign SE at the beginning of the period
  - See if the impact of H1B cap is stronger on Indian-Chinese innovation in those cities.
  - See if Indian-Chinese innovation crowds out Native Innovation

Fig. 1: Ethnic Share of US Domestic Patents



Source: Kerr and Lincoln (2008)

Method

- Very large data effort to identify ethnic inventions (patents) from names of inventors (could be second generation)

- Check Crowding-In or crowding out, simply as a ression

$$\ln(PAT_{c,t}^{Dep}) = \phi_c + \eta_t + \beta \cdot \ln(PAT_{c,t}^{Ind,Chn}) + \epsilon_{c,t},$$

Total or Native patents

Patents by Indians and Chinese

Effects of Indian+Chinese Patenting on English Patenting and on Total Patenting

Table 2: City-Year Correlations of English and Indian/Chinese Patenting

	City & Year Fixed Effects	Column (1) plus Expected Patenting Trends	Column (2) plus State-Year Fixed Effects	Column (2) plus Population Weights	Column (2) plus Dropping Largest 20% of Cities
	(1)	(2)	(3)	(4)	(5)
			A. Log English Patenting		
Log Indian and Chinese Ethnic Patenting	0.137 (0.024)	0.099 (0.020)	0.079 (0.021)	0.127 (0.023)	0.097 (0.022)
			B. Log Total Patenting		
Log Indian and Chinese Ethnic Patenting	0.211 (0.022)	0.172 (0.018)	0.158 (0.019)	0.202 (0.023)	0.176 (0.020)

Notes: City-year regressions consider 1995-2006 with 3372 observations. Column 5 contains 2700 observations. Regressions contain city and year fixed effects, are unweighted excepting Column 4, and cluster standard errors by city. The appendix extends this analysis.

Effects of immigrants on Innovation

- Analyze the impact of H1B cap interacted with level of dependence on foreign scientists across cities on ethnic, native and overall innovation.

$$\begin{aligned}\ln(PAT_{c,t}^{Dep}) &= \phi_c + \eta_t \\ &+\beta_1 \cdot [I_c(\text{Top Quintile}) \cdot \ln(\text{H-1B}_t)] \\ &+\beta_2 \cdot [I_c(\text{2nd Quintile}) \cdot \ln(\text{H-1B}_t)] \\ &+\beta_3 \cdot [I_c(\text{3rd Quintile}) \cdot \ln(\text{H-1B}_t)] + \epsilon_{c,t},\end{aligned}$$

Effect of H1B changes on cities that depend more or less on foreign scientists:

Positive effect on Foreign Invention, No Effectt or positive effect on English invention

Table 4A: City-Year Regressions of H-1B Program Dependency and US Invention

	Log Indian Patenting	Log Chinese Patenting	Log Other Ethnicity Patenting	Log English Patenting	Log Total Patenting
	(1)	(2)	(3)	(4)	(5)
			A. LCA-Based Dependency		
Log National H-1B Population x					
Third Dependency Quintile [LCA]	0.313	0.311	0.305	-0.010	0.037
	(0.087)	(0.095)	(0.106)	(0.101)	(0.107)
Second Dependency Quintile [LCA]	0.623	0.741	0.461	0.050	0.078
	(0.090)	(0.108)	(0.096)	(0.087)	(0.083)
Most Dependent Quintile [LCA]	0.982	1.179	0.593	0.109	0.172
	(0.078)	(0.091)	(0.092)	(0.086)	(0.086)
			B. Census-Based Dependency		
Log National H-1B Population x					
Third Dependency Quintile [Census]	0.207	0.569	0.134	0.048	0.064
	(0.104)	(0.123)	(0.109)	(0.097)	(0.099)
Second Dependency Quintile [Census]	0.398	0.489	0.285	0.064	0.080
	(0.096)	(0.115)	(0.103)	(0.100)	(0.098)
Most Dependent Quintile [Census]	0.550	0.718	0.215	-0.019	0.029
	(0.097)	(0.109)	(0.101)	(0.081)	(0.083)

Notes: City-year regressions consider 1995-2006. Regressions include city and year fixed effects, have 3372 observations, are unweighted, and cluster standard errors by city. Cities are grouped into quintiles based upon indicated H-1B dependency estimate. The H-1B population regressor is interacted with binary indicator variables for the top three dependency quintiles to measure effects relative to the bottom two quintiles, as in equation (2) in the text.

Conclusions

- Many other robustness checks confirm that:
  - there is no crowding-out of native scientists and innovation
  - There is a positive effect on ethnic innovation and total innovation, in states (cities) that rely more on immigrant scientists
  - The effects can be causal as it is there when we use instrument or use national variation on H1B to identify it.
- Hence immigration (circulation) of highly skilled is good for innovation in the receiving country
- Evidence on patent citations also shows that the Diaspora of scientists/engineers may increase the knowledge flows back to the country of origin and stimulate innovation there (Agarwal, Kapur, McHale 2007).

Last Channel:
International Networks may affect Trade

- If there is a fixed cost of setting up trading relation from a country to another, and this is larger if one country is less developed, immigrants by providing information diffusion, knowledge, trust may reduce this cost much and stimulate trade (Rauch and Trinidade, 2002)

- Within the frame of trading firms (Melitz 2003) extended to allow different fixed cost across trading countries (Chaney 2008) we can analyze the effect of immigration networks on trade, empirically within the context of a gravity equation

A gravity Equation for export from Chaney (2008)

$$\ln(Export_{ijt}) = Const + \ln(w_{it}^{-\gamma} Y_{it}) + \ln(Y_{jt}\theta_{jt}^{\gamma}) - \gamma \ln(\tau_{ij}) - \left(\frac{\gamma}{\sigma - 1} - 1\right) \ln(f_{ijt})$$

$w_{it}^{-\gamma} Y_{it}$ Accounts for cost of producing and Home market effect of exporting country

$(Y_{jt}\theta_{jt}^{\gamma})$ Accounts for market effect and remoteness of importing country

(τ_{ij}) Accounts for bilateral trade costs

$$ln(f_{ijt}) = ln(f(ln(Immi_{ijt}))$$

Accounts for (time-varying) fixed export costs. We assume that it depends (negatively) on migration networks

We can estimate:

$$\ln(X_{ijt}) = Const + \phi_{jt} + \theta_t + \delta_{ij} + \ln(Y_{it}Y_{jt}) + \alpha \ln(IMM_{ijt})$$

- If network of migrants reduce the fixed information cost
  - 1) they increase trade ($\alpha>0$)
  - 2) they increase it particularly for differentiated goods (low elasticity) where information on goods is important
  - 3) they increase it particularly by creating new trade relation (new firms) as fixed costs affect marginal entry. IN jargon they affect the extensive margin of trade, rather than the intensive.

Test the theory on Spanish data 1994-2007

- Exceptional surge of immigrants 2001-2007

  - Very unequal across provinces
  - Differentiated across countries of origin (mainly eastern Europe, Latin America and Africa)
  - We can instrument with distribution of immigrants by country of origin in 1996, augmented with national growth of that national group 1996-2008
  - We have data on traded goods and we can classify their degree of differentiation.
  - We have data on number of firm-transactions and value of transaction and we can separate the extensive and the intensive margin of export-trade

Figure 2:
Trade and immigration with Western Europe and South/Eastern Europe (1995=100)

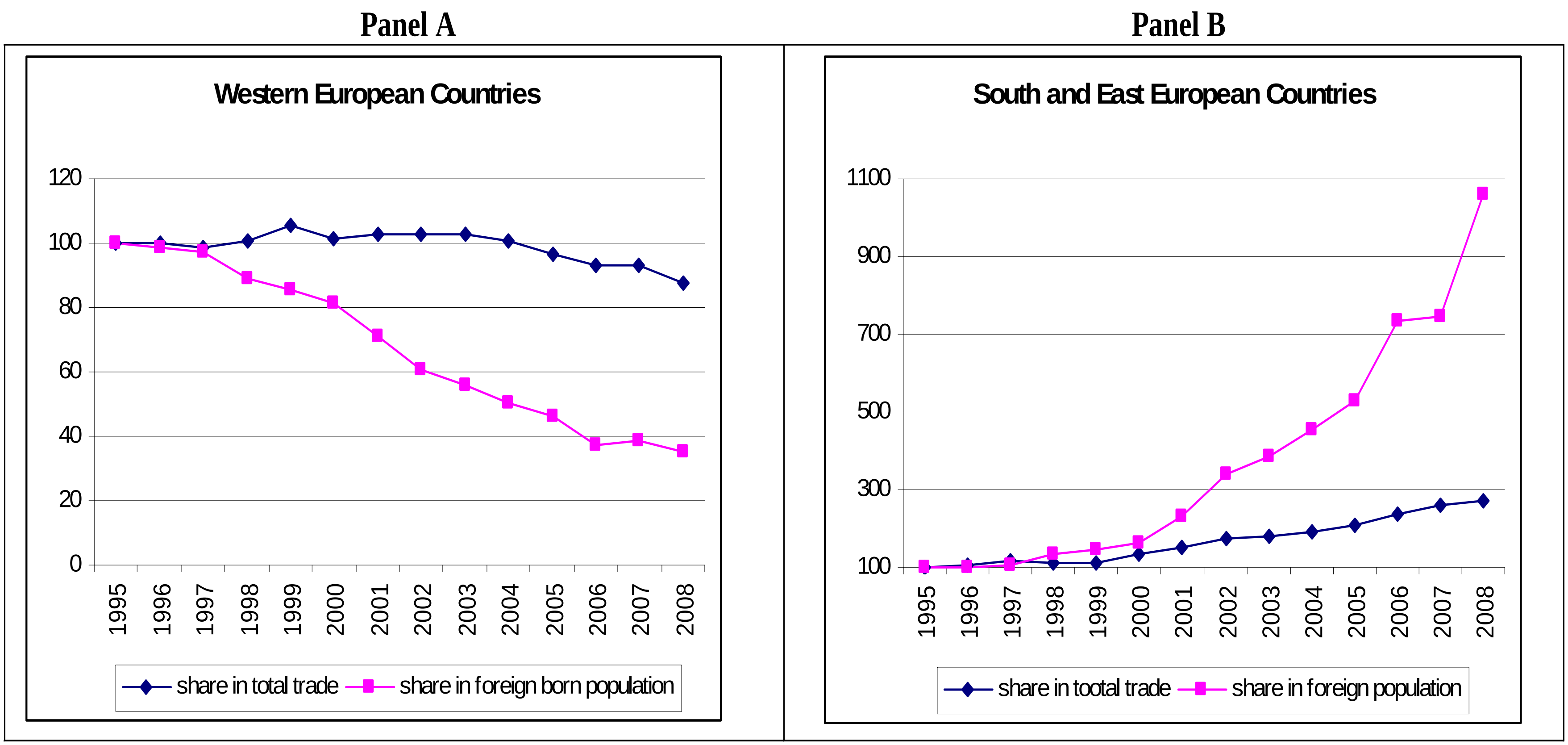


Figure 3:
Foreign-born population by Province
(Percentage of foreign-born population in total population in 2007)

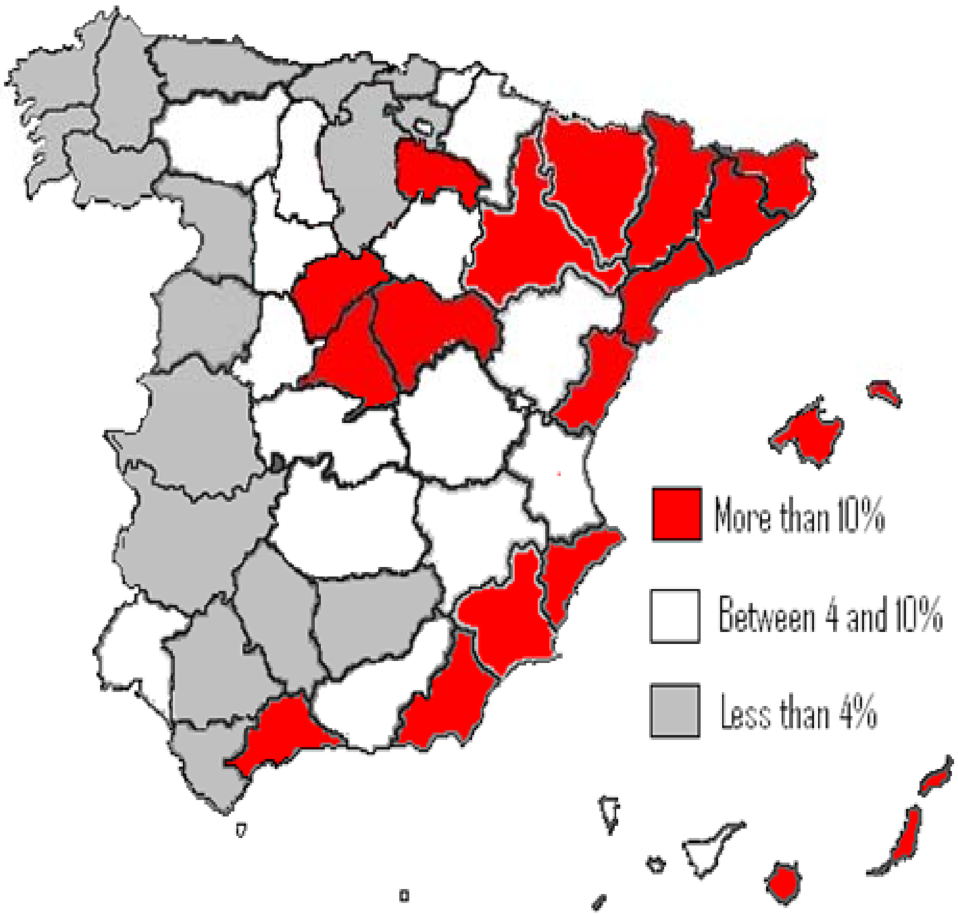


Table 4:
Decomposition of the effects of Immigrants;
The Intensive and Extensive margin of Export; Homogeneous and Differentiated Goods

	Exports					
	OLS estimates			**IV estimates**		
	Total Value (1)	**Extensive Margin (2)**	**Intensive Margin (3)**	**Total value (4)**	**Extensive Margin (5)**	**Intensive Margin (6)**
	Exports					
	Panel A: All Goods					
Ln (IMM)	0.086*	0.081*	0.009	0.078*	0.063*	0.015
	(0.011)	(0.005)	(0.008)	(0.015)	(0.007)	(0.011)
	Panel B: Highly differentiated products (elasticity of substitution less than 2)					
Ln (IMM)	0.076*	0.067*	0.009	0.109*	0.086*	0.023
	(0.011)	(0.005)	(0.008)	(0.016)	(0.007)	(0.012)
	Panel C Medium differentiated products (elasticity of substitution between 2 and 3.5)					
Ln (IMM)	0.123*	0.082*	0.041*	0.090*	0.063*	0.027
	(0.012)	(0.005)	(0.008)	(0.018)	(0.008)	(0.013)
	Panel D: Low differentiated products (elasticity of substitution above 3.5)					
Ln (IMM)	0.087*	0.075*	0.012	0.085*	0.069*	0.016
	(0.012)	(0.005)	(0.009)	(0.018)	(0.008)	(0.013)

Migration Networks and Trade

- Migration stimulates trade by creating new trade relation, in particular for differentiated goods. Hence the trade-creation effect generates trade of new varieties (extensive margin)

- This implies a gain from the network of immigrants. They spread knowledge that reduce set-up costs, uncertainty costs, communication costs.
- For some developing countries this may be very important (see effect for Africa)

- For trade between developed countries this mainly matter for differentiated goods (Effect for Europe and Eastern Europe).

Table 5:
Effect of Immigration on Exports by Region of Origin of Immigrants

	Highly Differentiated			Moderately Differentiated			Less Differentiated		
	Total	Extensive	Intensive	Total	Extensive	Intensive	Total	Extensive	Intensive
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
EU/EFTA	**0.071***	**0.044***	**0.027***	0.053	**0.043***	0.010	0.001	**0.048***	-0.046
	(0.032)	(0.015)	(0.014)	(0.035)	(0.015)	(0.030)	(0.038)	(0.017)	(0.028)
East Europe	**0.102***	**0.053***	**0.049***	0.028	0.022	0.006	-0.049	-0.015	-0.034
	(0.032)	(0.015)	(0.022)	(0.033)	(0.015)	(0.022)	(0.032)	(0.015)	(0.023)
Africa	**0.172***	**0.115***	**0.057***	**0.161***	**0.077***	**0.084***	**0.194***	**0.129***	**0.065***
	(0.022)	(0.011)	(0.015)	(0.033)	(0.013)	(0.024)	(0.027)	(0.014)	(0.020)
Latin America	-0.013	0.012	-0.025	0.012	0.016	-0.003	-0.017	0.002	-0.019
	(0.026)	(0.011)	(0.019)	(0.025)	(0.011)	(0.018)	(0.030)	(0.011)	(0.022)
Asia	0.029	**0.038***	-0.009	-0.027	0.003	-0.030	-0.064	0.004	-0.068
	(0.047)	(0.018)	(0.034)	(0.048)	(0.018)	(0.036)	(0.054)	(0.018)	(0.041)
Rest OECD	0.010	**0.037***	-0.026	**0.092***	**0.045***	0.048	0.043	**0.048***	-0.005
	(0.041)	(0.018)	(0.030)	(0.049)	(0.019)	(0.037)	(0.053)	(0.021)	(0.039)
Middle East	0.049	0.010	0.039	**0.226***	**0.082***	**0.144***	-0.047	-0.018	-0.030
	(0.071)	(0.027)	(0.054)	(0.073)	(0.027)	(0.056)	(0.071)	(0.028)	(0.051)

Highly Educated Immigrants

- 1) Contributed significantly to innovation in the Us 1980-today
- 2) from a global perspective they must have increased total innovation in the world.
- 3) Hard to quantify an aggregate effect 9possibly in the long run) but it I likely to be large.
- 4) New migrants are vehicle of information, increasing business and trade between countries.