

# High-Skill Immigration, Innovation, and Creative Destruction

Gaurav Khanna

Munseob Lee

UC San Diego

UC San Diego

*The conclusions drawn from the Nielsen data are those of the researchers and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.*

# Impact of Immigration on Product Reallocation

- ▶ Impact of immigration on **innovation** often looks at **patenting and citations** (Kerr and Lincoln 2010; Hunt and Gauthier-Loiselle 2010; Doran, Gelber and Isen 2018)
- ▶ A different kind of innovation is captured by the **entry and exit of products** (Aghion, Akcigit and Howitt 2014, Grossman and Helpman 1991)
- ▶ **Product Reallocation:** the entry and exit of products:
  - ▶ Is correlated with R&D expenditures
  - ▶ Drives revenue and TFP growth (Argente, Lee and Moreira 2018)
- ▶ What is the impact of high-skill immigration under the H-1B program, on firm-level product reallocation?

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## Patents

## Product Reallocation

### What might they capture?

Larger innovations

Ideas valuable to competitors

Incremental innovation

Includes firm-specific ideas

### Measurement Issues

Truncation issues; Propensities vary

Many innovations never patented

Are slight changes really valuable?

Some new products not “innovation”

# What We Do In This Paper

- ▶ Combine data sources at the firm-by-year level:
  1. Labor Condition Applications for H1Bs (2001-15)
  2. I-129s for H1Bs (2012-14)
  3. Retail Scanner data on products (2006-15)
  4. Compustat data on firm characteristics (2001-15)
- ▶ Matched on firm name and location
- ▶ Study the impact of H1Bs on outcomes:
  1. Product entry and exit rates
  2. Reallocation (sum of entry and exit) rates
- ▶ Research Design: Future reallocation on current H-1B
  1. Conditional on fixed effects
  2. Distributed lead and lag to study timing
  3. Variation from lottery

# Literature

1. High-skill immigration affects patenting, employment and profits
  - ▶ Shift-share approach Kerr and Lincoln (2010), Ghosh, Mayda and Ortega (2018)
  - ▶ Lottery variation: Doran, Gelber and Isen (2018), Peri, Shih and Sparber (2015)
2. Schumpeterian Growth and Product Reallocation
  - ▶ Aghion, Akcigit and Howitt (2014), Grossman and Helpman (1991), Aghion and Howitt (1992), Argente, Lee, Moreira (2018)

# 1. Data

# The H1B Process

- ▶ Since 1991 – firms looking to hire workers in “specialty occupations” (R&D, tech)
- ▶ Workers must have college degree and be paid prevailing wage
- ▶ Firms file a Labor Condition Application (LCAs)
  - ▶ Data we have (2001-15)
- ▶ Visas are capped and cap changes via Congress
- ▶ As more LCAs than visas: hold a lottery
- ▶ Winners come to US and get a I-129
  - ▶ We have 2012, 2013, 2014; waiting for more years (2001-11)



# H1B Data

- ▶ Labor Condition Application (LCA):
  - ▶ **Employment start date:** Years 2000-1 to 2016-17
  - ▶ Whether **certified**, withdrawn or denied, but not lottery winning
  - ▶ **Name of firm and location:** Possible to match to other data
  - ▶ Occupation, prevailing wage
- ▶ I-129s:
  - ▶ **Employment start date:** Years 2012,13,14
  - ▶ If granted H-1B (lottery winners in for-profit firms)
  - ▶ **Name of firm and location:** Possible to match to other data
  - ▶ Job title, wage, country of origin

# Baseline product- and firm-level dataset

## ▶ Nielsen Retail Scanner Data (2006-2015)

- ▶ 40,000 food, drug and mass merchandising stores (90 retail chains)
- ▶ \$220 billion of transactions/year
- ▶ Weekly sales/volume for products generated by point-of-sales systems

## ▶ Products

- ▶ Uniquely identified by 12-digit Universal Product Code
- ▶ **UPC**: finest level of disaggregation
- ▶ Approximately 200 thousand every quarter
- ▶ **Example**: a 31-ounce bag of Tide Pods Detergent.

## ▶ Firm-product data

- ▶ GS1 codes are part of the UPC code (first 6 or 10 digits of the code)
- ▶ Combined dataset: can identify portfolio of products of each firm

## GS1 Code: Example

Example of a 6-digit  
Company Prefix



Example of a 9-digit  
Company Prefix



# Defining The Three Outcomes

1. **Entry rates:**  $n_{it} = \frac{N_{it}}{T_{it}}$ 
  - ▶  $N_{it}$  number of entering products
  - ▶  $T_{it}$  total products
2. **Exit rates:**  $x_{it} = \frac{X_{it}}{T_{it-1}}$ 
  - ▶  $X_{it}$  number of exiting products
3. **Reallocation rates:**  $r_{it} = n_{it} + x_{it}$

# Compustat

- ▶ Financial and market information on global companies
- ▶ Variables from the fundamental annual database of North America:
  1. Number of employees
  2. R&D expenditure
  3. Total sales

# Matching Firms

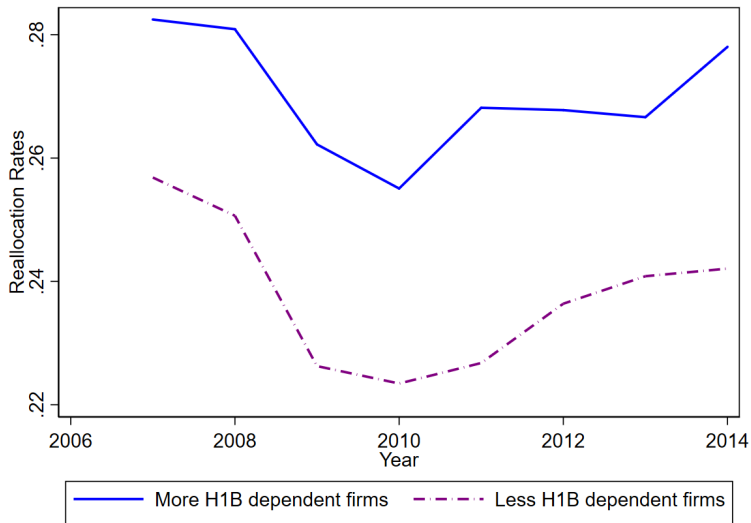
1. **Harmonize** H1B data, 2001-2017
  - ▶ Name of employer inconsistent across years
2. **Match** firms
  - ▶ By firm name and location
  - ▶ Record linkage method, verified manually
3. We create **three** merged samples:

Merged Samples:	(1) LCA-Nielsen	(2) LCA-Nielsen- Compustat	(3) I129-LCA- Nielsen-Compustat
Number of Firms Years	36,218 2006-2015	482 2006-2015	482 2012-2014
<u>Variables from LCA/I129</u>			
Avg # of Certified Workers	0.79	20.72	23.43
Avg # of I129 Workers	-	-	19.11
<u>Variables from Nielsen</u>			
# of Observations	235,522	4,022	1,201
Avg Firm Revenue (USD)	6.25 million	154 million	155 million
Avg Reallocation Rates (0-2)	0.1944	0.2585	0.2612
<u>Variables from Compustat</u>			
# of Observations	-	4,565	1,373
Avg # of Employees	-	43,841	45,158
Avg R&D to Sales	-	0.251	0.1715

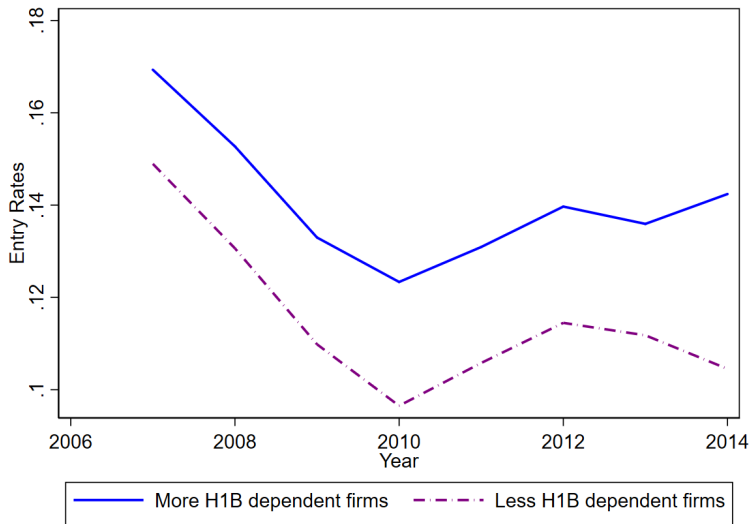
## 2. Descriptive Evidence



## Trends in Reallocation Rates by Baseline (2001) H1Bs



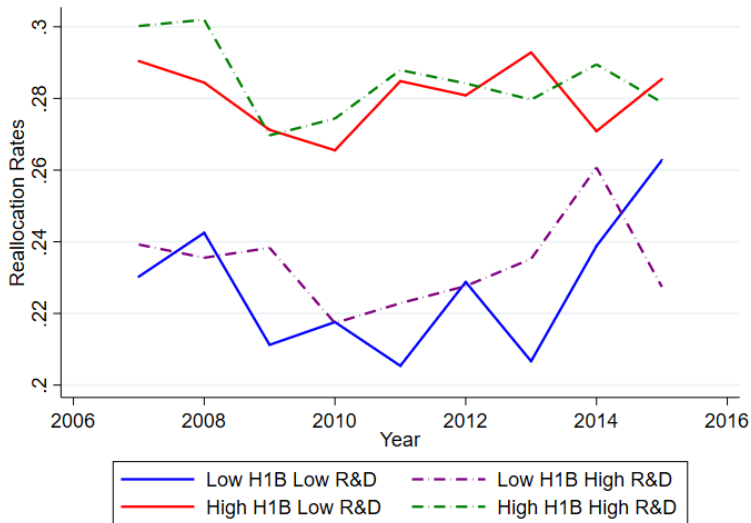
## Trends in Entry Rates by Baseline (2001) H1Bs



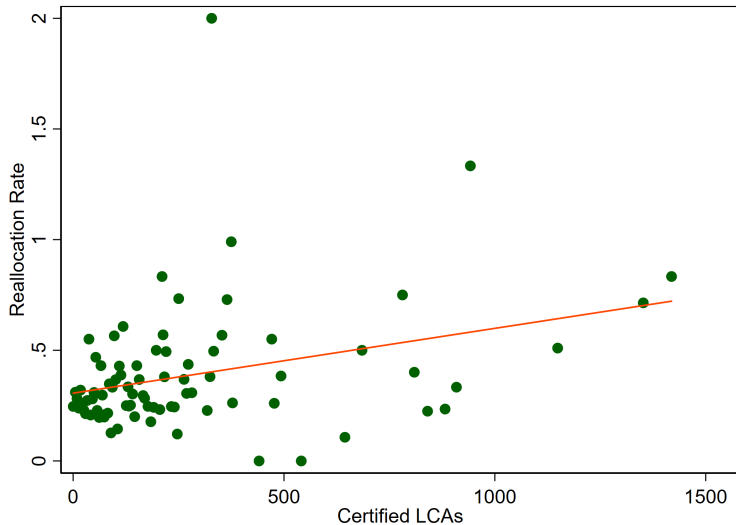
## Reallocation Matters for Revenue Growth

$\Delta \text{Log}(\text{Revenue})_{i,t+1}$	(1)	(2)	(3)
Reallocation Rate	0.432 (0.0235)***		
Product Entry Rate		1.240 (0.0210)***	
Product Exit Rate			0.355 (0.0377)***
Observations	147,723	179,502	147,723
R-squared	0.013	0.063	0.009
Number of Firm	27,574	31,626	27,574
Fixed Effects	Year and Firm	Year and Firm	Year and Firm
Cluster	Firm	Firm	Firm

## Reallocation Rates by Baseline (2001) H1Bs and R&D



## Scatters by Certified LCAs: Reallocation



### 3. Effect of H-1Bs on Reallocation

# 1st Research Design

Firm  $i$  and year  $t$

$$r_{i,t+1} = \alpha + \beta H1B_{i,t} + \mu_i + \tau_t + \epsilon_{i,t+1}$$

- ▶ Results for both current and future re-allocation rates  $r_{i,t}$
- ▶ “Future” is preferred specification: (1) no contemporaneous shocks, (2) changes occur with lag (Argente, Lee, Moreira 2018)
- ▶  $H1B_{i,t}$  measures:
  1. Number of certified LCAs,
  2. Number of workers on certified LCAs
  3. Occupations
  4. Certified workers as share of employees

# Magnitudes

► We find that:

1. 1% pt increase in share of certified workers (more than doubling at the mean share)  $\Rightarrow$  5% pt increase in reallocation (around 20% at mean)
2. *Elasticity* = 0.2 at the mean



# LCA Certification and CURRENT Reallocation Rates

Dep. var:	Reallocation Rate in year $t$		
	(1)	(2)	(3)
# of Applications	0.00217 (0.000413)***		
# of Certified Workers		0.00291 (0.000466)***	
By Occupations:			
Software			0.00217 (0.000471)***
Science, Math and Engineer			0.0300 (0.0446)
Manager			-0.00273 (0.00976)
Finance, Analyst and Marketing			0.0359 (0.0196)*
Observations	183,554	183,554	183,554
R-squared	0.003	0.003	0.003
Number of firm	31,876	31,876	31,876
Fixed Effects	Year and Firm	Year and Firm	Year and Firm
Cluster	Firm	Firm	Firm
Type	OLS	OLS	OLS

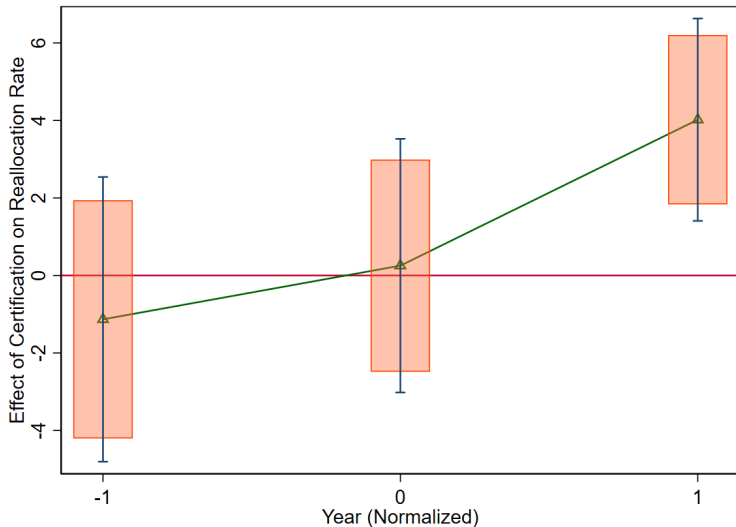
# LCA Certification and FUTURE Reallocation Rates

Dep. var:	Reallocation Rate in year $t + 1$		
	(4)	(5)	(6)
# of Applications	0.00118 (0.000615)*		
# of Certified Workers		0.00140 (0.000767)*	
By Occupations:			
Software			0.00166 (0.000294)***
Science, Math and Engineer			0.0206 (0.0274)
Manager			0.000558 (0.0260)
Finance, Analyst and Marketing			-0.000832 (0.0228)
Observations	181,451	181,451	181,451
R-squared	0.003	0.003	0.003
Number of firm	31,685	31,685	31,685
Fixed Effects	Year and Firm	Year and Firm	Year and Firm
Cluster	Firm	Firm	Firm
Type	OLS	OLS	OLS

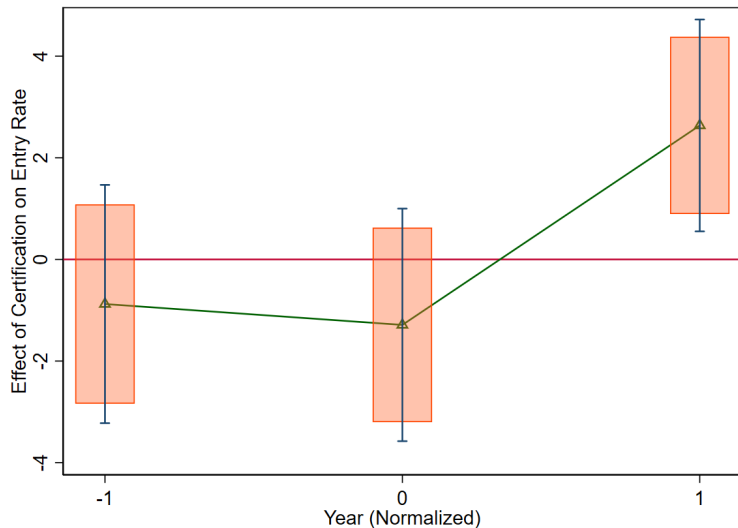
# Certified Shares (with Compustat) of Total Employment

Dep. var:	Reallocation Rate in year $t + 1$		
	(4)	(5)	(6)
Applications / Employees	5.077 (2.040)**		
Certified Workers / Employees		5.593 (2.034)***	
<u>Occupations (per Employee):</u>			
Software			9.344 (0.732)***
Science, Math and Engineer			0.203 (1.402)
Manager			5.854 (4.384)
Finance, Analyst and Marketing			1.098 (2.221)
Observations	2,800	2,800	2,800
R-squared	0.022	0.022	0.029
Number of firm	429	429	429
Fixed Effects	Year and Firm	Year and Firm	Year and Firm
Cluster	Firm	Firm	Firm
Type	OLS	OLS	OLS

# Distributed Lead and Lag: Reallocation Rates



# Distributed Lead and Lag: Entry Rates



4. I-129s

# Research Design

Firm  $i$  and year  $t$

$$r_{i,t+1} = \alpha + \beta H1B_{i,t} + \mu_i + \tau_t + \epsilon_{i,t+1}$$

- ▶  $H1B_{i,t} = I129s_{i,t} - LCA_{i,t}$
- ▶ 3 years of I-129s, we can include  $\mu_i$  and  $\tau_t$
- ▶ **Find:** a 1% increase in supply shock at mean  $\Rightarrow$  0.046% increase in reallocation rate at mean

# H-1B Supply Shock and Reallocation: All Firms

Samples:	All firms			
Dep. var:	# of I-129s (1)	$r_{i,t+1}$ (2)	$n_{i,t+1}$ (3)	$x_{i,t+1}$ (4)
H-1B supply shock	0.656 (0.0268)***	0.136 (0.0753)*	0.0422 (0.0320)	0.0960 (0.0386)**
Observations	1,446	749	777	774
R-squared	0.674	0.013	0.033	0.026
Number of firm	482	392	406	405
Fixed Effects		Year and Firm		
Cluster		Firm		
Type	First Stage	Reduced Form		



# H-1B Supply Shock and Reallocation: H-1B Firms

Samples:	Granted at least one certification			
Dep. var:	# of I-129s (5)	$r_{i,t+1}$ (6)	$n_{i,t+1}$ (7)	$x_{i,t+1}$ (8)
H-1B supply shock	0.658 (0.0270)***	0.138 (0.0759)*	0.0464 (0.0318)	0.0955 (0.0392)**
Observations	510	272	284	282
R-squared	0.677	0.046	0.033	0.061
Number of firm	220	166	173	172
Fixed Effects		Year and Firm		
Cluster		Firm		
Type	First Stage	Reduced Form		

# Placebo Test for H-1B Supply Shock

Samples:	All firms			Granted at least one certification		
Dep. var:	$r_{i,t-1}$ (1)	$n_{i,t-1}$ (2)	$x_{i,t-1}$ (3)	$r_{i,t-1}$ (4)	$n_{i,t-1}$ (5)	$x_{i,t-1}$ (6)
H-1B supply shock	-0.0148 (0.0258)	0.00283 (0.00866)	-0.0160 (0.0195)	-0.0134 (0.0261)	0.00335 (0.00892)	-0.0153 (0.0196)
Observations	755	780	779	272	283	284
R-squared	0.001	0.015	0.024	0.008	0.007	0.044
Number of firm	389	409	403	165	174	174
Fixed Effects	Year and Firm			Year and Firm		
Cluster	Firm			Firm		
Type	Reduced Form			Reduced Form		

## 5. Conclusions

# Concluding Thoughts

- ▶ Hiring H-1Bs associated with higher **product entry and exit**
- ▶ Some **patenting** literature finds similar effects (Kerr and Lincoln 2010, Hunt and Gauthier-Loiselle 2010)
- ▶ Yet, other work finds little impact on patenting (Doran, Gelber and Isen 2018)
- ▶ We study alternative measure: **Product reallocation**
- ▶ Capturing **incremental innovation**
- ▶ May impact **consumer welfare** (Khanna and Lee 2018)