What Drives TFP Differences?

EC502 Macroeconomics
Topic 5

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Why Do Countries Differ in A?

- Development accounting suggests differences in A are important
- Romer model endogenizes A as a process of knowledge (idea) accumulation
- So why can't India use the same ideas to achieve the same A as the US?
  - Ideas are non-rival, so the same idea can be used by India and the US
- Two hypotheses:
  1. Slow adoption and diffusion of new technologies (brief and suggestive)
  2. Misallocation (our main focus today)

1. Understanding the Diffusions of New Technologies

– Kalyani, Bloom, Carvalho, Hassan, Lerner, Tahoun (2025)

Goal

- Goal: understanding how new technologies diffuse geographically
- We will focus on the diffusion inside the US
  - would love to see global evidence

Defining New Technology

1. Record all **bigrams** that appear in the well-cited patents for the first time since 1970
   - Examples: “fingerprint sensor”, “greenhouse gases"
2. Keep the bigrams that appear in major entries of the Wikipedia
   - Needs to have a section mentioning the use/application
   - This excludes “greenhouse gases” and keeps “fingerprint sensor”
3. Define “emergence year” when # of patents mentioning it starts to grow
4. Define “pioneering locations” if CBSAs collectively account for 50% of patents
5. Use the online job postings data and record whether the technology is mentioned

Example from 1980s

Emergence year	Wikipedia title (technology)	Technology bigrams	Number of job postings
1979	Hard disk drive	hard disk; disk drive	34,211
1980	Barcode reader	barcode reader; code reader; code scanner; barcode scanner	43,279
1981	Laser diode	emitting laser; diode laser; semiconductor laser; laser diode	7,284
1982	Personal computer	personal computer	1,752,726
1983	Flat-panel display	panel display; flat panel	27,369
1984	User interface	user interface	747,586
1985	Mobile phone	mobile telephone; cellular telephone; phones mobile; cellular phone; mobile phone; cell phone	1,832,787
1986	Facial recognition system	frt system; recognition software; recognition system; recognition technology; facial recognition	25,109
1987	Digital video	digital video	88,887
1988	Model organism	animal model	24,722
1989	Mobile device	held computer; computer device;	1,046,079

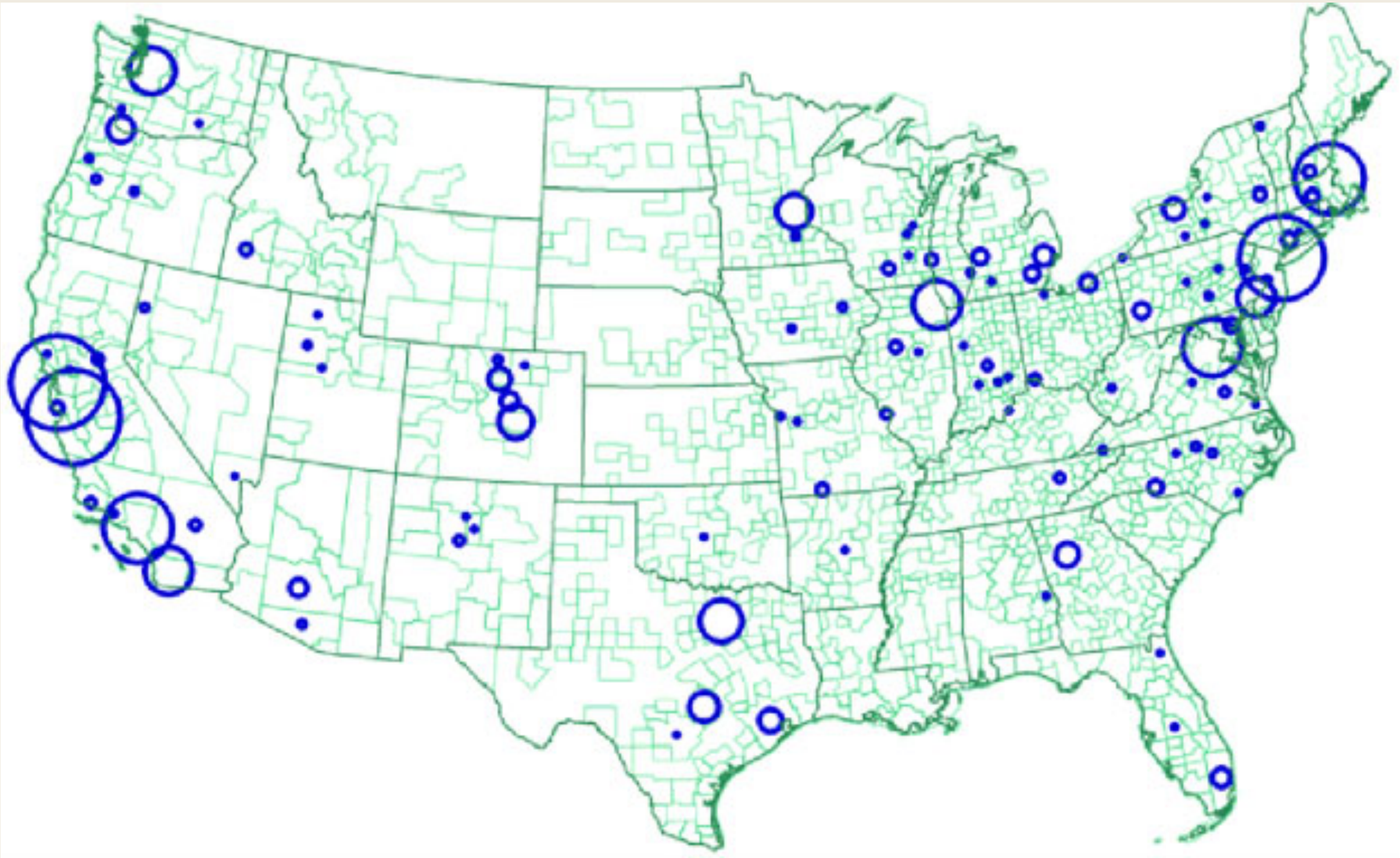
Example from 1990s

Emergence year	Wikipedia title (technology)	Technology bigrams	Number of job postings
1990	Debit card	cards debit; card debit; debit card	260,282
1991	Flash memory	flash device; nand flash; flash memory	22,882
1992	Machine learning	learning algorithm; machine learning	491,252
1993	Financial instrument	financial instrument	43,944
1994	Active users	active user	39,671
1995	Hybrid electric vehicle	hybrid electric	8,207
1996	Digital content	digital content	144,775
1997	Multicore processor	multi core; core processor	29,643
1998	Information privacy	data protection	176,110
1999	Unmanned aerial vehicle	aerial vehicle; unmanned aerial	24,148

Example from 2000s

Emergence year	Wikipedia title (technology)	Technology bigrams	Number of job postings
2000	Transaction account	transaction account	13,012
2001	Smartphone	smart phone	910,856
2002	Online game	online game	15,254
2003	Social networking service	networking site; social networking	244,610
2004	Electronic discovery	electronic format	56,438
2005	LED circuit	led driver	2,575
2006	Augmented reality	augmented reality	20,537
2007	Self-driving car	autonomous vehicle	18,641

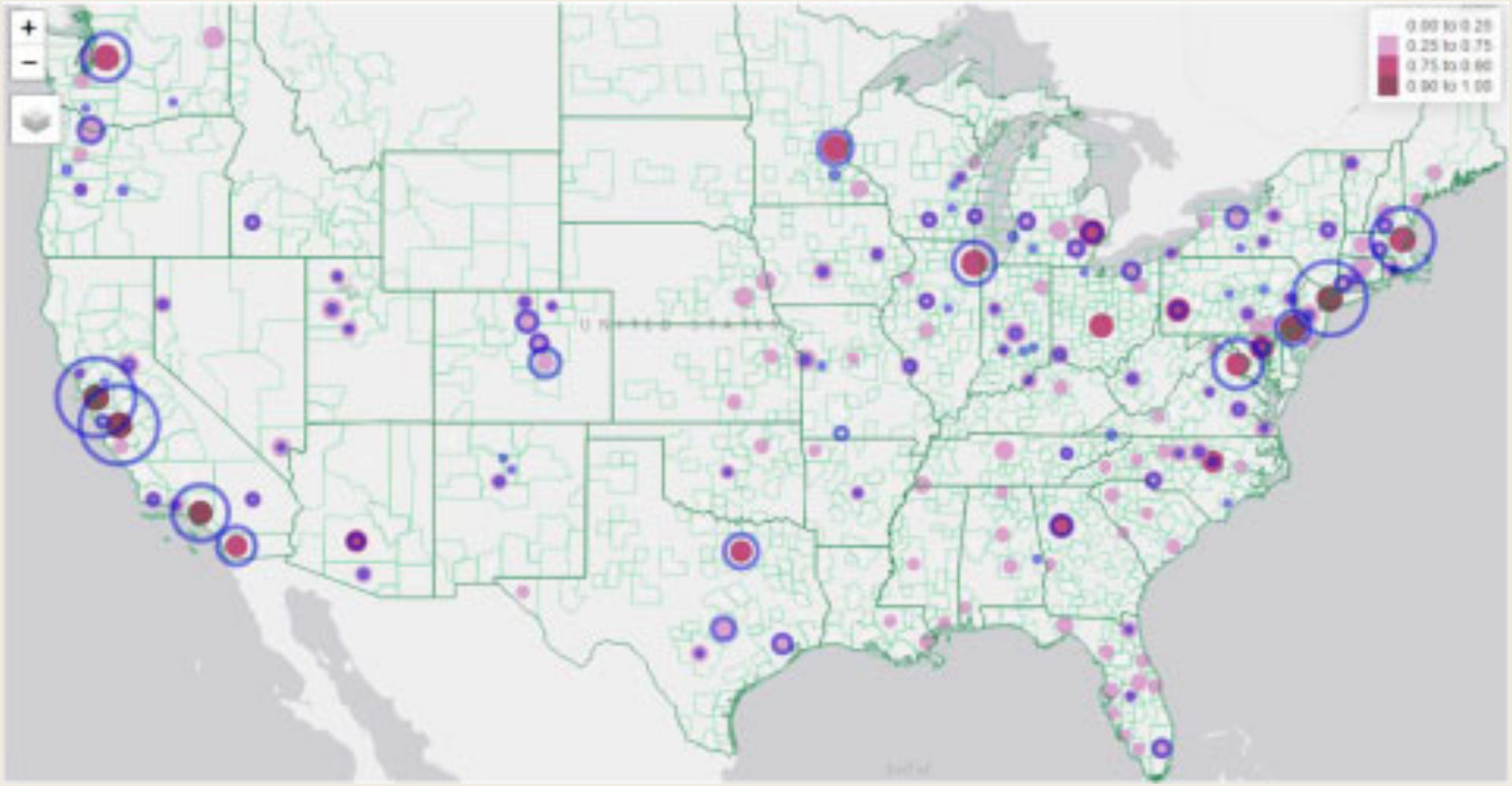
Pioneering Locations



1. Highly educated
2. More university

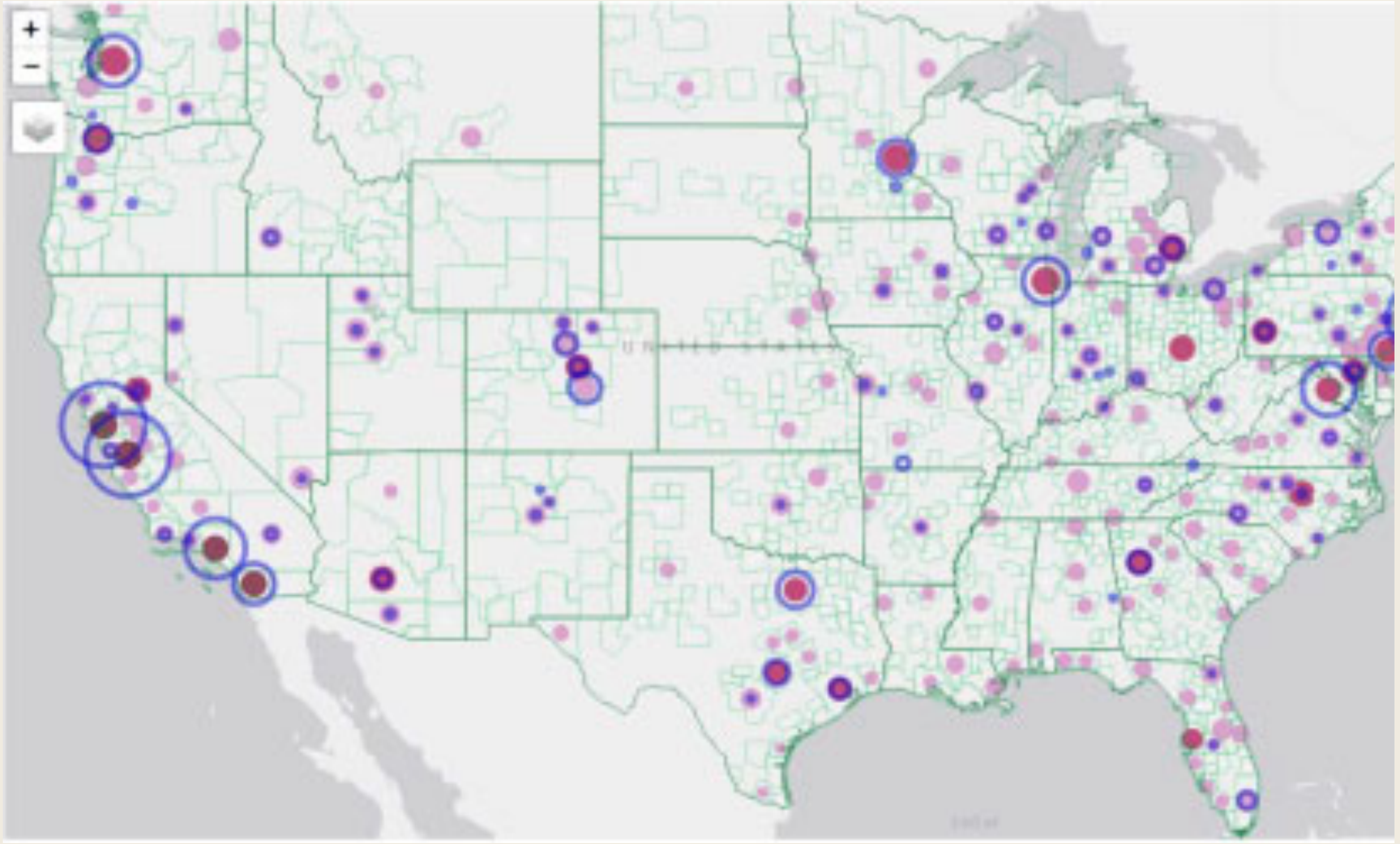
Share of Job Postings Mentioning Technologies

Years since emergence: 0-5



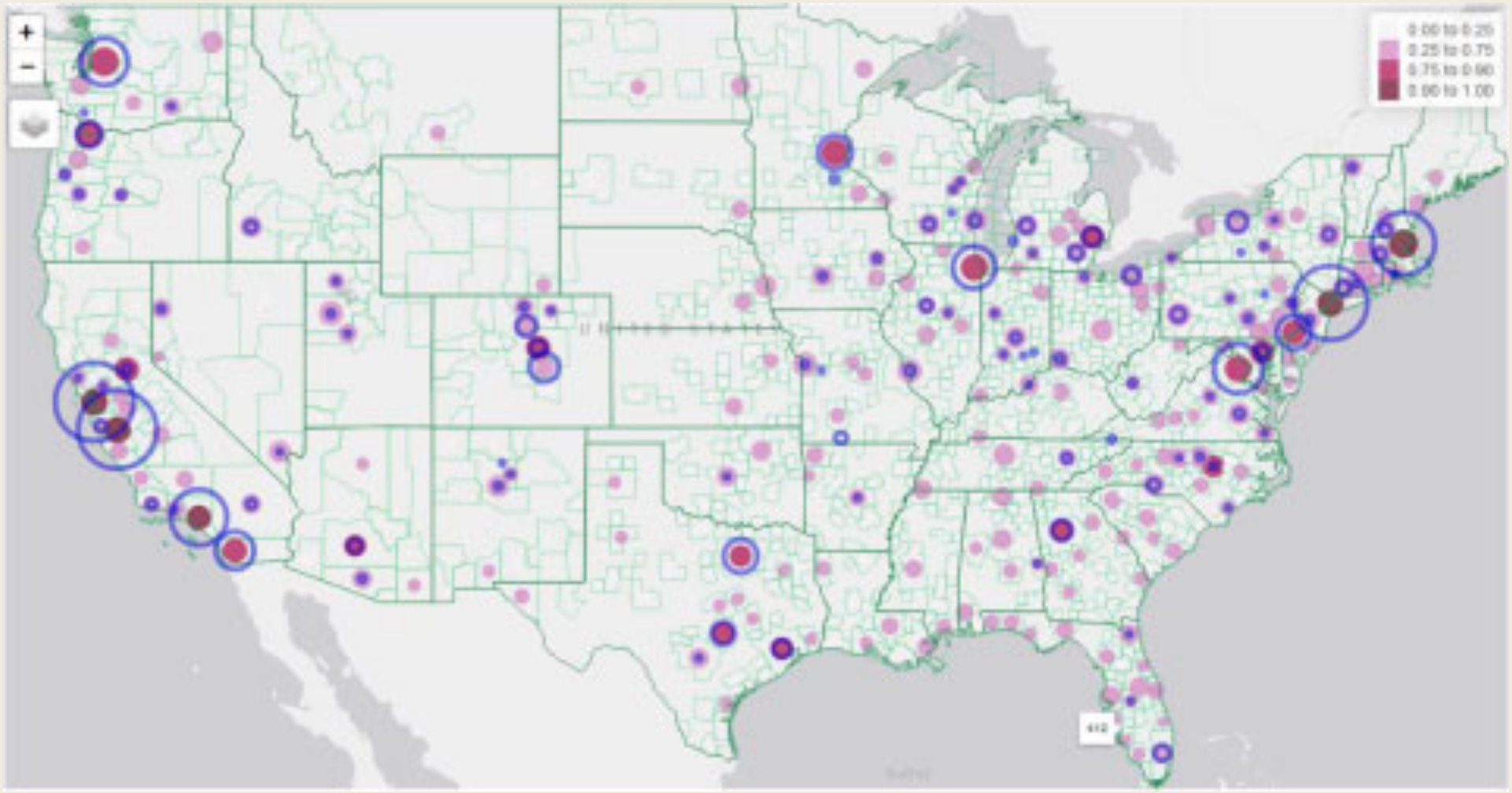
Share of Job Postings Mentioning Technologies

Years since emergence : 6-10



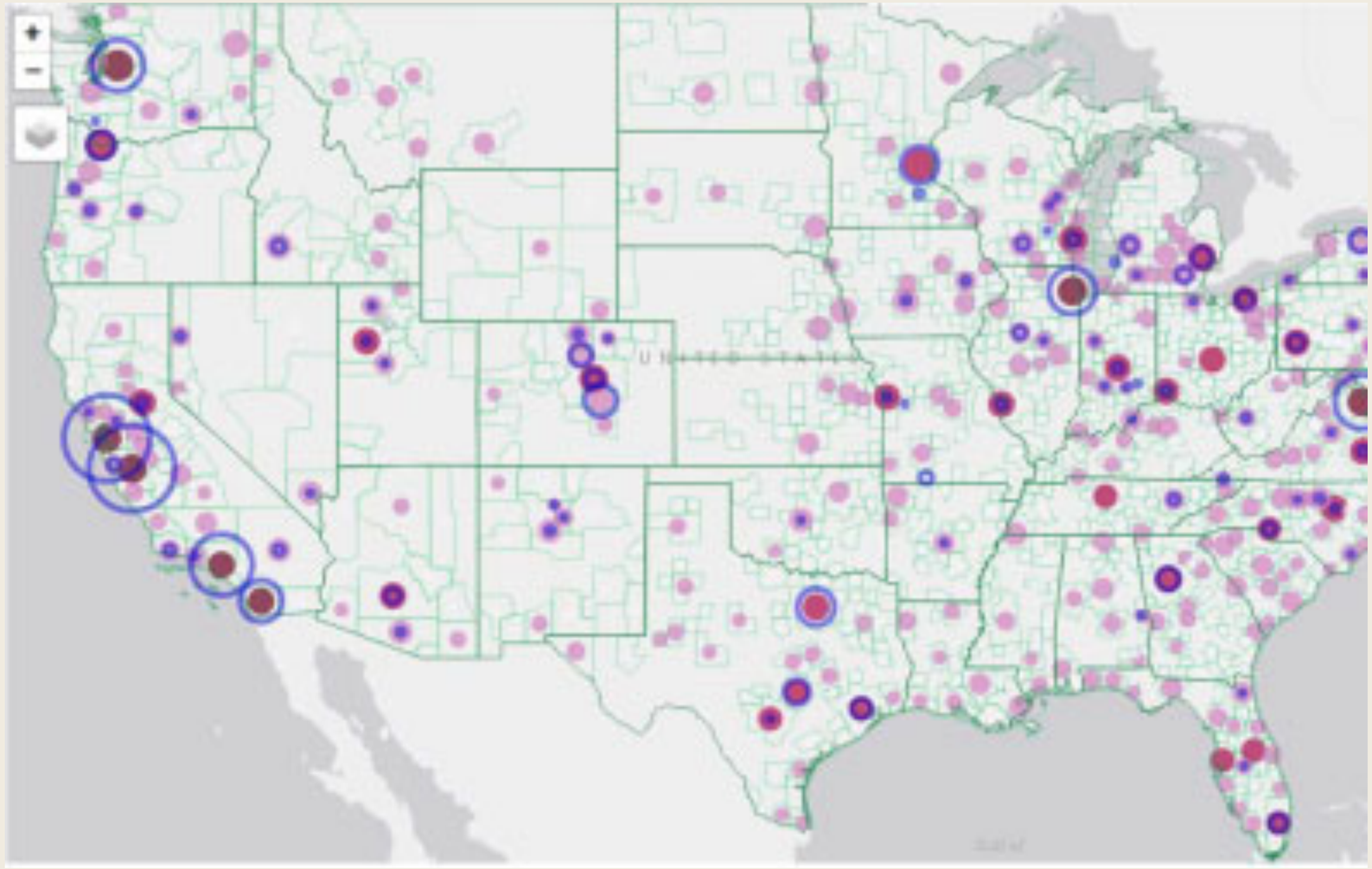
Share of Job Postings Mentioning Technologies

Years since emergence: 11-20

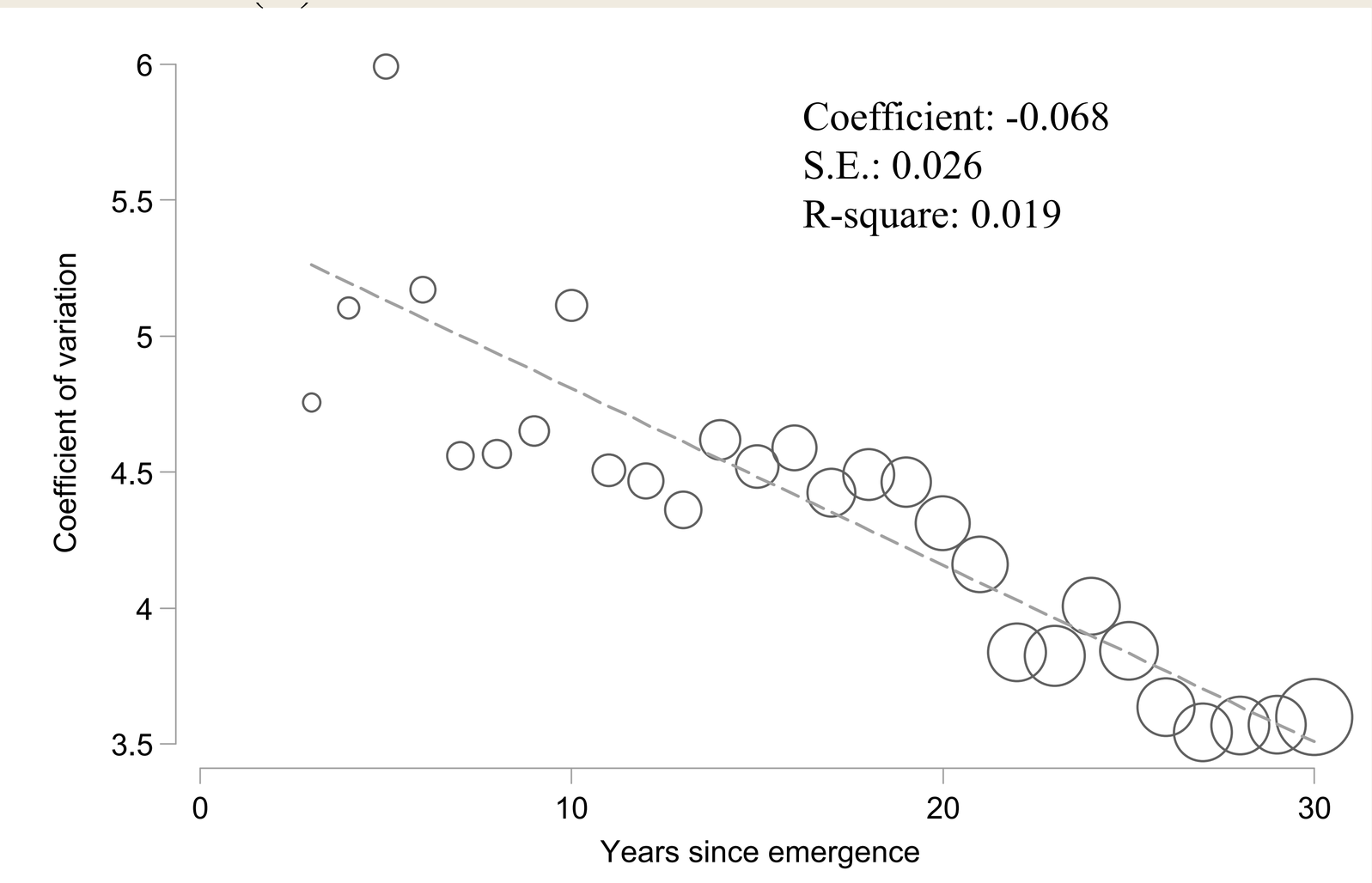


Share of Job Postings Mentioning Technologies

Years since emergence : 21-30



Diffusion is Slow



- Define:

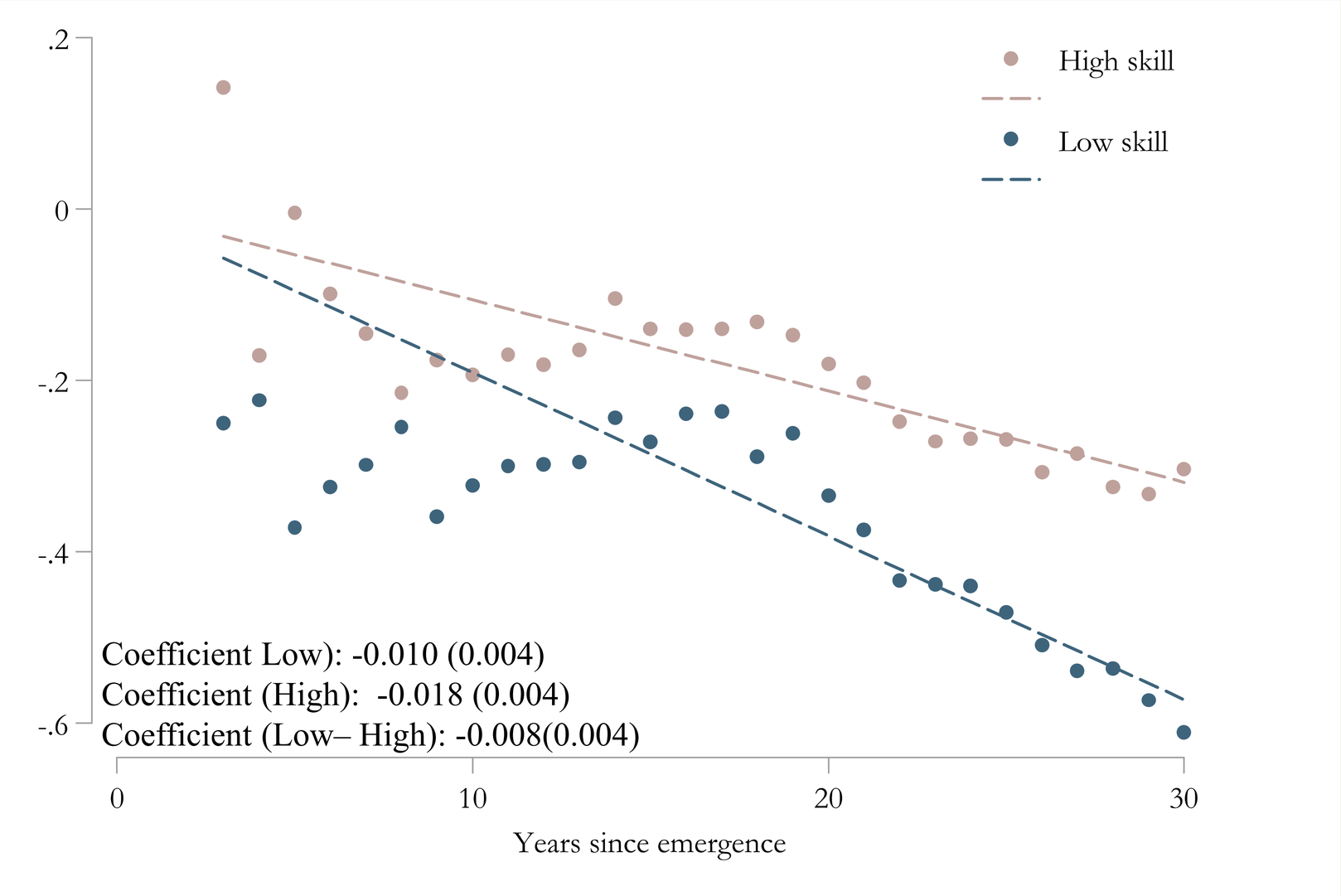
$$\text{Normalized Share} = \frac{(\text{share Tech Job})_i}{(\text{share all job})_i}$$

- If technologies fully diffuse

$$CV(\text{Norm. Share}) = 0$$

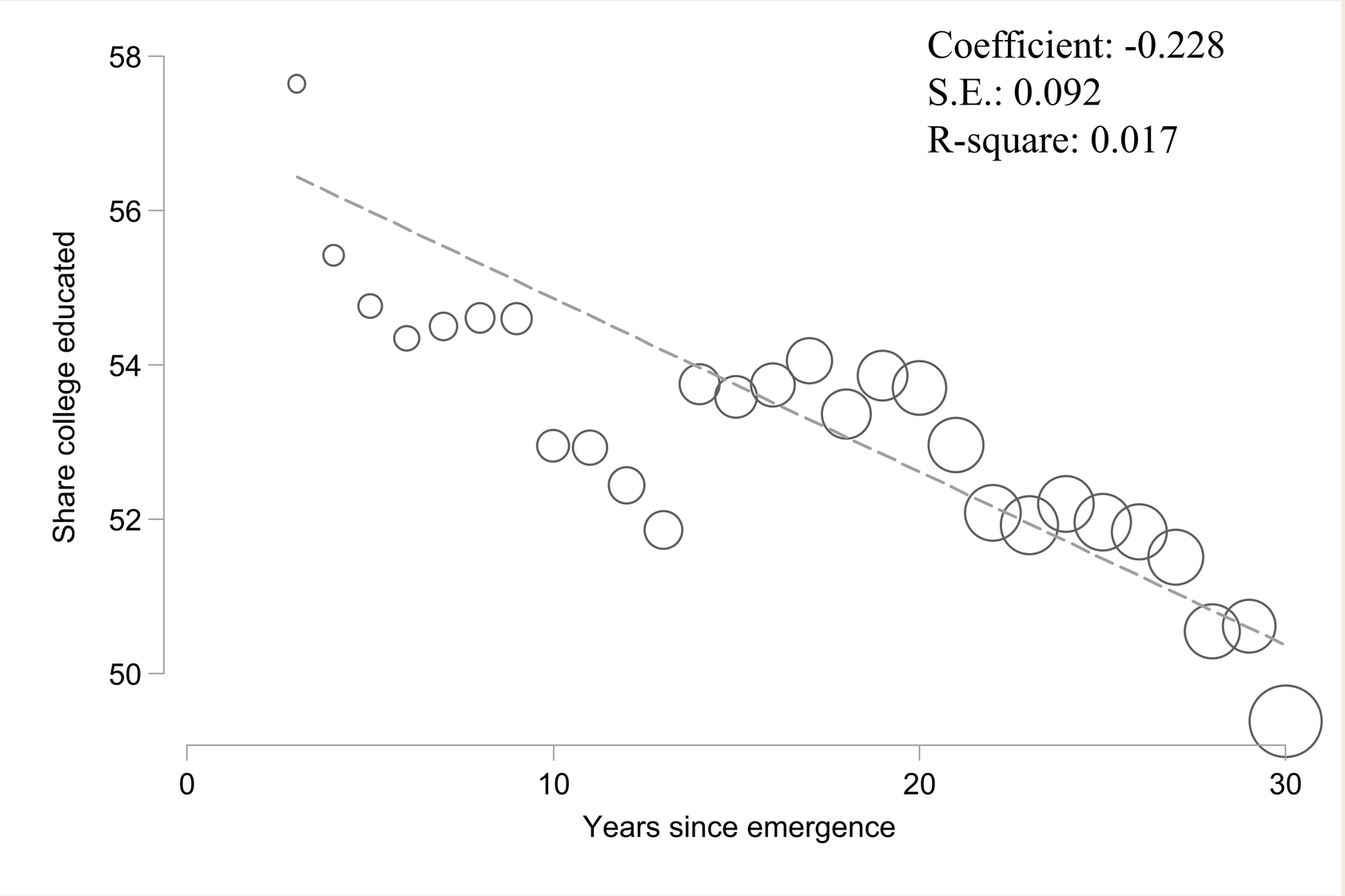
- Takes 85 years to $CV = 0$

Diffusion is Faster for Low-Skill Jobs



- High-skill jobs: occupations with 60%+ are college-educated
- Low-skill jobs: 30% or less are college-educated

New Tech is Skill Biased but Gradually Broadens



Taking Stock

- New technologies are born in highly skilled places
- New technologies diffuse very slowly
  - but diffuse relatively fast for low-skill jobs
- New technologies are initially skill-biased but broaden over time
- Suggestive mechanism:
  - Using, not just developing, the new technology requires skill
  - Tech. doesn't diffuse immediately because many don't have skills to use it
  - but diffuse slowly as the tech. becomes more standardized so that low-skill can use
- Likely to be an important mechanism to understand the cross-country differences in A

2. Misallocation Hypothesis

– Hsieh and Klenow (2009)

Misallocation Hypothesis

- Perhaps China and the US have access to the same technology
- But resources are more misallocated in China than US
  … due to regulations, corruption, financial frictions, etc
- Firms with low productivity produce more, high productivity produce less
- Misallocation manifests as a lower TFP, A
  - Lower output even with the same L and K

Environment and Market Equilibrium

- We now move away from one production function
- Suppose there are N firms in a country, $i = 1, \ldots, N$
- Each firm i has access to the following technology

$$y_i = \underbrace{\tilde{A}_i k_i^{\alpha}}_{\equiv A_i} l_i^{1-\alpha}$$

- For simplicity, we assume k_i is fixed
- Each firm takes wage w as given, decide l_i, and sells the goods at price of 1
- The labor markets clear (labor demand = labor supply):

$$\sum_{i=1}^{N} l_i = L$$

Equilibrium without Misallocation

- Let us start with the case there is no misallocation
- All firms solve

$$\max_{l_i} A_i l_i^{1-\alpha} - w l_i$$

- The first-order condition is

$$\underbrace{(1-\alpha) A_i l_i^{-\alpha}}_{\text{Marginal product of labor}} = w$$

- This implies that the marginal product of labor is equalized across all firms

$$(1-\alpha) A_1 l_1^{-\alpha} = (1-\alpha) A_2 l_2^{-\alpha} = \cdots = (1-\alpha) A_N l_N^{-\alpha}$$

Why is there no misallocation?

- Suppose a government (planner) forces firm 1 to hire more and firm 2 to hire less
- Can we increase total output?
- Firm 1's output increases by

$$\frac{dy_1}{dl_1} = (1-\alpha)A_1 l_1^{-\alpha}$$

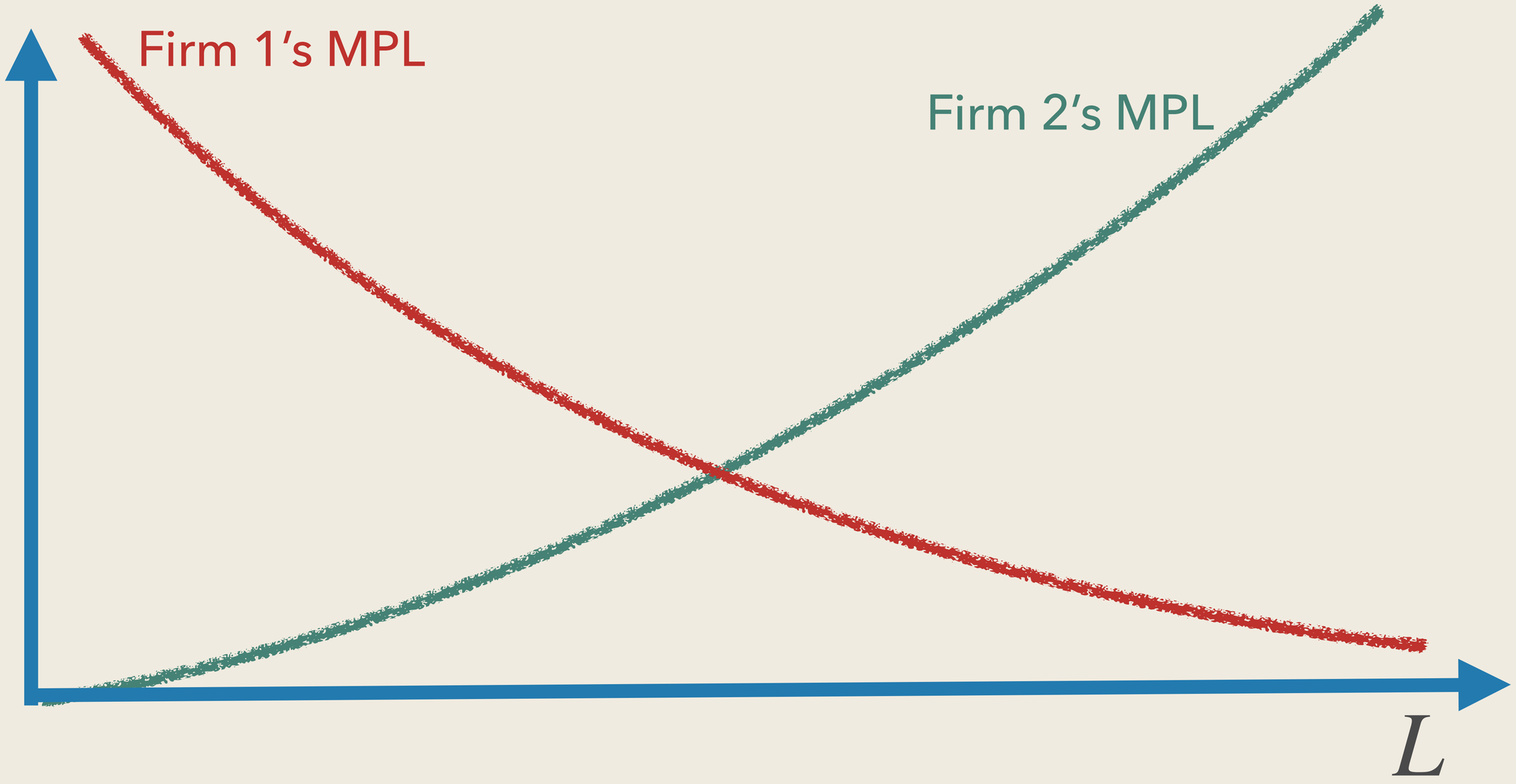
- Firm 2's output decreases by

$$\frac{dy_2}{dl_2} = (1-\alpha)A_2 l_2^{-\alpha}$$

- Changes in total output:

$$\frac{dy_1}{dl_1} - \frac{dy_2}{dl_2} = (1-\alpha)A_1 l_1^{-\alpha} - (1-\alpha)A_2 l_2^{-\alpha} = 0$$

Two Firms Example



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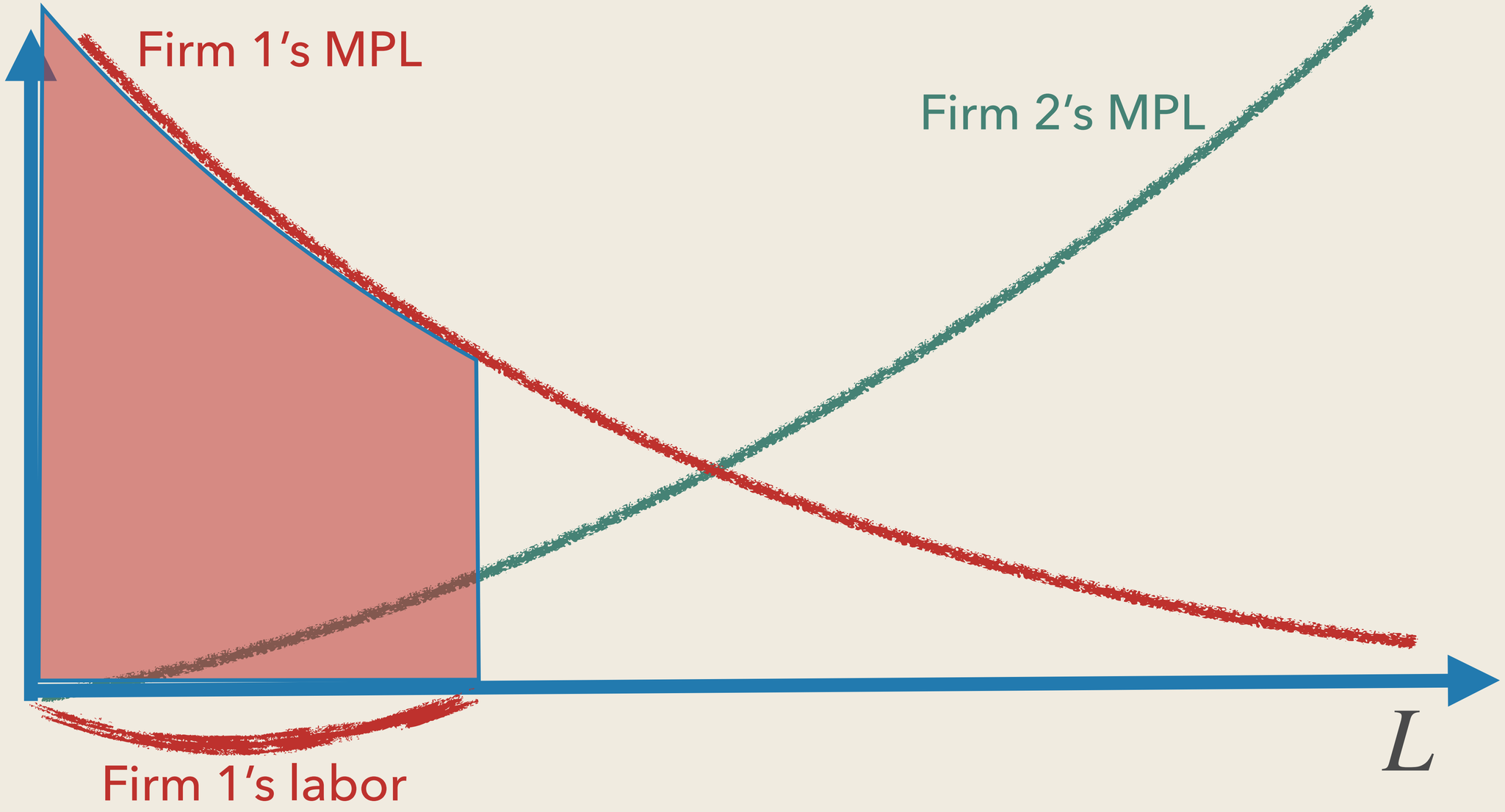

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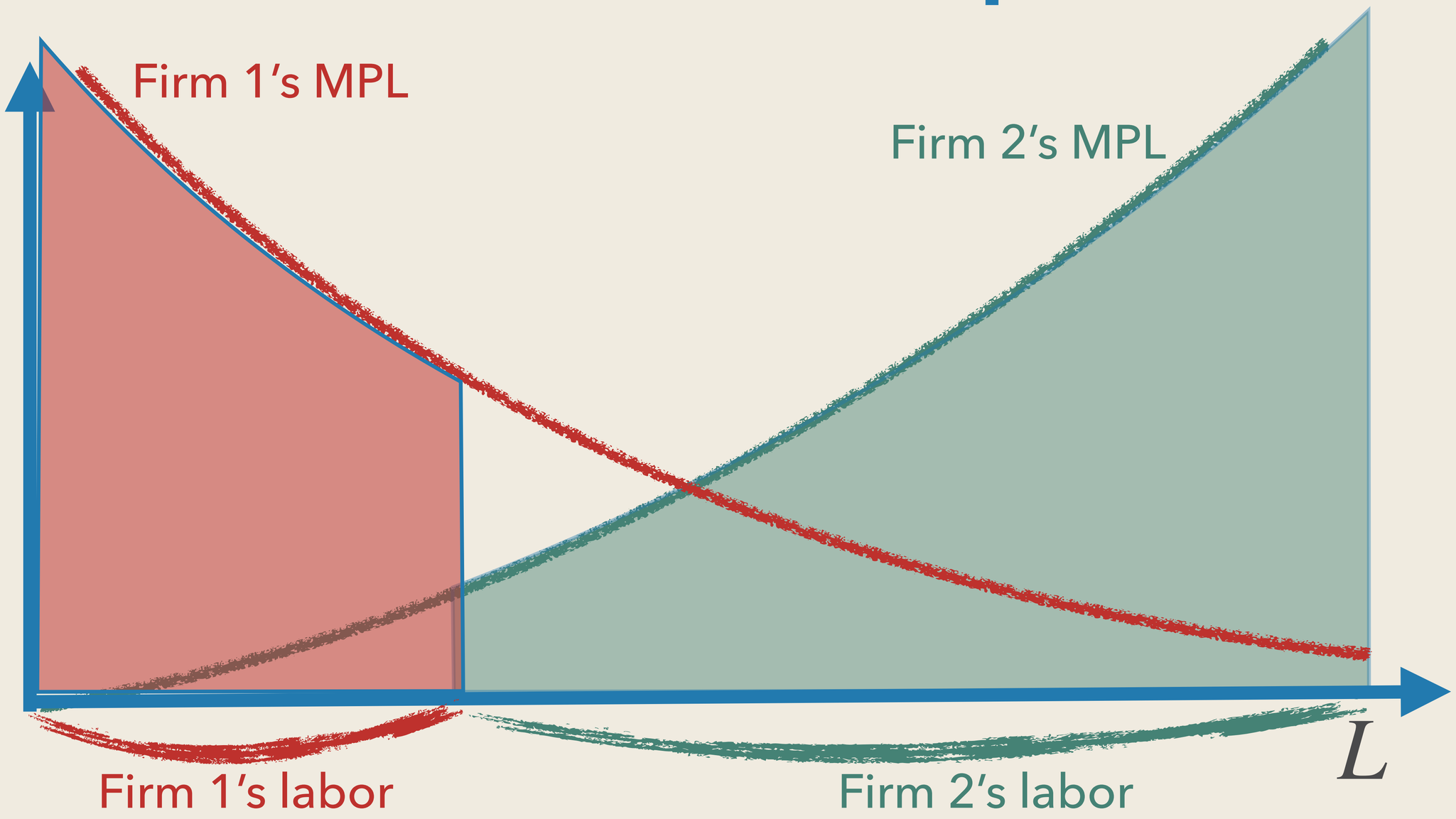

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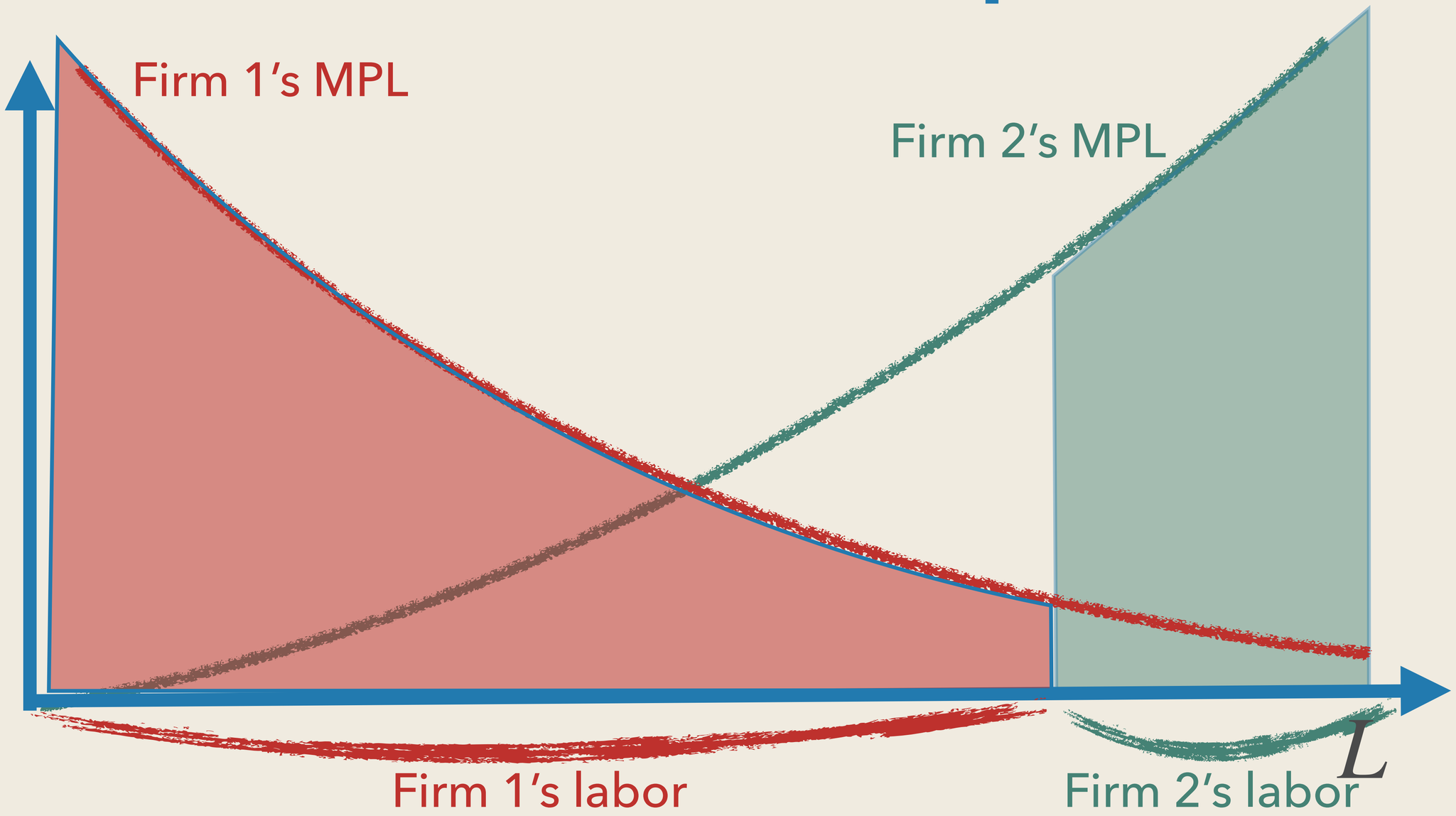

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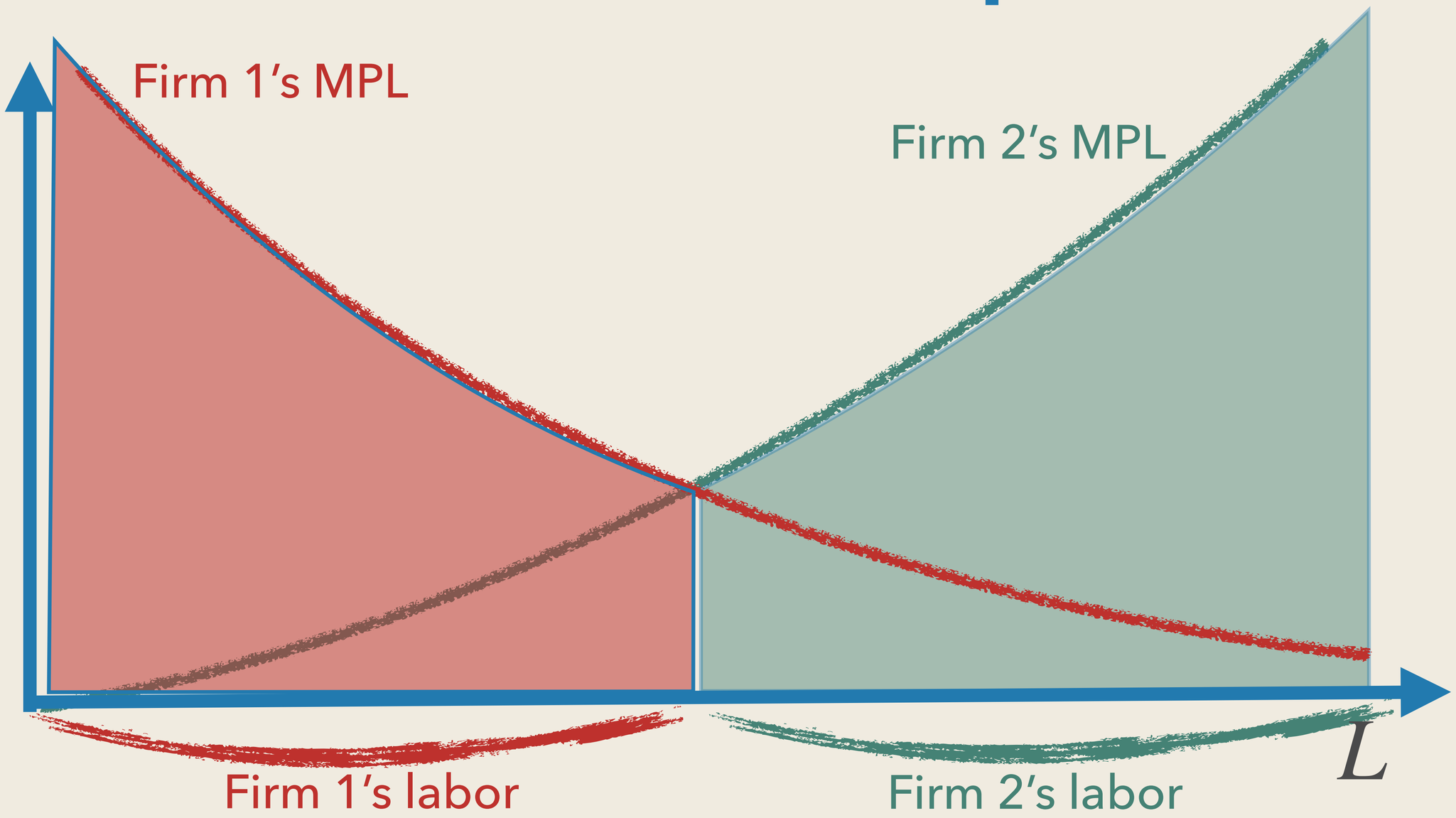


Efficient Allocation

- More generally, the efficient allocation of the economy is

$$\max_{l_1,\ldots,l_N} \sum_{i=1}^{N} A_i l_i^{1-\alpha}$$

$$\text{s.t.} \quad \sum_{i=1}^{N} l_i = L$$

- Lagrangian is

$$\mathscr{L} = \sum_{i=1}^{N} A_i l_i^{1-\alpha} + \lambda \left[L - \sum_{i=1}^{N} l_i \right]$$

- Taking the first-order condition,

$$(1-\alpha) A_1 l_1^{-\alpha} = (1-\alpha) A_2 l_2^{-\alpha} = \cdots = (1-\alpha) A_N l_N^{-\alpha} = \lambda$$

$\Rightarrow$ the marginal product of labor is equalized across all firms!

Firm's Hiring Decisions

- A well-functioning market allocates resources efficiently
- But maybe in reality, the market doesn't work like this
- For example, suppose firms face differing tax rates $(1 - \tau_i)$ from their revenue
  - regulation/corruption/frictions might treat different firms differently
- All firms now solve

$$\max_{l_i}(1 - \tau_i)A_i l_i^{1-\alpha} - w l_i$$

- First-order condition

$$\underbrace{(1 - \alpha)A_i l_i^{-\alpha}}_{\text{Marginal product of labor (MPL)}} = w\frac{1}{1 - \tau_i}$$

Why is there "misallocation"?

- Suppose a government (planner) forces firm 1 to hire more and firm 2 to hire less
- Can we increase total output?
- Changes in total output:

$$\frac{dy_1}{dl_1} - \frac{dy_2}{dl_2} = \underbrace{(1-\alpha)A_1 l_1^{-\alpha}}_{w/(1-\tau_1)} - \underbrace{(1-\alpha)A_2 l_2^{-\alpha}}_{w/(1-\tau_2)}$$

$$\neq 0 \quad \text{if } \tau_1 \neq \tau_2$$

- The total output increases if firm 1's MPL is higher than firm 2's ($\tau_1 > \tau_2$)
- Firm 1 was hiring too little, while firm 2 was hiring too much
  - Reallocating labor from firm 2 to 1 improves allocative efficiency

Dispersion in MPL ⇒ TFP Loss

- We can show that, to a second-order approximation around the efficient allocation,

$$Y \approx \bar{A} M L^{1-\alpha}$$

where

$$\bar{A} = \left(\sum_{i=1}^{N} A_i^{1/\alpha} \right)^{\alpha}$$

$$M = \exp\left[-\frac{1}{2}\frac{1}{\alpha} \text{Var}(\log MPL_i) \right] \leq 1$$

- **Dispersion** in the marginal product of labor, MPL_i, lowers aggregate productivity

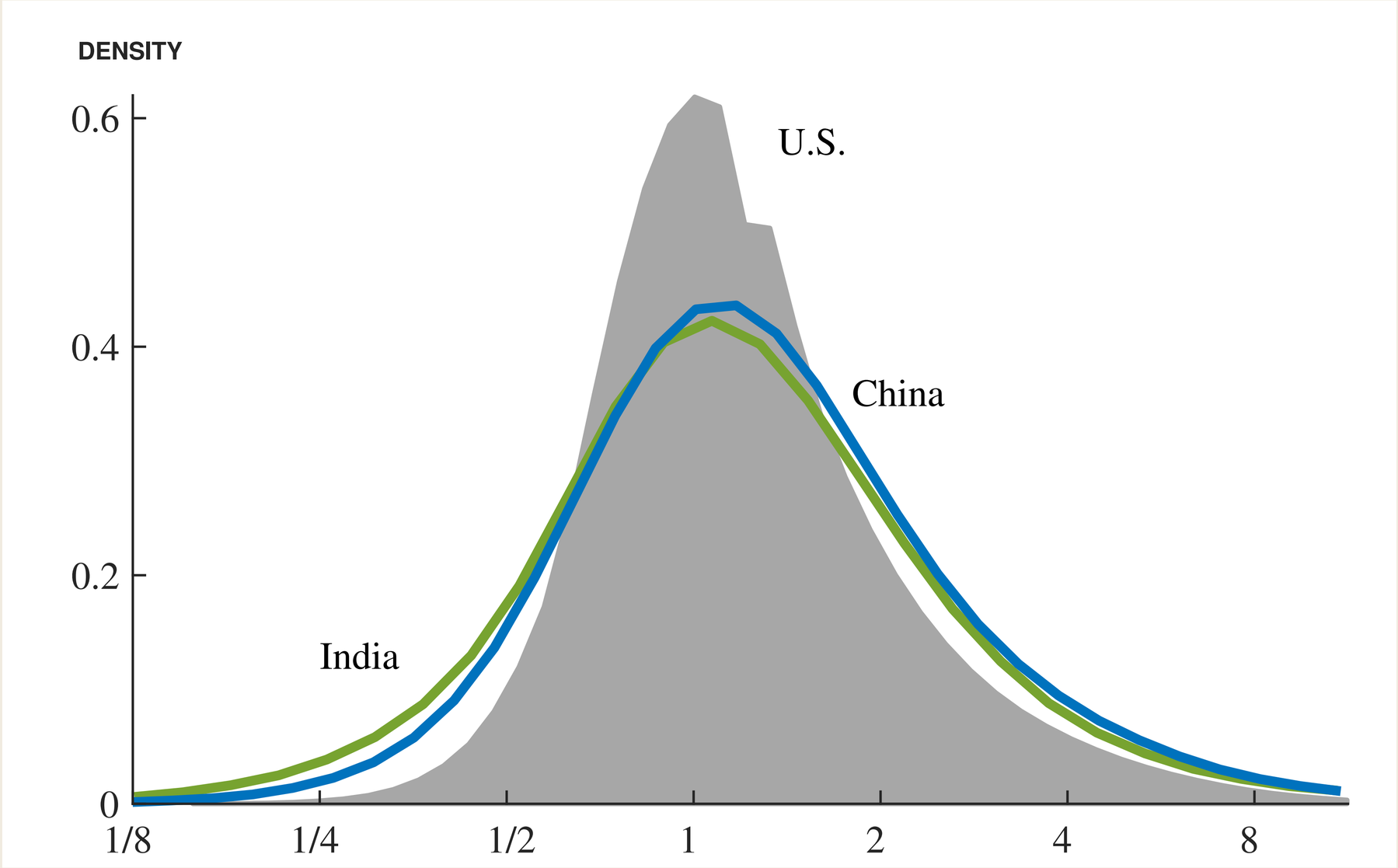
Measuring MPL

- How do we measure marginal product of labor?
- With our functional form assumption, this is easy:

$$MPL_i = (1-\alpha)\frac{y_i}{l_i}$$

- Hsieh and Klenow (2009):
  - Use manufacturing plant-level data from the US, India, and China
  - They measure dispersions in MPL_i at the plant-level using $MPL_i = (1-\alpha)y_i/l_i$
  - Quantify the TFP losses from misallocation

Dispersions in MPL



Huge Misallocation, More So in China & India

- More dispersions in MPL, and thereby misallocation, in China and India than the US
- Removing misallocation increases total output by
  - $\approx$ 100% in China
  - $\approx$ 120% in India
  - $\approx$ 40% in the US
- If China and India had the same level of misallocation as the US,
  - Manufacturing TFP goes up by $\approx$ 40% in China and by $\approx$ 50% in India
  - Close the manuf. TFP gap to the US by 50% for China and for 35% for India
- Misallocation accounts for 30-50% of the difference in TFP

2. Misallocation Hypothesis:

Is This the Number We Believe in?

– Carrillo, Donaldson, Pomeranz & Singhal (2023)

Do We Believe It?

- We relied on the following equation:

$$MPL_i = (1-\alpha)\frac{y_i}{l_i}$$

- This relies on a very strong functional form assumption, $y_i = A_i l_i^{1-\alpha}$
- Simple functional form assumptions are useful to obtain insights
  … but not something we seriously believe in
- Is there any way to test misallocation without relying on strong assumptions?

Nonparametric Test of Misallocation

- Carrillo, Donaldson, Pomeranz & Singhal (2023) develop such an approach
- If there is an exogenous demand shock to firms, and suppose we observe
  - changes in output in response to the shock, dy_i
  - changes in input in response to the shock, dl_i
- Consequently, we observe

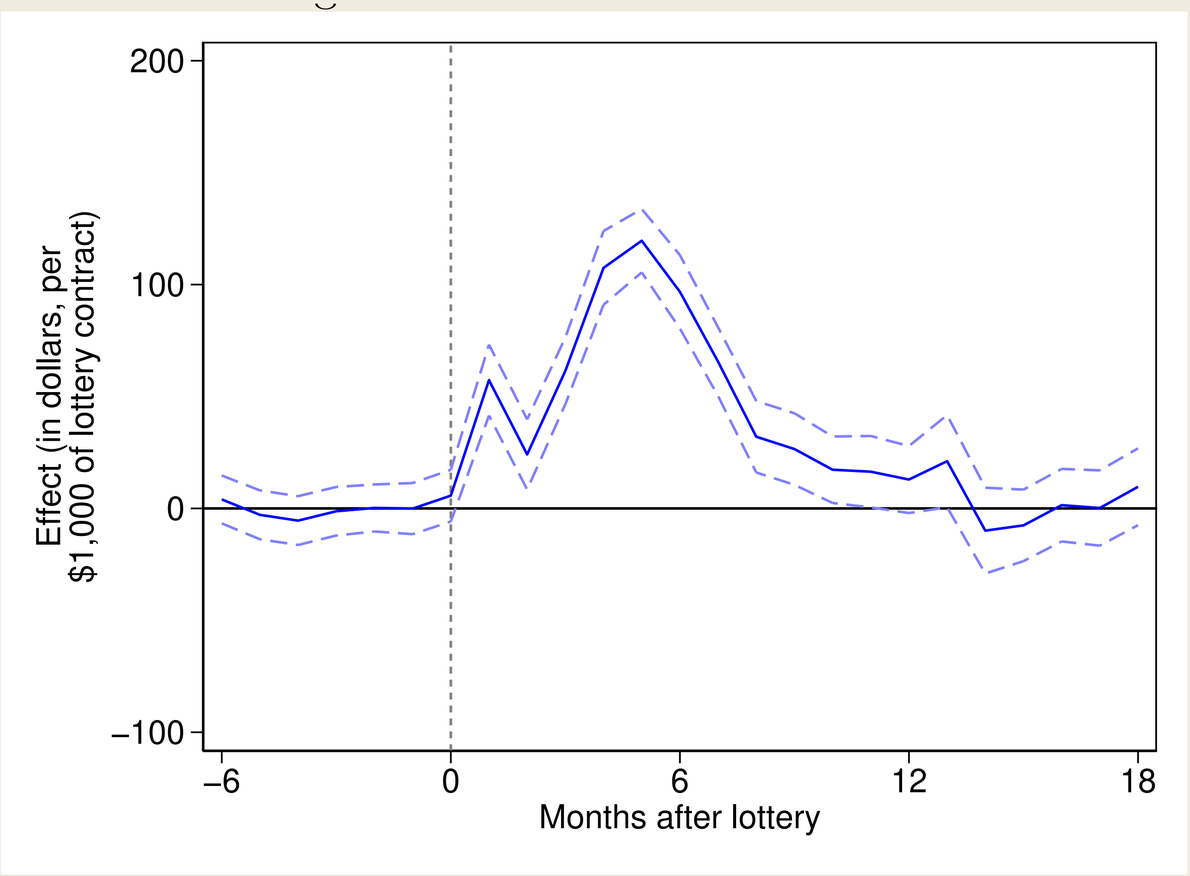
$$\frac{dy_i}{dl_i} = MPL_i$$

Construction Sector in Ecuador

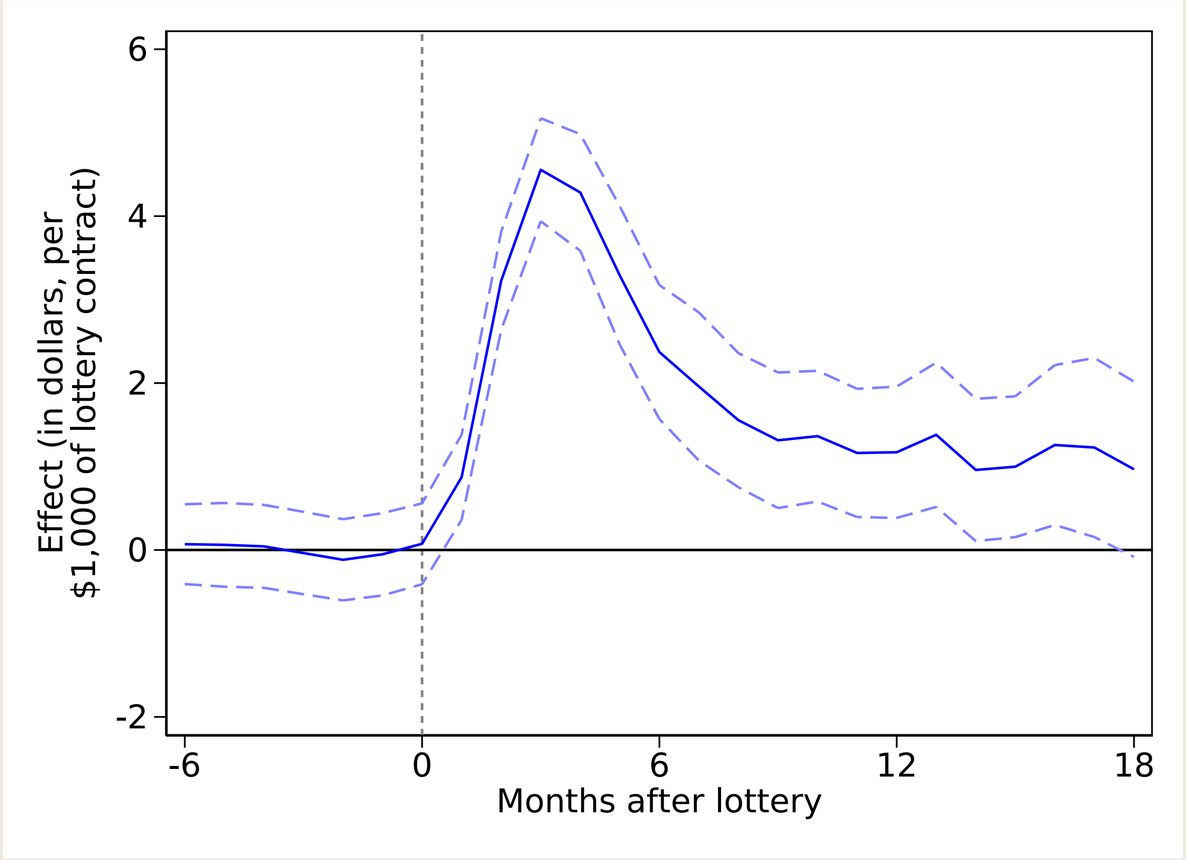
- They implement this approach in the context of the construction sector in Ecuador
- Ecuador's public procurement system allocates construction contracts by lottery
- Projects below a certain value allocated through lotteries among qualified suppliers
- This generates random demand shocks at the firm level (exactly what we want!)

Impact of Winning Lottery

Sales

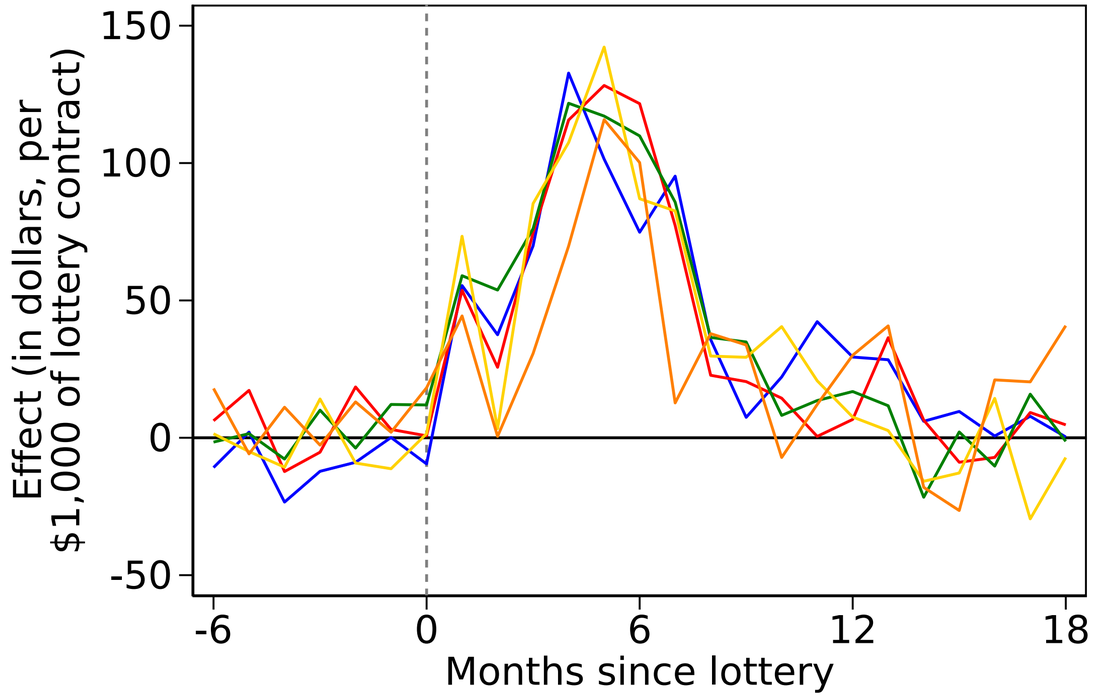


Labor Inputs



Heterogenous Responses by Firm Size

Sales



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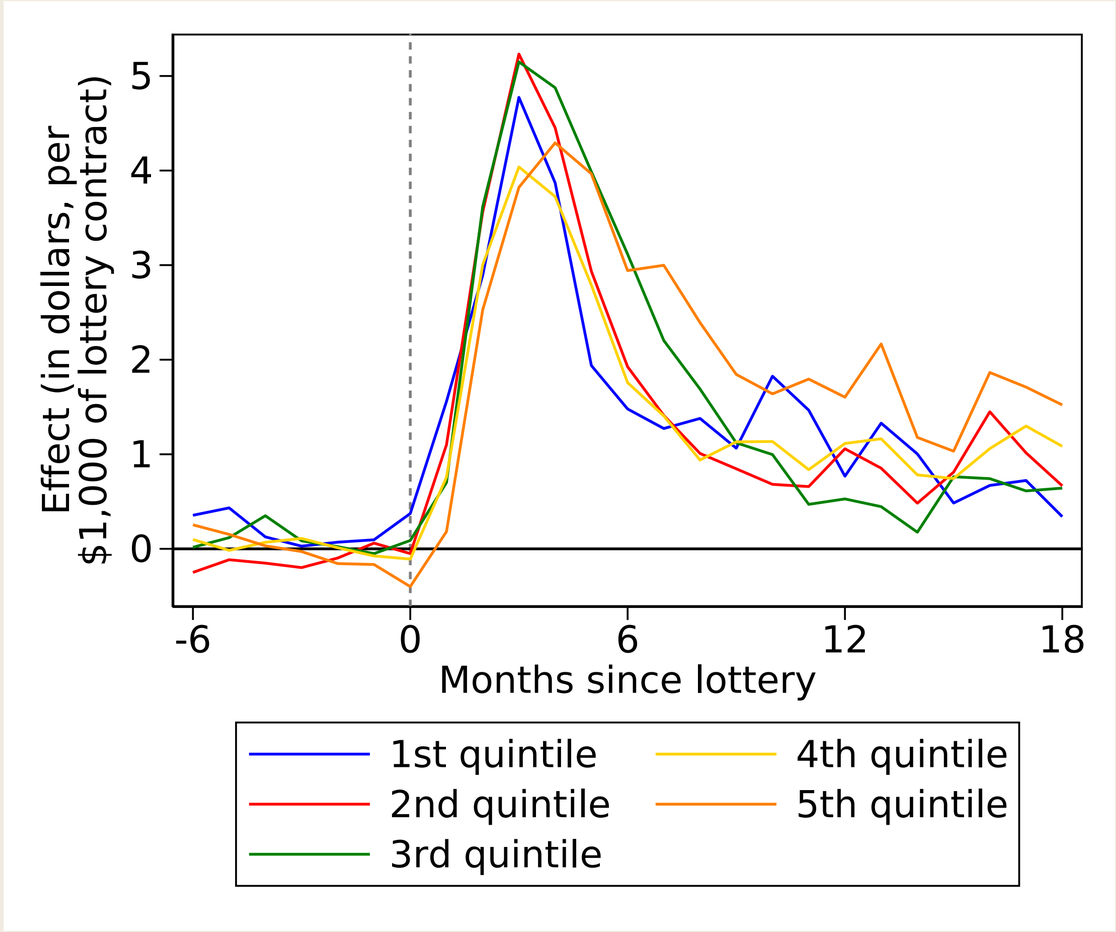
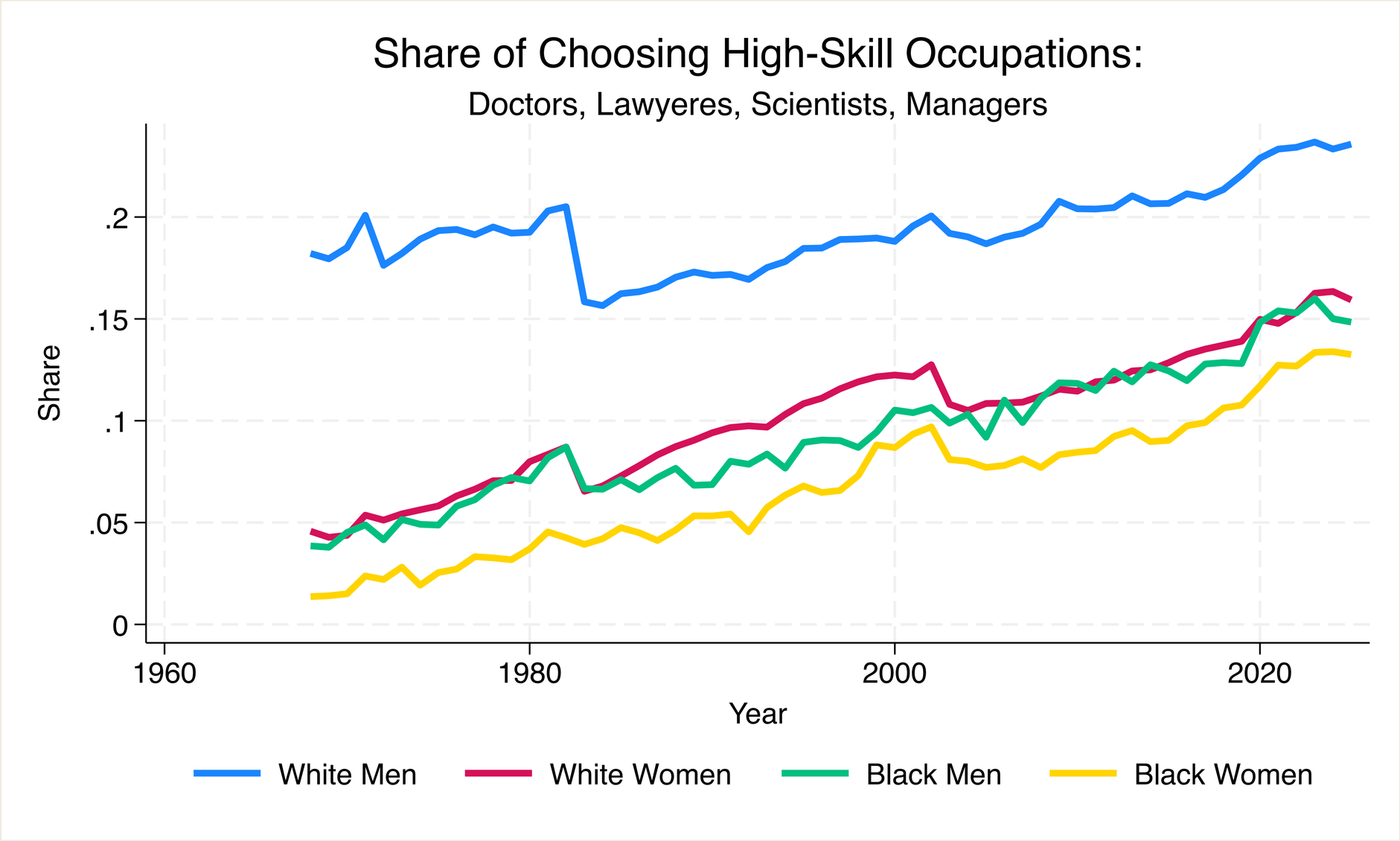


Negligible Cost of Misallocation

- Very little heterogeneity in dy_i or dl_i
- This suggests that very little differences in $MPL_i = dy_i/dl_i$ across firms
- Full calculation implies that removing misallocation increases output by 1.6%
- Compare this number to 100-140% in Hsieh-Klenow (2009)!

3. Misallocation and Economic Growth – Hsieh, Hurst, Jones & Klenow (2019)

Disappearing Discrimination?



Example

Source: https://www.nytimes.com/2023/12/01/us/sandra-day-oconnor-dead.html

- Sandra Day O'Connor was the first woman to serve on the Supreme Court justice
- She graduated from Stanford Law School in 1952, ranked 3rd in her class
- The only job she could get in 1952 was as a legal secretary

Model with Discrimination

- Suppose there are
  - N occupations (lawyers, doctors, nurses, secretaries, etc)
  - K groups of people (white men, black men, white women, black women, etc)
- Firms in occupation i hiring group k workers produces

$$y_{ik} = A_i l_{ik}^{1-\alpha}$$

- Firms can hire a group k workers with wage w_k
- However, firms face tax $(1 - \tau_{ik})$ when hiring group k workers
  - captures discrimination or barriers that a group k faces
- Firms in occupation i hiring group k workers solve

$$\max_{l_{ik}} A_i l_{ik}^{1-\alpha}(1 - \tau_{ik}) - w_k l_{ik}$$

Market Clearings

- The labor market clears for each group:

$$\sum_{i=1}^{N} l_{ik} = L_k$$

- The total output in this economy is

$$Y = \sum_{k=1}^{K} \sum_{i=1}^{N} A_i l_{ik}^{1-\alpha}$$

Discrimination and MPL

- The first-order conditions for each i, k are

$$(1-\alpha)A_i l_{ik}^{-\alpha}(1-\tau_{ik}) = w_k$$

- For each group k,

$$\underbrace{(1-\alpha)A_1 l_{1k}^{-\alpha}}_{MPL_{1k}} \underbrace{(1-\tau_{1k})}_{\text{discrimination in occ. 1}} = \cdots = \underbrace{(1-\alpha)A_N l_{Nk}^{-\alpha}}_{MPL_{Nk}} \underbrace{(1-\tau_{Nk})}_{\text{discrimination in occ. N}} = w_k$$

- Each group k workers is allocated across occupations to equalize MPL
  … adjusted with discrimination term

- Higher τ_{ik} (more discrimination) $\Rightarrow$ higher MPL_{ik}

Occupational Choice

- Solving for l_{ik}

Share of group k workers choosing occupation i

$$\frac{l_{ik}}{L_k} = \frac{[A_i(1-\tau_{ik})]^{1/\alpha}}{\sum_{j=1}^{N}[A_j(1-\tau_{jk})]^{1/\alpha}}$$

- If there were no discrimination, $\tau_{ik} = 0$, for all i, k:

$$\frac{l_{i1}}{L_1} = \cdots = \frac{l_{iK}}{L_K} = \cdots = \frac{A_i^{1/\alpha}}{\sum_{j=1}^{N} A_j^{1/\alpha}}$$

  - The same share of black women and white men should choose to be lawyers

- If black women face more discrimination as lawyers than as janitors
  $\Rightarrow$ black women more likely to choose janitors than lawyers

Discrimination ⇒ Lower TFP

- Discrimination manifests as misallocation
- Like before

$$Y \approx \sum_{k=1}^{K} \bar{A} M_k L_k^{1-\alpha}$$

$$\bar{A} = \left(\sum_{i=1}^{N} A_i^{1/\alpha} \right)^{\alpha}$$

$$M_k = \exp\left[-\frac{1}{2}\frac{1}{\alpha} \mathsf{Var}_i(\log MPL_{ik}) \right]$$

- Discrimination implies $\mathsf{Var}_i(\log MPL_{ik}) > 0 \Rightarrow M_k < 1$

Quantifying Macro Consequence of Discrimination

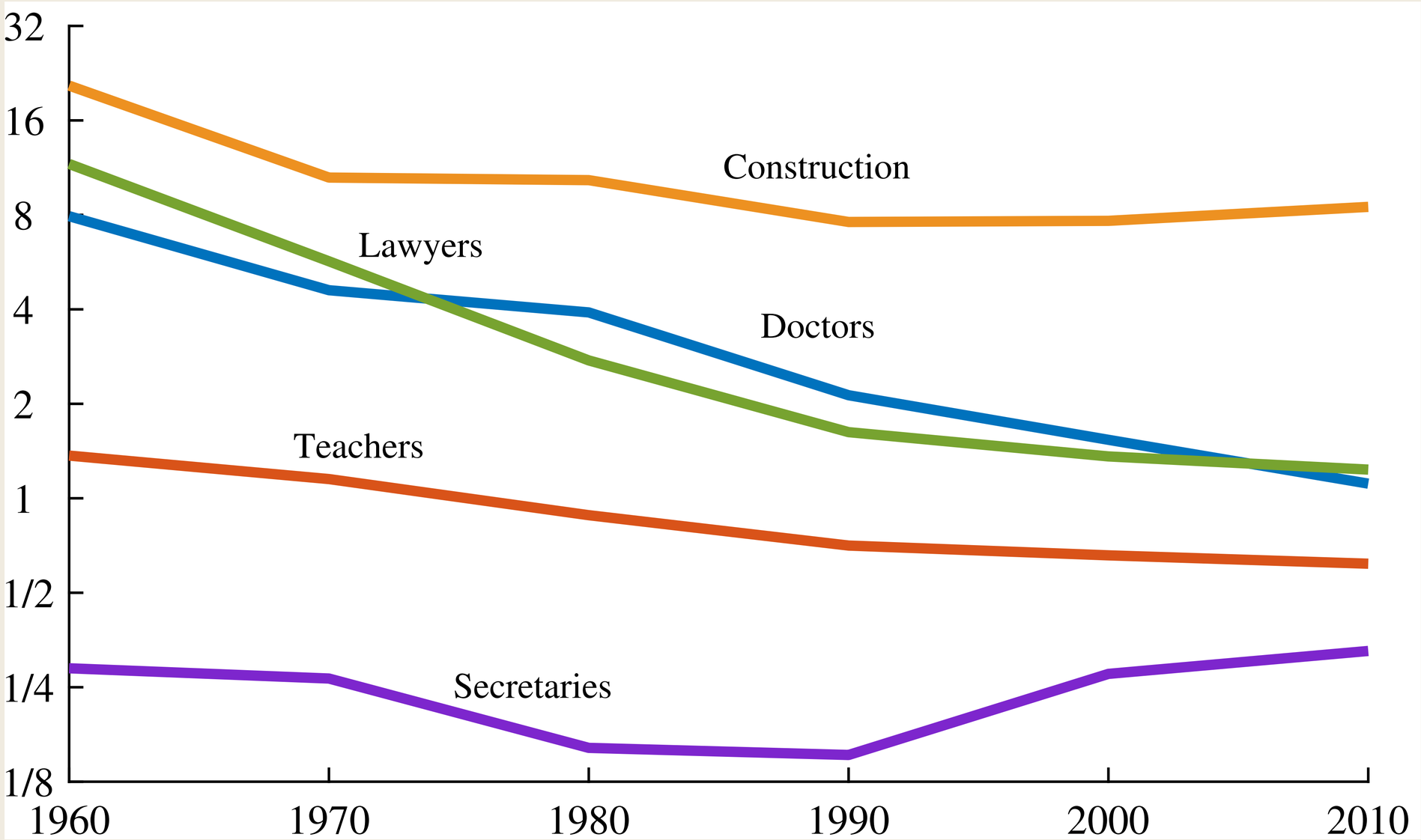
- Reductions in discrimination over the past 60 years have led to economic growth
- How do we quantify it?
- Assume that white men face no discrimination, $\tau_{ik} = 0$ for all i and $k = \text{WM}$
- We also normalize $\tau_{1k} = 0$ for all k (what matters is the dispersion in τ_{1k}!)
- Then occupational choice reveals the discrimination:

$$\frac{\frac{l_{ik}/L_k}{l_{1k}/L_k}}{\frac{l_{iWM}/L_{WM}}{l_{1WM}/L_{WM}}} = (1 - \tau_{ik})$$

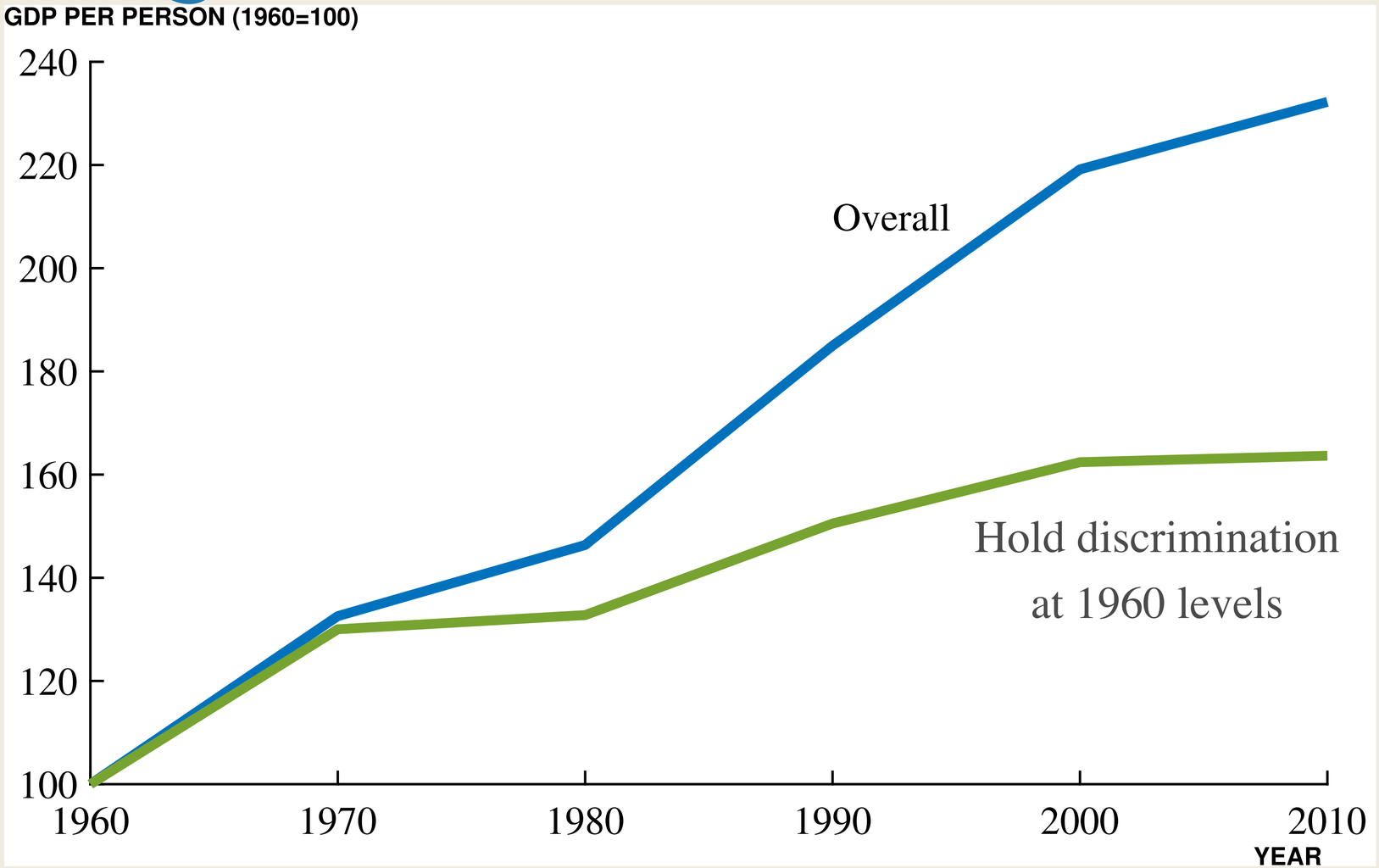
If white women are less likely to become lawyers compared to white men, we infer big discrimination for white women as a lawyer

- Choose $\{A_i\}$ to match observed l_{iWM}/L_{WM} and assume $\alpha = 1/3$

Inferred τ_{ik} for White Women



Declining Discrimination ⇒ Economic Growth



- Around 20% of US economic growth comes from a reduction in discrimination

Takeaway

- Economics often starts from an assumption that markets allocate resources efficiently
- In reality, various frictions prevent the efficient allocation of resources
  - Regulations, corruption
  - Market power, financial friction
  - Certain groups of people face barriers and discrimination
- Frictions may systematically vary across countries
  ⇒ potentially explain cross-country income differences
- Frictions may have been reduced in the past
  ⇒ potentially explain economic growth