Geographic Mobility of Youth and Spatial Gaps in Local College and Labor Market Opportunities

Shoya Ishimaru, *Hitotsubashi University*

This paper investigates the mechanisms underlying the causal link between childhood location and adulthood economic outcomes. I develop and estimate a dynamic model of individual choice of whether and where to attend college and where to work, accounting for home preferences, spatial search frictions, and moving costs. The estimated model suggests that spatial gaps in college and labor market opportunities, which stem from imperfect mobility in adulthood, play a more important role than variation in childhood neighborhood quality in explaining why children from different counties with similar family backgrounds achieve different economic outcomes in adulthood.

Overlapping college nests: 2-year vs. 4-year; public vs. private; in-state vs. out-of-state

RAND Journal of Economics
Vol. 28, No. 0, 1997
pp. S17–S44

Market segmentation and the sources of rents from innovation: personal computers in the late 1980s

Timothy F. Bresnahan*

Scott Stern**

and

Manuel Trajtenberg***

We evaluate the sources of transitory market power in personal computers in the late 1980s to explain how high rates of imitative entry coexisted with high rates of innovative investment. We measure the impact of different principles of differentiation (PDs); each PD reflects a distinct notion of product similarity, offering a potential source of market segmentation. One PD measures the substitutability between frontier and nonfrontier products, while a second PD measures the advantage afforded by a brand-name reputation. We find segmentation along both dimensions, which meant that the effects of competitive events (such as entry) were localized. A high rate of entry was consistent with slow erosion of incumbent rents.

Overlapping product nests: branded vs. non-branded; frontier vs. non-frontier

AI innovation paradox: High innovation rates coexist with high entry rates of LLMs

Why doesn't innovation deter entry here?

AI innovation paradox: High innovation rates coexist with high entry rates of LLMs

Why doesn't innovation deter entry here?

Two key dimensions of LLM differentiation:

- Frontier vs. Non-frontier capability (F/NF)

- Proprietary vs. Open-source models (P/O)

Maybe even a third—Branded vs. Non-branded (B/NB)

With two dimensions, four market segments emerge:

$\{P, F\}$ Proprietary Frontier (GPT-5, Claude Sonnet 4, Gemini 2.5 Pro)

$\{P, NF\}$ Proprietary Non-frontier (GPT-4o, Claude Opus 3, Gemini 2)

$\{O, F\}$ Open Frontier (Llama 4 Scout, Mistral Large 2)

$\{O, NF\}$ Open Non-frontier (Llama 3, Mistral Large, ...)

With two dimensions, four market segments emerge:

$\{P, F\}$ Proprietary Frontier (GPT-5, Claude Sonnet 4, Gemini 2.5 Pro)

$\{P, NF\}$ Proprietary Non-frontier (GPT-4o, Claude Opus 3, Gemini 2)

$\{O, F\}$ Open Frontier (Llama 4 Scout, Mistral Large 2)

$\{O, NF\}$ Open Non-frontier (Llama 3, Mistral Large, ...)

Key insight: Market segmentation creates isolation from competition within clusters while allowing substitution across dimensions

Overlapping nests framework:

$$\begin{aligned} G(e^{\delta}) = a_F \left(\sum_{j \in F} e^{\delta_j/\rho_F} \right)^{\rho_F} + a_{NF} \left(\sum_{j \in NF} e^{\delta_j/\rho_{NF}} \right)^{\rho_{NF}} \\ + a_P \left(\sum_{j \in P} e^{\delta_j/\rho_P} \right)^{\rho_P} + a_O \left(\sum_{j \in O} e^{\delta_j/\rho_O} \right)^{\rho_O} + e^{\delta_0} \end{aligned}$$

Overlapping nests framework:

$$
\begin{aligned}
G(e^{\delta}) = a_F \left(\sum_{j \in F} e^{\delta_j/\rho_F} \right)^{\rho_F} + a_{NF} \left(\sum_{j \in NF} e^{\delta_j/\rho_{NF}} \right)^{\rho_{NF}} \\
+ a_P \left(\sum_{j \in P} e^{\delta_j/\rho_P} \right)^{\rho_P} + a_O \left(\sum_{j \in O} e^{\delta_j/\rho_O} \right)^{\rho_O} + e^{\delta_0}
\end{aligned}
$$

where $a_F + a_{NF} = 1$, $a_P + a_O = 1$, and ρ parameters $\in (0, 1]$

Overlapping nests framework:

$$G(e^{\delta}) = a_F \left(\sum_{j \in F} e^{\delta_j/\rho_F} \right)^{\rho_F} + a_{NF} \left(\sum_{j \in NF} e^{\delta_j/\rho_{NF}} \right)^{\rho_{NF}}$$
$$+ a_P \left(\sum_{j \in P} e^{\delta_j/\rho_P} \right)^{\rho_P} + a_O \left(\sum_{j \in O} e^{\delta_j/\rho_O} \right)^{\rho_O} + e^{\delta_0}$$

where $a_F + a_{NF} = 1$, $a_P + a_O = 1$, and ρ parameters $\in (0, 1]$

$\rho < 1$ creates within-nest correlation, enabling market segmentation

Two key competition effects:

- Within-nest competition: New Llama primarily steals from other open models
- Cross-nest insulation: Limited impact on GPT-5/Claude 4 demand

Two key competition effects:

- Within-nest competition: New Llama primarily steals from other open models
- Cross-nest insulation: Limited impact on GPT-5/Claude 4 demand

Example: Meta's Llama 3 release had minimal effect on OpenAI revenues despite strong capabilities

Two key competition effects:

- Within-nest competition: New Llama primarily steals from other open models
- Cross-nest insulation: Limited impact on GPT-5/Claude 4 demand

Example: Meta's Llama 3 release had minimal effect on OpenAI revenues despite strong capabilities

Segmentation $\Rightarrow$ firms can innovate even when they can't prevent competitor entry

How can GEV improve LLM market analysis?

Demand estimation:

- Market shares will depend on task type, privacy needs
- Cross-price elasticities vary by market segment

How can GEV improve LLM market analysis?

Demand estimation:

- Market shares will depend on task type, privacy needs
- Cross-price elasticities vary by market segment

Innovation incentives:

- Overlapping nests $\Rightarrow$ sustainable R&D investment
- Explains simultaneous frontier competition & open-source development
- Policy implications for AI regulation