

# The Expansion of Varieties in the New Age of Advertising

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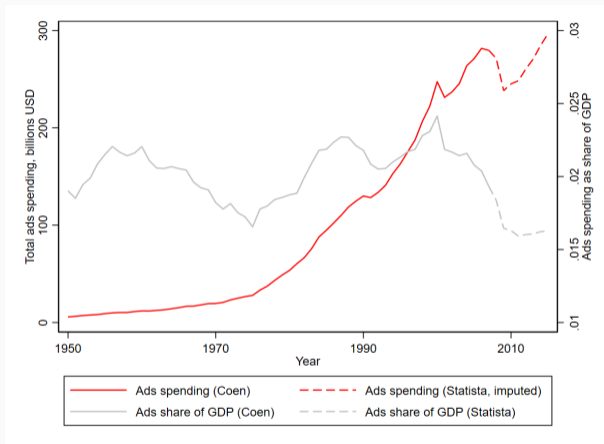
**Sara Moreira**

Northwestern

*Economic Growth Meeting*

*NBER Summer Institute 2023*

# Growth in Advertising Spending



- Increasing spending on advertising, mostly constant as a share of GDP.

# Changing Nature of Advertising: Traditional → Digital

The first online ad:

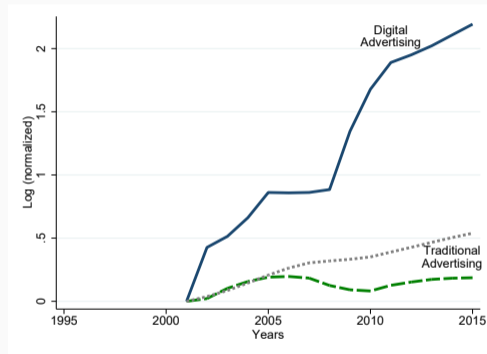
AT&T on HotWired.com in 1994



# Changing Nature of Advertising: Traditional → Digital

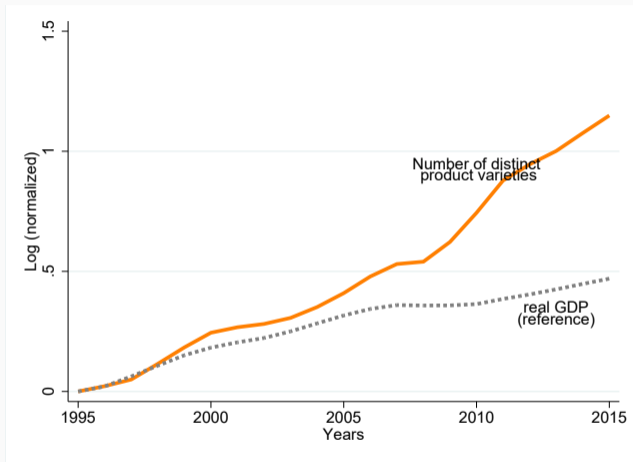
The first online ad:

AT&T on HotWired.com in 1994



- **Digital ads:** display ads, search, online video, mobile.

# Growth in Product Varieties



- The amount of distinct brands and products available to consumers has been growing over the last decades. other definitions

Question: How did the technological progress in digital advertising affect product varieties and consumer welfare over times?

- **Digital ads**: Big improvements in **targeting** (Goldfarb, 2013).
  - Demographic targeting; Contextual targeting; Behavioral targeting (incl. retargeting).
- **Firms** find it more profitable to tailor to diverse tastes and offer more product varieties.

## I. Model:

- Heterogeneous consumer **tastes**; firms choose **varieties** & **digital/traditional** ads.
- Informative view of advertising.

## II. Empirics:

- New data and evidence on digital ads and varieties.
- Causal estimates used to discipline the model.

## III. Quantitative analysis:

- Calibrate two economies in 1995 and 2015.
- 1995 → 2015: **digital ads targeting** ↑; operating cost efficiency ↑; entry costs ↑; generic tech. progress.
- Counterfactuals.

# I - Model

---



# Consumer's Problem

- Unit mass of consumers with heterogeneous **tastes** over varieties.
- Consumer  $i$ :

$$\max_{c_i, \{q_i(j)\}} \left\{ \theta \overbrace{\ln c_i}^{\text{generic good}} + (1-\theta) \overbrace{\int_{j \in \mathcal{M}_i} S_i(j)^\kappa \frac{q_i(j)^{1-\kappa}}{1-\kappa} dj}_{\text{specialized varieties}} \right\}$$

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*Match quality*

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- Consumer optimization:

$$q_i(j) = S_i(j) \left[ \frac{(1-\theta)\hat{y}}{p(j)} \right]^{1/\kappa}$$

→ Demand more if the match quality  $S_i(j)$  is higher.

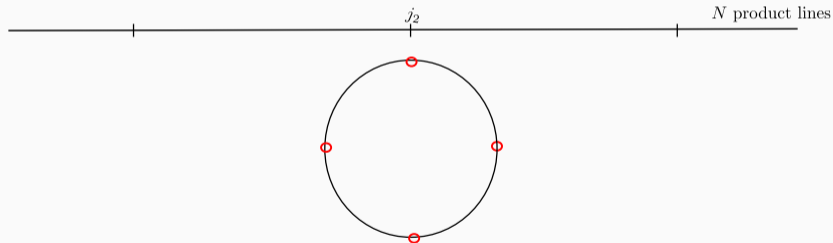
- **How is the match quality  $S_i(j)$  determined?**

# Tastes for a Variety within a Product Line

- Consider  $n$  eq-spaced varieties in the product line (unit-length circle).

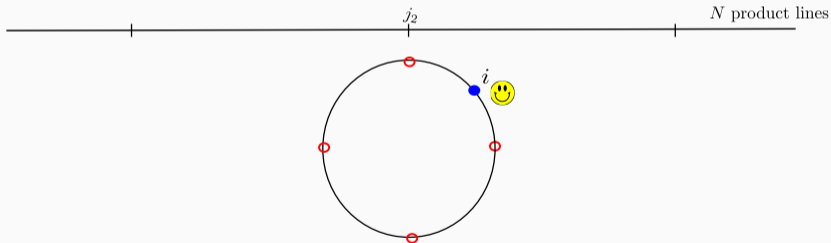
- $S$

- $S$



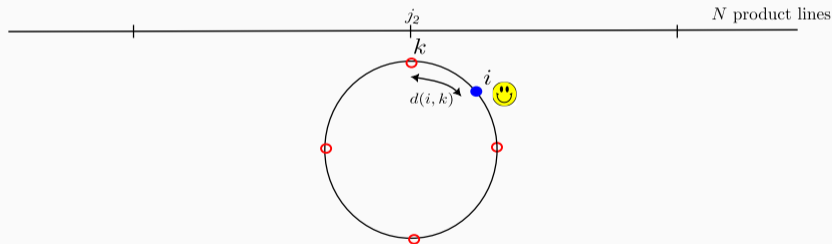
# Tastes for a Variety within a Product Line

- Consider  $n$  eq-spaced varieties in the product line (unit-length circle).
- Consumer  $i$ 's taste is located at  $i \sim U(0,1)$ .



## Tastes for a Variety within a Product Line

- Consider  $n$  eq-spaced varieties in the product line (unit-length circle).
- Consumer  $i$ 's taste is located at  $i \sim U(0,1)$ .
- $d(i, k)$  – distance btw the variety and consumer's taste.

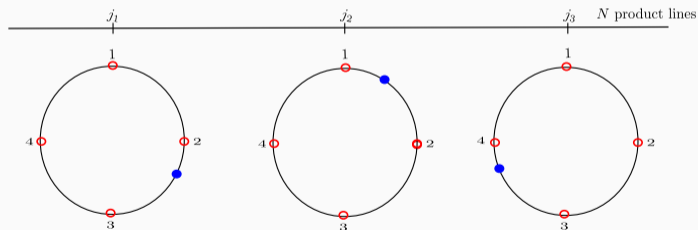


- Match quality  $S_i(j) = \chi - \lambda d(i, k_j^*)$ , where  $k_j^*$  is the consumed variety.

# Advertising & the Consumer-Variety Match

- $N$  (endog.) product lines – each sold by a monopolistically competitive firm.
- Firms produce  $n$  (endog.) varieties within the line; sell at price  $p$ .

• XXXX



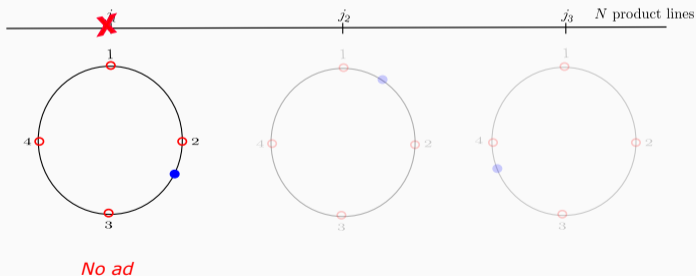


# Advertising & the Consumer-Variety Match

- **No ad:** no signal about any variety.

- XXX

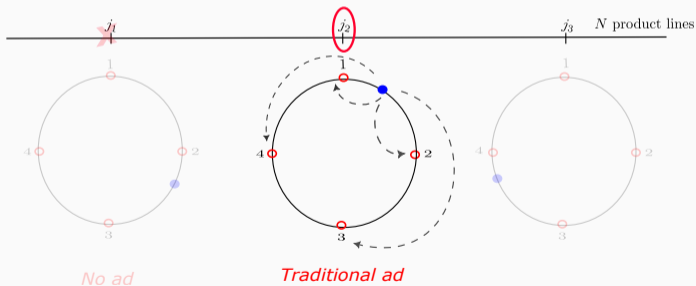
- XXX



# Advertising & the Consumer-Variety Match

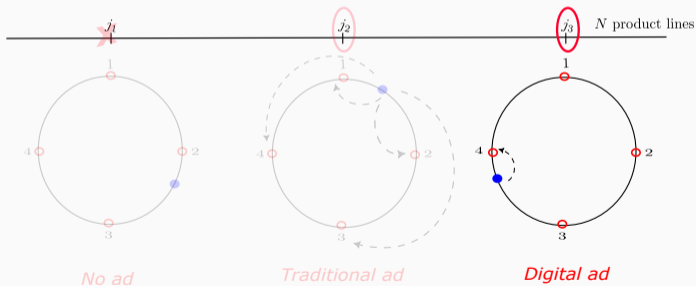
- **No ad:** no signal about any variety.
- **Traditional ad:** generic signal about all varieties in  $j$ .

• XXXX



# Advertising & the Consumer-Variety Match

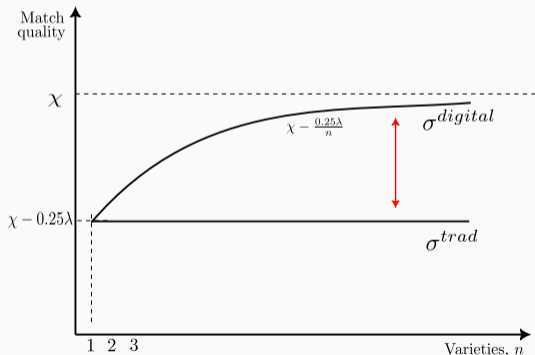
- **No ad:** no signal about any variety.
- **Traditional ad:** generic signal about all varieties in  $j$ .
- **Digital ad:** targeted signal about the most preferred variety in  $j$ .



# Traditional vs. Digital Advertising

- Average match quality with traditional vs. digital ads:

$$\sigma^{trad} = \chi - 0.25\lambda \quad \text{vs.} \quad \sigma^{digital}(n) = \chi - 0.25\lambda/n$$



- *Recall*: demand  $\uparrow$  with match quality.
- Returns from digital ads relative to traditional  $\uparrow$  with varieties  $n$ .

# Specialized Firm's Profit Maximization

$$\begin{aligned}
 \Pi = \max_{a_d, a_t, n, p} & \left\{ \underbrace{a_d p \sigma^{\text{digital}}(n) \left[ \frac{(1-\theta)\hat{y}}{p} \right]^{1/\kappa}}_{\text{revenue, digital}} + \underbrace{a_t (1-a_d) p \sigma^{\text{trad}} \left[ \frac{(1-\theta)\hat{y}}{p} \right]^{1/\kappa}}_{\text{revenue, traditional}} \right. \\
 & \left. - \underbrace{w A a_d^\zeta / \zeta}_{\text{ads cost, digital}} - \underbrace{w B a_t^\nu / \nu}_{\text{ads cost, traditional}} - \underbrace{w \Xi n^\eta / \eta Q(\cdot)}_{\text{operating cost}} - \underbrace{w \phi}_{\text{fixed cost}} \right\}.
 \end{aligned}$$

## Specialized Firm's Profit Maximization

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 \end{aligned}$$

- Tech progress in digital ads ( $A \downarrow$ )  $\Rightarrow a_d \uparrow$ .

But, marginal revenue from more varieties,  $n$ , increases with  $a_d$ , so  $\underline{n \uparrow}$ .

# Equilibrium

- Consumed product lines:

$$\forall i, |\mathcal{M}_i| = M = \underbrace{Na_d}_{\text{matched w/digital ads}} + \underbrace{Na_t(1-a_d)}_{\text{matched w/trad ads}} < N$$

- Two variety effects from more digital ads:

**Extensive margin (love for variety):** consumers learn about different product lines.

**Intensive margin (love for “correct” variety):** consumed products closer to taste.

- The rest of equilibrium:
  - Free entry into product lines.
  - Generic firms competitive.  $\sigma = \alpha/\alpha$ .
  - Labor markets clear.

## II - Empirics

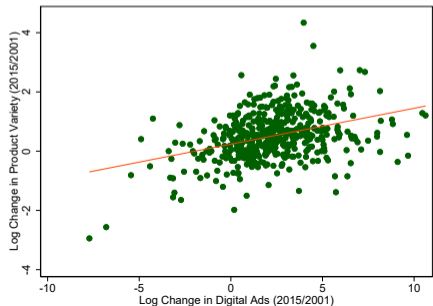
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# I. Digital Advertising and Growth in Varieties

- **Data:** firm-level products & advertising data.
  - **Kantar Media AdSpender**
    - Microdata on firm's product-level ads expenditure by media type. 1995-2019 & all industries.
    - Product varieties & traditional/digital ads expenditure by firms/products.
  - **NETS**– the universe of establishments/firms in the U.S., 1989-2017 (firm size).

## Growth in Digital Ads and Growth in Varieties



- **More digital ads associated with more varieties:** Regressions across/within categories & across/within firms (conditional on other controls).

## II. Do improvements in digital advertising increase product varieties?

$$\text{Varieties} = \beta \text{Digital ads} + \text{controls}$$

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$$\text{Varieties}_{st} = \beta \text{Residential Internet}_{st} + \text{controls}$$

- Digital advertising reaches viewers only if they have internet.
- Use **residential internet penetration** to proxy for digital ads viewing.

## II. Do improvements in digital advertising increase product varieties?

$$\text{Varieties}_{st} = \beta \widehat{\text{Residential Internet}}_{st} + \text{controls}$$

- Digital advertising reaches viewers only if they have internet.
- Use **residential internet penetration** to proxy for digital ads viewing.
- Internet penetration is endogenous.
  - **Instrument: Lightning strikes.**
  - Andersen-Bentzen-Dalgaard-Selaya (2012 REST); Guriev-Melnikov-Zhuravskaya (2021 QJE).
  - Frequent lightning strikes cause voltage spikes/dips hinder the rollout of internet technologies (ADSL, cable) bc they substantially increase costs of providing service and maintaining the infrastructure.

# Spatial Data on Varieties, Internet, and Lightning Strikes

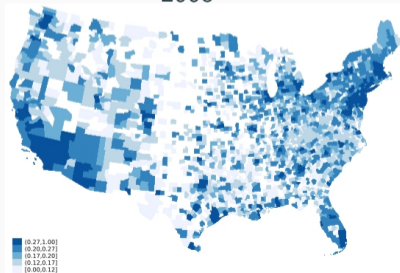
- Nielsen RMS
  - [Product varieties](#) (products (barcodes), brands) sold by county  $\times$  year; 2008-2018.
- Federal Communications Commission (Form 477 and FOIA)
  - [Household internet use](#) (residential fixed connections), by county  $\times$  year; 2008-2018.
- National Lightning Database Network, BEA.
  - [Lightning strikes intensity](#) by county  $\times$  year; 1986-2020.

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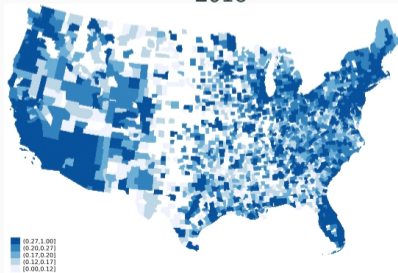
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The share of **product varieties** of a category sold in a county

2008



2018

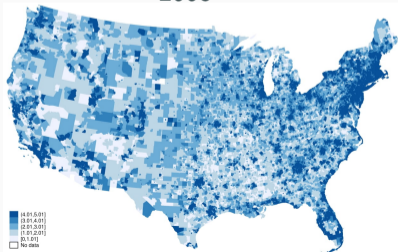


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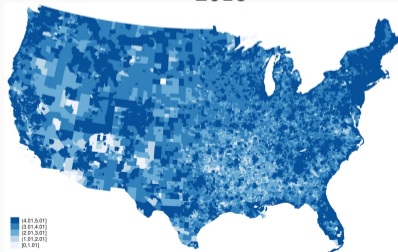
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Population share with access to **residential fixed connections**

2008



2018

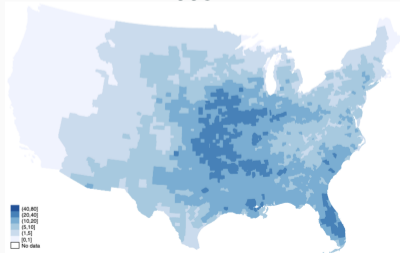


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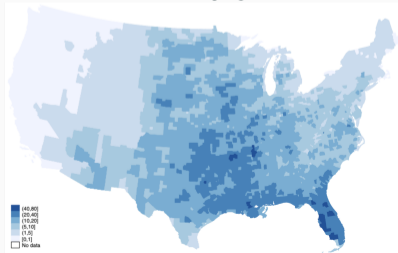
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**Lightning strikes** per square mile per year

2008



2018





## IV Estimation

- First-stage equation:

$$I_{lt} = \gamma Z_{lt-1} + \eta X_{lt} + e_{lt}$$

$I_{lt}$  - share of population w residential fixed internet connections (quintile) in county  $l$ , period  $t$ ;

$Z_{l,t-1}$  - number of lightning strikes per square mile;

$X_{lt}$  - fixed-effects, population, income, demographics, density, and urban-rural status.

- Second-stage equation:

$$N_{ltj} = \beta \hat{I}_{lt} + \alpha X_{ltj} + \epsilon_{ltj}$$

$N_{ltj}$  - number of product varieties sold in location  $l$ , period  $t$ , product category  $j$ ;

$X_{ltj}$  - fixed-effects, population, income, demographics, density, and urban-rural status.

## IV Results

Main results:

$$N_{Itj} = \beta \hat{I}_{It} + \alpha X_{Itj} + \epsilon_{Itj}$$

	<i>Log Products</i>			<i>Log Brands</i>		
	(1)	(2)	(3)	(1)	(2)	(3)
Household Internet	0.956*** (0.004)	1.077*** (0.008)	0.578*** (0.050)	0.718*** (0.003)	0.811*** (0.006)	0.093*** (0.040)
Observations (1,000s)	1,978	1,974	1,822	1,978	1,974	1,822
Time × Category FE	Yes	Yes	Yes	Yes	Yes	Yes
Time × County Controls	No	Yes	Yes	No	Yes	Yes
County × Category FE	No	No	Yes	No	No	Yes

(3): 20 pp ↑ in the share of population with internet increases product varieties by 10%-78%.

Alternative mechanisms

I stage

I stage Lags

Different technologies

Different categories

Variety robustness

OLS

## III - Quantitative Analysis

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# Calibration

- Calibrate to 1995 and 2015.
- Changes over time:  $A \downarrow$  – tech. progress in digital ads;  $\Xi \downarrow$  – variety production efficiency increases;  $x \uparrow$  – overall tech. progress;  $\phi \uparrow$  – entry cost increases.

Variable	Data		Model	
	1995	2015	1995	2015
Ad Spending-to-GDP, %	2.2	2.2	2.2	2.2
Digital-to-Traditional Ad Spending, %	2.3	96.6	2.3	96.6
Size of Specialized Sector, %	53	59	52	61
	1995-2015		1995-2015	
Growth in Varieties (n), %	115		115	
Growth in Product Lines (N), %	17		17	
Sales-to-ads elasticity	0.20		0.17	
Variety-to-digital elasticity	0.84		0.78	

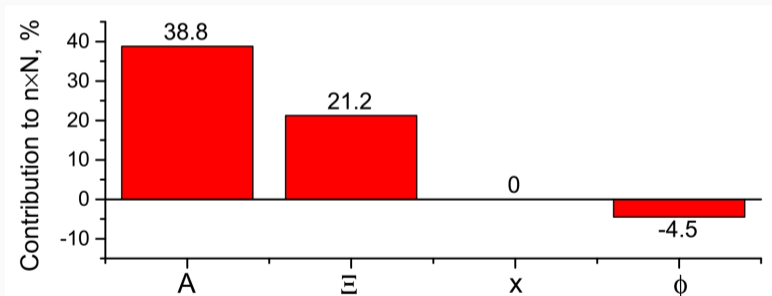
## Experiment: No Progress in Digital Ads Efficiency

- Keep the efficiency of digital advertising  $A$  in 2015 at the 1995 level.

Variable	Model, 2015	
	Benchmark	Fixed $A_{1995}$
Ad Spending-to-GDP, %	2.2	2.3
Digital-to-Traditional Ad Spending, %	96.6	36.3
Size of Specialized Sector, %	61.2	60.8
Growth in Varieties ( $n$ ), %	115	67
Growth in Product Lines ( $N$ ), %	17	15
Growth in Prices, %	8.9	7.3
Equivalent Variation, % of $c$	1.25	

# Contribution to Total Product Variety Growth from Various Mechanisms

- Experiments, shutting down one mechanism at a time.



*Hypothesis:* Improvements in the efficiency of digital ads led to the rise in digital advertising spending and the number of varieties.

- Investigated in two ways:
  1. Empirically, using micro-level data.
  2. Theoretically, using a quantitative model.
- Other important questions...
  - advertising and market power;
  - digital ads and firm size/age heterogeneity;
  - online privacy concerns.

## Appendix - motivation

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 **YOU WILL**

**You did!** Now let's see what else you'll do.

We hope you will find this area interesting and exciting. For those of you unfortunate souls who don't yet have fiber to the home, we've tried to keep file sizes small and download times short.

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**Have you ever toured an [art museum](#) without leaving your seat?** 

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**Have you ever wanted to learn more about the latest in technology from [AT&T](#)?** 

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**Please help us [improve this space](#).** 

*"Criticism is easy. Art is difficult."*  
Le Glorieux [1732], act II, scene 6

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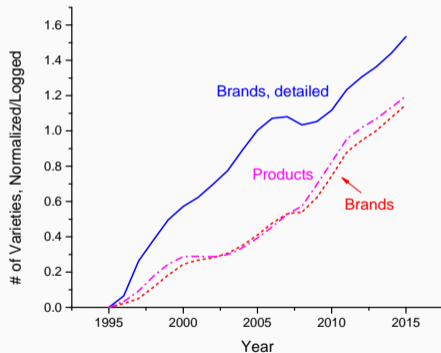
© Copyright 1994 AT&T

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Design and production: TANGENT Design/Communications, Inc.

# Growth in Product Varieties in Kantar:

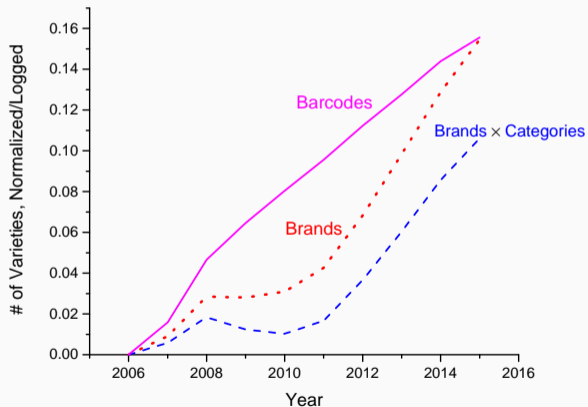
## Multiple definitions



back

# Growth in Product Varieties in Nielsen-RMS:

## Multiple definitions



# Relationship between measures of varieties and advertised varieties

- Kantar gives data on *advertised varieties*.
- At the aggregate level, *advertised varieties* comove with *all varieties*. But how about at the firm-level?
- Match RMS data on *all varieties* with AdIntel data on *advertised varieties* (Argente, Fitzgerald, Moreira and Priolo, 2022)
- Correlation between *advertised* and *all varieties*:
  1. Cross-sectional correlation across firms, average over 2010-2015
  2. Within-firm correlation, log changes between 2010 and 2015.

# Relationship between measures of varieties and advertised varieties

<i>RMS / AdIntel</i>	Level				Changes			
	brands	brands	types	types	$\Delta$ brands	$\Delta$ brands	$\Delta$ types	$\Delta$ types
brands	0.379*** (0.011)		0.249*** (0.008)					
barcodes		0.217*** (0.007)		0.147*** (0.005)				
$\Delta$ brands					0.113*** (0.023)		0.067*** (0.017)	
$\Delta$ barcodes						0.061*** (0.015)		0.040*** (0.011)
Obs.	6,506	6,506	6,506	6,506	2,280	2,280	2,280	2,280

Regression of the log number of advertised product varieties on the log number of all product varieties by firms in the CPG sector in the period 2010-2015. Firm-year level regressions. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

back

## Appendix - datasets

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## 1. Kantar Media AdSpender data

- Microdata on firm's product-level ads expenditure by media type. [What is a product?](#)
- Covers period 1995-2019 & all industries [Coverage](#) [Representativeness](#)
- Media coverage grows over time (default start year 1995): Network/cable/syndication/spot TV, magazines, local ('99)/national newspapers, network ('00)/national spot radio, outdoor, internet display ('01), internet search('10), online video('13), mobile web('15).
- Data on **ad prices**, **ad spending**, **ad medium**, and **varieties** [More on varieties](#).

## 2. NETS - National Establishments Time Series

- The universe of establishments/firms in the U.S., 1989-2017.
- Matched to Kantar to measure firm **size**.

...

## Datasets 3 + 4: Spatial Dataset for IV

### 3. Nielsen - RMS

- RMS (Kilts-Nielsen): 2006-2017 on consumer products (non-durable and semi-durable).
- Points-of-sale system in retail stores.
  - 40,000 distinct stores from around 2,500 counties (53% of sales in grocery stores, 55% in drug stores, 32% in mass merchandisers.)
  - Product **varieties** (products (barcodes), brands).

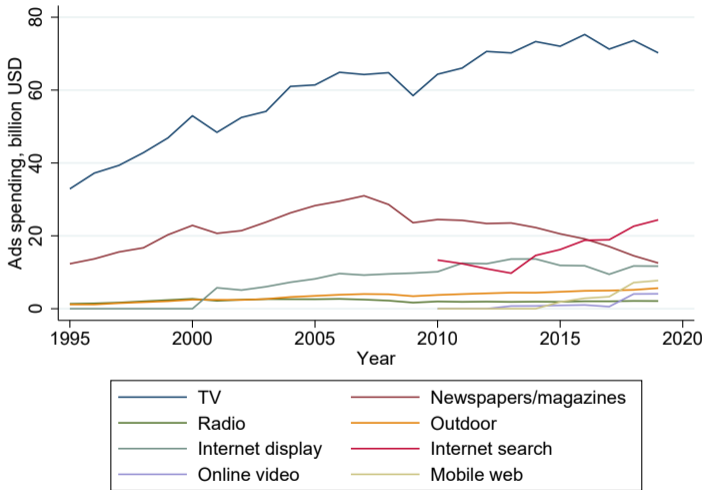
### 4. Household internet: Federal Communications Commission (Form 477 and FOIA)

- Residential fixed connections above 200kbps, 2008-2018.
- [0 – 20%], ... [80% – 100%] hh internet access categories.

( Other: National Lightning Database Network (NLDN) (1986-2020), BEA. )

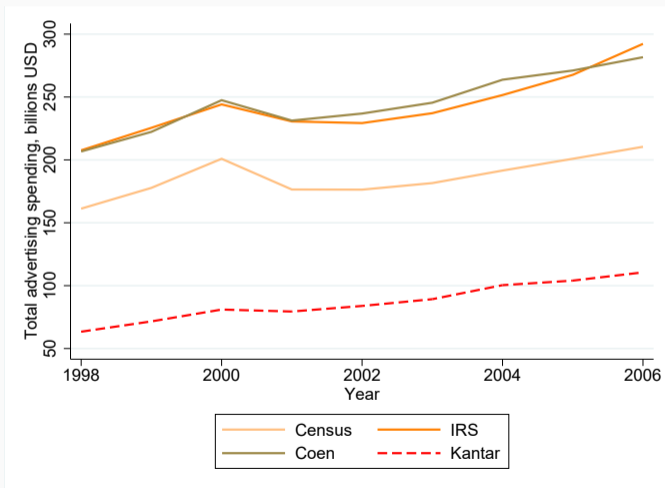


# Kantar Ads Spending by Media Type



# Comparing Kantar to Total Ads Estimates in the U.S.

Total ads spending in Kantar grows over time.



# Product Variety and Product Lines in Kantar

- Keep CPG/manufacturing industries.

Excluded: misc services and amusement, retail (store promos), automotive dealers, financial, government/politics/organizations, schools, restaurants, hotels, other services.

- **Product category:** subcategory (1,546), major (185), industry (39).
- **Product variety:** product (481,501), brand (270,862), sub-brand (62,915).

Example: [back](#)



Product: *Nike Air Max: Sneakers Men*

Brand: *Nike Air*

Sub-brand: *Nike Air Max*

Company/advertiser: *Nike*

Subcategory: *Sneakers*

Major: *Sport shoes* Industry: *Footwear*

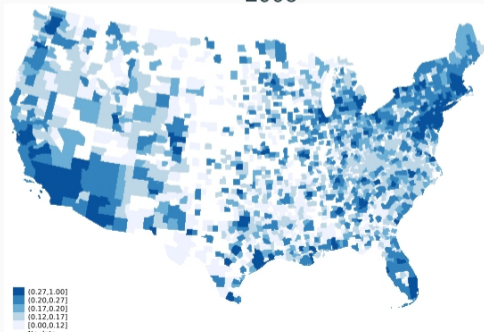
# Product Varieties: County & Year Variation

The weighted county-to-nationwide share of varieties:

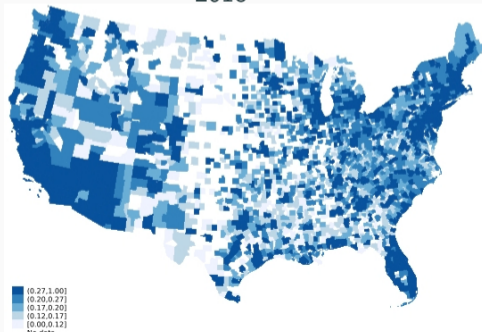
$$n_{lt} = \sum_{j=1}^J (\omega_{lj} \frac{N_{ltj}}{N_{0j}})$$

$N_{ltj}$  - number of varieties in  $l$  at  $t$  in category  $j$ .  $N_{0j}$  - varieties in category  $j$  nationwide in 2008,  $\omega_{lj}$  - average revenue share of category  $j$  in  $l$ .

2008



2018



## Appendix - empirical results

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## Product Varieties and Digital Ads

<i>Panel A: Category-level</i>	$\Delta \text{ Log Products}$		$\Delta \text{ Log Brands}$	
	Subcategory	Major	Subcategory	Major
$\Delta \text{Log Digital Ads}$	0.024*** (0.002)	0.014*** (0.004)	0.021*** (0.002)	0.015*** (0.004)
$R^2$	0.240	0.267	0.240	0.254
Observations	11,658	2,996	11,658	2,996
<i>Panel B: Firm-level</i>	$\Delta \text{ Log Products}$		$\Delta \text{ Log Brands}$	
	Cross-firms	Within-firms	Cross-firms	Within-firms
$\Delta \text{Log Digital Ads}$	0.042*** (0.002)	0.042*** (0.002)	0.030*** (0.002)	0.031*** (0.002)
$R^2$	0.096	0.186	0.052	0.127
Observations	17,931	16,920	17,931	16,920

*Note:* Panel A shows regressions of the growth in product varieties on growth in digital-ads spending in product categories over time. All regressions control for log number of firms and log traditional-ads spending in product categories over time, product line, and year fixed effects. Product variety: products and brands. Product categories: subcategory, major, and industry. Robust standard errors in parentheses. Panel B shows regressions of the growth in product varieties on the growth in digital-ads spending in firms over time. All regressions control for firm's log employment, log traditional-ads spending, year fixed effects, and product line/firm fixed effects in the "Cross-firms"/"Within-firms" columns, respectively. Product variety: products and brands. Product category: subcategory. Robust standard errors in parentheses. The \*\*\*, \*\*, and \* represent statistical significance at 1%, 5%, and 10% levels, respectively.

	<i>Log Products</i>			<i>Log Brands</i>		
	(1)	(2)	(3)	(1)	(2)	(3)
Household Internet	0.636*** (0.001)	0.106*** (0.002)	0.010*** (0.001)	0.046*** (0.003)	0.074*** (0.001)	0.009*** (0.001)
$R^2$	0.663	0.717	0.990	0.584	0.723	0.986
Observations (1,000s)	1,978	1,974	1,822	1,978	1,974	1,822
Period $\times$ Category FE	Yes	Yes	Yes	Yes	Yes	Yes
Period $\times$ County Controls	No	Yes	Yes	No	Yes	Yes
County $\times$ Category FE	No	No	Yes	No	No	Yes

	Household Internet		
	(1)	(2)	(3)
Lightning Strikes (t-1)	-0.005*** (0.001)	-0.002*** (0.001)	0.000 (0.001)
Lightning Strikes (t-2)	-0.006*** (0.001)	-0.002*** (0.001)	-0.000 (0.001)
Lightning Strikes (t-13)	-0.003*** (0.001)	-0.001 (0.001)	-0.000 (0.001)
Lightning Strikes (t-4)	-0.002** (0.001)	-0.001 (0.001)	-0.001 (0.001)
Lightning Strikes (t-5)	-0.002** (0.001)	-0.001 (0.001)	0.001 (0.000)
Lightning Strikes (t-6)	-0.004*** (0.001)	-0.002*** (0.001)	-0.001 (0.000)
Lightning Strikes (t-7)	-0.004*** (0.001)	-0.003*** (0.001)	-0.002*** (0.0010)
Lightning Strikes (t-8)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.000)
Lightning Strikes (t-9)	-0.002** (0.001)	-0.002*** (0.001)	-0.001** (0.000)
Lightning Strikes (t-10)	-0.002*** (0.001)	-0.001** (0.001)	-0.002*** (0.000)
$R^2$	0.282	0.638	0.880
Observations of Regression	24,697	24,653	24,697
Year FE	Yes	Yes	Yes
Year $\times$ County Controls	No	Yes	Yes
County FE	No	No	Yes



	Household Internet		
	(1)	(2)	(3)
Lightning Strikes (lagged)	-0.028***	-0.015***	-0.003***
	(0.000)	(0.000)	(0.000)
Observations (1,000s)	1,978	1,974	1,822
Time FE	Yes	Yes	Yes
Time $\times$ County Controls	No	Yes	Yes
County FE	No	No	Yes
1st stage F-stat	123,767	88,678	669

<b>1st Stage</b>	Households with Access to Technology:		
	DSL	Cable	Fiber
Lightning Strikes	-0.001*** (0.000)	-0.003*** (0.001)	-0.000 (0.001)
Observations	2,255	2,255	2,255
County Controls	Yes	Yes	Yes
1st stage F-stat	11.14	27.04	0.00
<b>2nd Stage</b>	Household Internet		
	DSL	Cable	Fiber
Households with Access to Technology	13.103*** (3.795)	5.998*** (1.118)	1,714 (119,624)
Observations	2,255	2,255	2,255
County Controls	Yes	Yes	Yes

Notes: Access to different technologies by county, average over 2013-2018. 2,225 counties. Controls: population, income per capita, share of teenagers, share of young, share of seniors, share with college or more, population density per square feet, categorical variables of urban-rural status, and share of households in urban areas.

## IV Results. First Stage— different speed levels [Back](#)

<i>Panel A</i>								
Speed	<i>Log Products</i>				<i>Log Brands</i>			
	>200kb	>768kb	>3mb	>10mb	>200kb	>768kb	>3mb	>10mb
Household Internet	2.186*** (0.027)	1.650*** (0.018)	3.954*** (0.083)	4.418*** (0.099)	1.588*** (0.020)	1.198*** (0.013)	2.872*** (0.061)	3.209*** (0.072)
Observations (1,000s)	928	928	928	928	928	928	928	928
Category FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period	08-12	08-12	08-12	08-12	08-12	08-12	08-12	08-12
1st stage F-stat	12,226	20,663	2,728	2,308	12,226	20,663	2,728	2,308

<i>Panel B</i>								
Speed	<i>Log Products</i>				<i>Log Brands</i>			
	>200kb	>10mb	>25mb	>100mb	>200kb	>10mb	>25mb	>100mb
Household Internet	1.620*** (0.019)	2.026*** (0.027)	1.268*** (0.015)	0.003*** (0.000)	1.261*** (0.015)	1.577*** (0.021)	0.987*** (0.011)	0.002*** (0.000)
Observations (1,000s)	1,029	1,029	1,029	1,029	1,029	1,029	1,029	1,029
Category FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period	14-18	14-18	14-18	14-18	14-18	14-18	14-18	14-18
1st stage F-stat	18,089	11,266	22,575	700	18,089	11,266	22,575	700

**Notes:** County-product category level data for two separate periods in Panels A and B. Panel A – FOIA request at the FCC (connections with downstream speed of at least 200kbps, 768 Kbps, 3 Mbps, and 10Mbps during the period 2008-2012); Panel B – FCC Form 477 data (connections with downstream speed of at least 200kbps, 10Mbps, 25Mbps, and 100Mbps during period 2014-2018). The county controls are population (in logs), income per capita (in logs) variables, the share of teenagers, share of young, share of seniors, share with college or higher degree, average population density per square foot, categorical variables for urban-rural status, and the share of households in urban areas.

<i>Panel A: Food and Health &amp; Beauty Products</i>						
	<i>Log Products</i>			<i>Log Brands</i>		
Household Internet	0.873***	0.956***	0.417***	0.649***	0.707***	0.034
	(0.003)	(0.006)	(0.036)	(0.003)	(0.005)	(0.030)
$R^2$	0.159	0.218	-0.168	0.162	0.229	-0.001
Observations (1,000s)	2,683	2,677	2,496	2,683	2,677	2,496
<i>Panel B: All Product Categories</i>						
	<i>Log Products</i>			<i>Log Brands</i>		
Household Internet	0.874***	0.978***	0.384***	0.654***	0.729***	0.092***
	(0.003)	(0.005)	(0.030)	(0.002)	(0.004)	(0.024)
$R^2$	0.176	0.245	-0.137	0.175	0.249	-0.010
Observations (1,000s)	3,727	3,719	3,481	3,727	3,719	3,481
Time $\times$ Category FE	Yes	Yes	Yes	Yes	Yes	Yes
Time $\times$ County Controls	No	Yes	Yes	No	Yes	Yes
County $\times$ Category FE	No	No	Yes	No	No	Yes

## IV Results. Different variety definitions [Back](#)

	<i>Log Agg1</i>		<i>Log Agg2</i>		<i>Log Agg3</i>	
	(1)	(2)	(1)	(2)	(1)	(2)
Household Internet	1.070*** (0.008)	0.582*** (0.050)	1.033*** (0.008)	0.518*** (0.048)	0.991*** (0.007)	0.360*** (0.045)
Observations (1,000s)	1,974	1,822	1,974	1,822	1,974	1,822
Time × Category FE	Yes	Yes	Yes	Yes	Yes	Yes
Time × County Controls	Yes	Yes	Yes	Yes	Yes	Yes
County × Category FE	No	Yes	No	Yes	No	Yes
1st stage F-stat	88,678	669	88,678	669	88,678	669

HH internet access → Varieties ✓ **But** other mechanisms not related to improved targeting of consumers' tastes?

- IT access also for firms ⇒ Firms more efficient at producing more varieties.

### Results Excluding Local Firms

	<i>Log Products</i>			<i>Log Brands</i>		
	(1)	(2)	(3)	(1)	(2)	(3)
Household Internet	0.874*** (0.004)	0.933*** (0.008)	0.541*** (0.056)	0.618*** (0.003)	0.650*** (0.006)	0.043 (0.046)
Observations (1,000s)	1,863	1,858	1,713	1,863	1,858	1,713
Time × Category FE	Yes	Yes	Yes	Yes	Yes	Yes
Time × County Controls	No	Yes	Yes	No	Yes	Yes
County × Category FE	No	No	Yes	No	No	Yes

HH internet access → Varieties ✓ **But** other mechanisms not related to improved targeting of consumers' tastes?

- IT access also for stores ⇒ Stores more efficient at distribution & mngmt of more varieties.

### Results Excluding Local Chains

	<i>Log Products</i>			<i>Log Brands</i>		
	(1)	(2)	(3)	(1)	(2)	(3)
Household Internet	0.417*** (0.005)	0.363*** (0.009)	0.425*** (0.038)	0.235*** (0.004)	0.149*** (0.006)	0.042 (0.032)
Observations (1,000s)	1,849	1,845	1,689	1,849	1,845	1,689
Time × Category FE	Yes	Yes	Yes	Yes	Yes	Yes
Time × County Controls	No	Yes	Yes	No	Yes	Yes
County × Category FE	No	No	Yes	No	No	Yes

## Appendix - quantitative results



## Experiment: no process innovation

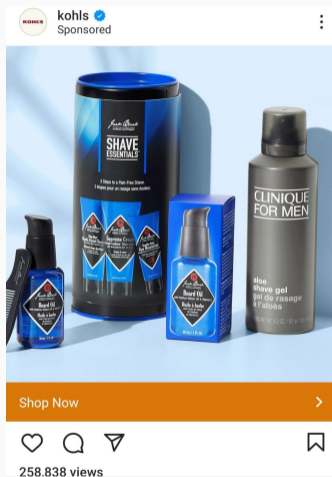
Variable	Model, 2015	
	Benchmark	Fixed $\Xi$
Ad Spending-to-GDP, %	2.2	1.9
Digital-to-Traditional Ad Spending, %	96.6	96.6
Size of Specialized Sector, %	61.2	52.4
Growth in Varieties per Product Line ( $n$ ), %	114.5	114.5
Growth in Product Lines ( $N$ ), %	17.0	2.1
Growth in Prices, %	8.9	37.7
Growth in Wages, %	38.4	32.5
Growth in Generic Consumption, %	9.7	31.3
Growth in Consumption per Variety, %	35.5	2.6

## Experiment: no change in fixed entry cost

Variable	Model, 2015	
	Benchmark	Fixed $\phi$
Ad Spending-to-GDP, %	2.2	2.2
Digital-to-Traditional Ad Spending, %	96.6	96.4
Size of Specialized Sector, %	61.2	61.4
Growth in Varieties per Product Line ( $n$ ), %	114.5	114.2
Growth in Product Lines ( $N$ ), %	17.0	20.3
Growth in Prices, %	8.9	9.0
Growth in Wages, %	38.4	38.6
Growth in Generic Consumption, %	9.7	9.3
Growth in Consumption per Variety, %	35.5	32.5

# Targeted advertising in our lives...

## Ricardo's Instagram feed



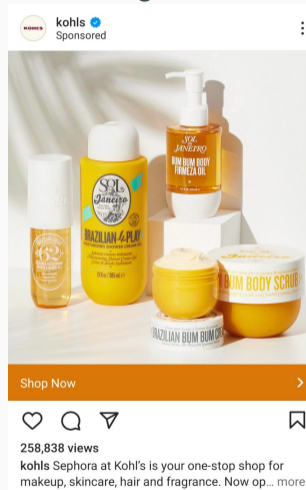
A screenshot of an Instagram post from the account 'kohls' (verified, sponsored). The post features a collection of men's grooming products from the 'Shave Essentials' and 'Clinique for Men' lines. The products include a large blue can of 'Shave Essentials' shaving cream, a small blue bottle of 'Beard Oil', a blue box of 'Shave Cream', and a grey bottle of 'Clinique for Men' 'shave gel'. The background is a light blue gradient. At the bottom of the post, there is an orange 'Shop Now' button with a right-pointing arrow. Below the button are icons for heart, comment, share, and bookmark. The text '258.838 views' is displayed at the bottom left.

kohls Sponsored

Shop Now

258.838 views

## Salome's Instagram feed



A screenshot of an Instagram post from the account 'kohls' (verified, sponsored). The post features a collection of Sephora brand products, including 'Brazilian Bum Cream', 'Brazilian Bum Body Firming Oil', and 'Brazilian Bum Body Scrub'. The products are arranged on a white surface against a light background. At the bottom of the post, there is an orange 'Shop Now' button with a right-pointing arrow. Below the button are icons for heart, comment, share, and bookmark. The text '258,838 views' is displayed above the caption. The caption reads: 'kohls Sephora at Kohl's is your one-stop shop for makeup, skincare, hair and fragrance. Now op... more'.

kohls Sponsored

Shop Now

258,838 views

kohls Sephora at Kohl's is your one-stop shop for makeup, skincare, hair and fragrance. Now op... more