# From Mad Men to Maths Men: Concentration and Buyer Power in Online Advertising

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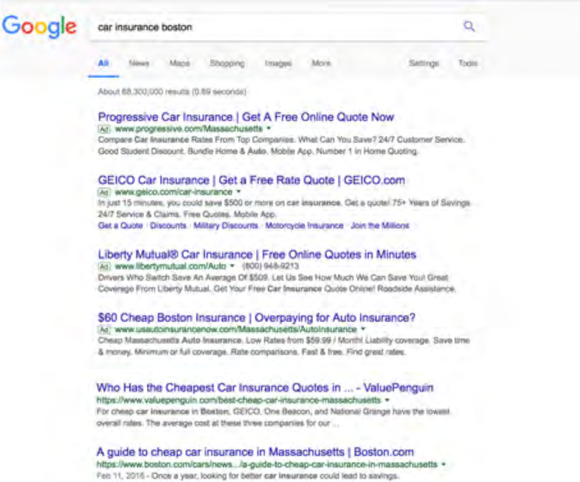
# Internet Advertising and Sponsored Search

- Internet advertising revenues in US: $88 billion dollars in 2017
- Sponsored search: main segment, 46% (next is banner 31%)



# Sponsored Search and Marketing Agencies

Highly **concentrated supply**: Google's revenues range between 75% and 80% of total

Traditional view of the other players in sponsored search:

1) **Consumers:**
    - Search for products/services: known or new (learning)
    - Shop for product/services: ubiquitous online buy options

2) **Advertisers:**
    - Seek attention of relevant consumers: targeting
    - Have complex, sometimes conflictual interactions with search engines

# Sponsored Search and Marketing Agencies

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2) **Advertisers:**
    - Seek attention of relevant consumers: targeting
    - Have complex, sometimes conflictual interactions with search engines
3) **Intermediaries - Digital Marketing Agencies (DMAs):**
    - Modern version of the traditional "Madison Avenue" agencies
    - At least since 2011, delegation of bidding to DMAs, who further delegate to their agency network's centralized Agency Trading Desk (ATD)

# Intermediated Bidding and Demand Concentration

The demand side has vastly changed thanks to intermediaries:

- **Technological innovations**: automated bidding systems to address the need for more speed (high frequency or even real-time) and better data usage
- **Growing concentration**: 7 large ATDs, active at the agency network level ATD list

| | Search Volume Share | | | | Presence across Keywords | | | |
|---|---|---|---|---|---|---|---|---|
| | 2014 | 2015 | 2016 | 2017 | 2014 | 2015 | 2016 | 2017 |
| IPG | 0.21 | 0.19 | 0.21 | 0.19 | 0.26 | 0.32 | 0.33 | 0.38 |
| WPP | 0.17 | 0.20 | 0.16 | 0.23 | 0.29 | 0.29 | 0.33 | 0.43 |
| Omnicom | 0.17 | 0.16 | 0.17 | 0.14 | 0.39 | 0.38 | 0.37 | 0.38 |
| Publicis | 0.14 | 0.13 | 0.13 | 0.18 | 0.30 | 0.30 | 0.29 | 0.30 |
| MDC | 0.09 | 0.09 | 0.08 | 0.09 | 0.17 | 0.17 | 0.17 | 0.24 |
| Havas | 0.05 | 0.07 | 0.06 | 0.02 | 0.12 | 0.14 | 0.12 | 0.06 |
| Dentsu-Aegis | 0.05 | 0.08 | 0.10 | 0.09 | 0.14 | 0.17 | 0.19 | 0.25 |
| Indep Age | 0.13 | 0.09 | 0.08 | 0.06 | 0.42 | 0.38 | 0.35 | 0.22 |

# Motivation and Findings

Intermediaries can significantly impact the marketplaces with effects that are both positive (more bidders/keywords) and negative (coordinated bids) for search engines' revenues

We use new, extensive data on both keyword bidding (40 million keyword **auctions**) and links advertisers-DMAs-ATDs (all DMAs and ATDs of 6,000 large advertisers) to quantify how increases in intermediaries' concentration affect Google's sponsored search revenues

Using an IV strategy, we find a sizeable, negative relationship between Google's revenues and buyers' HHI (an HHI increase of 200 points - the threshold typically used to identify mergers likely to enhance market power - leads to an 8.04% drop in Google's revenues)

Implies that countervailing power can play a key role in disciplining market power in online platform markets and suggests that competition policy should monitor two aspects:

1. price pass-through to advertisers/consumers (algorithmic collusion, but beneficial?)
2. abuses in Google's response (increased reserve price; disintermediation; else?)

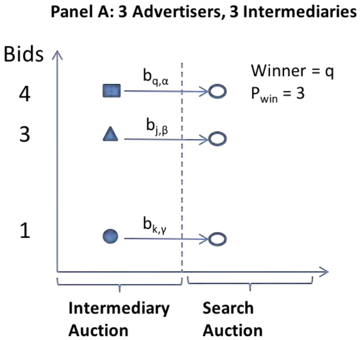
# Related Literature and Contributions

- **Market concentration, superstar firms, and buyer power** (Academics: [Autor et al., 2017; De Loecker and Eeckhout, 2017; Gutierrez and Philippon, 2017], Press: [Economist, 2016; Stiglitz, 2016], Policy: [Mullan and Timan, 2018]) ⇒ Effectiveness of buyer power in countervailing market power [Galbraith, 1952];
- **Online markets, ad space sales and intermediaries** (Ad sales: [Edelman, Ostrovsky and Schwarz, 2007; Varian, 2007; Athey and Nekipelov, 2014], Intermediaries efficiencies: [McAfee, 2011]) ⇒ Role of intermediaries and information sharing in improving outcomes;
- **Collusion in auctions and algorithmic pricing** (General: [Graham and Marshall, 1987; Hendricks, Porter and Tan, 2008], Online: [Mansour, Muthukrishnan and Nisan, 2012; Decarolis, Goldmanis and Penta, 2017], AI pricing: [OECD, 2017; Calvano et al., 2018]) ⇒ Role of the "coordinated bidding" incentive in driving the industry dynamics, and the role of Agency Trading Desks;
- **Industry definition** (Antitrust: [DOJ merger guidelines, EC merger regulation], Natural Processing Language: [Pennington, Socher and Manning, 2014]) ⇒ Machine learning for industry definition.

# Outline

# Theoretical Example

- Suppose there is a monopolist search engine selling 1 ad slot
- There are three advertisers ($q$, $j$, $k$) interested in the slot
- They have arbitrary bids: $b_q = 4$, $b_j = 3$ and $b_k = 1$
- They must bid through an intermediary ($\alpha$, $\beta$ or $\gamma$)
- 2-level Second Price Auction system



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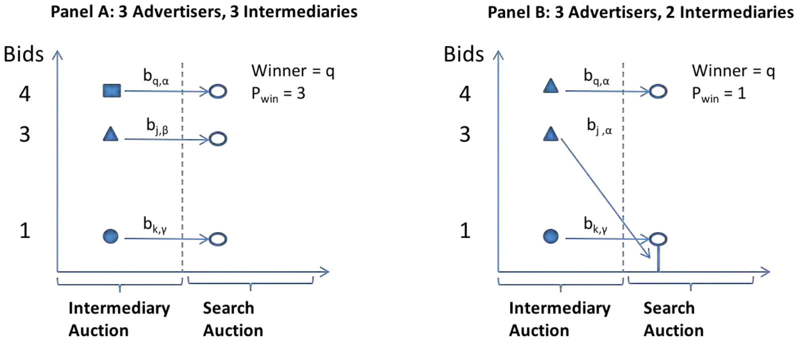


# Generalization of the Example

Main implication: $\uparrow$ intermediaries' concentration, $\downarrow$ SE revenues

- Generalizable to arbitrary assignment of N advertisers to K intermediaries: $E(Revenues) = \sum_{n=2}^{N} b_n(\frac{K-1}{K^{n-1}})$
- Generalizable to multiple slots (GSP): revenues & efficiency worse than VCG (Decarolis, Goldmanis and Penta, 2017)
- Caveat: technological and contractual constraints

But **potential efficiencies** driven by coordinated bidding:

- Externalities [Jeziorski and Segal, 2015]
- Winners' curse [McAfee, 2011]
- Budget constraints [Balseiro and Candogan, 2017]

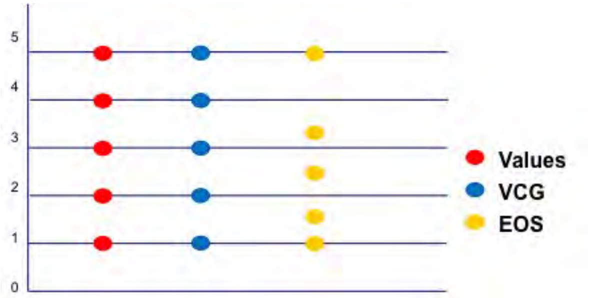
Overall: $\uparrow$ intermediaries' concentration, $\uparrow ? \downarrow$ SE revenues

# Review of Competitive Bidding: EOS/Varian)

**Lemma (Individual-level underpinnings of EOS refinement)**

*There is a unique fixed-point of $BR_i^*(b_{-i})$ (up to the highest bid), and it coincides with Edelman Ostrovsky and Schwarz (2007, EOS) lowest envy-free equilibrium. Hence, the unique equilibrium of the GSP induces the same allocation and the same payments as in the dominant-strategy equilibrium of the VCG.*

$n = 5$; $S = 4$; $CTR = \{20, 10, 5, 2, 0\}$



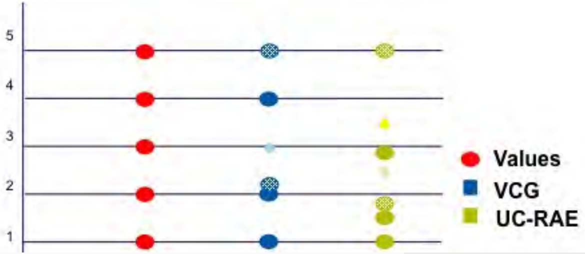
# Review of Collusive Bidding: Decarolis, Goldmanis and Penta (2019)

**Theorem**

*For any $\mathcal{C}$, the UC-RAE of the GSP auction is unique up to the highest bid of the coalition and up to the highest overall bid. In each of these equilibria:*

- ***Efficiency:*** *advertisers are assigned to positions efficiently;*
- ***VCG-Equivalence:*** *payments & allocations identical to VCG without UC*
- ***Unconstrained:*** *inefficiency and lower than VCG revenues with UC restriction*

$n = 5$; $S = 4$; $CTR = \{20, 10, 5, 2, 0\}$; $\mathcal{C} = \{1, 3\}$

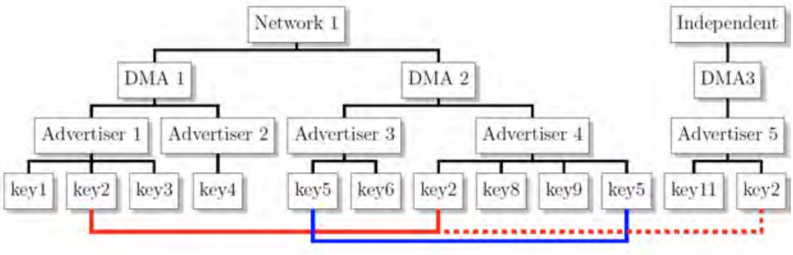


# Outline

# Data

- *Redbooks:*
  - Data on links advertisers-to-agencies
  - Yearly data 2011-2017 covering around 6,000 advertisers (i.e., web domains) per year active in all sectors advertisers
    - US: 4,400 publicly traded companies, plus largest private
    - Non US: top 2,000 global companies
  - For 2014-2017, link agencies to networks (ATD) networks
- *SEMrush:*
  - Data on links keywords-advertisers (URLs)
  - Google data on both paid and organic search
  - Up to the 50,000 most important keywords bid for each advertiser 2012 - 2017 (January), but with possibility to use higher frequency data (monthly/daily)
  - Keyword level: data on CPC, search volume, competition
  - Keyword/advertiser level: position, previous position, traffic

# Data Structure




Data structure: keywords (SEMrush), advertisers (Redbooks/SEMrush), agencies and networks (Redbooks). Solid lines represent examples of coalitions: within DMA (blue) and network (red).

The relevant intermediary level is the **agency network** (in the example, Advertisers 1, 2, 3 and 4 are together under Network 1) descriptives

# Example of Data and Coalition

Case Study - DD

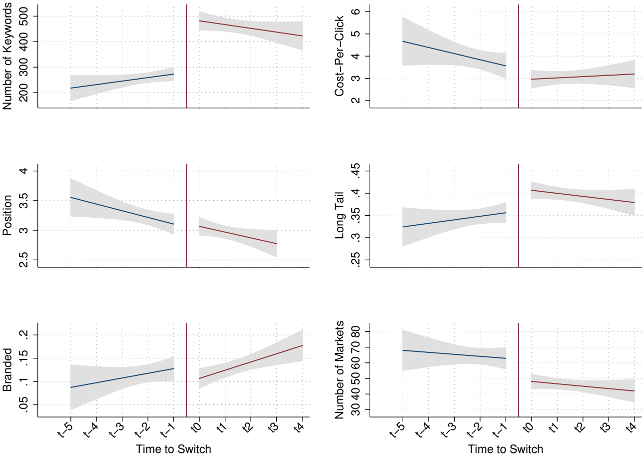
Merkle: large DMA with multiple clients (Redbooks data) active on the same keywords (SEM Rush data)

Example from charity sector: *Habitat for Humanitas* and *Salvation Army*

| Keyword | CPC ($) | Volume (mil) | Position *Habitat* | Position *Salv.Army* |
|---|---|---|---|---|
| habitat for humanity donations pick up | 4.01 | 40 | 1 | 4 |
| charities to donate furniture | 1.08 | 20 | 3 | 9 |
| donate online charity | 0.93 | 20 | 11 | 10 |
| website for charity donations | 0.90 | 19 | 11 | 6 |
| salvation army disaster relief fund | 0.03 | 20 | 2 | 1 |

In July 2016, Merkle acquired by Dentsu-Aegis for $1.5 billion dollars. Change in concentration in many markets with Merkle/Dentsu-Aegis advertisers

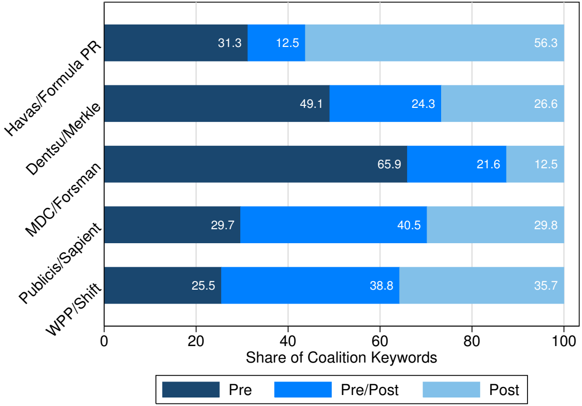
# DMA strategies: effects of affiliation



# Network Strategies: Coalitions and Market Split

Case Study - DD

- One illustrative M&A per network DMA strategies
- Sample of common keywords (pre, post, or both) in a 2-years window around the acquisition



# Outline

# Question and Strategy

- How do changes in intermediaries' concentration affect Google's revenues?
- A baseline regression model would be:

$$In(R^G_{mt}) = \beta DemandConcentration_{mt} + \phi X_{mt} + \tau_t + \gamma_z + \epsilon_{mt}$$

  - ${R^G}_{mt}$ = Search engine revenues in market $m$ at time $t$
  - $DemandConcentration_{mt}$ = Measure of demand concentration
  - $X_{mt}$ = Controls; time ($\tau_t$), industry ($\gamma_z$) FE

- But three main challenges:
  1. Definition of the relevant markets
  2. Measurement of relevant quantities
  3. Causal identification of $\beta$

# 1) Market Definition: two-layer clustering

Advertisers' industries are *too broad*, but keywords are *too narrow*

Our solution entails a two-layer clustering:

- Step 1: pool keywords together, but we have millions and many are related but not sharing any term. Solution: *GloVe*, unsupervised learning, pre-trained on 840B documents with 2.2M unique terms, from Common Crawl in English, featuring 300 dimensions ▸ details

# Step 1: from Keywords to Thematic Clusters

| Keyword | Industry |
|---|---|
| sleep number bed | Houseware |
| white duvet cover queen | Houseware |
| sleep number beds | Houseware |
| therapedic mattress | Houseware |
| memory foam mattress | Houseware |
| electrolux walmart | Houseware |
| elactrolux | Houseware |
| home theater seating | Houseware |
| amazon electrolux | Houseware |
| plum duvet cover | Houseware |
| shark vs electrolux | Houseware |
| pink duvet cover | Houseware |
| sleep number bed reviews | Houseware |
| purple duvet covers | Houseware |
| fabric sofa | Houseware |
| floral couch | Houseware |
| pink chair | Houseware |
| small sectional | Houseware |
| electrolux ambassador | Houseware |

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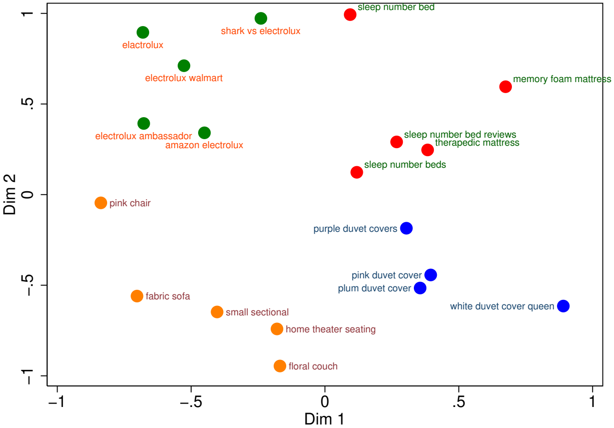

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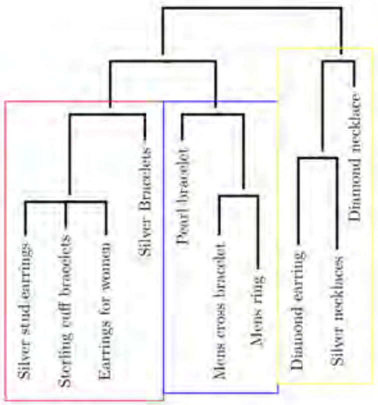
- Step 2: Hierarchical clustering *within the thematic clusters of step 1* to account for competition (for any pair of keywords in a cluster, dissimilarity matrix built on co-occrrences of same advertisers)

# Step 2: Hierarchical Clustering




*Notes:* Structure of competitive clusters: the three clusters - red, blue and yellow boxes - are identified through the Kelley, Gardner and Sutcliffe [1996] penalty parameter.

descriptives

# Thematic Clusters and Markets

| | Thematic Clusters | | | | Competitive Clusters (Markets) | | | |
|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Median | Observations | Mean | SD | Median | Observations |
| **Market Characteristics** | | | | | | | | |
| # Advertisers | 6.7 | 10.5 | 3.0 | 8,324 | 4.0 | 4.8 | 3.0 | 25,947 |
| # Keywords | 116.1 | 180.3 | 55.0 | 8,324 | 37.2 | 104.9 | 4.0 | 25,947 |
| Competitive Clusters | 5 | 5 | 3 | 8,324 | - | - | - | - |
| **Market Variables** | | | | | | | | |
| $log(\hat{R}_{m,t})$ | 10.89 | 2.27 | 10.92 | 29,796 | 10.41 | 1.96 | 10.37 | 52,476 |
| $HHI_{m,t}$ | 2,765 | 2,311 | 2,000 | 29,899 | 2,740 | 2,257 | 2,000 | 52,476 |
| Long Tail | 0.32 | 0.35 | 0.18 | 29,899 | 0.27 | 0.37 | 0.01 | 52,476 |
| $\Delta\hat{R}_{m,t}$ | -0.05 | 1.78 | 0.00 | 21,256 | 0.40 | 1.53 | 0.28 | 43,973 |
| # of Results (mil) | 76.93 | 269.19 | 21.52 | 29,899 | 75.97 | 231.28 | 19.7 | 52,476 |
| # Clusters | 8,324 | | | | 25,947 | | | |

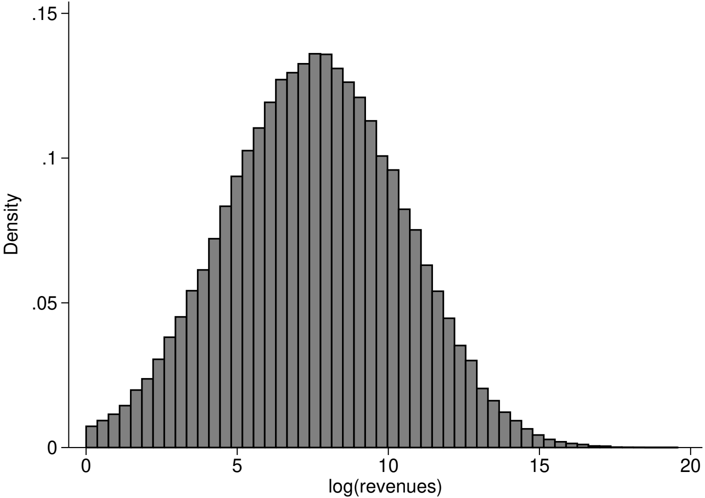
# 2) Measurement of the Main Variables

We compute a proxy for $R^G$ using data on the $i = 1, ..., N_r$ keywords bid by the sample of Redbooks' advertisers:

$$R_{mt} = \sum_{k \in K_m} CPC_{kmt} * Volume_{kmt} * CTR_{kmt}$$

- $CPC_{kmt}$: average Cost-per-Click of keyword $k$ in market $m$ at time $t$
- $Volume_{kmt}$ is the overall number of searches of $k$ over an year
- $CTR_{kmt}$ is the cumulative Click-through-Rate of all the sponsored ad slots shown for keyword $k$

# Distribution of $log(\hat{R})$



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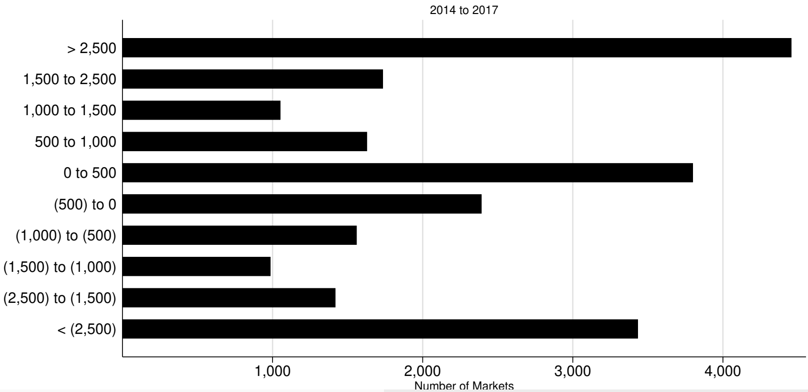
And a proxy for demand concentration: $HHI_{mt} = \sum_{i=1}^{I} ({s^i}_{mt})^2$

- Market size ($S_{mt}$): sum of all the clicks of all the ad slots allocated in all the keywords in $m$: $S_{mt} = \sum_{k \in K_m} Volume_{kmt} * CTR_{kmt}$
- For intermediary $i$, representing the set of advertisers $A_i$, the market share in market $m$ at time $t$ is: $s^i_{mt} = \frac{1}{S_{mt}} \sum_{a \in A_i} \sum_{k \in K_m} \sum_{j \in J_k} CTR_{jkmt} * Volume_{kt} * 1\{a \text{ occupies } j \in J_k\}$

# Change in local concentration - 2014 to 2017

descriptives-mkt

- we observe 21 M&A and 2 divestures
- $HHI_{m,2017} - HHI_{m,2014}$
- $HHI \in [0 - 10,000]$



# 3) Causal Identification: IV Approach

- OLS unlikely to deliver causal effect due to OVB. Example: media attention to a phenomenon changes keyword entry/bid
- We adapt ideas from Dafny et al. (2012) of using M&A events as shocks to "local" market concentration
- Hence, if in year $t$ intermediary $\alpha$ merges with intermediary $\beta$, the merger-induced change in HHI is: details

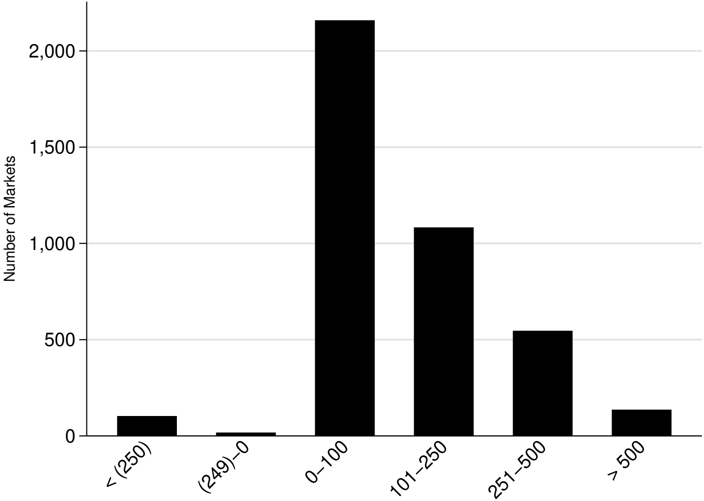
$$sim\Delta HHI_{mt} = \underbrace{(s^{\alpha}_{m,t} + s^{\beta}_{m,t})^2}_{\text{Share of merged firm } \alpha+\beta} - \underbrace{((s^{\alpha}_{m,t})^2 + (s^{\beta}_{m,t})^2)}_{\text{Shares of single firms } \alpha \text{ and } \beta}$$

- Alternatives: we might want to exclude mergers too likely to be driven by specific keywords (too "local"); few overlapping markets; mergers with insufficient pre or post periods pre/post

# Merger Events

| Agency | Acquiring Network | Acquisition year | Number of Advertisers | Number of Industries | Number of Markets |
|---|---|---|---|---|---|
| The Brooklyn Brothers | IPG | 2016 | 6 | 2 | 23 |
| Essence Digital Limited | WPP | 2015 | 1 | 1 | 145 |
| Quirk | WPP | 2015 | 5 | 2 | 272 |
| SHIFT Communications | WPP | 2017 | 13 | 8 | 1,049 |
| Deeplocal Inc. | WPP | 2017 | 5 | 1 | 117 |
| Maruri GREY | WPP | 2017 | 1 | 1 | 150 |
| Zubi Advertising Services, Inc. | WPP | 2017 | 3 | 2 | 345 |
| Campfire | Publicis | 2015 | 3 | 1 | 27 |
| La Comunidad | Publicis | 2015 | 9 | 5 | 271 |
| Sapient Corporation | Publicis | 2015 | 17 | 6 | 1,038 |
| Blue 449 | Publicis | 2016 | 4 | 2 | 93 |
| Forsman & Bodenfors | MDC | 2017 | 5 | 1 | 315 |
| Formula PR | Havas | 2015 | 6 | 4 | 309 |
| FoxP2 | Dentsu-Aegis | 2015 | 1 | 2 | 42 |
| Rockett Interactive | Dentsu-Aegis | 2015 | 1 | 1 | 22 |
| Covario, Inc. | Dentsu-Aegis | 2015 | 3 | 1 | 78 |
| Achtung | Dentsu-Aegis | 2016 | 2 | 1 | 226 |
| Gravity Media | Dentsu-Aegis | 2016 | 5 | 3 | 433 |
| Grip Ltd. | Dentsu-Aegis | 2016 | 3 | 2 | 92 |
| Merkle | Dentsu-Aegis | 2017 | 18 | 7 | 973 |
| Gyro | Dentsu-Aegis | 2017 | 12 | 6 | 363 |

# Distribution of $sim\Delta HHI$



# Results: Baseline Estimates (Sample selection: $75^{th}$ pct. largest markets w/o mergers)

| | (1) | | (2) | | (3) | | (4) | | (5) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | RF | FS | RF | FS | RF | FS | RF | FS | RF | FS |
| sim$\Delta\hat{HHI}$ | -6.761*** | 0.618*** | -4.070*** | 0.957*** | -3.842*** | 0.830*** | -3.831*** | 0.829*** | -3.723*** | 0.831*** |
| | (1.110) | (0.170) | (1.133) | (0.0790) | (1.162) | (0.0914) | (1.165) | (0.0915) | (1.165) | (0.0913) |
| Weak Id. F-Test | | 13.21 | | 146.99 | | 82.37 | | 82.18 | | 82.94 |
| Underid. F-test | | 4.56 | | 13.67 | | 11.02 | | 11.01 | | 11.02 |
| Observations | 52,476 | 52,476 | 52,476 | 52,476 | 52,476 | 52,476 | 52,476 | 52,476 | 52,476 | 52,476 |
| Cluster FE | | | ✓ | | ✓ | | ✓ | | ✓ | |
| Year FE | | | | | ✓ | | ✓ | | ✓ | |
| Organic Results | | | | | | | ✓ | | ✓ | |
| Keyword Characteristics | | | | | | | | | ✓ | |

| | OLS | | | | | IV | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| $\hat{HHI}$ | -2.217*** | -2.120*** | -2.129*** | -2.122*** | -2.130*** | -10.93*** | -4.252*** | -4.630*** | -4.620*** | -4.479*** |
| | (0.0718) | (0.0567) | (0.0573) | (0.0572) | (0.0569) | (2.902) | (1.068) | (1.200) | (1.204) | (1.201) |
| Organic Results (billion) | | | | 0.252*** | 0.263*** | | | | 0.206*** | 0.225*** |
| | | | | (0.0437) | (0.0458) | | | | (0.0463) | (0.0477) |
| **Keywords Characteristics** | | | | | | | | | | |
| Branded Keyword | | | | | 0.396*** | | | | | 0.458*** |
| | | | | | (0.0537) | | | | | (0.0639) |
| Long-tail Keywords | | | | | -0.0908** | | | | | -0.0491 |
| | | | | | (0.0367) | | | | | (0.0423) |
| $R^2$ | 0.07 | 0.62 | 0.62 | 0.62 | 0.62 | | | | | |
| Observations | 52,476 | 52,476 | 52,476 | 52,476 | 52,476 | 52,476 | 52,476 | 52,476 | 52,476 | 52,476 |
| Cluster FE | | ✓ | ✓ | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ |
| Year FE | | | ✓ | ✓ | ✓ | | | ✓ | ✓ | ✓ |

# Robustness and Extensions

- **Robustness**
  - IV validity: largest mergers
  - Different definition of clusters $\longrightarrow$ Table
  - Alternative proxies for $R_{mt}$ and $HHI_{mt}$ $\longrightarrow$ Robustness
- **Channels and Validation**
  - Channels: CPC, Volume and Number of Keywords
  - Heterogeneous effects at industry level $\longrightarrow$ $\beta_{IV}$ industry-level
  - Cluster validation $\longrightarrow$ Amazon Mechanical Turk
- **Extra**
  - Sample selection
  - "Merged" markets only $\longrightarrow$ $\beta_{OLS}$ and $\beta_{IV}$
  - Keyword type (length; long tail; branded; etc.) $\longrightarrow$ DMA effect

# Largest Individual Mergers of Four Different Agency Networks

| Panel a): Individual Mergers - Reduced Forms and First Stages | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Sapient | | Merkle | | Shift | | Forsman&Bodenfors | |
| | RF | FS | RF | FS | RF | FS | RF | FS |
| sim$\Delta\hat{HHI}$ | -4.911* | 1.026*** | -5.981*** | 1.388*** | 4.536 | 0.707*** | -16.30** | 6.357*** |
| | (2.882) | (0.387) | (1.181) | (0.0386) | (2.998) | (0.230) | (6.388) | (0.159) |
| Observations | 4,776 | 4,776 | 3,047 | 3,047 | 3,013 | 3,013 | 981 | 981 |

| Panel b): Individual Mergers - OLS and IV Estimates | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Sapient | | Merkle | | Shift | | Forsman & Bodenfors | |
| | OLS | IV | OLS | IV | OLS | IV | OLS | IV |
| $\hat{HHI}$ | -5.302*** | -4.786* | -4.516*** | -4.308*** | -3.823*** | 6.415 | -5.236*** | -2.563** |
| | (0.208) | (2.547) | (0.293) | (0.871) | (0.175) | (4.963) | (0.672) | (0.999) |
| Observations | 4,776 | 4,776 | 3,047 | 3,047 | 3,013 | 3,013 | 981 | 981 |
| Industry FE | ✓ | | ✓ | | ✓ | | ✓ | |
| Year FE | ✓ | | ✓ | | ✓ | | ✓ | |
| Organic Results | ✓ | | ✓ | | ✓ | | ✓ | |

# Robustness Checks

| | Market Definition | | Two-layers Clustering | | |
|---|---|---|---|---|---|
| | Industry Level | Thematic Clusters | GloVe mean | 500K | N/30K |
| | (1) | (2) | (3) | (4) | (5) |
| $\hat{HHI}$ | 9063.3 | -10.75*** | -3.870*** | -2.600*** | -3.404*** |
| | (1427185.6) | (1.572) | (0.600) | (0.716) | (0.860) |
| Observations | 68 | 22,353 | 68,368 | 54,621 | 52,867 |
| Industry FE | ✓ | | | | |
| Cluster FE | | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ |

# Results: Different Channels (IV estimates)

| | $log(\hat{R})$ | $log(cpc)$ | $log(volume)$ | $log(\#keyword$ |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\hat{HHI}$ | -4.620*** | -1.271*** | -0.669 | -0.842 |
| | (1.204) | (0.427) | (0.983) | (0.741) |
| Observations | 52,476 | 52,476 | 52,476 | 52,476 |
| Cluster FE | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ |

# Outline

# Conclusions

**Main findings:**

- First evidence that intermediaries' concentration reduces Google's revenue
- Novel approach for market definition in sponsored search

**Considerations for competition policy:**

1. Risk of abuses in Google's response to intermediaries:
   - Higher reserve prices: Google started increasing its reserve price in May 2017. AdRank made them "context specific" and more heavily based on max CPC. Who are the real losers?
   - Disintermediation: pay attention where Google's seeks to replace agencies, like with DoubleClick Search
2. When is growing buyers' power desirable:
   - Pass-through to advertisers (consumers) of lower prices or algorithmic collusion for the benefit of intermediaries?
   - Heterogenous impacts on smaller platforms (Bing, etc.)?

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