Digital Advertising and Market Structure, Niels Wernerfelt, Digital Economics Conference

# Discussion of "Digital Advertising and Market Structure" by Deisenroth, Manjeer, Sohail, Tadelis & **Niels Wernerfelt**

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### Summary

- **Setting** : Privacy concerns: A natural experiment: introduction (April 21) of a privacy feature in Apple (ATT!) and their impact on users and platforms.
- Very rich data sources from Facebook and Instagram as well as administrative data
- **Parameter(s) of interest:** What if users are offered the possibility of limiting access to their data? Outcomes: advertisement volume, market structure & prices.
- Main assumptions: Parallel trend assumption + exogeneity of the treatment variable

#### Contribution 1: Economic model

Decrease in effectiveness of advertisement (Z private) :

 $Pr(Purchase \mid Advertising, Z) \neq Pr(Purchase \mid Advertising)$ 

Under plausible conditions:

- Firms exit market (e.g. the advertising market on Facebook and Instagram!)
- Advertisement volumes decrease
- Prices increase

**Question**: Pure technological shock on advertisement, what about the reactions of the platform to this shock? Prices in particular?

## Contribution 2: Matching internal/external data

- Data on advertising from internal sources: advertising, number of firms
- Data on prices from administrative sources: prices, number of firms

Careful matching of the two (multiple matching, checking expost by randomization,  $\dots$ )

**Question:** Yet, some firms might not advertise on Facebook, Instagram : final goods/intermediate goods? small/large firms?.

Check that common variables (e.g. number of firms) in internal/external sources react in the same way to treatment?

#### Contribution 3: Treatment effects

The structure of the natural experiment without any other assumptions leads to a before/after estimate whose quality is low since time is a confounder.

*Idea*: Use a variable,  $X_i$ , (say exposure to treatment), at the industry level. Construct the treatment group  $(D_i = 1)$  as industries such that  $X_i \ge 90\%$  *Percentile* of its distribution and the control group  $(D_i = 0)$  as industries with  $X_i \le 10\%$  *Percentile*. Compute the means over time in these two groups between 2020Q2 to 2023Q3 and adopt a difference in differences estimation procedure (*i* is industry specific).

$$Y_{it} = \delta_t + \gamma_i + \beta D_i * | t - 2021Q2 | + \varepsilon_{it}.$$

**Remark**: to avoid simultaneity of outcomes and treatment, use information on X that predates the date of the switch

#### Issues

- **Parallel trend assumption**: the estimates are Average Treatment on the Treated (ATT!) estimates if trends are the same in treated & control groups *in the absence of the treatment*. In other words, the treatment is exogenous to the "long" differenced outcomes,  $Y_{it} - Y_{i2021Q2} \perp D_i$ .
- Endogeneity of exposure to treatment: some unobserved heterogeneity affect treatment, Y<sub>it</sub> - Y<sub>i2021Q2</sub> correlated with X<sub>i</sub>
- **Reference level**: the impact of the experiment on outcomes is not 0 even for the control group. How do we interpret the estimate?
- Continuous treatment with DiD: See Callaway, Goodman-Bacon & Sant'Anna, WP NBER, 2024.