AI & Customer Acquisition in Retail Financial Services: Experimental Evidence from Insurance Distribution

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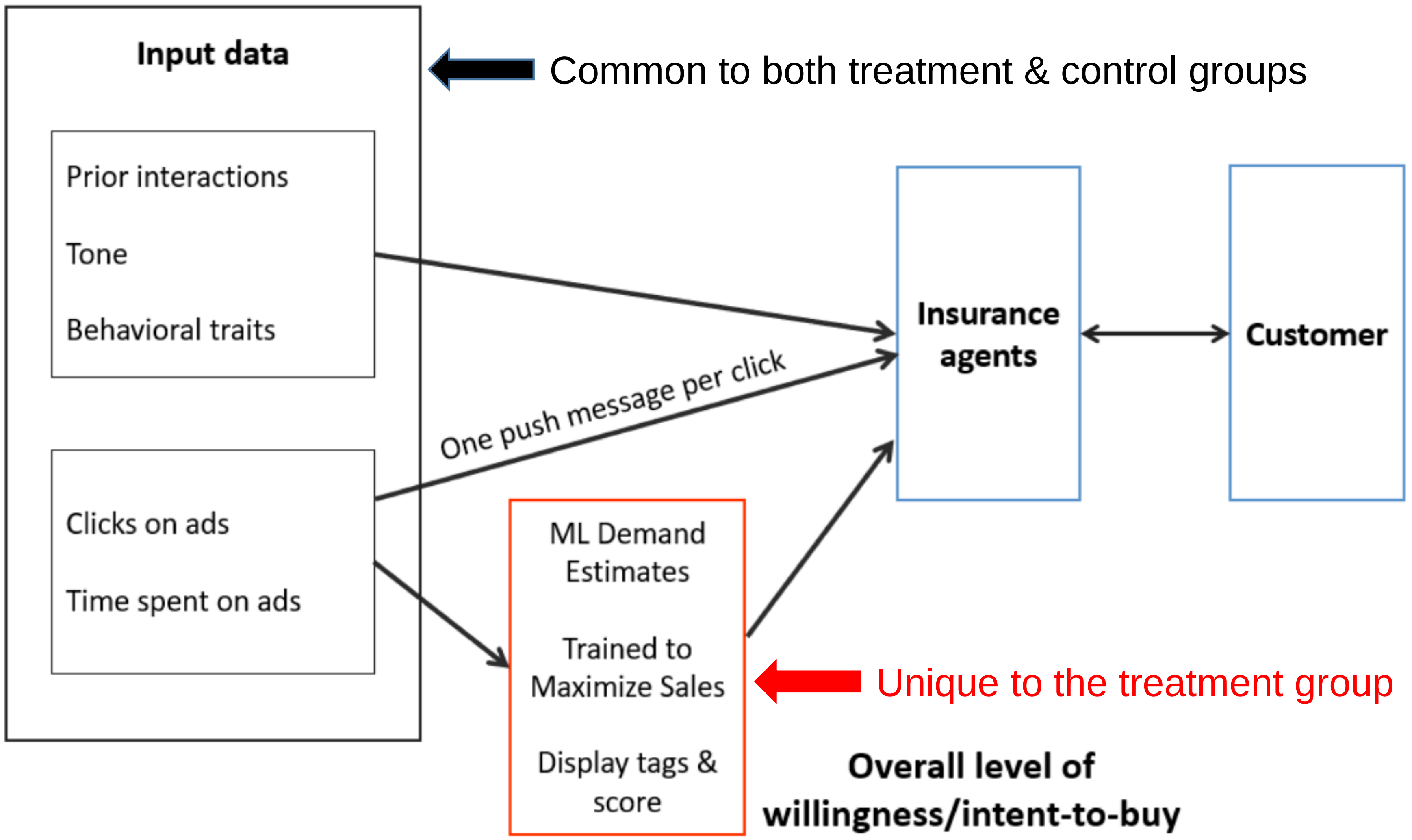
Summary of paper: question & setting

- Question: How does AI affect attention allocation & information production in retail financial intermediation?

- Empirical setting:
    - Randomized field experiment on insurance agents
    - Treatment/Control: Access/no access to AI-generated demand estimates

Experimental setting



Summary of paper: main findings

- Agents respond to AI-generated demand estimates
  - Focus on high-purchase-intent customers
  - Achieve higher sales and commissions

- What is the catch?
  - Agents' own information production decrease
  - Adverse selection increase
  - Prices are "wrong": ex-post riskier customers brought by treated agents do not buy more expensive products

Outline of discussion

- Fantastic paper that I enjoy reading:
  - Important and timely question
  - Novel experimental design and tests
  - Far-reaching implications for the broader consumer finance markets

- Comments and ideas
  - Different uses of technology in consumer finance
  - Selection into the sample
  - Sources of information asymmetries

Different uses of technology in consumer finance markets

Two flavors of technology in consumer finance markets (based on the framework of FinTech lending by Berg, Fuster, & Puri, 2022)

1. “**process**” technology affects how customers (borrowers, investors, insurance buyers, etc) interact with suppliers (lenders, funds, financial advisors, insurers)

2. “**data**” technology affects demand prediction, screening, risk evaluation, pricing, etc

Different uses of technology in consumer finance markets

- The two aspects can interact with each other: app-based interactions generate digital footprints that can be used as inputs for the “data” technology

- The paper also highlights the role of internal (as opposed to the above-mentioned “customer-facing”) process technology: the availability of AI-generated demand estimates changes behaviors of insurance agents

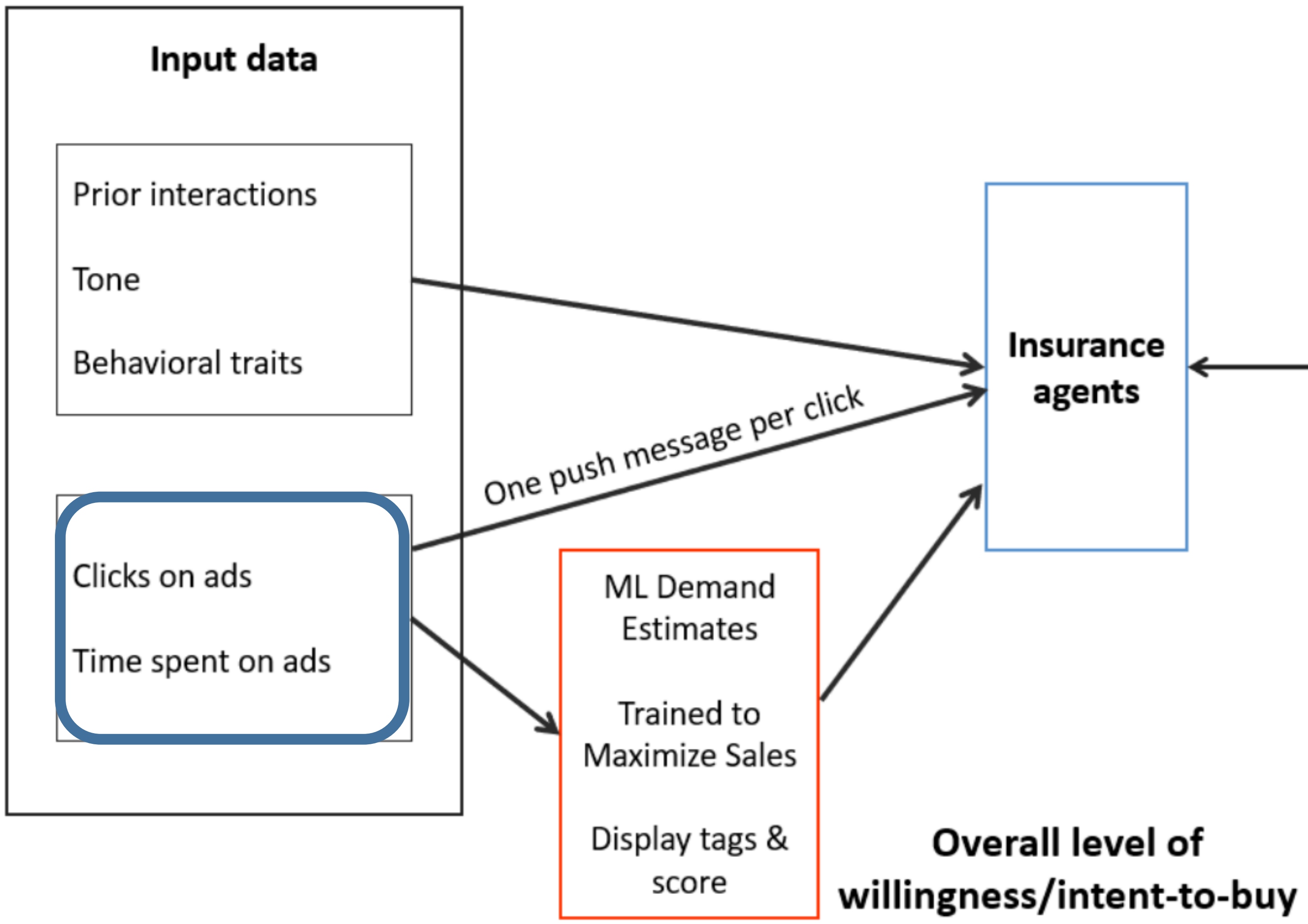
- Can you put a money metric of the overall effect (additional sales vs riskier customers) for the insurer?

- Also, any impacts on structural or organizational factors?

Insurance agents versus underwriters

- Agents help customers apply for new insurance policies & help them file claims
- Underwriters evaluate the risk associated with insuring applicants, approve/reject applications, determine coverage terms
- Agents' compensation: % of premium as commission at policy start
- For agents, consequences of pursuing high-risk customers include:
  - (In the extreme) application is rejected → direct negative consequences: no commission, wasted effort in customer acquisition
  - If application is approved, no direct negative consequences
  - Indirect negative consequences: reputation damage, ban, blacklist
- Legal liability imposed on incorrect disclosures
- Overall, there are strong incentives for agents to ignore risks! Would the internal process technology change the dynamics?

Who are the customers in the sample?



Who are the customers in the sample?

- Who can see the ads (a necessary condition of clicking)?
  - Customers who receive direct messages from agents
  - Customers who see agents' postings to their friend circles
  - Customers who see re-postings of agents' original postings (→ may not be direct contacts of agents)
- Re-postings of ads by non-agents is limited → majority of customers in the sample are likely to be existing direct contacts of agents!
- This does not necessarily invalidate the experimental design but it does affect the interpretation
  - Existing contacts → the value added from AI is limited → lower bound effect?
  - Heterogeneity w.r.t. prior interactions can shed some light on this
  - What are the sources of value-added from AI?

Sources of information asymmetries

- The positive correlation test to detect adverse selection (e.g., Chiappori and Salanie, 2000)
  - + Positive correlation between risk & coverage: adverse selection
  - − Negative correlation between risk & coverage: advantageous selection
- Overall, stronger adverse selection for treatment X high & middle-intent segments
- The treatment X low-intent segment actually exhibits advantageous selection, although not always significant due to small N
  - One interpretation: when agents override AI's prediction and sell low-intent customers, they actually do a better job? Perhaps they are confident that these are customers undervalued by AI
  - How do the high/middle/low-intent composition & correlation b/w risk & coverage look like in the control sample?

Sources of information asymmetries

- The positive correlation test is essentially a **joint test**
  - It also detects **moral hazard**: who buy more insurance are less likely to quit smoking, etc.
  - Einav, Finkelstein, and Mahoney (2021, Handbook of IO Chapter 14): difficulty in separating adverse selection from moral hazard using observational data
- Some solutions proposed in the literature
  - The "cost curve test" (Einav, Finkelstein, and Cullen, 2010, QJE) use variation in insurance premiums
  - Karlan and Zinman (2009, ECMA): experimentally vary initial offer price & contractual price (revealed only after agreeing to the initial price) to separate the two
- Adverse selection and moral hazard can co-exist in this setting
- I would keep both interpretations open and do what's feasible to detect moral hazard