Artificial Intelligence and Customer Acquisition in Retail Financial Services: Experimental Evidence from Insurance Distribution

Xing Liu

Tsinghua University
PBC School of Finance

ABFER
May 22, 2024

Multitasking

- Effort choices among tasks that compete for time and attention
- Inefficiencies induced by incentive contracts and job design

  Holmstrom and Milgrom (1991)

Multitasking and AI information disparity

- Rising automation of information processing tasks
- Along certain job dimensions/tasks – only local decision support
- Efficient attention allocation in decision-making at work becomes increasingly important for understanding labor productivity dynamics.
  Autor, Levy, and Murnane (2003); Deming (2021); Caplin et al. (2023)

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Questions:

- How might AI redirect humans' attention allocation across tasks?
- Will AI-generated information crowd in or crowd out humans' collection of other types of information?
- Can AI mitigate or exacerbate agency frictions?

Financial services industry


Demand & Cost

- Both consumer demand and risk information are important to sellers.

  Einav, Finkelstein, and Levin (2010); Einav, Finkelstein, and Mahoney (2021)

Jobs of intermediary labor force

- Often involve both customer acquisition and risk screening
  - Agents, brokers, advisors, etc.
  - Loan officers prospect for loans and screen loan applicants.
    Heider and Inderst (2012)
  - Two main aspects of FinTech lending: using technology to enhance customer-lender interactions & borrower screening and monitoring
    Berg, Fuster, and Puri (2022)

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  - Two main aspects of FinTech lending: using technology to enhance customer-lender interactions & borrower screening and monitoring Berg, Fuster, and Puri (2022)
- Advances in technology, however, may create information disparities across different tasks.
  - Technology specialization within industry/organization/division
  - Segmented evaluation system
  - Unsynchronized technology advancements

Example

This paper: AI in insurance markets

Why study insurance markets?

- Important market with enormous size
- Highly human-intermediated
- Soft information matters
- Customer acquisition & screening is a prediction problem
- An agent-level field experiment with random variation in accessing AI

Insurance markets

- A sector that has traditionally relied heavily on humans to intermediate the sales process
  - Agent needs to increase consumer take-up.
  - Agent acts as first underwriter collecting risk information. agent's view
    Rejda and McNamara (2014)

$\Rightarrow$ Ideal laboratory to study how AI-generated information affects behavior when **individuals have a screening role**!

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- Predicting risk – learning about loss distribution by insurers
- **Predicting demand** – learning about WTP by **agents**

$\Rightarrow$ Does AI-generated demand information **crowd in** or **crowd out** information gathering about risk?

Randomized experiment

- By a top Chinese insurance agency
- Independent agents selling products of different insurers
- Life & Health & Accident
- 11,125 agents, Aug to Nov 2021
- On mobile app - insurance agents are app users
- Half of agents get AI-generated purchase intent of consumers
- Prediction based on consumer digital footprints on advertisements

Incentive structure

- Paid commission on products sold
  - e.g., 1,000 RMB on 10,000 RMB premium insurance policy
- Costs of poor risk assessment
  - likely to be rejected during final underwriting
  - blacklisted by the agency or insurers
  - temporary or permanent ban from selling (kicked off)
  - customer complaint and trust
  - career or reputation concern
  - post-sales service

agents' view on costs

What can agents do for risk selection?

- Agents choose **whether to deal with** a potentially risky customer.
  - *Desk rejection*
- Conditional on selling, agents choose the **amount of effort** for risk assessment and **information collection**.
  - Level of full disclosure largely depends on agents' guidance.
  - Insurers make final underwriting decisions based on those information.

▸ agents' view on risk selection

Experiment

Control Group: Data

One push message per click on ads:

2022-11-01 15:40:26 Visitor A has read article 1 for 30s
2022-10-31 10:10:45 Visitor A has read article 1 for 10m 28s
2022-10-31 21:20:25 Visitor B has read article 2 for 5s
2022-09-10 14:30:10 Visitor A has read article 3 for 2m 15s
2022-08-20 08:25:55 Visitor C has read article 2 for 6m 38s
......

Treatment Group: Data + AI-generated Data

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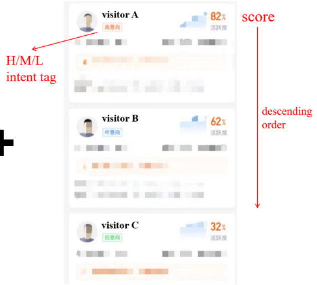
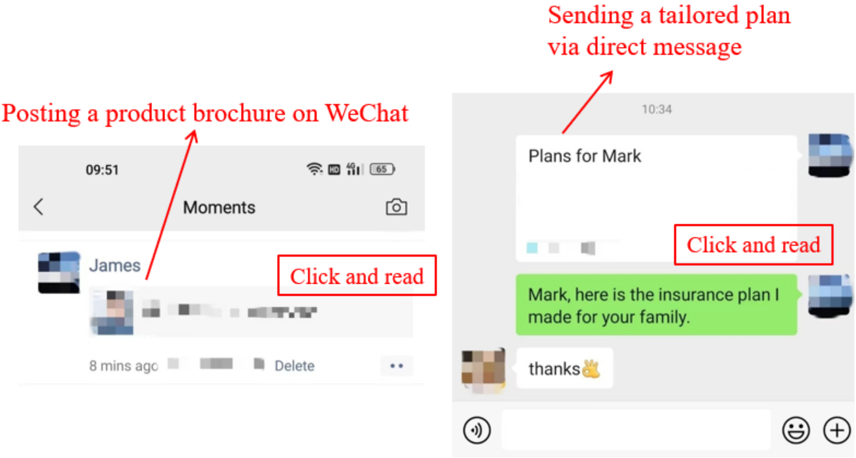


⇒ Treatment on **information processing** of consumer digital footprints

⇒ Based only on information **available** to agents

Consumer digital footprints on ads



Push notifications
– available to **all** agents prior to the experiment

- **One push message per click** (raw data)

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- ...

⇒ Costly monitoring and continuous attention to information flow

⇒ Filtering out noise from big (raw) data

Algorithm

- Name [non-disclosure]
  - complex non-linearity and rich interactions among predictors
- **1K+ features** constructed from consumer digital footprints on ads
- **Target**: prob. of sales for each "visitor" (potential customer)

$\Rightarrow$ **overall intent-to-buy**

AI-generated data is only available to treated agents

Experiment

- **Control Group**:
  - Consumer response to ads – push message per click (raw data)
- **Treatment Group**:
  - Consumer response to ads – push message per click (raw data)
  - AI demand predictions

Preview of results

- **AI demand information improves agents' sales by 14%.**
  - Shifts agents' attention to converting high-intent consumers
  - Effect stronger among less-experienced and underperforming agents
  - No evidence of offering poor-fitting products – by variety & cancellation

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  - Rational inattention & Myopia
  - AI picks lemons – high demand, high risk? No.

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- **App clicks – less attention to risk vs. demand information**

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- **App clicks – less attention to risk vs. demand information**
- **Pricing instruments become less effective.**
  - Riskier consumers not matched to more expensive products
  - Agents' match-making role weakened

Contributions

1. **AI and FinTech on intermediary labor force**
   - Role of advisors, brokers, and **agents**
     Linnainmaa, Melzer, and Previtero (2021); Egan, Matvos, and Seru (2019); Egan, Ge, and Tang (2022); D' Acunto and Rossi (2021, 2022)
   - Marketing and **customer acquisition** stage understudied (**demand** vs. risk content of digital footprints)
   - Micro-level; large-scale randomized experiment in a real-world setting
     Brynjolfsson, Li, and Raymond (2023); Babina et al. (2024)
2. **Technology in selection markets (insurance in particular)**
   - Demand and cost are tightly linked; coordination/agency problems
     Einav, Finkelstein, and Levin (2010); Einav, Finkelstein, and Mahoney (2021); Heider and Inderst (2012); Berg (2015)
   - Endogenous information acquisition
     Goldstein and Yang (2017); Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014, 2016); Veldkamp and Farboodi (2020); Dugast and Foucault (2018)

Contributions

3 **Attention and inattention in decision making**
Stigler (1961); Sims (2003); Gabaix (2014)

- Side effects of information intervention
  Bartos (2016); Mackowiak et al. (2022); Medina (2021)

4 **Advertising in consumer finance**
Bertrand et al. (2010); Gurun, Matvos, and Seru (2016)

- Agents maximize their own surplus when enabled by AI.

Data

- Agent characteristics Gender, age, education degree, location, registration date, branch company, etc.
- Sales and commissions
- Policy, policyholder, and product
- Claims
- App behaviors One obs. is one click by an agent.
- Visitor records on WeChat One obs. is one click/read by a visitor.
- AI-based demand predictions

  Although agents in the control group could not access the predictions, the algorithm predicted purchase intent of visitors for all agents.

Summary statistics & balance checks

	All	Treatment	Control	Mean Diff.	T-stat
	(1)	(2)	(3)	(4)	(5)
	N=11,125	N=5,430	N=5,695		
Demographics & Experience					
Age	40.55	40.46	40.63	-0.17	-0.80
Female	0.51	0.51	0.51	-0.00	-0.30
College	0.30	0.30	0.29	0.01	1.49
Branch in First-tier City	0.43	0.43	0.42	0.01	0.68
APP Experience (months)	27.14	27.08	27.20	-0.12	-0.31
Work Experience (months)	10.63	10.57	10.68	-0.11	-0.58
Pre-treatment Sales Performance & Composition					
Any Policy	0.53	0.54	0.53	0.01	1.04
# Policy	10.01	10.32	9.71	0.61	0.89
Total Premium	10265.28	10478.63	10061.86	416.77	0.47
Avg. Premium Per Policy	1417.86	1483.60	1354.01	129.59	0.64
% Policy - Long-term	0.16	0.16	0.15	0.01	1.13
% Premium - Long-term	0.28	0.28	0.27	0.01	1.38
% Policy - New Clients	0.85	0.85	0.85	-0.00	-0.76
% Premium - New Clients	0.84	0.84	0.85	-0.00	-0.67
Commission Income & Rate					
Total Commission	3049.60	3104.98	2996.79	108.19	0.49
Avg. Commission Rate	0.24	0.24	0.24	-0.00	-0.48
Unique # Commission Rate	4.57	4.66	4.49	0.18	1.26

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	(1)	(2)	(3)	(4)	(5)
	N=11,125	N=5,430	N=5,695		
Claims					
# Claims	1.56	1.60	1.52	0.08	0.34
Claimed Amount	2122.00	2024.26	2218.37	-194.11	-0.41
Claim Ratio	0.08	0.08	0.08	-0.00	-0.02
Policy Cancelation					
# Canceled Policy	0.27	0.26	0.27	-0.01	-0.25
Cancelation Ratio	0.03	0.03	0.03	-0.00	-0.38
Product Variety					
Unique # Products	5.90	6.03	5.77	0.26	1.46
Product HHI	0.50	0.49	0.50	-0.01	-1.61
App Usage					
# View Health Declaration Page	13.54	14.15	12.92	1.23	1.06
# View Visitor Management Page	21.00	21.20	20.84	0.36	0.24
% View Health Declaration Page	0.46	0.46	0.46	-0.00	-0.11
# Avg. Length of Disease Search Input Characters	3.14	3.13	3.16	-0.03	-0.68
# View Underwriting Result Page	21.54	22.62	20.45	2.17	1.54

- Balance checks suggest randomization is successful.

Treatment effects on sales performance

$$Y_a = \beta_0 + \beta_1 Treat_a + Z_a + \varepsilon_a$$

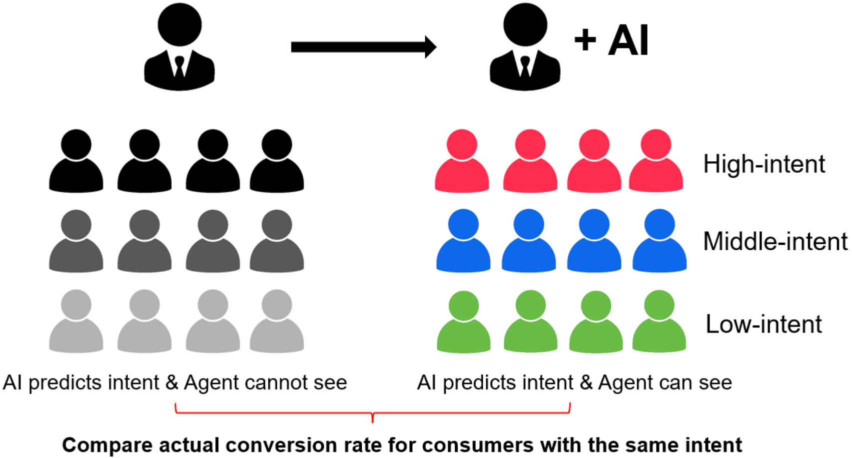
	# Policy		Tot. Premium		Avg. Premium	
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	0.326**	0.311**	300.068**	275.733**	120.411	121.344
	(0.152)	(0.134)	(138.003)	(123.602)	(89.023)	(86.471)
Observations	11,125	11,125	11,125	11,125	4,687	4,687
Baseline Controls	No	Yes	No	Yes	No	Yes
R-squared	0.000	0.223	0.000	0.203	0.000	0.061
Control Mean	2.940	2.940	1965.433	1965.433	1081.500	1081.500

- policy count: 11% $\Uparrow$ to control mean
- total premium: 14% $\Uparrow$ to control mean

Mean Difference Plots | Outcome in Log and IHS | Varying Sample By Timing of Entry | Model | Earnings | Commission Rates | DID

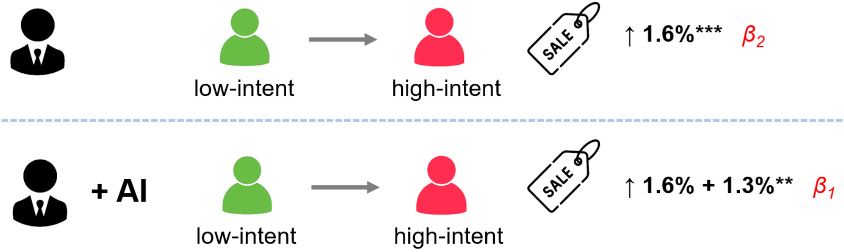
Learning channel

- Agents learn from AI-processed information about consumer demand.



Learning channel:
Shifting agents' attention to converting high-intent

$$Y_{a,c} = \beta_0 + \beta_1 Treat_a \times A_{a,c} + \beta_2 A_{a,c} + \beta_3 Treat_a + Z_{a,c} + \varepsilon_{a,c}$$



- Sales become **2X** more sensitive to high-intent visitors
- Mean of Y: 3% (average conversion rate of ads visitors)

▸ Model ▸ Table

Heterogeneity

- Learning effects are stronger among
  - less experienced agents
  - underperforming agents

  ▸ By Work Experience ▸ By Pre-Treatment Performance

$\Rightarrow$ **Agents with ex-ante weaker information processing capacity**

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- Sales composition
  - More long-term polices
  - Sales to new customers

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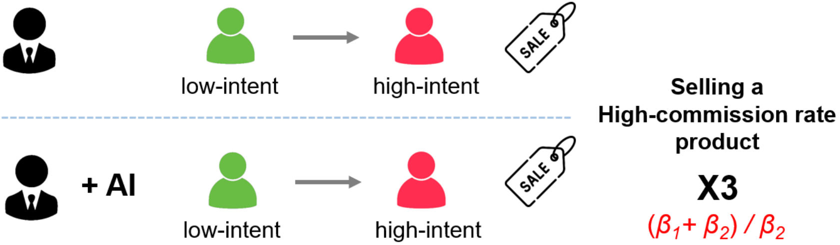
$\Rightarrow$ **Information frictions more severe**

- **Wilder customer outreach**
  - Effects stronger among agent-visitor pairs with different gender
    - treated male agents are more likely to acquire female clients
  - In regions with lower consumer ratings for commercial insurance

Information-driven consumer discrimination

$$Y_{a,c} = \beta_0 + {\color{red}\beta_1} Treat_a \times A_{a,c} + {\color{red}\beta_2} A_{a,c} + \beta_3 Treat_a + Z_{a,c} + \varepsilon_{a,c}$$



▸ Table ▸ Implications for Consumers

Does AI-generated demand information **crowd in** or **crowd out** information gathering about risk?

- Agents can invest time in
  1) assess the demand
  2) assess the risk
  3) develop new markets

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    AI saves scarce human time/attention to deal with the other task.

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- With AI increasing the efficiency of 1)
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    AI saves scarce human time/attention to deal with the other task.
  - **crowding out** – time saved by AI is spent on 3)
    Humans capitalize on AI and invest more on AI-assisted task.

Testing selection: Model

$$Risk_i = \beta_0 + \beta_1 Coverage_i + Z_i + \varepsilon_i$$

- Risk-Coverage correlation model at the policy level (i)
  Cohen and Siegelman (2010); Eling, Jia, and Yao (2017)
- $Risk_i$: logarithm of claimed amount
- $Coverage_i$: logarithm of insurance amount
- β_1: A positive and significant correlation between risk and coverage is the necessary condition of adverse selection – high risks buy more insurance coverage.
- Z_i: a vector of controls that insurers may use for risk classification and reducing asymmetric information. ▸ Model

Treatment effects on selection: Seperate estimations

	DV: Log Claim Amount				
	Control-All	Treat-All	Treat-High	Treat-Middle	Treat-Low
	(1)	(2)	(3)	(4)	(5)
Log Insurance Amount	0.002	0.427***	0.458*	0.504*	-0.241
	(0.112)	(0.160)	(0.250)	(0.269)	(0.186)
Observations	2,969	2,625	923	1,396	185
Premium Rate	Yes	Yes	Yes	Yes	Yes
Age/Gender/Location	Yes	Yes	Yes	Yes	Yes
Insurance Type FE	Yes	Yes	Yes	Yes	Yes
Applicant-Insurant Relation FE	Yes	Yes	Yes	Yes	Yes
Insurer FE	Yes	Yes	Yes	Yes	Yes
Agent FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.196	0.272	0.248	0.276	0.652
Outcome Mean	0.250	0.277	0.244	0.283	0.315

- Adverse selection exists in
  - Treatment, high-intent ✓
  - Treatment, middle-intent ✓
  - Treatment, low-intent X
  - Control X
- Insurance amount per person ⇑ by 1%, claimed amount ⇑ by 0.4-0.5% Effects

Treatment effects on selection: Interaction approach

DV: Log Claim Amount

	(1)	(2)	(3)
Log Insurance Amount	0.015	0.087	0.147
	(0.034)	(0.065)	(0.121)
Log Insurance Amount × Middle-intent	0.049	0.030	0.016
	(0.046)	(0.046)	(0.072)
Log Insurance Amount × High-intent	0.000	-0.024	-0.081
	(0.041)	(0.048)	(0.071)
Log Insurance Amount × Middle-intent × Treat	0.235**	0.229**	0.104
	(0.106)	(0.104)	(0.125)
Log Insurance Amount × High-intent × Treat	0.221**	0.263**	0.261**
	(0.106)	(0.113)	(0.126)
Log Insurance Amount × Treat	-0.184**	-0.207**	-0.097
	(0.092)	(0.096)	(0.124)
... ...			
Observations	6,026	6,024	5,604
Premium Rate	Yes	Yes	Yes
Age/Gender/Location	Yes	Yes	Yes
Insurance Type FE	Yes	Yes	Yes
Applicant-Insurant Relation FE	Yes	Yes	Yes
Insurer FE	No	No	Yes
Agent FE	No	Yes	Yes
R-squared	0.027	0.036	0.220
Outcome Mean	0.265	0.265	0.263

- Adverse selection in treatment-middle-intent group and treatment-high-intent group is significantly more severe than that in the respective control groups.

Why greater adverse selection?

Why greater adverse selection?

- Rational inattention ✓
  - Acquire information to maximize utility net of information costs and adjust attention allocation in response to changes in incentives
  - Stronger among customers with higher monetary rewards

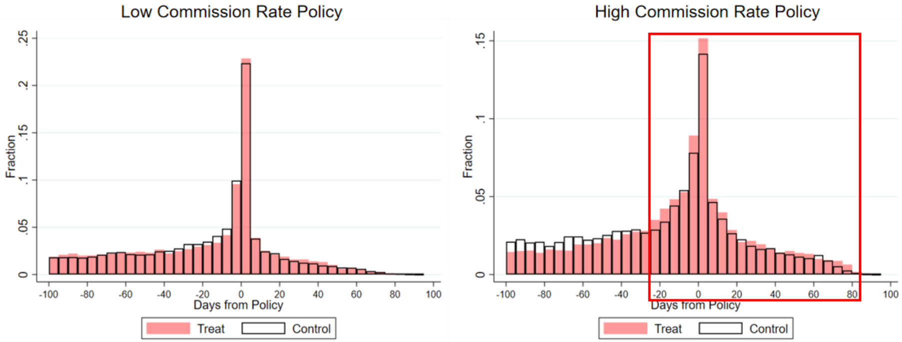
Rational inattention: By former vs. new clients

DV: Log Claim Amount

	(1)	(2)	(3)
Panel A: Rational Inattention			
Log Insurance Amount × Treat × Middle-intent × Former Client	0.511**		
	(0.251)		
Log Insurance Amount × Treat × High-intent × Former Client	0.248		
	(0.184)		
Panel B: Salience-driven Inattention			
Log Insurance Amount × Treat × Middle-intent × Has Recent Visiting Records		1.452	
		(1.181)	
Log Insurance Amount × Treat × High-intent × Has Recent Visiting Records		1.566	
		(1.203)	
Panel C: Weak Incentives for Collecting Risk Information			
Log Insurance Amount × Treat × Middle-intent × High Insurer Concentration (#)			-0.558**
			(0.260)
Log Insurance Amount × Treat × High-intent × High Insurer Concentration (#)			-0.889***
			(0.241)
Observations	5,604	5,604	5,604
Premium Rate	Yes	Yes	Yes
Age/Gender/Location	Yes	Yes	Yes
Insurance Type FE	Yes	Yes	Yes
Applicant-Insurant Relation FE	Yes	Yes	Yes
Insurer FE	Yes	Yes	Yes
Agent FE	Yes	Yes	Yes
R-squared	0.221	0.223	0.222
Outcome Mean	0.263	0.263	0.263

- Adverse selection worsened among former clients, compared to new clients
- Former clients – lower cost of conversion and higher chance of second sales

Consumers' mobile visiting patterns around policy sales: By high vs. low commission rate



- Consumers in the treatment group are more active in visiting agents' posts around a sale of high-commission rate policy than those in control group.

Why greater adverse selection?

- Rational inattention ✓
  - Stronger among customers with higher monetary rewards
- Myopia: Weak incentives for providing high-quality risk info ✓
  - Weaker among agents with smaller # of insurers
    (6% of sample agents ever punished by the agency)

Weak incentives for collecting risk information

DV: Log Claim Amount

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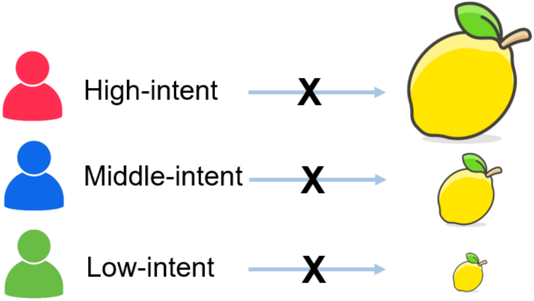
- Crowding-out is weaker among agents selling products from a small set of insurers.

Why greater adverse selection?

- Rational inattention ✓
  - Stronger among customers with higher monetary rewards (Former vs. New clients)
- Myopia: Weak incentives for providing high-quality risk info ✓
  - Weaker among agents with smaller # of insurers
  - (6% of sample agents ever punished by the agency)
- Salience-driven inattention **X**
  - No difference based on customers' order of arrival (recent or not)
- Treatment effects on moral hazard of consumers ▸ Go
- AI picks lemons – high demand, high risk **X**

AI picks lemons?



- No demand-risk (claim) correlation

AI demand estimates do not predict claim outcomes.

	DV: Log Claim Amount		
	(1)	(2)	(3)
Middle-intent	-0.087		
	(0.098)		
High-intent	-0.093		
	(0.096)		
Score		-0.001	
		(0.011)	
Rank			0.001
			(0.001)
Observations	5,604	5,604	5,604
Log Insurance Amount	Yes	Yes	Yes
Premium Rate	Yes	Yes	Yes
Age/Gender/Location	Yes	Yes	Yes
Insurance Type FE	Yes	Yes	Yes
Applicant-Insurant Relation FE	Yes	Yes	Yes
Insurer FE	Yes	Yes	Yes
Agent FE	Yes	Yes	Yes
R-squared	0.219	0.218	0.219
Outcome Mean	0.263	0.263	0.263

- Drivers of purchase beyond risk, especially in digital environment
  - health of self, family, friends, or neighbors; media; disasters; risk perception; insurance literacy, etc.

agent's view on correlation   interview quotes

AI's substitution of risk information acquisition

- AI demand information is **substitutive** to risk information collected by agents, thus reducing their **own** information acquisition (from other sources).
- Measure the extent to which AI demand predictions can **clearly reveal** consumer risk profile

AI's substitution of risk information acquisition

7 Ways Staying Up Late Could Harm Your Health

5 Signs of Cardiovascular Disease

Insurance 101

AI's substitution of risk information acquisition

7 Ways Staying Up Late Could Harm Your Health

5 Signs of Cardiovascular Disease

Insurance 101

AI demand predictions $\xrightarrow{?}$

- # of unique advertisements

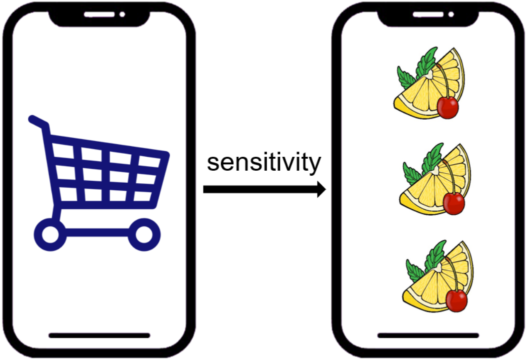
AI's substitution of risk information acquisition

DV: Log Claim Amount

	(1)	(2)
Panel A: Continuous		
Log Insurance Amount × Treat × # Ads	-0.025**	
	(0.011)	
Panel B: Dummy		
Log Insurance Amount × Treat × High # Ads		-0.283*
		(0.161)
Observations	5,604	5,604
Premium Rate	Yes	Yes
Age/Gender/Location	Yes	Yes
Insurance Type FE	Yes	Yes
Applicant-Insurant Relation FE	Yes	Yes
Insurer FE	Yes	Yes
Agent FE	Yes	Yes
R-squared	0.218	0.220
Outcome Mean	0.263	0.263

- Crowding out effect is weaker when it's harder for an agent to infer consumer risk profile from AI deterministically, thus being less substitutive to agents' own information acquisition.

Attention allocation to demand vs. risk information - App usage behavior from clickstream data



View
product detail page

View
underwriting-related page

View
health declaration page
↓ **64% ***

Avg. length of the input characters when searching diseases
↓ **100% *****

View underwriting result page
↓ **67% *****

▸ Table: Attention Allocation Sales vs. Risk

Pricing

	DV: Log Premium		
	(1)	(2)	(3)
Log Claim Amount	0.016**	0.008**	0.008**
	(0.006)	(0.004)	(0.004)
Log Claim Amount × Treat	0.018	0.016	0.005
	(0.015)	(0.012)	(0.006)
Treat	0.016	0.009	
	(0.028)	(0.015)	
Observations	6,026	6,024	5,604
Log Insurance Amount	Yes	Yes	Yes
Age/Gender/Location	Yes	Yes	Yes
Insurance Type FE	Yes	Yes	Yes
Applicant-Insurant Relation FE	Yes	Yes	Yes
Insurer FE	No	Yes	Yes
Agent FE	No	No	Yes
R-squared	0.641	0.809	0.912
Outcome Mean	5.021	5.020	5.005

- **Risk-price correlation: No difference**
- Treated agents bring in riskier consumers but do not match them to more expensive products to achieve stronger incentive compatibility.
- Agents' marketing role strengthened while match-making role weakened

Conclusion

- AI-generated information can **crowd out** human-collected information and **exacerbate agency conflicts** in **multitasking** environment.
- A **side effect** of **demand prediction** in **selection markets** could be information loss about consumer risk, worsening market efficiency.
- **Agents** maximize their own surplus from AI.
- **Implications** on organizational and contractual design to foster information production in the face of AI information disparity
- **Marketing vs. Risk assessment** – more **coordinated supply of AI**. Quantity-quality trade-off broadly exists in many markets.

liuxing@pbcsf.tsinghua.edu.cn