Time-Varying Risk Aversion?
Evidence from Near-Miss Accidents

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Time-Varying Risk Aversion

- Risk aversion is key preference parameter determining economic choices
  - Investment decisions, saving behavior
  - Insurance plans (health, auto)
  - Adoption of new goods, technologies, etc.

- Recent **(mainly survey)** evidence that risk aversion varies over time, shaped by *recent (adverse) experiences*:
  - Financial crisis: Guiso et al. (2018), Cohn et al. (2015), etc.
  - Natural disasters: Cameron and Shah (2015), Hanaoka et al. (2018), etc.
  - Violent conflicts: Jakiela and Ozier (2019), Brown et al. (2019), etc.

- We seek **field evidence** for time-varying risk aversion
  - Unique high-frequency data on driving behavior.
  - Do adverse events (driving mishaps) trigger change in risk preferences? (in which direction? welfare implications?)

Near-Miss

- We observe **near-miss accidents/"close calls"**
  - Driving mishaps – hard brakes and/or hard turns.
- Unlike real accidents:
  - More frequent, *do not* trigger a change in insurance contracts.
  - No pecuniary incentive to adjust driving behavior.
- Lab evidence that NM's induce behavior change. (Dixon and Schreiber (2004), Clark et al. (2012), Billieux et al. (2012), etc.)
- NMs attenuate risky behavior if they "can be recognized and interpreted as disasters that *almost happened*" (Tinsley et al., 2012).

Institutional Background

- A Chinese insurance tech firm:
  - produces a mobile phone app that tracks users' driving patterns using phone functions. Screenshots of the app
    Trip start and end pages
- While firm serves as a "front-end" auto ins brokerage, few users utilize this.
  - 6.25% of users actually request insurance quotes
- Information on users' driving patterns is *not* used in insurance pricing; drivers know this.
  - Drivers have little incentive to improve driving based on feedback from app.

Data

- Detailed trip-level info:
  - A nationwide representative sample of 56,000+ drivers, 2015–2018.
  - Observe starting and ending time and location
  - Observe driving mishaps ("near-misses", "close-calls"): hard brakes/turns, aggressive accelerations.
  - Observe risky actions: use of cellphones while driving, driving at night, driving on highways (risk factors for accidents)

- For a subset of these users, who *request insurance quotes* via the app:
  - We observe demographics, characteristics of their vehicles, insurance quotes/purchase decisions.
  - We match with insurance claims data: filed claims, repair history (use in robustness checks, evaluating welfare implications)

Measures of Near-Miss

Variable	Mean	Std. Dev.	Min	Max	Obs
	(a) Hard brakes				
No agg in the trip	0.3171	0.4654	0	1	1,602,177
No agg in the last 5 min	0.5812	0.4934	0	1	1,602,177
Original	0.7410	0.4381	0	1	1,602,177
	(b) Hard turns				
Left turns	0.1504	0.3575	0	1	1,602,177
Right turns	0.0905	0.2869	0	1	1,602,177
U turns	0.1589	0.3656	0	1	1,602,177
Any turns	0.2659	0.4418	0	1	1,602,177
	(c) Have both hard brakes and turns				
No agg in the trip	0.1033	0.3044	0	1	1,602,177
No agg in the last 5 min	0.2035	0.4026	0	1	1,602,177
Original	0.2419	0.4282	0	1	1,602,177

- Preferred measures: hard brakes/turns unaccompanied by aggressive acceleration – More likely to be *preventive actions*.
- NM's coincident with real accidents

Measures of Risky Driving Behavior

Variable	Mean	Std. Dev.	Min	Max	Obs
# of phone uses	0.0108	0.4020	0	130	1,602,177
Distance (km)	36.6608	57.8538	0	1671.9800	1,602,177
Duration (h)	1.3204	1.5435	0.0003	29.7122	1,602,177
Speed (km/h)	25.3514	14.4986	0	199.8323	1,602,177
Drive at night	0.2431	0.4290	0	1	1,602,177
# of highway uses	0.2107	0.7737	0	27	1,602,177

Summary statistics – other covariates

First Glimpse: Change in Risky Behavior after NM

- At face value: NM precipitate a sizeable drop in risky behavior.

Day t	Phone use	Distance	Duration	Speed	Drive at night	Highway
0	0.0194	47.3733	1.7360	25.2869	0.2966	0.2841
1	0.0079	36.3753	1.3226	25.2024	0.2450	0.1986
2	0.0075	34.3800	1.2397	25.2892	0.2332	0.1867
3	0.0075	33.1763	1.1882	25.4404	0.2264	0.1842
4	0.0061	32.3847	1.1594	25.4371	0.2226	0.1812
5	0.0049	31.9934	1.1295	25.5978	0.2217	0.1765
6	0.0046	31.4716	1.1151	25.5706	0.2166	0.1799
7	0.0032	31.0410	1.0923	25.6637	0.2137	0.1756
8	0.0016	30.4276	1.0736	25.7018	0.2130	0.1719
9	0.0016	30.3020	1.0598	25.6910	0.2120	0.1664
10	0.0027	29.8254	1.0426	25.6889	0.2112	0.1645

Estimating the Effects of NM on Risky Behavior

- A *dynamic panel* model with fixed effects.

$$y_{it} = \gamma y_{it-1} + \beta NM_{it-1} + X_{it}\phi + \alpha_i + \varepsilon_{it},$$

  - y_{it}: one of our six measures of risky behavior.
  - X_{it}: additional conditioning covariates.
  - α_i: driver fixed effects (can be correlated with NM_{it-1}).
  - ε_{it}: assumed orthogonal to all RHS variables.

- Take FD to get rid of α_i (Arellano and Bond, 1991)

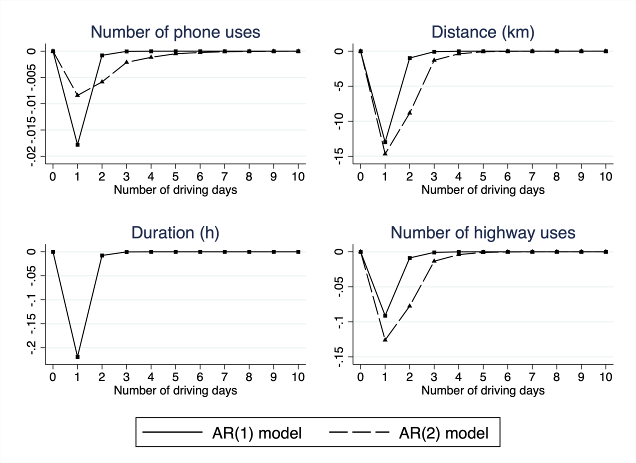
$$\Delta y_{it} = \gamma \Delta y_{it-1} + \beta \Delta NM_{t-1} + \Delta X_{it}\phi + \Delta\varepsilon_{it}$$

Users experience shocks that jointly precipitate near-misses and risky behavior. We use $weather_{t-2}$ as instruments.

Regression Results

	Phone use	Distance	Duration	Speed	Drive at night	Highway
	(a) Hard brakes					
No agg in the trip	-0.0178***	-12.98***	-0.219***	0.660**	0.00271	-0.0911***
	(0.00486)	(1.323)	(0.0372)	(0.289)	(0.00955)	(0.0130)
No agg in the last 5 min	-0.0100***	-13.49***	-0.214***	0.845***	0.000414	-0.0771***
	(0.00269)	(1.322)	(0.0372)	(0.251)	(0.00826)	(0.0111)
Original	-0.0121***	-16.29***	-0.278***	1.064***	-0.000439	-0.0935***
	(0.00320)	(1.549)	(0.0445)	(0.303)	(0.0100)	(0.0134)
	(b) Have both hard brakes and turns					
No agg in the trip	-0.0207***	-25.56***	-0.344***	1.465***	0.00130	-0.143***
	(0.00555)	(2.550)	(0.0689)	(0.460)	(0.0151)	(0.0205)
No agg in the last 5 min	-0.0110***	-24.16***	-0.199***	1.428***	-0.00149	-0.103***
	(0.00297)	(2.363)	(0.0606)	(0.342)	(0.0114)	(0.0154)
Original	-0.0109***	-24.56***	-0.169***	1.444***	-0.00196	-0.101***
	(0.00291)	(2.398)	(0.0605)	(0.336)	(0.0113)	(0.0152)
Average values	0.0108	36.6608	1.3204	25.3514	0.2431	0.2107
Observations	1,485,428	1,485,428	1,485,428	1,485,428	1,485,428	1,485,428

How Long Do Effects of NM Last?



- 5-6 driving days in data ≈ 2-3 calendar weeks. Strong "recency" effect.

Robustness Checks

- Experienced vs. less-experienced drivers
- NM's occurring on familiar vs. unfamiliar roads
- Routine (commuting) vs. non-routine trips

Structural Estimation

- Next, we build a simple structural model of drivers' choice of risky behaviors.
- Estimate **whether** and **how much** change in risk aversion can explain changes in behavior before and after NM's.

Model

- Drivers have CARA utility

$$u(c;\rho) = -\exp(-\rho c),$$

  - c is risky payoff, depends on whether there is an accident
  - ρ is the risk-aversion parameter to be calibrated; having a near-miss triggers change in risk-aversion

- Payoffs:

$$c = \begin{cases} \prod_j y_j^{\zeta_j} & \text{without accident} \\ \prod_j y_j^{\zeta_j} - \kappa & \text{with accident} \end{cases}$$

  - $\prod_j y_j^{\zeta_j}$: "subutility" from risky behaviors: phone uses, distance, highway
  - Once an accident occurs, agents incur a cost, $\kappa \approx \$1065$ (out of pock), \$213 (=20% deductible), \$107 (=10% deductible)

Model

- Agent chooses risky behavior to maximize expected utility:

$$\boldsymbol{y}^*(X;\rho,\zeta) = \arg\max_{\boldsymbol{y}} \Bigg[\underbrace{Pr(A|\boldsymbol{y},X)}_{\text{prob of an accident}} \; u\Big(\prod_{j=1}^{J} y_j^{\zeta_j} - \kappa;\rho\Big) + \underbrace{(1 - Pr(A|\boldsymbol{y},X))}_{\text{prob of no accident}} \, u\Big(\prod_{j=1}^{J} y_j^{\zeta_j};\rho\Big) \Bigg].$$

Estimation Results

	(1) $\kappa = \$1065$	(2) $\kappa = \$213$	(3) $\kappa = \$106.5$
Risk aversion before NM: ρ_0	0.0037	0.0214	0.0478
	(0.0004)	(0.5060)	(0.0083)
Percentage change of RA after NM 1: δ_1	0.1054	0.1197	0.1248
	(0.0123)	(0.2836)	(0.0476)
Percentage change of RA after NM 2: δ_2	0.2823	0.3494	0.4377
	(0.0287)	(0.1733)	(0.1258)
Parameter in payoff function: ζ_1	0.0020	0.0043	0.0002
	(0.0043)	(0.1503)	(0.0027)
Parameter in payoff function: ζ_2	0.4177	0.2458	0.2012
	(0.0467)	(0.0816)	(0.0514)
Parameter in payoff function: ζ_3	0.0079	0.0046	0.0038
	(0.0024)	(0.0114)	(0.0013)

Implied Accident Cost Reduction after Near-Misses

- NM $\Longrightarrow$ drivers become more risk averse $\Longrightarrow$ reduce risky behavior $\Longrightarrow$ reduction in the cost of insuring drivers.

- Estimate from the data
  - Average cost of an accident: 7342 CNY.
  - How long the level of risky behavior reverts back to the original level: about 2 weeks.
  - Near-miss (def 2) occurred on 10.33% of the driving days.
  - Users drive 215 days in a year (from survey).
  - Average annual auto insurance premium $\approx$ 5710.03 Yuan (est from quotes).

	Before NM	After NM 1	After NM 2
Pr(accident)	0.1296%	0.1242%	0.1194%
Reduction in Pr(accident)		0.0054%	0.0102%
Reduction in Accident Cost (Yuan)		2.7754	5.2424
Reduction in Accident Cost (Annualized; Yuan)		189.22	116.43
Reduction in Accident Cost (% of Avg Premium)		3.31%	2.04%

Summary of Findings

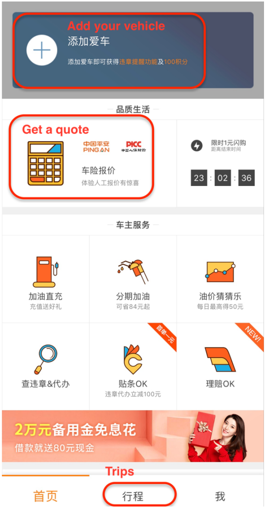
- Following near-misses, drivers drive *more conservatively*:
  - A reduction in driving distance of 12.98 km
  - Big drop in cellphone and highway uses.
- The effects last roughly 2–3 weeks.
- Such changes in behavior are consistent with an increase in risk aversion of 10.54–43.77%.
- Implied accident cost reduction: amounts to 2.04–3.31% of avg car insurance premium (116.43–189.22 CNY/person).

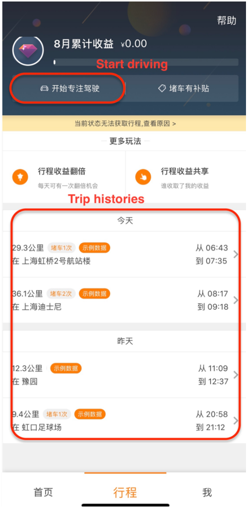
Policy Implications

- The finding of time-varying risk aversion has implications for insurance pricing.
    - Experience rating – raise premiums after at-fault claims – is the dominant pricing scheme;
    - Logic underlying this reverses if drivers become more risk-averse after accidents.

- Our paper focuses on measuring *high-frequency* variation in driving behavior, whereas changes in insurance premiums occur at much lower frequency.
    - Our results may have direct implications for the design of "real-time" dynamic pricing policies.

Login and Trip Summary Pages





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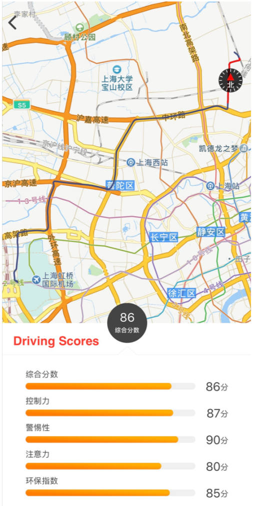
Trip Start and End Pages



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Summary Statistics: Other Covariates

Variable	Mean	Std. Dev.	Min	Max	Obs
	(a) Driving scores				
Control score	81.0513	5.5614	1	100	1,602,177
Cautious score	81.7256	2.7264	45	100	1,602,177
Focused score	82.2600	9.4508	17	100	1,602,177
Driving score	81.2518	4.1803	28	100	1,602,177
	(b) Traffic conditions				
Weekend	0.2681	0.4430	0	1	1,602,177
Rush hour (7-9am, 5-7pm)	1.2943	1.1743	0	31	1,602,177
# of traffic jams	0.5365	1.0110	0	31	1,602,177
	(c) Weather information				
High temperature (° C)	22.0915	9.8028	-30	45	1,602,177
Low temperature (° C)	13.9506	10.0043	-36	32	1,602,177
Sunny	0.2165	0.4118	0	1	1,602,177
Rain/snow	0.2992	0.4579	0	1	1,602,177
Cloudy/windy/foggy	0.4655	0.4988	0	1	1,602,177

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Are Drivers Learning from Near-Misses? (test 1)

- Changes in risk-aversion? Alternative explanation: drivers learn and improve their driving after NM.

- Compare **experienced vs. inexperienced users:**
  - Learning is likely less of a concern among experienced drivers.
  - Use drivers who requested insurance quotes through the app: information on car registration date.
  - Experienced drivers: vehicle registered before 2015.

- Findings:
  - Indeed: near-misses have a larger impact on inexperienced users – effects on driving distance and duration are much larger.
  - But even for experienced drivers, multiple RB's decrease after near-miss.

Are Drivers Learning from Near-Misses? (test 2)

- A second assessment of the learning story: changes in risky behavior after near-misses on **familiar roads** are unlikely to result from learning.
- Familiar trips:
  - If similar routes have been taken by the user in the past based on the geographic coordinates of the starting and ending locations of each trip.
- Findings:
  - For three out of six measures (distance, duration, and highway uses), risky behavior significantly decreases after the user experienced near-misses on familiar roads.

Validity of Using Weather as Instruments

- Problem: Serial correlation in weather
  - $weather_{t-2}$ may not be orthogonal to ε_{t-1}.
  - Drivers may adjust their plans in period $t-1$ (in ε_{t-1}) in response to $weather_{t-2}$
  - Especially pertinent for measures – duration, distance, drive at night – which can be plausibly adjusted in difficult weather conditions.

- Consider "routine" drivers, who have little leeway in adjusting their driving plans.
  - Weekday commuters, driving at regular times/routes.
  - (also more likely to be a driver, rather than a passenger)

- Findings:
  - Four out of six measures still significantly negative; directions and magnitudes are comparable to the benchmark.