Sharing rides on ride-hailing services

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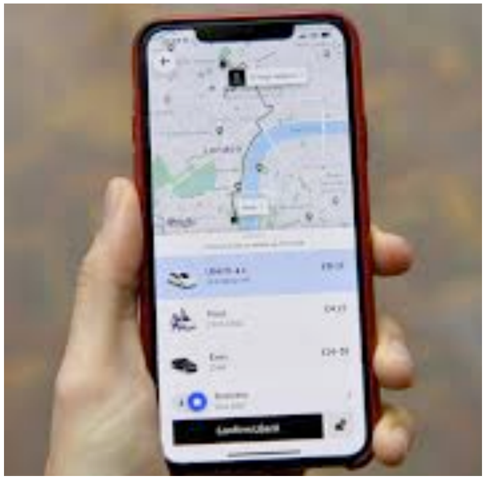

Passenger

Driver

Ride-hailing service

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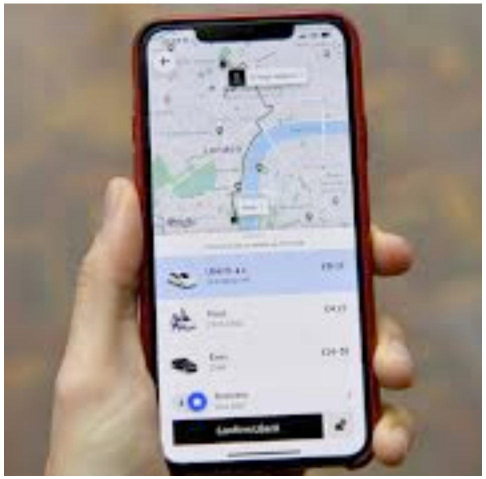


Passenger

Driver

Ride-hailing service

- **Question:** what is the relationship between **ride sharing** and **tipping**?

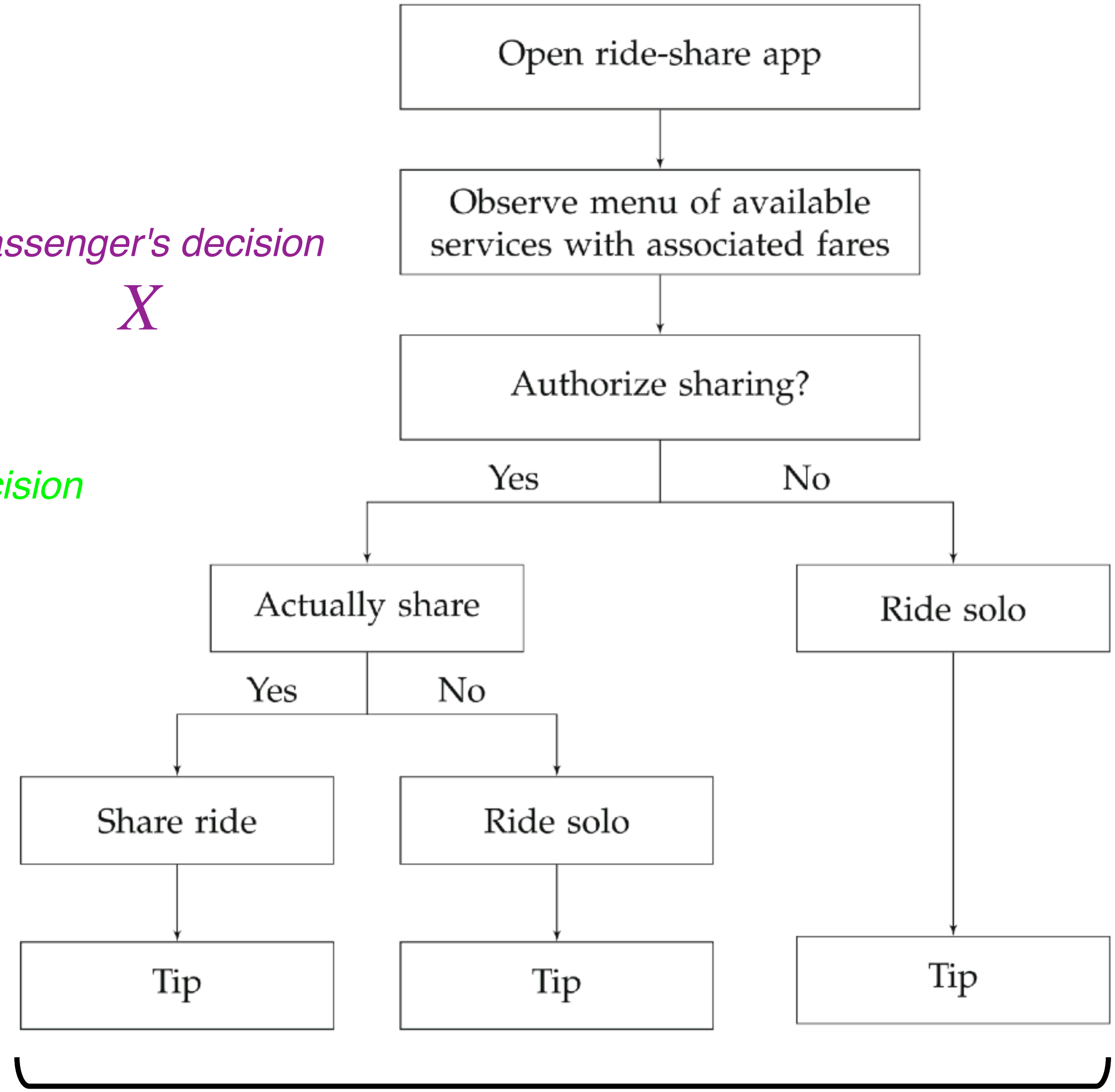
Sharing rides on ride-hailing services

- Flow-chart of ride-sharing authorization:

Ride-hailing service's decision

Passenger's decision
X

Driver's decision
M

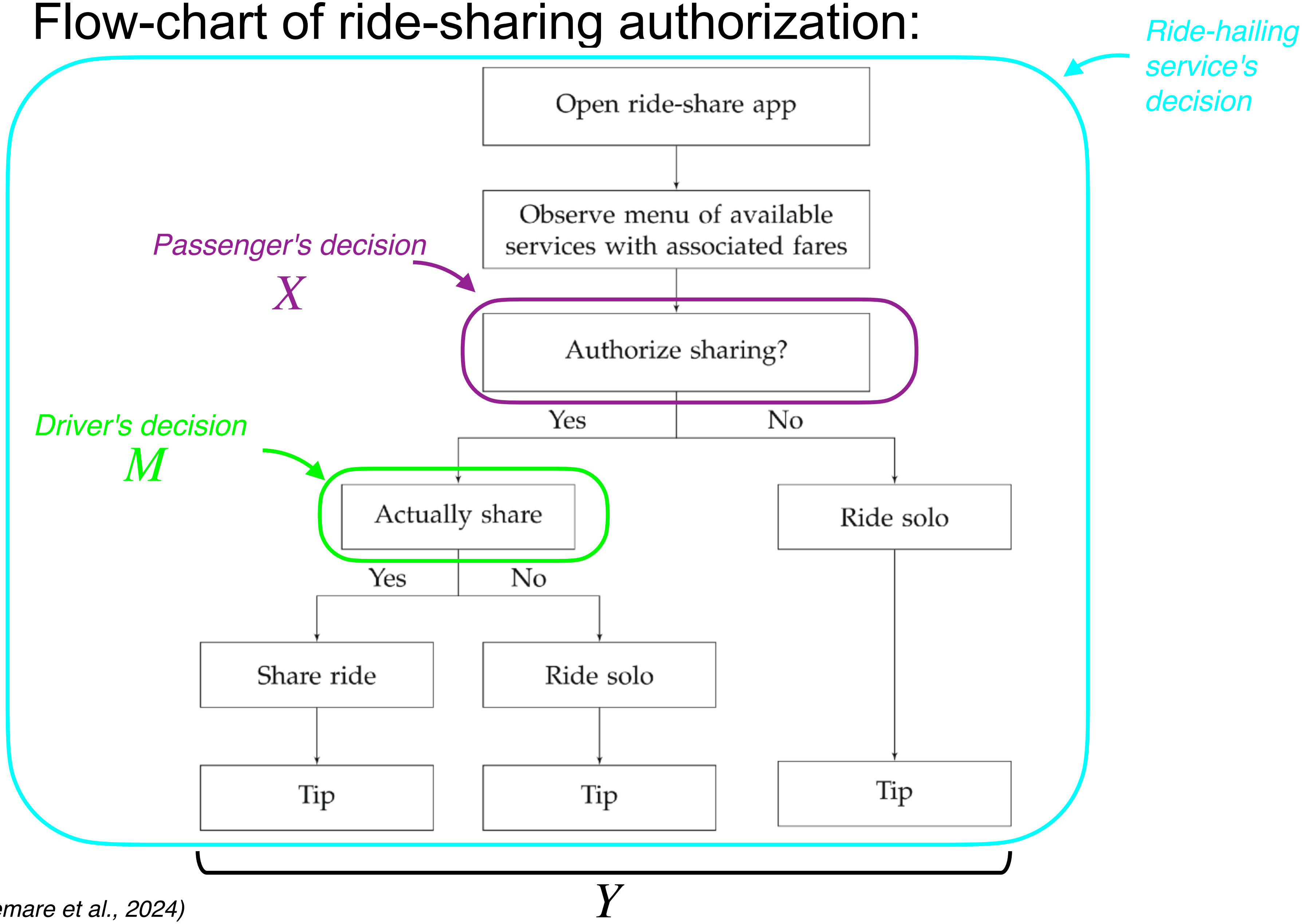


Y

(Bellemare et al., 2024)

Sharing rides on ride-hailing services

- Flow-chart of ride-sharing authorization:



(Bellemare et al., 2024)

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Full sample	Dedicated	13.388	(7.605)	0.592	(1.455)
	Sharing authorized	9.686	(5.269)	0.181	(0.698)
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- What should services do?

(Bellemare et al., 2024)

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- Can we estimate these quantities from observational data?

Trouble with unobserved variables

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$$\begin{tikzcd} X \arrow[r] & Y \\ U \arrow[u] \arrow[ur] & \end{tikzcd}$$

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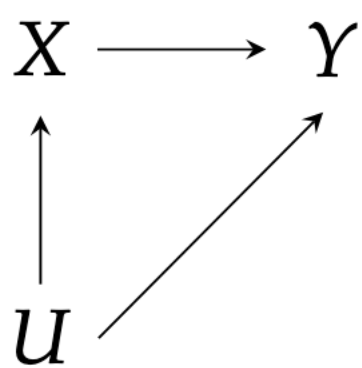

- And, we can't resort to back-door adjustment (i.e., controlling for back-door confounders)

Front-door adjustment

(Pearl, 2009)

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$$P(y \mid \text{do}(X = x)) = \sum_{z} P(z \mid x) \sum_{x'} P(y \mid x', z) P(x')$$

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Front-door adjustment, conceptually

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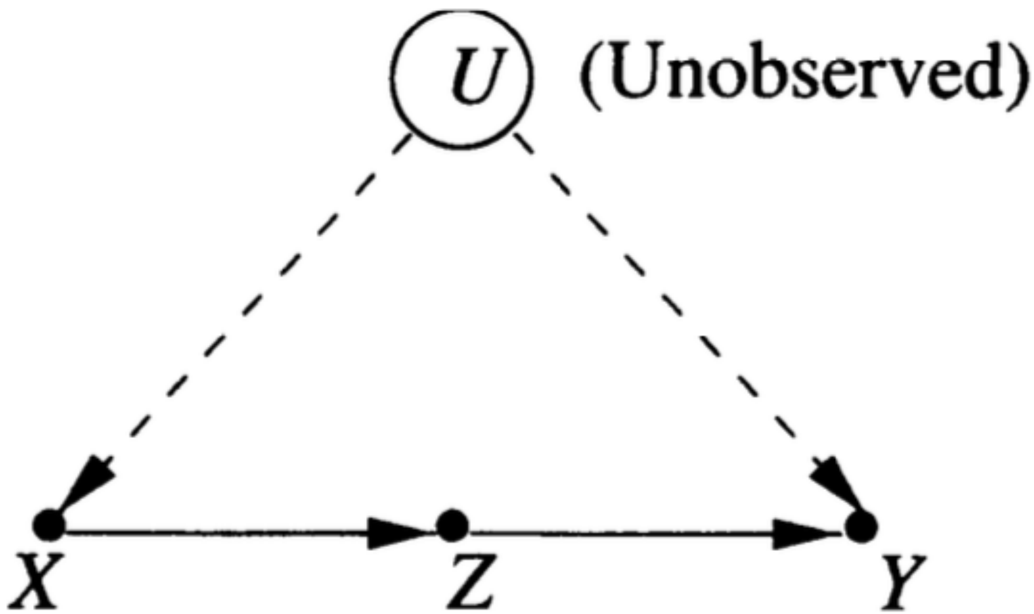

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Exercise for today

- Based on these slides, set up a causal model of the tipping problem, treating Y as dichotomous (the rider does or doesn't tip):
  - Determine your model structure
  - Choose example conditional probability distributions
  - Sample observational data from your model
  - Use the observational data to estimate the causal "nudge the passenger" quantity of interest, $P(Y \mid \mathrm{do}(X = 1))$
- Time allowing, we can discuss this scenario further