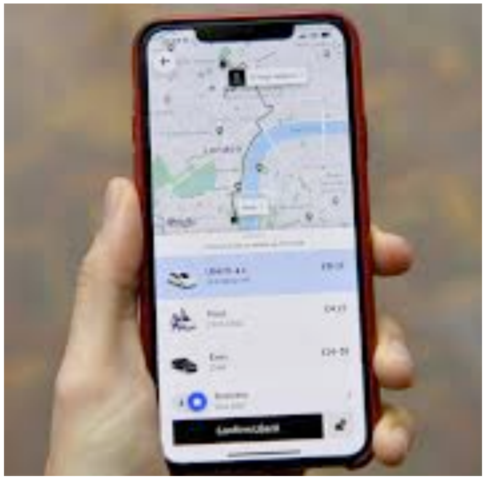
Sharing rides on ride-hailing services

- Three perspectives:



Passenger

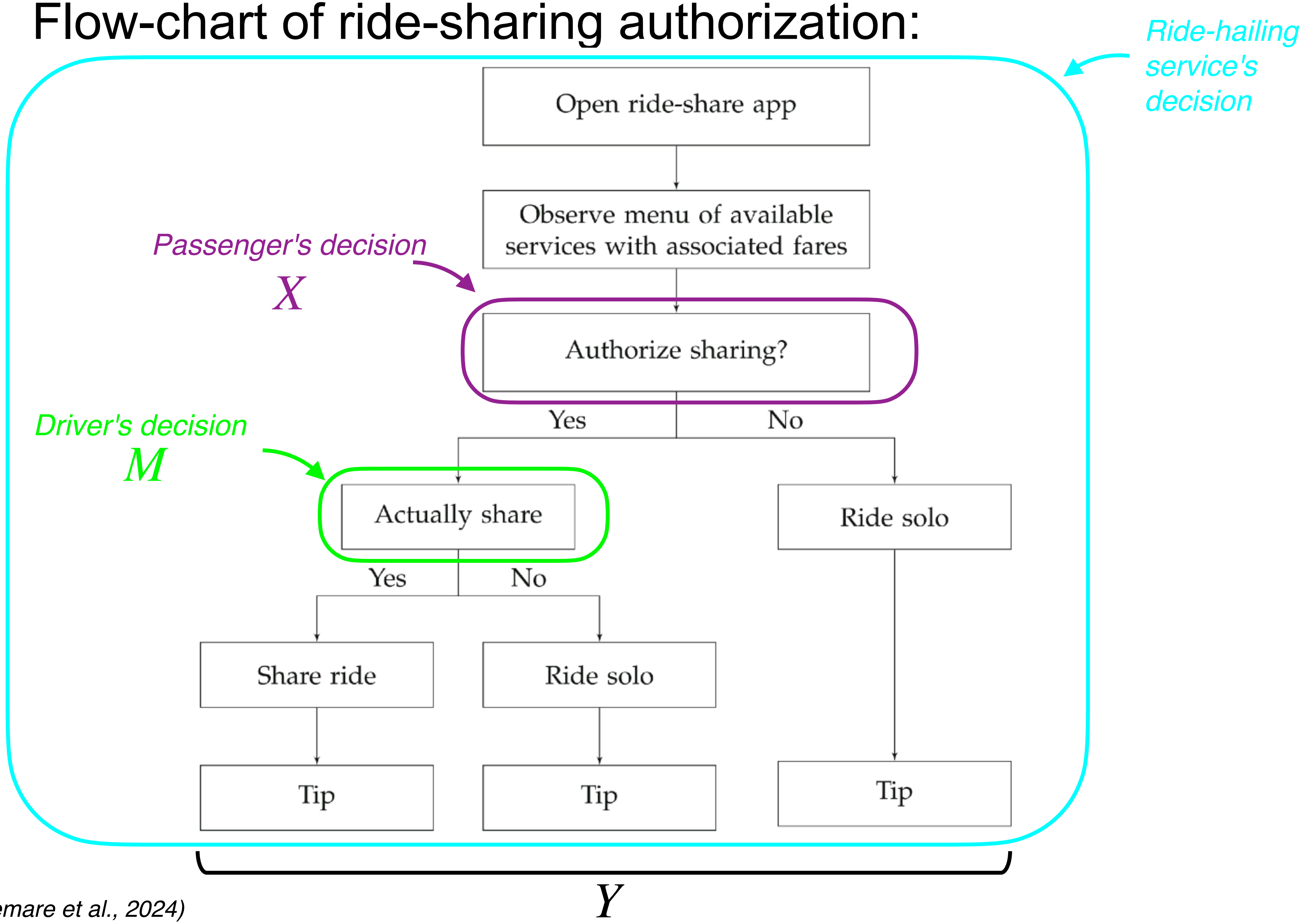
Driver

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:



(Bellemare et al., 2024)

Our question of interest

- Clearly, it is in the interest of ride-hailing services for their drivers to get plentiful tips
- If a driver does shared rides, the driver potentially gets two tips – seems good for the service and for the driver!
- So services might "nudge" riders to authorize sharing
- But, superficially, sharing is associated with lower tipping:

		Total charge ($)		*Tip ($)*	
	Ride type	*Mean*	*SD*	*Mean*	*SD*
Full sample	Dedicated	13.388	(7.605)	0.592	(1.455)
	Sharing authorized	9.686	(5.269)	0.181	(0.698)
Sharing authorized	Shared	9.827	(5.365)	0.175	(0.683)
	Not shared	9.356	(5.024)	0.193	(0.731)

- What should services do?

(Bellemare et al., 2024)

In the calculus of causal inference:

- X: does a passenger opt in to ride sharing? (1=yes, 0=no)
- M: does a passenger actually ride share? (1=yes, 0=no)
- Y: does the driver get a tip? (Or, how much does the driver tip?)
- What are the relevant quantities in the calculus of causal inference?
  - **Driver's question:** $P(Y \mid \mathrm{do}(M = 1), X = 1)$
  - **"to nudge?" question** (simplified) **:** $P(Y \mid \mathrm{do}(X = 1))$
- Can we estimate these quantities from observational data?

Trouble with unobserved variables

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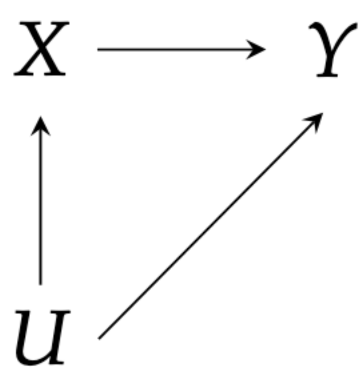
- $E[Y \mid X = 1] \ll E[Y \mid X = 0]$, but we can't conclude that $E[Y \mid \text{do}(X = 1)] \ll E[Y \mid \text{do}(X = 0)]$



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

Front-door adjustment

- A set of variables Z satisfies the FRONT-DOOR CRITERION relative to an ordered pair of variables $\langle X, Y \rangle$ if:
  - Z intercepts all directed paths from X to Y;
  - there is no unblocked back-door path from X to Z; and
  - all back-door paths from Z to Y are blocked by X.
- If Z satisfies the front door criterion relative to $\langle X, Y \rangle$ and if $P(x, z) > 0$, then the causal effect of X on Y is identifiable and is given by:

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

(Pearl, 2009)

Front-door adjustment, conceptually

- A set of variables Z satisfies the FRONT-DOOR CRITERION relative to an ordered pair of variables $\langle X, Y \rangle$ if:
  - Z intercepts all directed paths from X to Y;
  - there is no unblocked back-door path from X to Z; and
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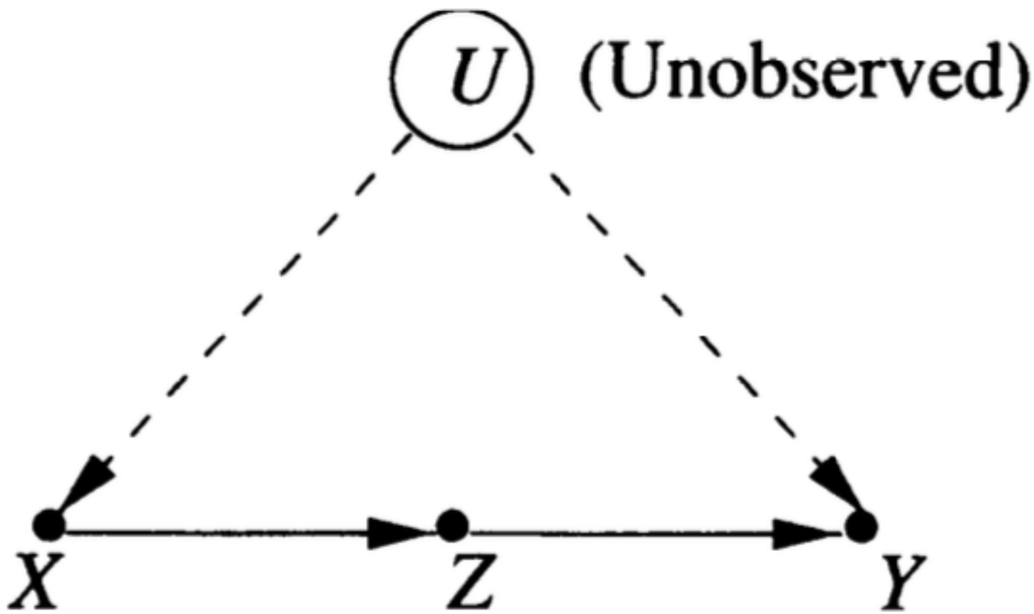

$$P(y \mid \mathrm{do}(X = x)) = \sum_{z} P(z \mid x) \sum_{x'} P(y \mid x', z) P(x')$$

(Pearl, 2009)

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