# The Value of Time: a Dynamic Approach to Passenger Expectations

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## Basic Overview

- Iran is a country of 90 million
- Greater Tehran, the capital, houses 14 million people
- Ride-hailing market size: 1.3 billion rides a year
- Two players: Snapp and Tapsi
    - Tapsi has roughly 30 % market share
- Data: subsample of Tapsi rides in Tehran over six months in 2023
- Goal: estimate the value of time for ride-hailing using data from Tapsi

## Basic Estimation Idea

- Tapsi app: basically just like Uber: previews, requests
- Offers numerous ride options
- Focus on two: Normal & Urgent
  - Urgent is only more expensive than Normal (1.3x)
  - More desirable for drivers
- At any given moment a passenger has three options: Normal, Urgent and Outside option (cancel/quit)
  - Passenger chooses Normal because the time difference isn't worth the price difference
  - As time goes on, passenger updates belief about average wait time for Normal and Urgent: $E(w|w > T)$
    - w is waiting time
    - T is the actual passage of time while waiting for a ride
  - Eventually leads to Urgent being optimal

# Model

- Need to estimate demand:
- Static model:

$$U_{jt} = \beta^{w} E_t(w_{jt}) + \beta^{p} p_j + \beta^{x} x_j + \epsilon$$

- Novelty: dynamic E(w)
- Two steps:
  1. Estimate the belief-updating: $E(w_j | t_a > T)$
  2. Insert into utility function and estimate demand
- Hybrid model
  - One characteristic is latent

## Dynamic Model

- Natural progression: dynamic discrete choice

$$V(A_t, m_t, t) = \max_{a_t \in D}[u(A_t, m_t, a_t) + \beta \int V(A_{t+1}, m_{t+1}, t+1) \times dF(A_{t+1}, m_{t+1}, t+1 | A_t, m_t, t, a_t)]$$

- In which $u(A_t, m_t, a_t)$ is:
  - $0$ if $a_t = cancel$
  - $-c_w - p(a_t)$ if not assigned a driver
  - $\bar{u} - p(a_t)$ if assigned
- The whole model, including F(belief updating), is estimated at once

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## Place in Literature

- VOT: essentially, need to estimate demand
- Four major papers on demand estimation in ride-hailing published recently (forthcoming)
  - Buchholz *et al*. 2025. Econometrica
  - Castillo. 2025. Econometrica
  - Rosaia. 2025. Econometrica
  - Goldszmidt, List *et al.* 2026. CA AEJ: Policy
- Novelty: none allow expected wait time to change dynamically
- Dynamic expected wait time explains phenomena these models cannot:
  - A passenger orders a ride, waits and then cancels
  - Passenger orders Normal, waits, upgrades to Urgent

# Literature Review

We also draw from other strands of the literature

- Labour economics- job search
    - Wait time updating model
    - Alvarez, Borovickova and Shimer. 2024. RES
    - Mueller, Spinewijn and Topa. 2021. AER
    - Arni, Lalive and Van Ours . 2013. J of App. Econ.
- Estimation of mixture models
    - Heckman and Singer. 1984. Econometrica
    - Kim et al. 2020. J of Comp. graph. Stat.
    - Bunting, Diegert and Maurel, 2025. R & R JPE

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## Context and Data

App times out after 300 seconds

Table 1: Summary Statistics by Request Type

| | | mean | std | p5 | p95 |
|---|---|---|---|---|---|
| Normal | Price (Thousand Tomans) | 67.69 | 35.52 | 24.00 | 134.00 |
| | Assignment time | 56.50 | 61.04 | 9.83 | 200.28 |
| | PickupETA | 226.35 | 102.75 | 62.00 | 404.00 |
| Urgent | Price (Thousand Tomans) | 83.82 | 42.43 | 30.00 | 162.00 |
| | Assignment time | 44.43 | 50.21 | 9.12 | 159.46 |
| | PickupETA | 228.74 | 101.71 | 64.00 | 403.00 |

# Number of different rides

- 2686404 Normal requests (90 % of all requests)
- 283077 Urgent requests
- 259368 Normal requests are upgraded to urgent (91 % of all Urgent requests)

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## Hazard Rate

- Survival data: "time of death"-style data
- We usually use the pdf to introduce the distribution: $f(t) = Pr(t < T < t + \Delta t)$
- However, to study survival data we use the hazard rate: $\theta(t) = Pr(t < T < t + \Delta t | t < T)$
- $\theta(t) = \frac{f(t)}{S(t)}$, $S(t) = Pr(t < T) = 1 - F(t)$

## Hazard Rate: Intuition

- $\theta(t) = Pr\left(t < T < t + \Delta t | t < T\right)$
- In "normal" data, e.g. wage data, conditioning on survival is meaningless
- In survival data, because the data represents a process in which observations passed through all previous values without dying, conditioning on survival, conditioning on survival means "among the survivors"
- Which is the probability we actually care about
- example: mortality:
    - Low pdf of death for elderly may simply indicate low population
    - Nobody is alive in the end-not a lot of of death
    - OR actual high probability of death?- condition on survival
- Also, dynamic model: $dF(A_{t+1}, P_{t+1}, m_{t+1}, t+1 | A_t, P_t, m_t, t, a_t)$

## Hazard Model

- In order to be able to compute $E(t_a | t_a > T, X)$
- We estimate the distribution of $t_a$
- Use the hazard rate as primitive of distribution
- Could assume a distribution:
    - Weibull
    - Exponential
- This is a strong assumption to impose

## Hazard Model Specification

- Instead: Cox proportional hazards model:
- $\theta(t_a) = \lambda(t_a) exp(X\beta_a + D\delta_a + \nu_a)$
- $\lambda$ is semi-parametric:
- $\lambda(t_a) = \sum(\lambda_k I_k(t_a))$
  - Step function
  - We choose the k intervals
- Estimate via NPMLE

## Estimation Strategy

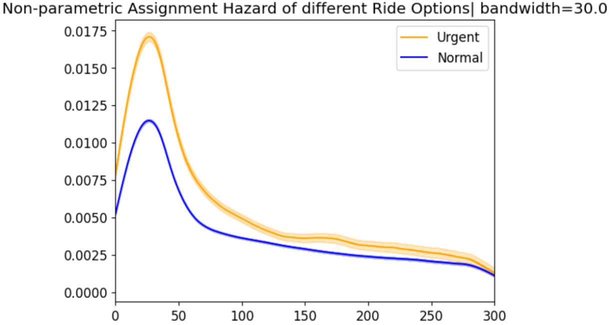
- Based on Heckman and Singer. 1984. Econometrica
  - In mixing problems we have $\theta$'s and $\nu$'s
    - $\theta$: structural parameters we want to estimate
    - $\nu$: unobserved heterogeneity parameters
  - Joint distribution of the $\nu$'s can be approximated using a discrete distribution
  - The resulting estimation of the structural parameters is consistent even if estimation of the $\nu$'s is not

# Estimation Strategy

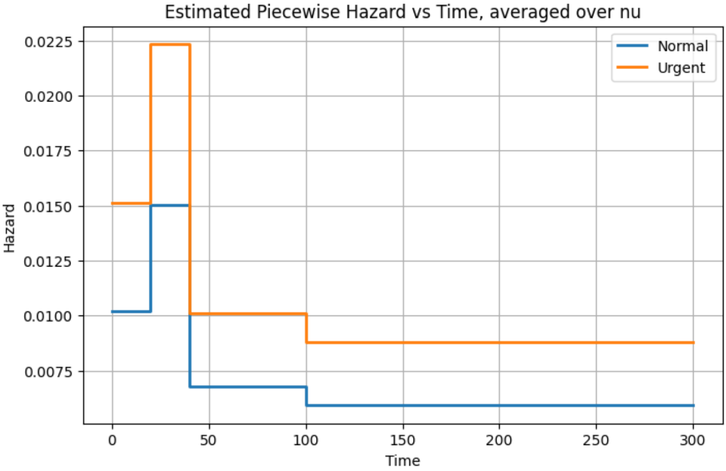
- Based on Bunting, Diegert and Maurel, 2025. R & R JPE
- Basic idea: profile likelihood:
- Break down $\max_{\theta,\nu} L(\theta, \nu)$ into:
  1. $\max_{\nu} L(\theta, \nu)$
     - Assume a large net of fixed mass points, and find optimal probabilities
  2. and $\max_{\theta} L(\theta, \hat{\nu}(\theta))$
     - With optimal probabilities as functions of $\theta$, find optimal $\theta$'s using BFGS

# Non-parametric Hazard graph

- Estimated Nelson-Aalen non-parametric hazard
  - General shape as expected
  - Proportional hazards does not necessarily hold



# Estimated graph



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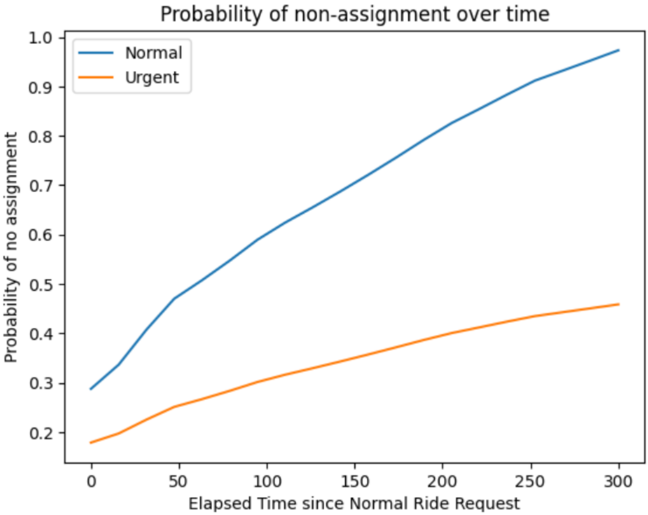
# Bayesian Updating for $\nu$

- Once we estimate the hazard function, we have the joint distribution of $t_a$ and $\nu$
- This means we can update the pdf of $\nu$ using Bayes:

$$g(\nu|t_a > T, X) = \frac{g(\nu)S_a(T|X)}{\int_\nu g(\nu)S_a(T|X)d\nu}$$

- This allows us to compute: $pr(t_a^u > 300|t_a^n > T)$
    - Probability of the upgraded urgent ride not being assigned given T has passed since normal request

# Probability of non-assignment over 300 s



## Computing Expected Wait Time

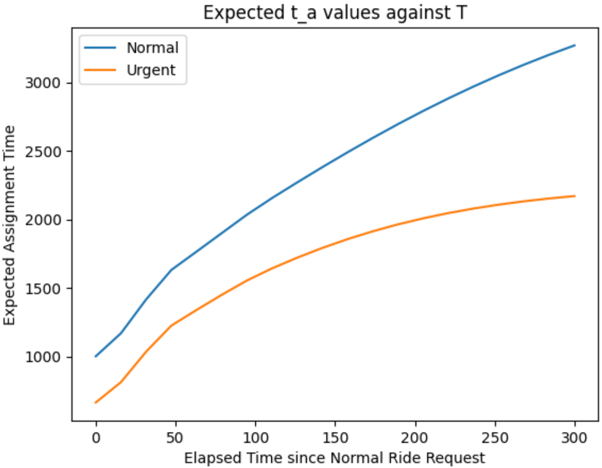
- In order to compute total expected wait time:

$$E(t_a|t_a > T) = pr(A=1|t_a > T)E(t_a|t_a > T, A=1) + pr(A=0|t_a > T)E(t_a|t_a > T, A=0)$$

- We need to have a time-equivalent for not being assigned a ride
- Once the full discrete choice model is estimated, we will have this
  - $-c_w$
- For now, we can compute the expectation by adding simple assumptions

# Estimated graph

Using simple assumptions on the hazard



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## Conclusion

- Contributions:
  - Developed a new theory to explain passenger behaviour over time
  - Estimated a belief updating model
- Next steps:
  - Improve expectation model
    - Add covariates
  - Estimate discrete choice model

# Thank You!

## Statistics on repeat requests

App times out after 5 minutes

- Sum of all request outcomes: 3490078
- assigned requests: 1929435 - 55 %
- upgrades to urgent: 297118 - 9 %
- passenger cancellations before assignment: 937133 - 27 %
- timed-out requests: 326392 - 9 %
  - timed-out requests which lead to the passenger making another request: 137520 - 42 %

# Expectation Model Specification

- Based on Arni, Lalive and Van Ours . 2013. J of App. Econ.
  - Study the effects of unemployment insurance warnings and sanctions on the unemployed
- In order to be able to compute $E(w|t_a > T, X)$
  - in which $w = t_a + t_p$
- We estimate the joint distribution of $t_a$, $t_p$, $t_c$, and $t_u$
  - $t_c$, and $t_u$ cause endogenous censoring
- Use the hazard rate as primitive of distribution
- Could assume a distribution:
  - Weibull
  - Exponential
- This is a strong assumption to impose

## Expectation Model Specification

- Instead: Cox proportional hazards model:
- $\theta(t_l) = \lambda(t_l) exp(X\beta_l + D\delta_l + \nu_l) \quad l \in \{a, p, c, u\}$
  - $\nu_a$, $\nu_p$, $\nu_c$, $\nu_u$ are correlated
- $\lambda$ is semi-parametric:
- $\lambda(t_a) = \sum(\lambda_k I_k(t_a))$ and we choose the K intervals
- Estimate via NPMLE

## Computing Expected Wait Time

- Once estimation of the hazard model is done, we can compute the expected wait time: $E(w|t_a > T) = E(t_a + t_p|t_a > T)$
- First, update $\nu = [\nu_a, \nu_p, \nu_c, \nu_u]$ using Bayes:

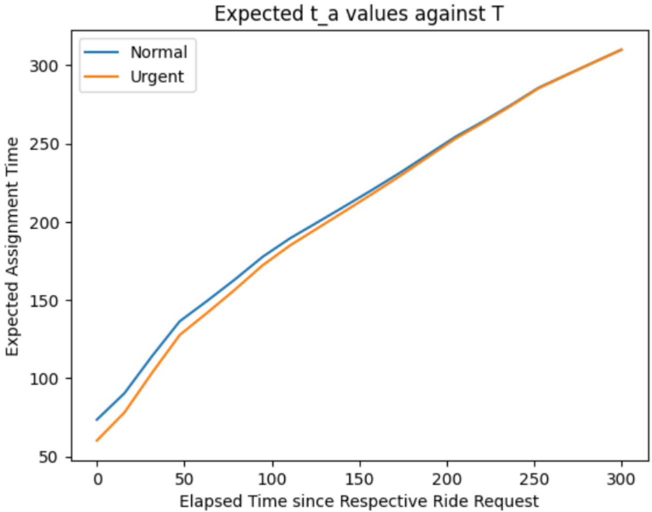
$$g(\nu|t_a > T, X) = \frac{g(\nu)S_a(T|X)}{\int_\nu g(\nu)S_a(T|X)d\nu}$$

- Then compute expectations:

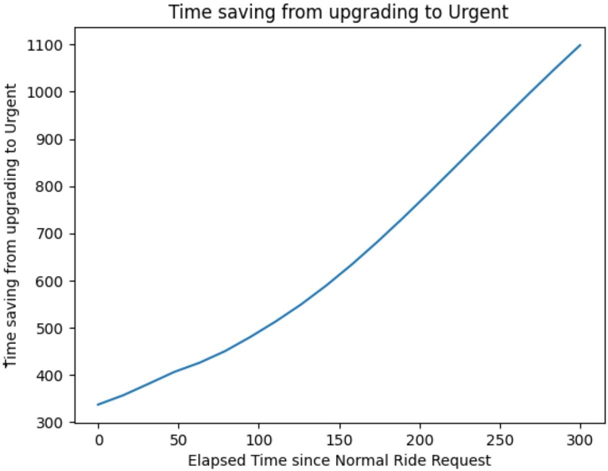
$$E(t_a^u|t_a > T) = \int_{t_a^u}\int_\nu t_a^u f(t_p|\nu)g(\nu|t_a > T, X)dt_a^u d\nu_a$$

$$E(t_a^N|t_a > T) = \frac{\int_{t_a=T}^\infty \int_\nu t_a f(t_a|\nu)g(\nu_a)dt_a d\nu_a}{S_a(T|X)}$$

# Estimated Expectations of Assignment time assuming assignment-compared to respective durations



## Estimated graph



# Expected remaining assignment time