# Optimizing Mobility-on-Demand Systems for High Throughput

Ph.D. Oral Exam

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BOSTON UNIVERSITY

# Problem Motivation

# Mobility-on-Demand Systems

**U.S. Department of Transportation**

"Mobility-on-Demand (MoD) is an innovative, user-focused approach which leverages emerging mobility services, integrated transit networks, real-time data, and cooperative Intelligent Transportation Systems to allow for a more traveler-centric transportation, providing improved mobility options to all travelers and users of the system in an efficient and safe manner."

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- **Ride-hail**: Uber, Lyft, etc.

# Common issue of the demand heterogeneity

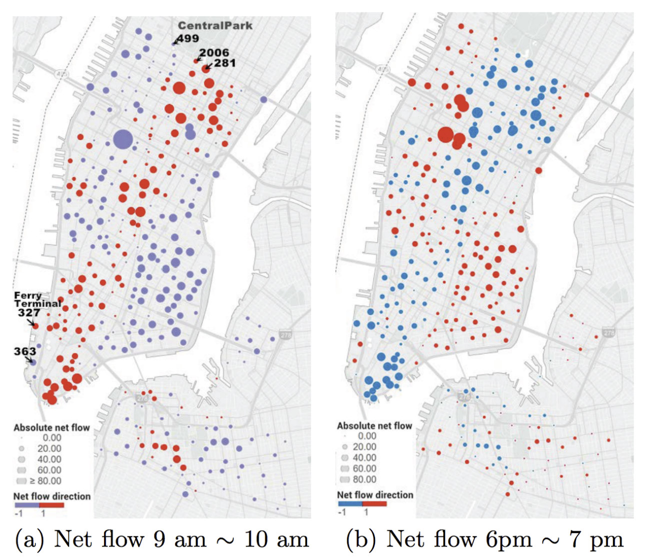


**Figure 1:** NYC CitiBike pickups and drop-offs during rush hours[1].

## Literature

- Modeling:

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- Applications:

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- Applications:
  - **Taxi dispatch:** Zhang et al. (2017)
  - **Customer incentives:** Singla et al. (2015)
  - **Dynamic pricing:** Castillo, Knoepfle, and Weyl (2017), Banerjee, Johari, and Riquelme (2016)

# Service Level Requirements

## Paper 1: Inventory Rebalancing and Vehicle Routing in Bike Sharing Systems


- Jasper Schuijbroek
  *Eindhoven University of Technology*
- Robert Hampshire
  *Carnegie Mellon University*
- Willem-Jan van Hoeve
  *Carnegie Mellon University*

# Definition

Let $\mathcal{S}$ represent the set of bike sharing stations. For each station $i \in \mathcal{S}$:

- $C_i$ denotes capacity of the station.
- Poisson process for bike drop-offs with rate $\lambda_i$
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The service level requirements at station $i \in \mathcal{S}$ are:

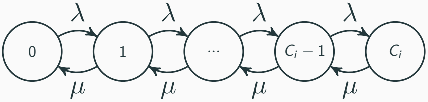
$$\frac{\mathbb{E}[\text{Satisfied pickup demands}]}{\mathbb{E}[\text{Total pickup demands}]} \geq \beta_i^-$$

$$\frac{\mathbb{E}[\text{Satisfied dropoff demands}]}{\mathbb{E}[\text{Total dropoff demands}]} \geq \beta_i^+$$

for given $\beta_i^-, \beta_i^+ \in [0, 1]$.

# Markov Chain Formulation

Each station is a $M/M/1/K$ queue with $K = C_i$. Markov Chain for inventory $S_i(t)$ is:



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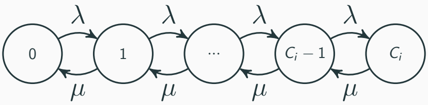


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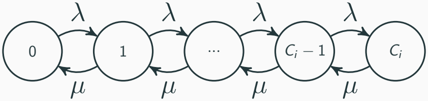


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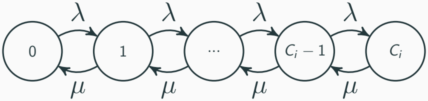


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**Service Level Requirements:**

$$\frac{\mathbb{E}[\text{Satisfied pickup demands}]}{\mathbb{E}[\text{Total pickup demands}]} = 1 - g_i(s, 0)$$

$$\frac{\mathbb{E}[\text{Satisfied dropoff demands}]}{\mathbb{E}[\text{Total dropoff demands}]} = 1 - g_i(s, C_i)$$

# Service Level Requirements for Hubway

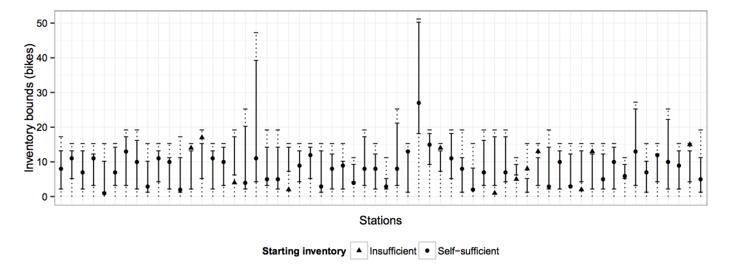


**Figure 2:** Observation period 8–9AM on weekdays with $\beta_i^- = \beta_i^+ = 95\%$ on Friday, June 1, 2012[2].

[2] Schuijbroek, Hampshire, and Van Hoeve 2017.

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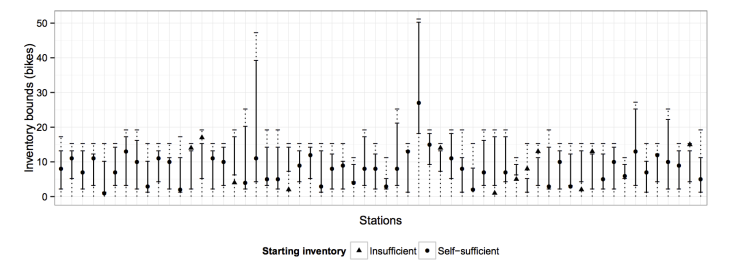


**Figure 2:** Observation period 8–9AM on weekdays with $\beta_i^- = \beta_i^+ = 95\%$ on Friday, June 1, 2012[2].

Authors use Maximum Likelihood Estimator for Poisson variables, but they do not have data for unfulfilled demand!

[2] Schuijbroek, Hampshire, and Van Hoeve 2017.

# Routing Problem for bike-share

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**Problem (P1):** Given $\mathcal{V}$ re-balancing trucks, each with a capacity of $Q$, re-balance the bike inventory such that service level at each station is met, minimize the maximum tour length of the re-balancing truck to obtain $H^*(\mathcal{S}, \mathcal{V})$.

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- vehicle and station capacity constraints
- flow conservation

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Pure MIP approach: Intractable for realistic scenarios with $|\mathcal{S}| \geq 50$ and $|\mathcal{V}| \geq 3$.

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**Maximum Spanning Star approximation:** $SPS_i(\mathcal{S}_v) = \sum_{j \in \mathcal{S}_v} d_{ij}$.

Maximum-cost spanning star $\left(\max_{i \in \mathcal{S}_v} SPS_i(\mathcal{S}_v)\right)$ approximates within-cluster routing cost.

# Heuristic 1

**Clustered MIP (H1):**

1. Solve (P2)
2. Solve (P1) for each cluster of stations $\mathcal{S} = \mathcal{S}_v$ and $\mathcal{V} = \{v\}$ to obtain $H^*(\mathcal{S}_v, \{v\})$
3. $H^* = \max_{v \in \mathcal{V}} H^*(\mathcal{S}_v, \{v\})$

# Heuristic 1

**Clustered MIP (H1):** (Sub-optimal)

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# Heuristic 2

**Clustered MIP with Cuts (H2):**

1. Initialize a cut set of stations $\mathcal{C} = \emptyset$
2. Solve (P2) with additional constraint $\forall v : \mathcal{S}_v \not\subseteq \mathcal{C}$ to obtain $H^*$
3. Solve (P1) for each cluster of stations $\mathcal{S} = \mathcal{S}_v$ and $\mathcal{V} = \{v\}$ to obtain $H^*(\mathcal{S}_v, \{v\})$
    - If $\max_{v \in \mathcal{V}} H^*(\mathcal{S}_v, \{v\}) < H^*$ or $\mathcal{C} = \emptyset$, redefine $H^*$ and store routing solution.
    - For each $v \in \mathcal{V}$ with $H^*(\mathcal{S}_v, \{v\}) \geq H^*$, redefine $\mathcal{C} = \mathcal{C} \cup \{\mathcal{S}_v\}$
4. Go to step 2.

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Break sub-optimal clusters by dividing their stations over many different vehicles.

# Computation Results for Hubway

| | | *MIP* | | | *Clustered MIP* | | *Clustered MIP with Cuts* | | |
|---|---|---|---|---|---|---|---|---|---|
| Family | $\|\mathcal{V}\|$ | LP bound | Best found | Time | Solution | Time | Solution | Iterations | Time |
| 8–9AM | 2 | 3228.18 | 4625 | 5220.51 | 4495 | 0.66 | 4229 | 82 | 60.05 |
| 8–9AM | 3 | 1660.29 | 3758 | 6139.66 | 3097 | 0.55 | 2669 | 57 | 60.09 |
| 4–5PM | 2 | 3347.55 | 4674 | 5787.08 | 4656 | 0.88 | 4429 | 76 | 60.03 |
| 4–5PM | 3 | 1674.90 | 3399 | 6558.48 | 3285 | 0.53 | 2699 | 51 | 60.14 |

**Figure 3:** Averaged results over 41 runs of algorithms[3].

[3] Schuijbroek, Hampshire, and Van Hoeve 2017.

# Summary

**Positives:**

- Simple framework for evaluating service level requirements.
- Heuristic algorithm for re-balancing problem in bike-share.

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- Heuristic algorithm for re-balancing problem in bike-share.

**Concerns:**

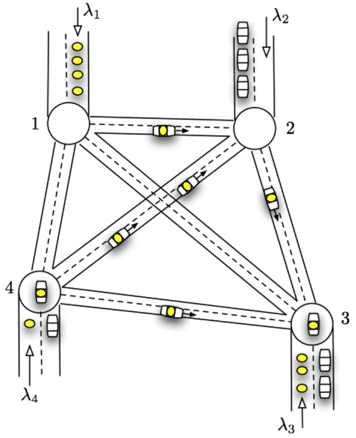
- Tradeoff between routing costs and revenue loss due to imbalance.
- Assumption of negligible demand during the re-balancing operation.

# Routing problem for autonomous ride-share

## Paper 2: Robotic load balancing for mobility-on-demand systems


- Marco Pavone
  *Stanford University*
- Stephen L. Smith
  *University of Waterloo*
- Emilio Frazzoli
  *Massachusetts Institute of Technology*
- Daniela Rus
  *Massachusetts Institute of Technology*

# Fluid model




| | Definition |
|---|---|
| $c_i$ | # of customers |
| $v_i$ | # of vehicles |
| $\lambda_i$ | customer arrival rate |
| $\mu_i$ | departure rate |
| $T_{ij}$ | travel time to $j$ |
| $p_{ij}$ | fraction of customers destined for $j$ |
| $\alpha_{ij}$ | rebalancing rate to $j$ |
| $\gamma_i$ | $\sum_j \alpha_{ij}$ |
| $H(\cdot)$ | Heaviside function |

**Figure 4:** Fluid model for autonomous cars[4].

[4] Pavone et al. 2012.

# Existence of equilibrium

Let $\mathcal{A}$ be set of assignments of $\alpha$ that verify equation

$$\sum_{j \neq i} \alpha_{ij} + \lambda_i = \sum_{j \neq i} \alpha_{ji} + \sum_{j \neq i} \lambda_j p_{ji}$$

for each $i \in \mathcal{S}$,

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$$V_\alpha = \sum_{ij} T_{ij}(p_{ij}\lambda_i + \alpha_{ij})$$

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then,

1. if $V > V_\alpha$, then there exists an equilibrium assignment of $\alpha$.
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1. if $V > V_\alpha$, then there exists an equilibrium assignment of $\alpha$.
2. if $V \leq V_\alpha$, then no equilibrium exists.

$V^* = \min_{\alpha \in \mathcal{A}} V_\alpha$ is minimum number of vehicles required for existence of equilibrium.

# Optimal Re-balancing

Minimize

$$\sum_{ij} T_{ij}\alpha_{ij}$$

subject to

$$\sum_{j\neq i}\alpha_{ij} + \lambda_i = \sum_{j\neq i}\alpha_{ji} + \sum_{j\neq i}\lambda_j p_{ji} \qquad \forall i \in \mathcal{S}$$

$$\alpha_{ij} \geq 0 \qquad \forall i, j \in \mathcal{S}$$

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Minimizing $\sum_{ij} T_{ij}\alpha_{ij}$ also leads to minimizing $V_\alpha$ (total vehicle utilization).

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$$\alpha_{ij} \geq 0 \qquad \forall i, j \in \mathcal{S}$$

If we impose triangle inequality on travel times $T_{ij}$, then stations can be divided into those with a *surplus* ($S$) and those with a *deficit* ($D$), where $S = \left\{ i \in \mathcal{S} | \lambda_i < \sum_j \lambda_j p_{ji} \right\}$ and $D = \mathcal{S} \setminus S$.

# Continuous bipartite matching

Minimize

$$\sum_{i \in S, j \in D} T_{ij} \alpha_{ij}$$

subject to

$$\begin{aligned} \sum_{j \in D} \alpha_{ij} &= -\lambda_i + \sum_{j \neq i} \lambda_j p_{ji} && \forall i \in S \\ \sum_{i \in S} \alpha_{ij} &= \lambda_j - \sum_{i \neq j} \lambda_i p_{ij} && \forall j \in D \\ \alpha_{ij} &\geq 0 && \forall i, j \in \mathcal{S} \end{aligned}$$

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- Fewer variables and fewer constraints.

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- Fewer variables and fewer constraints.
- Linear Program.

# Summary

**Positives:**

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- Allows us to study stability of equilibrium.

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**Concerns:**

- Only for the case of constant flow rates.
- Susceptible to perturbations in $p_{ij}$.

# Role of dynamic pricing in Uber

**Paper 3: Surge Pricing Solves the Wild Goose Chase**


- Juan Camilo Castillo
  *Stanford University*
- Dan Knoepfle
  *Uber Technologies*
- E. Glen Weyl
  *Microsoft Research*

# Ride Hailing

- Uber, Lyft: more efficient matching technology than taxis
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  - Potential welfare gain is substantial
- Challenges to get market design right
  - Matching passengers with drivers
  - Pricing (dynamic?)

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Research problem: How to avoid Wild Goose Chases?

- WGCs can be avoided by setting higher prices

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- $S(T, L)$ : Supply function

# Demand

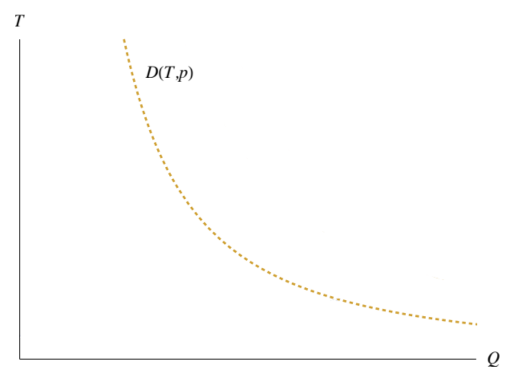


**Figure 5:** Demand curve[5].

[5] Castillo, Knoepfle, and Weyl 2017.

# Supply

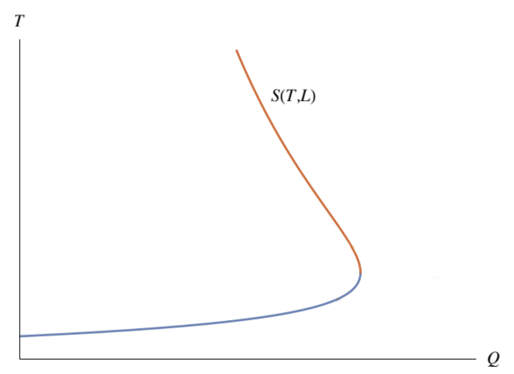


**Figure 6:** Supply curve[6].

[6] Castillo, Knoepfle, and Weyl 2017.

# Empirical supply

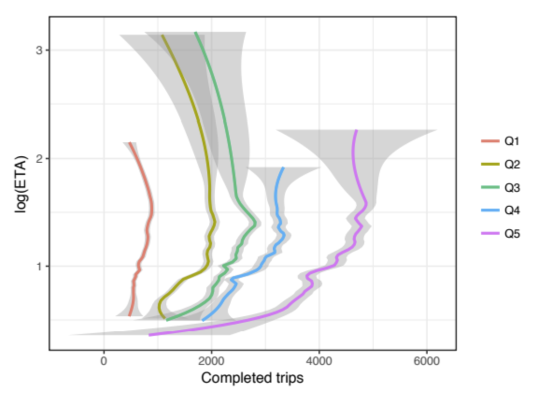


**Figure 7:** Quintiles of empirical supply[7].

[7] Castillo, Knoepfle, and Weyl 2017.

# Equilibrium

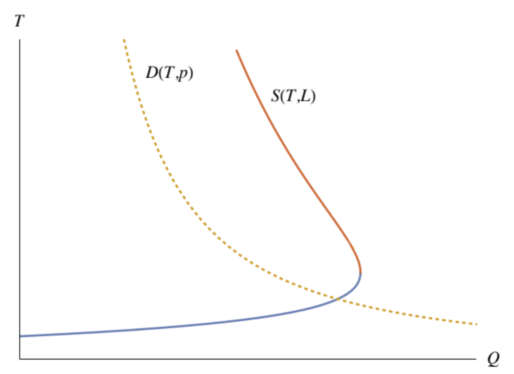


**Figure 8:** Equilibrium point[8].

[8] Castillo, Knoepfle, and Weyl 2017.

# Equilibrium

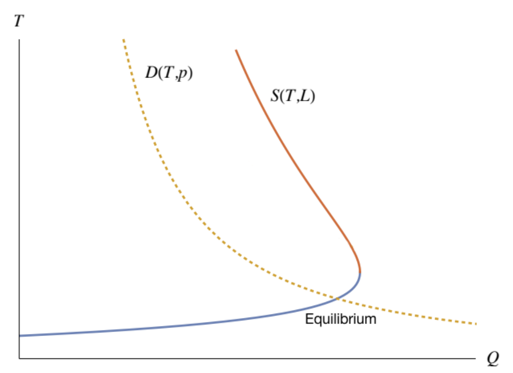


**Figure 9:** Equilibrium point.

# Wild Goose Chase

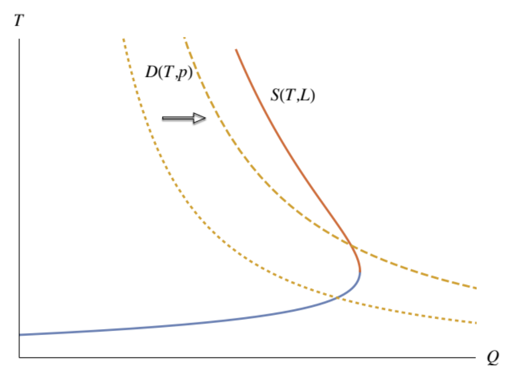


**Figure 10:** Wild Goose Chase.

# Wild Goose Chase

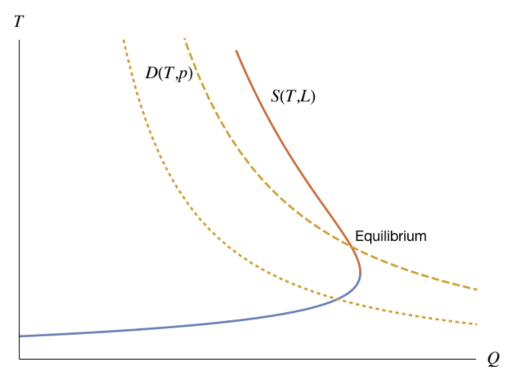


**Figure 11:** Wild Goose Chase.

# Market Collapse

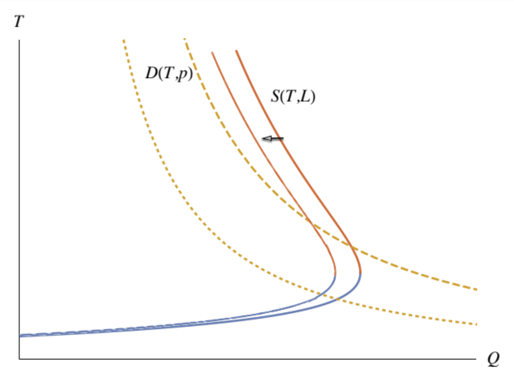


Figure 12: Market Collapse.

# Market Collapse

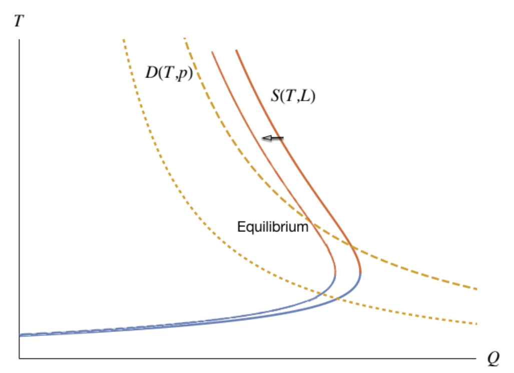


**Figure 13:** Market Collapse.

## Pricing for Strong vs. Weak Market

Welfare = Customer Utility + Driver earnings + Platform earnings

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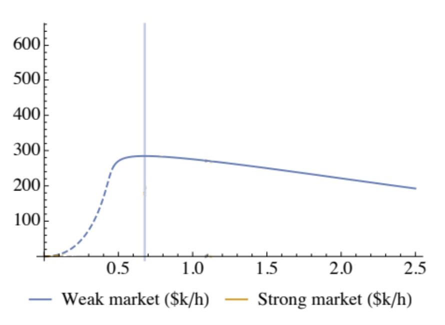


**Figure 14:** Need for dynamic pricing[9].

[9] Castillo, Knoepfle, and Weyl 2017.

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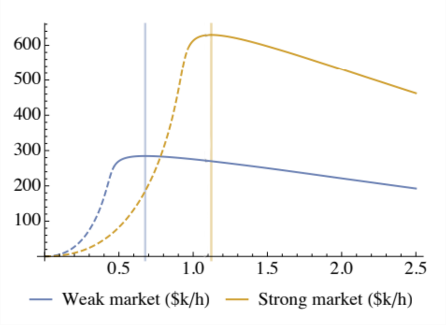


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[9] Castillo, Knoepfle, and Weyl 2017.

# Summary

**Positives:**

- Formulation of endogenous relationship between supply and demand.

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- Formulation of endogenous relationship between supply and demand.

**Concerns:**

- Location-based discrimination?
- Oblivious to re-balancing problem. Uber POV - surge pricing helps with re-balancing.

# Open Problems

# Discussion

- **Strategic drivers**
  Putting Data in the Driver's Seat: Optimizing Earnings for On-Demand Ride-Hailing *(To appear in WSDM 2018 proceedings)*

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- **Strategic platform monitoring**
  Efficient Markov Chain Monitoring *(To appear in SDM 2018 proceedings)*

# Thank You!

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