The Tragedy of the Last Mile: Congestion Externalities in Broadband Networks

Jacob Malone\textsuperscript{1} Aviv Nevo\textsuperscript{2} Jonathan Williams\textsuperscript{3}

\textsuperscript{1}University of Georgia
\textsuperscript{2}University of Pennsylvania
\textsuperscript{3}UNC - Chapel Hill

October 2016
Increased use of the Internet continues

- residential broadband (BB) usage has grown 30-40% annually over last two decades
- file-sharing drove early growth, over-the-top video (OTTV) recently

BB capacity has largely kept pace with demand

- Investment averaged $75 billion per year since 1996 (FCC 2015), or $1.5 trillion over past two decades

Despite investment, congestion continues to periodically impact networks
Introduction

- Congestion can occur in multiple places within BB network
  - Two most-likely places are interchanges and “last mile”
  - ISPs control congestion on “last mile” (our focus), but not upstream
  - Difficult to identify source of congestion, leads to high-profile disputes (e.g. Comcast and Netflix)

- Regulators now track and publish network performance statistics (FCC in Measure Broadband America)

- Our goal: estimate BB demand and measure value of different solutions to growth and congestion (investment, economic, and technological)
  - Division of surplus among ISP, content providers, and consumers alter incentives
Useful to understand BB demand for numerous ongoing issues in telecommunications industry:

- **Pricing**: Usage-based pricing (UBP), zero rating, (un)bundling and tying practices
- **Entry**: Google Fiber, municipal broadband
- **Evolving Choice Set**: OTTV, cord cutting, satellite
- **Mergers**: Charter-TWC, Comcast-TWC, ATT-DirecTV (horizontal and vertical elements)
- **Regulation**: net neutrality, opening set-top boxes, expanding residential networks
Research Strategy

- Collect panel of high-frequency (hourly) data for each subscriber
  - Descriptive analysis of relationship between usage and congestion, exploiting network investment
- Build on Nevo et al (2016) model of demand for residential BB
  - Capture intra- and inter-day usage choice
  - Incorporate uncertainty wrt congestion and dynamics arising from three-part tariff (3PT: access/overage fees and allowance)
- Flexibly estimate model (substantial consumer heterogeneity)
  - Adapt flexible fixed-grid methodology of Fox et al (2015) and Nevo et al (2016) to exploit long panel
Research Strategy

- Comparative statics on model estimates
  - Value from eliminating congestion entirely
  - Preference for speed and usage allowances (shadow price of usage informative for zero-rating issue)

- Counterfactual on economic and technological solutions to congestion
  - Throttling of connection during peak hours after exceeding allowance
  - Simple forms of peak-use pricing (count off-peak differentially)
  - Local caching of OTTV content (think Tivo for OTTV)
    - Amazon and Netflix claim to accurately predict viewing behaviors
    - Amazon’s advanced streaming and predictive (ASAP) feature locally caches content on Amazon Fire device, but intended to improve quality not efficiency
    - Rumors Netflix will introduce soon
  - Not independent, expect peak-use pricing to drive introduction of technology
Data: Source

- Proprietary Internet Protocol Data Records (IPDR) from NA ISP
  - Hourly observations at subscriber level
  - Data include bytes down/up and packet drops and delays
  - Covers roughly 45,000 subscribers from Feb–Dec 2015 (334 days)
  - IPDR include *node* variable, which gives network topology

- Hourly average network (*node*) utilization

- Daily subscriber billing records
  - Includes speed, usage allowance, and price information

- Complement IPDR data with deep-packet inspection (DPI) data from another NA ISP to demonstrate additional usage patterns
  - Representative nationwide sample of nearly million users
  - Motivate model assumptions and demonstrate external validity
Data: Internet Plan Features

- Plans are 3PTs: access fee, usage allowance, and overage fee
- More expensive plans come with faster speeds and larger usage allowances: complicates identification if only plan choice observed
- Average user pays $58.89 for 22 Mbps down and a 287 GB allowance
## Data: Daily Usage Distributions by Tier

<table>
<thead>
<tr>
<th>Tier</th>
<th>Tier 1</th>
<th>Tier 2</th>
<th>Tier 3</th>
<th>Tier 4</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>1.4 GB</td>
<td>3.4 GB</td>
<td>5.4 GB</td>
<td>8.2 GB</td>
<td>2.3 GB</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>2.9</td>
<td>5.0</td>
<td>7.3</td>
<td>10.4</td>
<td>4.5</td>
</tr>
<tr>
<td>25th %tile</td>
<td>0.0</td>
<td>0.3</td>
<td>0.6</td>
<td>1.3</td>
<td>0.1</td>
</tr>
<tr>
<td>Median</td>
<td>0.4</td>
<td>1.5</td>
<td>3.1</td>
<td>5.3</td>
<td>0.6</td>
</tr>
<tr>
<td>75th %tile</td>
<td>1.5</td>
<td>4.7</td>
<td>7.6</td>
<td>11.4</td>
<td>2.7</td>
</tr>
<tr>
<td>90th %tile</td>
<td>4.1</td>
<td>9.0</td>
<td>13.6</td>
<td>19.4</td>
<td>6.7</td>
</tr>
<tr>
<td>95th %tile</td>
<td>6.3</td>
<td>12.5</td>
<td>18.5</td>
<td>26.1</td>
<td>10.2</td>
</tr>
<tr>
<td>99th %tile</td>
<td>12.8</td>
<td>22.3</td>
<td>32.0</td>
<td>46.2</td>
<td>20.3</td>
</tr>
<tr>
<td>N</td>
<td>8,539,830</td>
<td>2,910,234</td>
<td>1,117,680</td>
<td>320,085</td>
<td>12,887,829</td>
</tr>
</tbody>
</table>

- ~90% of sample from Tiers 1 and 2
  - Plan features ahead of preferences
- Strong (optimal) selection effect into plans, substantial heterogeneity
- Little plan switching, focus on 95% of users that do not switch plans
Data: Proportion of Monthly Allowance Utilized

(a) Proportion - Subscriber-Month

- \( \sim 2.5\% \) exceed allowance (avg. 40\% of allowance used), less shadow-price variation than Nevo et al (2016)
- \( \sim 15\% \) exceed allowance during sample, long panel is crucial for within-user variation

(b) Max Proportion - Subscriber
- Peak average usage 5 times greater than trough, 90% downstream
- Potential gains from peak-use pricing or technological advances to more efficiently use network
Substantial heterogeneity in levels

Median user’s peak usage less than 15% of 95th%
Average proportion at each hour by monthly-usage decile

Service cost proportional to monthly usage
Despite no relationship to monthly level, substantial heterogeneity in hourly pattern (nearly flat to highly peaked)
Data: Heterogeneity in Usage Patterns by Day

- Average usage by hour similar across day, small intuitive differences between weekdays and weekends
- Reasonably ignore day of week in model
<table>
<thead>
<tr>
<th>Groups</th>
<th>Description (Examples)</th>
<th>% of All Usage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Administration</td>
<td>System administrative tasks (STUN, ICMP)</td>
<td>1.19</td>
</tr>
<tr>
<td>Backup</td>
<td>Online storage (Dropbox, SkyDrive)</td>
<td>0.58</td>
</tr>
<tr>
<td>Browsing</td>
<td>General web browsing (HTTP, Facebook)</td>
<td>26.70</td>
</tr>
<tr>
<td>CDN</td>
<td>Content delivery networks (Akamai, Level3)</td>
<td>2.95</td>
</tr>
<tr>
<td>Gaming</td>
<td>Online gaming (Xbox Live, Clash of Clans)</td>
<td>3.06</td>
</tr>
<tr>
<td>Music</td>
<td>Streaming music services (Spotify, Pandora)</td>
<td>3.40</td>
</tr>
<tr>
<td>Sharing</td>
<td>File sharing protocols (BitTorrent, FTP)</td>
<td>0.20</td>
</tr>
<tr>
<td>Streaming</td>
<td>Generic media streams (RTMP, Plex)</td>
<td>6.26</td>
</tr>
<tr>
<td>Tunneling</td>
<td>Security and remote access (SSH, ESP)</td>
<td>0.07</td>
</tr>
<tr>
<td>Video</td>
<td>Video streaming services (Netflix, YouTube)</td>
<td>55.47</td>
</tr>
<tr>
<td>Other</td>
<td>Anything not included in above groups</td>
<td>0.13</td>
</tr>
</tbody>
</table>

- Deep-Packet Inspection (DPI) data from nationwide sample of users, different ISP and not used in estimation
Data: Monthly Usage by Quantile and Traffic Type

(a) Average Monthly Usage
(b) Proportions of Monthly Usage

- Video larger proportion of usage for heavier users
- Encouraging for economic and technological solutions to congestion since video is passive activity (download any time, watch later)
Temporal pattern observed in all data collected (external validity)

Video disproportionally peak-intensive activity, encouraging again for local-cache technology
Two items in data related to network performance
   1. Hourly average network (node) utilization
   2. Packet loss (% of packets that are dropped or delayed)

Packet loss our preferred measure of network performance
   ▶ User-specific and captures instantaneous failure of request
   ▶ Tracked by FCC to measure network performance

Engineering relationship between packet loss, network utilization, and realized speed (proportional degradation during congestion)

Sources of variation in congestion
   ▶ Time-series: network investments
   ▶ Cross-sectional: across nodes of network
Congestion: Comparison Across ISPs

- Reproduced from FCC (2015)
- For comparison, we report the packet loss at the average \textit{subscriber-hour} level
Congestion: Packet Loss by Hour

(a) Average Packet Loss

- 1% packet loss is considered very high, average at peak exceeds 1%
- Packet loss right-skewed across users (10% over 1% at peak)

(b) Variation in Packet Loss
80% average node utilization critical level

Substantial across-node and time-series variation
Node is first point of aggregation on ISP’s network
- Common place for bottlenecks to occur
- Often demarcate “last mile” portion of networks
- Typically between 300 and 500 users per node

A node split is a common technique to reduce congestion
- Typically subscribers evenly split across two new nodes

Observe 7 node splits in our panel (over 3000 users) along with substantial licensing upgrades
## Congestion: Changes after Node Split

<table>
<thead>
<tr>
<th></th>
<th>Before</th>
<th>After</th>
<th>Diff</th>
<th>% Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Utilization</td>
<td>87%</td>
<td>62%</td>
<td>-25%</td>
<td>-29%</td>
</tr>
<tr>
<td>Packet Loss</td>
<td>1.0%</td>
<td>0.61%</td>
<td>-0.39%</td>
<td>-39%</td>
</tr>
<tr>
<td>Off-Peak Usage</td>
<td>0.75 GB</td>
<td>0.74 GB</td>
<td>-0.01 GB</td>
<td>-1.3%</td>
</tr>
<tr>
<td>Peak Usage</td>
<td>1.80 GB</td>
<td>1.99 GB</td>
<td>0.19 GB</td>
<td>10.5%</td>
</tr>
<tr>
<td>Daily Usage</td>
<td>2.55 GB</td>
<td>2.73 GB</td>
<td>0.18 GB</td>
<td>7.1%</td>
</tr>
</tbody>
</table>

- Examine 7 days before and after node split
- Large drop in network congestion, increase in usage
- Evidence of slight intra-day substitution in congested networks
Model: Utility Function

- Utility from content of consumer type $h$ on plan $k$ (for each day $t$):

$$u_{hk}(c_p, c_{op}, \psi, \nu) = \nu_1 \left( \frac{(c_{op} + c_p)^{1-\alpha_h}}{1 - \alpha_h} \right) - c_{op}^2 \left( \frac{\nu_2 \kappa_h}{\ln(s_k)} \right) - c_p^2 \left( \frac{\kappa_h}{\ln(\psi s_k)} \right)$$

where: $c$ – GB of content; $s_k$ – connection speed; $\nu_1$ and $\nu_2$ – shocks to preferences for content; $\psi$ – network state

- $\psi$ follows first-order Markov process $G_\psi$ (data)

- $\nu_1 \sim EXP(\lambda_1)$ and $\nu_2 \sim EXP(\lambda_2)$

- Consumer type $(\alpha_h, \kappa_h, \lambda_{1h}, \lambda_{2h})$: $\alpha_h$ – curvature to utility; $\kappa_h$ – content wait time/preference for speed; $\lambda_{1h}$ and $\lambda_{2h}$ – time-varying shock parameters capture level and temporal variation in usage

- Satiation in usage for finite speeds, proportional rationing of speed, and additive usage determines benefit
Model: Optimal Usage

- Assume consumers can afford satiation level of content (no income effects)
- Assume $\nu_1$ and $\nu_2$ known at beginning of each day $t$, $\psi$ only realized during peak hours
- Consumers solve finite-horizon ($T$) dynamic program
  - Optimally choose plan, and then peak and off-peak usage each day
Model: Optimal Usage Day $T$

- Optimal peak usage on day $T$, $c_{hkT_p}^*$, is either satiation level, up unto allowance, or satisfies

$$
\frac{\partial u_{hk}(c_{hkT_{op}}, c_{hkT_p}^*, \psi_T, \nu_T)}{\partial c_{Tp}} = p_k
$$

- Denote cumulative consumption entering day $t$ as $C_{t-1}$ and day-$T$ overages as $O_{tk}(c_{top} + c_{tp} + C_{t-1}) \equiv \text{Max}\{c_{top} + c_{tp} + C_{t-1} - C_k, 0\}$

- Given optimal peak-use policy, off-peak optimal policy satisfies

$$
c_{hkT_{op}}^* = \arg\max_{c_{hkT_{op}}} \int_{\psi} \left[ \nu_1 T \left( \frac{c_{hkT_{op}} + c_{hkT_p}^*}{1 - \alpha_h} \right)^{1-\alpha_h} - (c_{hkT_{op}})^2 \left( \frac{\nu_2 T \kappa_h}{\ln(s_k)} \right) - (c_{hkT_p}^*)^2 \left( \frac{\kappa_h}{\ln(\psi s_k)} \right) - p_k O_{tk}(c_{hkT_{op}} + c_{hkT_p}^* + C_{t-1}) \right] dG_\psi(\psi|\psi_{T-1})
$$
The optimal policy functions on day $T$, $c_{hkT_{op}}^*$ and $c_{hkT_p}^*$, imply an expected value function, $E(\psi,\upsilon) [V_{hkT}(C_{T-1}, \psi_{T-1})]$, for entering day $T$ at state $(C_{T-1}, \psi_{T-1})$ that equals

$$\int_{\psi} \left[ \int_{\upsilon} V_{hkT}(C_{T-1}, \psi_{T-1}, \upsilon) dG^h_{\upsilon}(\upsilon) \right] dG^\psi(\psi|\psi_{T-1})$$

Using day $T$ value function, recursively solve for optimal policies for each day $t < T$, $c_{hkt_{op}}^*$ and $c_{hkt_p}^*$

Store expected policy functions and expectations of various functions of policy functions for each type $h$ on each plan $k$. 

Model: Optimal Usage Day $t < T$
Variation in network congestion and shadow price alter usage and provide identification
Model: Plan Choice

- Subscriber optimally chooses either one of 4 plans or no plan and stays on that plan (very little switching)
- Chosen plan $k^*_h$ satisfies for each type $h$

\[
k^*_h = \arg\max_{k \in \{0, \ldots, 4\}} E[V_{hk1}(C_1 = 0, \psi_1)] - F_k,
\]

where $F_k$ is the plan’s fixed fee and $E[V_{hk1}(C_1 = 0, \psi_1)]$ is expected utility at beginning of billing cycle
- Each type $h$, described by vector $(\alpha_h, \kappa_h, \lambda_{1h}, \lambda_{2h})$, maps uniquely to their optimal plan, $h \rightarrow k^*_h$
- Weak tests of plan-choice optimality (i.e., lower cost and higher speed) support assumption
Estimation procedure is a panel-data modification of fixed-grid approach of Fox et al. (2015) and Nevo et al. (2016)

Two separable steps:

1. Computational:
   - type defined by vector, \((\alpha_h, \kappa_h, \lambda_{1h}, \lambda_{2h})\)
   - solve dynamic program for 4,096 different types (4 parameters with 8 points of support)
   - store optimal plan, policy function, and value function for each type

2. Estimation using least-squares criterion:
   - identify the type on fixed grid of types that best matches each consumer’s behavior in a least-squares sense (likelihood possible)
   - aggregate across consumers to calculate each type’s population weight
Econometrics: Objective Function

- Goal is to find which type ($h$) best matches subscriber’s ($i$) behavior
- We use a least squares objective function

$$\hat{h}_i = \min_{\{h=1,\ldots,H\}} \left[ \sum_{t=1}^{T} \tilde{z}_{iht} \tilde{z}_{iht} \right],$$

where

$$\tilde{z}_{iht} = \left( \begin{array}{c} c_{it_{op}} - c_{h_k t_{op}}^* (C_{t-1}, \psi_{t-1}, \nu_t) \\ c_{it_{p}} - c_{h_k t_{p}}^* (C_{t-1}, \psi_{t}, \nu_t) \\ c_{i_{op}}^2 - c_{h_k t_{op}}^{*2} (C_{t-1}, \psi_{t-1}, \nu_t) \\ c_{it_{p}}^2 - c_{h_k t_{p}}^{*2} (C_{t-1}, \psi_{t}, \nu_t) \end{array} \right)$$

- Once type ($h$) is identified for each subscriber ($i$), aggregate to get each type’s population weight, $\tilde{\theta}_h$
Moments Used

- Calculate moments at each of the 120,000 state space points for each plan, during peak and off-peak hours
- Mean usage for each plan \((k)\), billing day \((t)\), and cumulative usage \((C)\)
  - Recovered using nearest-neighbor estimator
- CDF of cumulative usage \((C)\) for each plan \((k)\) and day \((t)\)
  - Recovered using smoothed Kaplan-Meier estimator
- Variance-covariance matrix, \(V_k^{-1}\), calculated using block-resampling to account for dependence
Optimal plan choice maps each type to a plan (divides type space), usage moments refine type distribution for each plan

- Weak source: positive correlation between allowance and speed

Parameters identified by different types of variation in usage

- $\alpha$: variation in shadow price and network state (iso-elastic with respect to total cost of usage)
- $\lambda_1$: mean and variance of daily usage
- $\lambda_2$: mean and variance of intra-day allocation of usage
- $\kappa$: responsiveness to variation in network state
Results: Type Distribution

- Difficult to succinctly summarize results, 4,096 parameters
- 129 types with positive weights (of 4,096 considered)
- Slightly more uniform weights across types than Nevo et al. (2016)
- Model fits the data quite well (over 97% correlation between data and fitted optimal-type’s expected behavior)
- Most of the estimated positive types (85) come from top tier
  - Top tier only around 2.5% of sample
  - Wide variety of behavior to explain within tier differences in usage (choose plan for either speed or allowance)
Results: Marginal Type Distributions

(a) Marginal of $\lambda_2$

(b) Marginal of $\alpha$

- $\lambda_2$ distribution nearly normal, intuitive values since off-peak usage roughly 20% on average of peak usage
- $\alpha$ distribution irregular and bimodal, consistent with Nevo et al (2016)
Bimodal nature distribution of $\alpha$ clear visible, mixture of two normals might be reasonable
Results: Implications of Estimates

- Mean WTP for one additional Mb/s for one month is $0.79
  - Return to speed falls off very rapidly
- Mean (median) WTP for one additional GB of allowance on first day of month is $0.09 ($0.04)
  - Shadow price of usage on first day of billing cycle
  - Important for current debate surrounding zero rating of content: price differential for types of content that count against allowance (e.g., Netflix) and those that don’t (e.g., Comcast Stream)
  - Magnitude suggests price differential is quite small
Much has been made of the existence and source of congestion (Netflix and Comcast).

Before concluding substantial private or municipality investment is required to improve BB networks, it is important to understand return to ISP and consumers:

- Measure value created by eliminating all congestion on the network.
- Permit consumers to re-optimize (choose new plan and usage), but keep ISP’s plan features fixed.
- No cost information is available to measure total return.

Surplus to consumers of $6 per consumer-month (reallocated if firm re-optimizes).
Throttling during peak hours is a commonly proposed solution to congestion.

- Rather than overages, simply limit connection speed during peak hours once allowance is exceeded.
- Mobile operators employ solution: AT&T and FCC dispute resolved over failure to notify in 4/2016 and Verizon permits consumers to opt in to avoid overages.

- Permit consumers to opt in to throttling of 7 Mb/s during peak hours after exceeding allowance.
  - About speed required for 1-2 HD streams.
## Counterfactual: Throttling

<table>
<thead>
<tr>
<th>Usage and Surplus</th>
<th>Baseline</th>
<th>7 Mb/s</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daily Usage (GB)</td>
<td>2.5</td>
<td>2.9</td>
</tr>
<tr>
<td>Peak Usage (GB)</td>
<td>1.8</td>
<td>1.9</td>
</tr>
<tr>
<td>Off-Peak Usage (GB)</td>
<td>0.7</td>
<td>1.0</td>
</tr>
<tr>
<td>Consumer Surplus ($)</td>
<td>70.22</td>
<td>78.67</td>
</tr>
<tr>
<td>Revenue ($)</td>
<td>57.42</td>
<td>57.09</td>
</tr>
</tbody>
</table>

- Quite promising, substantially increases consumer surplus
- Re-optimization of prices to capture surplus easily covers additional network costs
Counterfactual: Local-Caching Technology

- Technology is available, but not deployed, to permit many OTTV services to locally cache content like DVR technologies.
- Amazon Fire devices already locally cache, but relies on predictive algorithms to queue first few seconds of likely-watched content, improves performance not efficiency.
- Measure value created by technology that reduces differential cost of usage between peak and off-peak hours (downloading but not necessarily consuming)
  - Either accurate predictive algorithm or application permitting user to choose what/when to cache.
- Implemented by reducing $\lambda_2$ by different proportions
  - Likely to be heterogenous effect based on preference for different types of content (OTTV and BitTorrent most responsive).
Counterfactual: Local-Caching Technology

<table>
<thead>
<tr>
<th>Usage and Surplus</th>
<th>Baseline</th>
<th>$\lambda_2$ 50% Reduction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daily Usage (GB)</td>
<td>2.5 GB</td>
<td>3.1 GB</td>
</tr>
<tr>
<td>Peak Usage</td>
<td>1.8 GB</td>
<td>1.7 GB</td>
</tr>
<tr>
<td>Off-Peak Usage</td>
<td>0.7 GB</td>
<td>1.4 GB</td>
</tr>
<tr>
<td>Consumer Surplus ($)</td>
<td>70.22</td>
<td>85.44</td>
</tr>
<tr>
<td>Revenue ($)</td>
<td>57.42</td>
<td>58.22</td>
</tr>
</tbody>
</table>

- Compare to baseline without congestion
- Surplus gains greater than those created by investment, surely offset any additional hardware costs
- Gains larger if $\lambda_2$ reduction is larger for heavier users (more OTTV)
Counterfactual: Peak-Use Pricing

- OTTV content providers currently have weak incentive to introduce local-caching technologies (quality improvement during peak hours)
- Peak-use pricing introduces right incentive
- Consider very simple form: reduce allowance by varying levels (30% and 50%) but only count peak usage against allowance, overage fee held constant
- Disadvantage is that it only weakly decreases off-peak cost (eliminates shadow price), so reduces overall cost of usage by less than local-cache technology
Counterfactual: Peak-Use Pricing

### Usage and Surplus

<table>
<thead>
<tr>
<th></th>
<th>Baseline</th>
<th>30% Reduction</th>
<th>50% Reduction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daily Usage (GB)</td>
<td>2.5</td>
<td>2.6</td>
<td>2.4</td>
</tr>
<tr>
<td>Peak Usage (GB)</td>
<td>1.8</td>
<td>1.7</td>
<td>1.5</td>
</tr>
<tr>
<td>Off-Peak Usage (GB)</td>
<td>0.7</td>
<td>0.9</td>
<td>0.9</td>
</tr>
<tr>
<td>Consumer Surplus ($)</td>
<td>70.22</td>
<td>72.33</td>
<td>69.01</td>
</tr>
<tr>
<td>Revenue ($)</td>
<td>57.42</td>
<td>57.21</td>
<td>58.54</td>
</tr>
</tbody>
</table>

- Not too successful in isolation (low intra-day elasticity)
- Small peak allowance leads to small consumer-firm transfer
- Substantially increases shadow price of peak-usage ($0.45 per GB on average), which provides strong incentive for introduction of local-cache technology
Conclusion

- Enriched model to capture congestion and intra-day usage decisions fits data well
- Counterfactuals reveal likely success of alternatives to investment for abating congestion
  - Local-cache technology appears promising, large surplus gains
  - Peak-use pricing not promising in isolation, but useful for encouraging introduction of local-cache technologies
- Next steps: exploit richer data to study composition of traffic to allocate gains from investment, and incorporate linear TV usage into the model