On Ridership and Frequency

Modeling elasticity on a hyper-local scale between 2012 and 2017

Simon Berrebi, Ph.D.
Sanskruti Joshi
Taylor Gibbs
Kari Watkins, Ph.D.
2018 – Lowest Bus Ridership on Record

1990-2018: APTA Ridership 1990-Present, American Public Transportation Association
Bus Ridership Vs. Service Miles

Point In Time 2012

\[ y = 3.83x - 2E+07 \]

\[ R^2 = 0.91 \]

Percent Change 2012-2016

Data Sources

APC
Automatic Passenger Counters
2012 - 2017
• Lasers on vehicle doors
• Typically connected to GPS
• 30M – 1B Records
• Seldom used for planning

GTFS
General Transit Feed Specification
2012/13 - 2017
• Standardized format for transit schedules
• Historical data available openly through 3rd parties

Census
Longitudinal Employer-HH Dynamics
2011-2015
• Population and jobs
• Available yearly by Block
• Provided by Census Bureau
Four Case Studies

<table>
<thead>
<tr>
<th></th>
<th>TriMet</th>
<th>Miami-Dade</th>
<th>Metro-Transit</th>
<th>MARTA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unlinked Passenger Trips (000’s)</td>
<td>56,727</td>
<td>49,716</td>
<td>54,910</td>
<td>49,788</td>
</tr>
<tr>
<td>Vehicle Revenue Hours (000’s)</td>
<td>1,988</td>
<td>1,961</td>
<td>2,050</td>
<td>2,249</td>
</tr>
<tr>
<td>MSA population (000’s)</td>
<td>2,425</td>
<td>6,066</td>
<td>3,551</td>
<td>5,790</td>
</tr>
<tr>
<td>% living in transit-supportive density</td>
<td>43.1</td>
<td>58.7</td>
<td>22.9</td>
<td>10.8</td>
</tr>
</tbody>
</table>
Framework

1. APC
   - Aggregate daily frequency & ridership by SRD in each mark-up

2. Comparison of frequency between APC and GTFS

3. GTFS

4. LEHD
   - Combine ridership, frequency, population and jobs data at segment level

5. Create Segments
   - Identify constant SRD
Route Segments

**Definition:** groups of 7-14 adjacent stops in the same route and direction

Population and jobs data were recorded in ¼ mi radius around each stop
Cross-Sectional Model: Poisson Regression

\[ E(\text{Rid}|x) = e^{\beta_0} \times \text{Freq}^{\beta_1} \times (\text{Pop}+\text{Job})^{\beta_2} \times e^\epsilon \]

- Multiplicative effect since ridership requires both buses and people
- Is endogenous
- Total number of trip attraction points
## Cross-Section Results

<table>
<thead>
<tr>
<th>Response Variable: Rid</th>
<th>Portland</th>
<th>Miami</th>
<th>Minneapolis/St-Paul</th>
<th>Atlanta</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(Freq)</td>
<td>1.36 (0.03)***</td>
<td>1.21 (0.03)***</td>
<td>1.50 (0.04)***</td>
<td>1.33 (0.08)***</td>
</tr>
<tr>
<td>log(Pop + Job)</td>
<td>0.52 (0.02)***</td>
<td>0.53 (0.02)***</td>
<td>0.52 (0.02)***</td>
<td>0.33 (0.04)***</td>
</tr>
<tr>
<td>(Intercept)</td>
<td>-4.87 (0.19)***</td>
<td>-4.45 (0.17)***</td>
<td>-5.86 (0.19)***</td>
<td>-3.57 (0.40)***</td>
</tr>
<tr>
<td>Pseudo $R^2$</td>
<td>0.82</td>
<td>0.72</td>
<td>0.81</td>
<td>0.39</td>
</tr>
<tr>
<td>Deviance</td>
<td>9447.14</td>
<td>13138.63</td>
<td>10732.59</td>
<td>14363.80</td>
</tr>
<tr>
<td>Num. obs.</td>
<td>874</td>
<td>1165</td>
<td>959</td>
<td>718</td>
</tr>
</tbody>
</table>

* ***p < 0.001; **p < 0.01; *p < 0.05; p < 0.1
Frequent Routes Are The Most Productive
Fixed-Effects Model: Poisson Regression

For each individual segment, $i$, ridership and frequency are observed at time $t$.

$$E[Rid_{it} | x_{it}] = \text{Freq}_{it}^{\beta_1 + \beta_2 \log(\text{Freq}_{it0})} \times (\text{Pop}_{it} + \text{Job}_{it})^{\beta_3} \times e^{\alpha_i} \times e^{\mu_t}$$

The effect of frequency on ridership is interacted with prior frequency (time = $t_0$).

Individual and time specific effects are estimated and removed from the model.

Changes in population and jobs are controlled for.
Panel Results

<table>
<thead>
<tr>
<th></th>
<th>Response Variable:</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Rid(_{it})</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Portland</td>
<td>Miami</td>
<td>Minneapolis/St-Paul</td>
<td>Atlanta</td>
<td></td>
</tr>
<tr>
<td>log(Freq(_{it}))</td>
<td>0.71 (0.04)**</td>
<td>0.80 (0.04)**</td>
<td>0.75 (0.03)**</td>
<td>0.67 (0.01)**</td>
<td></td>
</tr>
<tr>
<td>log(Pop(<em>{it}) + Job(</em>{it}))</td>
<td>−0.00 (0.04)</td>
<td>0.02 (0.03)</td>
<td>0.11 (0.04)**</td>
<td>0.06 (0.01)**</td>
<td></td>
</tr>
<tr>
<td>(\mu_t)</td>
<td>−0.01 (0.00)*****</td>
<td>−0.04 (0.00)*****</td>
<td>−0.03 (0.00)*****</td>
<td>−0.05 (0.00)*****</td>
<td></td>
</tr>
<tr>
<td>Log-Likelihood</td>
<td>−10135.99</td>
<td>−10341.42</td>
<td>−10891.49</td>
<td>−19433.92</td>
<td></td>
</tr>
<tr>
<td>Num. obs.</td>
<td>4884</td>
<td>5264</td>
<td>5647</td>
<td>3453</td>
<td></td>
</tr>
<tr>
<td>n</td>
<td>874</td>
<td>1165</td>
<td>959</td>
<td>718</td>
<td></td>
</tr>
<tr>
<td>T</td>
<td>6</td>
<td>5</td>
<td>6</td>
<td>5</td>
<td></td>
</tr>
</tbody>
</table>

***\(p < 0.001\); **\(p < 0.01\); *\(p < 0.05\); . \(p < 0.1\)
Frequent Routes Are The Most Productive
Elasticity of Rid to Freq Vs. Prior Freq

Figure 6: Elasticity of ridership to frequency as a function of frequency

7. Discussion and Conclusion

Through this...can guide future research to address some of the most pressing contemporary problems facing public transportation.
Conclusion

• When comparing the variation between route-segments at a point in time, ridership is elastic to frequency
• When comparing the variation within each route-segment over time, ridership is inelastic to frequency
• Low-frequency routes are the most elastic in Portland, Miami, and Atlanta but not in Minneapolis/St-Paul
• Controlling for frequency allows to model the effects of other local dynamics on ridership
Thank You!

Contact
Simon J. Berrebi, Ph.D.
simon@berrebi.net