Using Big Data to Estimate Consumer Surplus: The Case of Uber

Peter Cohen, Uber
Robert Hahn, University of Oxford
Jonathan Hall, Uber
Steven Levitt, University of Chicago & NBER
Robert Metcalfe, Boston University & NBER

February 2018

Consumer Surplus Is Easy to Draw, but Hard to Measure

[Diagram showing price and quantity axes with a shaded area labeled CS between the supply and demand curves]
Estimating Consumer Surplus: The Existing Literature

- Use structure to fill in for data and identification limitations
  - BLP (ECMA, 1995; Automobiles)
  - Petrin (JPE, 2002; VW Minivan)
  - Goolsbee and Petrin (ECMA, 2003; Cable TV)
  - Brynjolfsson, Hu, and Smith (MS, 2003; Online books)
  - Quan and Williams (WP, 2014; Online retail)

- An alternative approach: look for better data
Uber

• **The digital matching:** The app allows consumers with smartphones to submit a trip request which is then routed to Uber drivers who use their own cars.

• Founded in 2009
  – Operating in SF, NYC, Chicago, & LA during 2012

• Key features:
  – Huge scale (large market shares)
  – Dynamic pricing
  – Observe “non-purchases”
  – Local supply and demand conditions are measured and recorded
  – The business rules generate natural experiments
PICKUP LOCATION
29-49 3rd Street

Surge Pricing
Demand is off the charts! Fares have increased to get more Ubers on the road.

2.0x
The normal fare

$9 minimum fare

$0.52 / min $2.60 / mile

Save up to 50%, try UberPOOL

Notify me when surge drops

I accept higher fare

This rate expires in 2 min
Note: This figure presents the email riders receive upon completion of their ride which details the fare breakdown and additional information about the trip.
Distribution of Surge Prices
Distribution of Surge over the Week
<table>
<thead>
<tr>
<th></th>
<th>Full Data</th>
<th>Surge = 1</th>
<th>1 &lt; Surge ≤ 2.0</th>
<th>Surge &gt; 2.0</th>
</tr>
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<tbody>
<tr>
<td>Surge</td>
<td>1.141</td>
<td>1.000</td>
<td>1.509</td>
<td>2.531</td>
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<tr>
<td>Expected wait time</td>
<td>4.118</td>
<td>4.205</td>
<td>3.731</td>
<td>4.046</td>
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<tr>
<td>Purchase rate</td>
<td>59%</td>
<td>62%</td>
<td>53%</td>
<td>39%</td>
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<tr>
<td>City</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chicago</td>
<td>22%</td>
<td>20%</td>
<td>29%</td>
<td>32%</td>
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<tr>
<td>Los Angeles</td>
<td>25%</td>
<td>26%</td>
<td>20%</td>
<td>24%</td>
</tr>
<tr>
<td>New York</td>
<td>29%</td>
<td>31%</td>
<td>21%</td>
<td>19%</td>
</tr>
<tr>
<td>San Francisco</td>
<td>24%</td>
<td>22%</td>
<td>30%</td>
<td>25%</td>
</tr>
<tr>
<td>Time of Day</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Evening rush</td>
<td>8%</td>
<td>8%</td>
<td>10%</td>
<td>13%</td>
</tr>
<tr>
<td>Morning rush</td>
<td>6%</td>
<td>6%</td>
<td>7%</td>
<td>14%</td>
</tr>
<tr>
<td>Slow nighttime</td>
<td>12%</td>
<td>13%</td>
<td>10%</td>
<td>8%</td>
</tr>
<tr>
<td>Weekday day</td>
<td>23%</td>
<td>25%</td>
<td>15%</td>
<td>12%</td>
</tr>
<tr>
<td>Weekday evening</td>
<td>14%</td>
<td>15%</td>
<td>13%</td>
<td>10%</td>
</tr>
<tr>
<td>Weekend day</td>
<td>15%</td>
<td>14%</td>
<td>18%</td>
<td>17%</td>
</tr>
<tr>
<td>Weekend evening</td>
<td>6%</td>
<td>6%</td>
<td>7%</td>
<td>6%</td>
</tr>
<tr>
<td>Weekend event</td>
<td>15%</td>
<td>14%</td>
<td>20%</td>
<td>20%</td>
</tr>
<tr>
<td>Rides in Period</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 ride in period</td>
<td>6%</td>
<td>6%</td>
<td>4%</td>
<td>4%</td>
</tr>
<tr>
<td>1 &lt; rides in period ≤ 3</td>
<td>9%</td>
<td>10%</td>
<td>8%</td>
<td>7%</td>
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<tr>
<td>3 &lt; rides in period ≤ 8</td>
<td>14%</td>
<td>15%</td>
<td>13%</td>
<td>13%</td>
</tr>
<tr>
<td>&gt; 8 rides in period</td>
<td>71%</td>
<td>70%</td>
<td>75%</td>
<td>75%</td>
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<tr>
<td>Sessions</td>
<td>47469440</td>
<td>37667052</td>
<td>8135793</td>
<td>1666595</td>
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</tbody>
</table>

This table presents summary statistics for the analysis sample. Column (1) presents statistics for the entire sample. The remaining columns present statistics for three mutually exclusive and exhaustive subsets of the data: Column (2) presents rider sessions with baseline pricing; Column (3) presents rider sessions facing a moderate surge between 1.0x and 2.0x; and Column (4) presents rider sessions facing a surge greater than 2.0x.
Estimating price elasticities
Regression Discontinuity around 1.3x Surge

Confidential - Do not discuss
Purchase Behavior around Price Discontinuities
<table>
<thead>
<tr>
<th>Surge Threshold</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
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<tbody>
<tr>
<td>1.2</td>
<td>-0.26</td>
<td>-0.43</td>
<td>-0.52</td>
<td>-0.52</td>
<td>-0.52</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>1.3</td>
<td>-0.32</td>
<td>-0.31</td>
<td>-0.35</td>
<td>-0.36</td>
<td>-0.34</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.04)</td>
<td>(0.04)</td>
<td>(0.04)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>1.4</td>
<td>-0.42</td>
<td>-0.47</td>
<td>-0.53</td>
<td>-0.53</td>
<td>-0.58</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.05)</td>
<td>(0.05)</td>
<td>(0.05)</td>
<td>(0.05)</td>
</tr>
<tr>
<td>1.5</td>
<td>-0.42</td>
<td>-0.47</td>
<td>-0.50</td>
<td>-0.50</td>
<td>-0.49</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.05)</td>
<td>(0.05)</td>
<td>(0.05)</td>
<td>(0.05)</td>
</tr>
<tr>
<td>1.6</td>
<td>-0.33</td>
<td>-0.33</td>
<td>-0.43</td>
<td>-0.45</td>
<td>-0.50</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.06)</td>
<td>(0.06)</td>
<td>(0.06)</td>
<td>(0.06)</td>
</tr>
<tr>
<td>1.7</td>
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<td>-0.60</td>
<td>-0.66</td>
<td>-0.68</td>
<td>-0.68</td>
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<tr>
<td></td>
<td>(0.03)</td>
<td>(0.08)</td>
<td>(0.08)</td>
<td>(0.08)</td>
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</tr>
<tr>
<td>1.8</td>
<td>-0.73</td>
<td>-0.80</td>
<td>-0.85</td>
<td>-0.88</td>
<td>-0.89</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.10)</td>
<td>(0.10)</td>
<td>(0.10)</td>
<td>(0.10)</td>
</tr>
<tr>
<td>1.9 - 2.3</td>
<td>-0.77</td>
<td>-0.99</td>
<td>-1.02</td>
<td>-1.06</td>
<td>-1.01</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.07)</td>
<td>(0.07)</td>
<td>(0.07)</td>
<td>(0.07)</td>
</tr>
<tr>
<td>2.4 - 3.0</td>
<td>-0.37</td>
<td>-0.34</td>
<td>-0.38</td>
<td>-0.39</td>
<td>-0.25</td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
<td>(0.17)</td>
<td>(0.17)</td>
<td>(0.17)</td>
<td>(0.17)</td>
</tr>
<tr>
<td>3.1 - 5.0</td>
<td>-0.72</td>
<td>-0.61</td>
<td>-0.75</td>
<td>-0.78</td>
<td>-0.65</td>
</tr>
<tr>
<td></td>
<td>(0.14)</td>
<td>(0.46)</td>
<td>(0.46)</td>
<td>(0.46)</td>
<td>(0.46)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Source of identification</th>
<th>All variation</th>
<th>RD only</th>
<th>RD only</th>
<th>RD only</th>
<th>RD only</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control for wait time</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Instrument for wait time</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Additional controls</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

This table presents price elasticity estimates for each discontinuous jump in price. Column (1) reports the raw elasticity estimates; Column (2) reports RD elasticity estimates; Column (3) reports RD estimates with expected wait time as a control; Column (4) reports RD estimates where expected wait time serves as an instrument; Column (5) reports instrumented RD estimates with additional controls for city and time of week. Standard errors are reported in parentheses. In each specification, the bottom three rows are the inverse variance weighted estimates taken from multiple discontinuities.
From price elasticities to consumer surplus

• Ideal data
  – Same pool of consumers offered all prices, holding all else constant
  – We observe $Q_D$ at each price

• What we have:
  – $Q_D|_{\text{surge}=1.0}$
  – $Q_D|_{\text{surge}=1.2}$
  – $Q_D|_{\text{surge}=1.3}$, etc.
The Basic Method

• Ignore, for now, the issues raised by the previous slide
  – Treat our elasticities like they represent a demand curve

• Compute the area under the curve and above the price for consumers who saw 1.0x surge

• Repeat for consumers who saw 1.2x, 1.3x, etc.

• Total everything up = $2.9 billion
Three Complications

• 1) Only see elasticity at a discrete set of surge prices
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• 2) See what the 1.2x sessions do, *not* what the 1x sessions would have done if facing 1.2x prices
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• 3) We can’t be sure all else is held constant as surge level changes because we do not observe outside options
  – (We think we have identification from RD, this is a subtler point)
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How Would 1.0x Sessions Have Behaved if They Were Shown Higher Prices?

• Approach #1: Re-weight data at higher surge prices so that the observables match the observables at 1.0x
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• (144 Geo-code) X (8 time of week) X (4 measures of customer usage intensity) X (2 measures of early or late in sample) = 9,216 cells

• Re-weight data at each surge level so that each of those 9,216 cells has the same share of observations as it did at 1.0x surge
How Would 1.0x Sessions Have Behaved if They Were Shown Higher Prices?

• Approach #2: Exploit the fact that both supply and demand conditions influence surge pricing; restrict ourselves to cases where high surge is present, even though demand is not unusually high
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• Approach #2: Exploit the fact that both supply and demand conditions influence surge pricing; restrict ourselves to cases where high surge is present, even though demand is not unusually high

• For each geographic area, regress ride requests on week fixed effects and time of week fixed effects
• Drop all observations where residual of that regression is >0
• Redo RD price elasticities and consumer surplus estimates
Three Complications

• 1) Only see elasticity at a discrete set of surge prices

• 2) See what the 1.2x sessions do, not what the 1x sessions would have done if facing 1.2x prices

• 3) We can’t be sure all else is held constant as surge level changes because we do not observe outside options
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Are Outside Options Changing as Surge Rises?

• Approach #1: Exploit the fact that consumers facing the same surge pricing experience different market conditions
Are Outside Options Changing as Surge Rises?

• Approach #1: Exploit the fact that consumers facing the same surge pricing experience different market conditions
• If outside options are not changing with market conditions, these consumers should have similar purchase rates
• Run regression of conversion rate on surge price and on company’s continuous measure of market conditions
• When surge changes by 1, conversion changes by .01
Are Outside Options Changing as Surge Rises?

• Approach #2: Exploit business rules that don’t allow surge to rise too quickly
Are Outside Options Changing as Surge Rises?

• Approach #2: Exploit business rules that don’t allow surge to rise too quickly

• No matter how bad market conditions get, surge only rises to 1.5x initially

• So consumers who “should” be seeing much higher surges don’t

• Do conversion rates systematically differ across these customers who see the same prices, even though market conditions radically differ?
Who Is Deriving the Benefit from This Product?

• Consumer surplus in U.S.: $6.8 billion

• Revenue to drivers: $8 billion
  – Most of that is not surplus
  – New entrants better off by revealed preference
  – Cramer (2016) suggests incumbent taxi drivers not hurt much

• The company receives only $2 billion in revenues