Economics of Transportation: Looking Ahead

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Motivation

• Recent theoretical and empirical breakthroughs for understanding transportation and the spatial distribution of economic activity

• Theoretical advances
  – New quantitative spatial models are rich enough to connect to features of the data (e.g. gravity) and undertake counterfactuals for realistic public policy interventions (e.g. new subway line)
  – New methods for thinking about optimal public policy interventions

• Recent empirical advances
  – Geographical Information Systems (GIS) revolution has provided more data at smaller spatial scales than hitherto possible
  – “Credibility revolution” in econometrics with greater attention to finding plausibly exogenous sources of variation to identify the causal effects of transport infrastructure improvements
Example #1: US Transport Network (Water) 1840
(Donaldson and Hornbeck 2016)
Example #1: US Transport Network (Water and Rail) 1911
(Donaldson and Hornbeck 2016)
Example #2: Benefits US Highway Investments 2012
(Allen and Arkolakis 2018)
Example #2: Benefits / Costs US Highway Investments 2012
(Allen and Arkolakis 2018)
Example #3: London Rail Network 1831
(Heblich, Redding and Sturm 2020)

Figure 1: Administrative Boundaries

Note: Home counties surrounding London (thick black outer boundary); Greater London Authority (GLA) referred to as Greater London (red outer boundary); London County Council (LCC) (purple outer boundary); City of London (green outer boundary); River Thames (thick blue); boroughs (medium black lines); and parishes (medium gray lines).

Figure 2: Overground Railway Network in Greater London 1841

Note: Greater London outside County of London (white background); County of London outside City of London (blue background); City of London (gray background); River Thames shown in blue; overground railway lines shown in black.
Example #3: London Rail Network 1921
(Heblich, Redding and Sturm 2020)

Note: Greater London outside County of London (white background); County of London outside City of London (blue background); City of London (gray background); River Thames shown in blue; overground railway lines shown in black; underground railway lines shown in red.

Example #4: London 1841-1921
Heblich, Redding and Sturm (2018)

Note: Greater London outside County of London (white background); County of London outside City of London (blue background); City of London (gray background); River Thames shown in blue; overground railway lines shown in black; underground railway lines shown in red.
Looking Ahead

• Theoretical opportunities
  – New methods to estimate the impact of transport improvements on the spatial distribution of economic activity
  – Improved understanding of heterogeneous effects
  – Greater knowledge of the determinants of the agglomeration forces that are central to the impact of transport improvements

• Empirical opportunities including big data
  – Ride-hailing data (e.g. Uber and Lyft)
  – Smartphone data with Global Positioning System (GPS) information
  – Firm-to-firm data from sales (VAT) tax records
  – Credit card data with consumer and firm location
  – Barcode scanner data with consumer and firm location
  – Public transportation commuting data (e.g. Oyster card)
  – Satellite imaging data
Example #1: Uber Data for Chicago (Cook, Diamond, Hall, List and Oyer 2019)

Figure 3: Features of geohashes
Note: This figure maps various features at the geohash-level for the City of Chicago. The distribution of trip locations is based on where trips originate. The geohashes used are more precise than those used in regressions, measuring about 0.75 miles on each side. Population numbers—both driver home locations as well as total adult population from the 2016 ACS—are smoothed by measuring population within one mile of a given geohash. Crimes include all non-residential crimes and are normalized by the number of crimes per 1,000 adult residents. Liquor licenses are based on number of unique businesses with a liquor license active during our time sample in a given geohash. Median household income is from the 2016 ACS. For crime and liquor licenses, the distributions are winsorized at 250 and 30, respectively, to allow for more informative coloring.

As drivers work more, they can begin to learn optimal driving behaviors to maximize earnings. As a result, none of the increased earnings with experience comes from a pre-set pay schedule that "mechanically" raises pay with experience. Any experience premium results from learning and increased driver productivity.

Another activity that may generate a return to experience is "dual-apping," which is when drivers accept trips from both Uber and a competitor (primarily Lyft). Dual-apping has the potential to increase earnings due to less time waiting for a dispatch and the ability to filter higher-value trips if the surge multiplier differs across platforms. We do not have a credible way to determine the degree to which this affects earnings nor whether specific drivers are dual-apping, so we cannot isolate dual-apping's contribution to the return to experience.

Haggag et al. (2017) show that learning-by-doing and experience are important for New York City taxi drivers. While drivers on Uber may learn in some ways similar to taxi drivers, there are likely important differences. For example, Uber rates fluctuate with surge prices (unlike fixed taxi fares), Uber uses an assignment algorithm to offer...
Example #2: Ride Hailing Data for Prague
(Buchholz, Doval, Kastl, Matejka and Salz 2020)

Core / Periphery
Boundary

Value of Time (USD/hr)
- 9.60 - 12.90
- 12.90 - 13.20
- 13.20 - 13.70
- 13.70 - 14.20
- 14.20 - 15.00
- 15.00 - 15.60
- 15.60 - 16.10
- 16.10 - 21.00
Example #3: US Visa Card Data
(Dolfen, Einav, Klenow, Klopack, Levin, Levin and Best 2020)
Example #4: Tokyo Smartphone Data
(Miyauchi, Nakajima and Redding 2020)
Example #5: London Public Transport Data
(Larcom, Rauch, Willems 2019)

The map illustrates the number of passengers using the stations as the first entry to their journey between 7:00am and 10:00am. Stations listed are the top 10 by volume. The area of the circles above equates to the number by their right.
Thank You