The Last Mile Matters: Impact of Dockless Bike Sharing on Subway Housing Price Premium

Junhong Chu, Yige Duan, Xianling Yang and Li Wang

ASSA 2020 Annual Meeting, San Diego
Motivation

- **Bike sharing as an effective solution to the last-mile problem**
  - With urban public transits, the first/last mile (door to station) of a trip is particularly costly
  - Dockless bike sharing offers a convenient and affordable means of transportation from/to subway stations
  - Stats in China (2017): 68% shared bike riders combine bikes with public transit; 90% report riding within 3km
Motivation

- **Bike sharing as an effective solution to the last-mile problem**
  - With urban public transits, the first/last mile (door to station) of a trip is particularly costly
  - Dockless bike sharing offers a convenient and affordable means of transportation from/to subway stations
  - Stats in China (2017): 68% shared bike riders combine bikes with public transit; 90% report riding within 3km

- **Effects on the Housing Market**
  - To avoid the last mile commuting costs, urban dwellers prefer to live close to subway stations ⇒ housing price premium
  - In the presence of shared bikes, living close to subway stations becomes less attractive ⇒ attenuate the housing price premium
Motivation

- **Bike sharing as an effective solution to the last-mile problem**
  - With urban public transits, the first/last mile (door to station) of a trip is particularly costly
  - Dockless bike sharing offers a convenient and affordable means of transportation from/to subway stations
  - Stats in China (2017): 68% shared bike riders combine bikes with public transit; 90% report riding within 3km

- **Effects on the Housing Market**
  - To avoid the last mile commuting costs, urban dwellers prefer to live close to subway stations ⇒ housing price premium
  - In the presence of shared bikes, living close to subway stations becomes less attractive ⇒ attenuate the housing price premium

- **Research Question**
  - How does bike sharing affect subway housing price premium?
  - Does the effect imply a reduction in commuting costs/solution to the last-mile problem?
Hedonic prices and equilibrium sorting: Use housing prices to reflect the “value” of living amenities (Rosen 1974, Chay and Greenstone 2005, Bayer et al. 2008, Freeman et al. 2017, etc.)
### Related Literature

- **Hedonic prices and equilibrium sorting**: Use housing prices to reflect the “value” of living amenities (Rosen 1974, Chay and Greenstone 2005, Bayer et al. 2008, Freeman et al. 2017, etc.)

- **Housing prices and access to subway**: Opening of new subway stations as quasi-natural experiments (Dewees 1976, Yiu and Wong 2005, Fesselmeyer and Liu 2017, etc.)
Hedonic prices and equilibrium sorting: Use housing prices to reflect the “value” of living amenities (Rosen 1974, Chay and Greenstone 2005, Bayer et al. 2008, Freeman et al. 2017, etc.)

Housing prices and access to subway: Opening of new subway stations as quasi-natural experiments (Dewees 1976, Yiu and Wong 2005, Fesselmeyer and Liu 2017, etc.)

Empirical Strategy

- A quasi-natural experiment: entry of bike sharing to 10 Chinese cities
- Exploit the difference in entry dates to implement DID

Solid lines: Ofo, Dashed lines: Mobike, Trends: Internet search
Empirical Strategy

\[ Y_{it}^{cs} = \beta_1 Dist_{it}^{cs} + \beta_2 Bike_t^c + \beta_3 Dist_{it}^{cs} Bike_t^c + \gamma X_{it}^{cs} + \alpha_s + t_c + \epsilon_{it}^{cs} \]

- \( Y_{it}^{cs} \): apartment \( i \)'s (log) price at time \( t \), in city \( c \)
- \( Dist_{it}^{cs} \): distance from apartment \( i \) to its nearest station \( s \) at time \( t \)
- \( Bike_t^c \): indicator of bike sharing’s entry to city \( c \) by time \( t \)
- \( X_{it}^{cs} \): apartment \( i \)'s characteristics at time \( t \)
- \( \alpha_s \) and \( t_c \): subway station F.E. and city-year-month F.E.
- \( \epsilon_{it}^{cs} \): standard errors clustered by subway station
Resale apartment data from a large Chinese real estate agency

- All apartments listed in mid-2015 to 2017, with housing characteristics, previous & up-to-date price listing
Data

- Resale apartment data from a large Chinese real estate agency
  - All apartments listed in mid-2015 to 2017, with housing characteristics, previous & up-to-date price listing

- Each apartment matched to the nearest subway station
  - By geodesic and walking distance
  - Limit to apartments within 3km to the nearest station
  - Limit to stations open before 2016 to avoid sample expansion over time
  - The resultant distance will decrease whenever a closer station is built

Sample: 617,271 price records from 399,840 apartments
Two-thirds apartments have 1 record
⇒ apartment F.E. not feasible
Can identify “building F.E.” from geo-coordinates
Data

- Resale apartment data from a large Chinese real estate agency
  - All apartments listed in mid-2015 to 2017, with housing characteristics, previous & up-to-date price listing

- Each apartment matched to the nearest subway station
  - By geodesic and walking distance
  - Limit to apartments within 3km to the nearest station
  - Limit to stations open before 2016 to avoid sample expansion over time
  - The resultant distance will decrease whenever a closer station is built

- Sample: 617,271 price records from 399,840 apartments
  - Two-thirds apartments have 1 record $\Rightarrow$ apartment F.E. not feasible
  - Can identify “building F.E.” from geo-coordinates
### Results

<table>
<thead>
<tr>
<th>Variables</th>
<th>Geodesic distance</th>
<th>Walking distance</th>
<th>Building F.E.</th>
<th>Bootstrap std. err.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Distance</td>
<td>-0.042 (0.003)</td>
<td>-0.026 (0.002)</td>
<td>0.006 (0.004)</td>
<td>-0.041 (0.004)</td>
</tr>
<tr>
<td>Bike sharing</td>
<td>-0.011 (0.005)</td>
<td>-0.014 (0.005)</td>
<td>-0.003 (0.004)</td>
<td>-0.002 (0.006)</td>
</tr>
<tr>
<td>Distance \times Bike sharing</td>
<td>0.012 (0.003)</td>
<td>0.009 (0.002)</td>
<td>0.012 (0.003)</td>
<td>0.011 (0.004)</td>
</tr>
<tr>
<td>Housing characteristics</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Subway station F.E.</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>City-year-month F.E.</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>617,271</td>
<td>593,429</td>
<td>617,271</td>
<td>617,271</td>
</tr>
<tr>
<td>Subway stations</td>
<td>1,424</td>
<td>1,424</td>
<td>1,424</td>
<td>1,424</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.91</td>
<td>0.91</td>
<td>0.98</td>
<td>0.91</td>
</tr>
</tbody>
</table>

*Implied willingness-to-pay for lower commuting costs $\approx 1,893–2,127$ CNY (282–317 USD) per household per year over 30 years*
Results

<table>
<thead>
<tr>
<th>Variables</th>
<th>Geodesic distance</th>
<th>Walking distance</th>
<th>Building F.E.</th>
<th>Bootstrap std. err.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Distance</td>
<td>-0.042</td>
<td>-0.026</td>
<td>0.006</td>
<td>-0.041</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.002)</td>
<td>(0.004)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Bike sharing</td>
<td>-0.011</td>
<td>-0.014</td>
<td>-0.003</td>
<td>-0.002</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.004)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>Distance</td>
<td>0.012</td>
<td>0.009</td>
<td>0.012</td>
<td>0.011</td>
</tr>
<tr>
<td>× Bike sharing</td>
<td>(0.003)</td>
<td>(0.002)</td>
<td>(0.003)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Housing characteristics</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Subway station F.E.</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>City-year-month F.E.</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>617,271</td>
<td>593,429</td>
<td>617,271</td>
<td>617,271</td>
</tr>
<tr>
<td>Subway stations</td>
<td>1,424</td>
<td>1,424</td>
<td>1,424</td>
<td>1,424</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.91</td>
<td>0.91</td>
<td>0.98</td>
<td>0.91</td>
</tr>
</tbody>
</table>

- Implied willingness-to-pay for lower commuting costs $\approx 1,893–2,127$ CNY (282–317 USD) per household per year over 30 years
Non-linear Estimates

The graph shows the estimated subway housing premium (% of price) as a function of distance to the nearest subway station (km). The data is divided into two categories: before entry and after entry. The graph indicates a significant drop in the premium as the distance increases, with a more pronounced decrease after the entry of the subway. The error bars suggest variability in the data points.
Alternative Explanations

- **Endogenous entry (e.g. anticipated entry, housing market price control, other confounding):**
  - City characteristics in 2015 cannot predict entry dates
  - Estimates robust to narrower time windows (90 or 183 days) and district-year-month fixed effects

- Expansion of public transit: Bus services declined in this period; estimates robust to excluding matches to new stations

- Chaos near subway stations: Exclude apartments within 500m

- Non-transiting rides: 68% users ride shared bikes for transiting purpose; estimates robust to excluding stations near shopping malls

- Reduced transaction costs for distant apartments: Frequency of visits by potential buyers does not increase
  - For the same potential buyer, the average distance-to-subway of his/her visits does not increase
Alternative Explanations

- **Endogenous entry (e.g. anticipated entry, housing market price control, other confounding):**
  - City characteristics in 2015 cannot predict entry dates
  - Estimates robust to narrower time windows (90 or 183 days) and district-year-month fixed effects

- **Expansion of public transit**: Bus services declined in this period; estimates robust to excluding matches to new stations
Alternative Explanations

- **Endogenous entry (e.g. anticipated entry, housing market price control, other confounding):**
  - City characteristics in 2015 cannot predict entry dates
  - Estimates robust to narrower time windows (90 or 183 days) and district-year-month fixed effects

- **Expansion of public transit:** Bus services declined in this period; estimates robust to excluding matches to new stations

- **Chaos near subway stations:** Exclude apartments within 500m

- Non-transiting rides: 68% users ride shared bikes for transiting purpose; estimates robust to excluding stations near shopping malls

- Reduced transaction costs for distant apartments: Frequency of visits by potential buyers does not increase
  - For the same potential buyer, the average distance-to-subway of his/her visits does not increase
Alternative Explanations

- **Endogenous entry (e.g. anticipated entry, housing market price control, other confounding):**
  - City characteristics in 2015 cannot predict entry dates
  - Estimates robust to narrower time windows (90 or 183 days) and district-year-month fixed effects

- **Expansion of public transit:** Bus services declined in this period; estimates robust to excluding matches to new stations

- **Chaos near subway stations:** Exclude apartments within 500m

- **Non-transiting rides:** 68% users ride shared bikes for transiting purpose; estimates robust to excluding stations near shopping malls
Alternative Explanations

- **Endogenous entry (e.g. anticipated entry, housing market price control, other confounding):**
  - City characteristics in 2015 cannot predict entry dates
  - Estimates robust to narrower time windows (90 or 183 days) and district-year-month fixed effects

- **Expansion of public transit:** Bus services declined in this period; estimates robust to excluding matches to new stations

- **Chaos near subway stations:** Exclude apartments within 500m

- **Non-transiting rides:** 68% users ride shared bikes for transiting purpose; estimates robust to excluding stations near shopping malls

- **Reduced transaction costs for distant apartments:**
  - Frequency of visits by potential buyers does not increase
  - For the same potential buyer, the average distance-to-subway of his/her visits does not increase
### Robustness & Additional Estimates

<table>
<thead>
<tr>
<th>Variables</th>
<th>Ofo entry</th>
<th>Mobike entry</th>
<th>Internet search</th>
<th>Within 2km</th>
<th>Within 4km</th>
<th>Within 5km</th>
</tr>
</thead>
<tbody>
<tr>
<td>Distance</td>
<td>-0.042</td>
<td>-0.042</td>
<td>-0.040</td>
<td>-0.041</td>
<td>-0.040</td>
<td>-0.039</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Distance × Bike sharing</td>
<td>0.013</td>
<td>0.011</td>
<td>0.010</td>
<td>0.014</td>
<td>0.008</td>
<td>0.007</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Observations</td>
<td>617,271</td>
<td>617,271</td>
<td>617,271</td>
<td>541,482</td>
<td>655,719</td>
<td>676,231</td>
</tr>
<tr>
<td>Subway stations</td>
<td>1,424</td>
<td>1,424</td>
<td>1,424</td>
<td>1,417</td>
<td>1,424</td>
<td>1,425</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.91</td>
<td>0.91</td>
<td>0.91</td>
<td>0.91</td>
<td>0.91</td>
<td>0.91</td>
</tr>
</tbody>
</table>
Main findings

- Exploiting the entry of bike sharing to 10 Chinese cities as a quasi-natural experiment, we find bike sharing reduces subway housing price premiums by approximately one-third.
- Various robustness checks validate that our estimates represent a causal effect.
- Using the estimates, we quantify the monetary value of bike sharing on solving the last mile problem.
Conclusion

**Main findings**
- Exploiting the entry of bike sharing to 10 Chinese cities as a quasi-natural experiment, we find bike sharing reduces subway housing price premiums by approximately one-third
- Various robustness checks validate that our estimates represent a causal effect
- Using the estimates, we quantify the monetary value of bike sharing on solving the last mile problem

**Contributions**
- We provide the first empirical evidence on the causal effect of dockless bike sharing on subway housing price premium & commuting costs
- The findings deliver policy implications for bike sharing companies (pricing and operation), policy makers (regulation and subsidy), urban residents and housing market practitioners (housing amenities)