The Impact of Opportunity Zones on Zone Residents

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OZ’s in context

- OZ’s are a new place-based policy that operates via incentives to investors in property
- Key prior place-based policy is EZs, which directly target hiring of low-skill workers
- Track record of EZs is spotty at best
  - Absence of clear evidence that policies have created jobs or raised incomes for low-income residents (Neumark and Simpson, HRUE, 2015; Neumark and Young, RSUE, 2019 [on EZs])
  - Even in cases when they do (federal EZs – Busso et al., 2013), benefits do not appear to go to low-income residents of targeted places (Reynolds and Rohlin, JUE, 2015)
- Most similar prior policy is New Markets Tax Credit
  - Led to more real-estate investment, but modest and costly poverty reductions (Freedman, JPubE, 2012)
Do OZs do any better? (Overview)

- Provide early evidence on impact of OZ designation on residents of zones
- Outcomes: employment, earnings, and poverty
- Use restricted-access ACS microdata at the census-tract level for 2013-2019
- Different identification strategies to compare treated and non-treated tracts
- Limited evidence of any positive impacts on residents of targeted neighborhoods
Outcomes in OZ research

- Other work has studied:
  - Jobs in tracts (Arefeva et al., 2020; Atkins et al., 2020)
  - Residential property prices (Chen et al., 2019)
  - Commercial property prices (Sage et al., 2019)
  - Real estate transactions and other activity (Frank et al., 2020)

- We provide early evidence on impact of OZ designation on residents of zones
Focus on residents aligns with program goals

• We focus on residents for two reasons
  – Major motivation for OZs is to improve outcomes for residents of distressed communities, as evidenced by LIC criteria (which are basis for nearly all designated zones)
  – Past work on place-based policies casts doubt on benefits for residents
• A priori, not clear why a program structured like OZs would be the most effective way to help zone residents
Data in brief

- Restricted-access ACS data at census tract level
  - Can measure outcomes at annual level; public data at tract level is averaged over 5 years
  - Census confidentiality likely limits our ability to disaggregate further – e.g., by type of OZ (LIC, contiguous, rural)
- Outcomes are overall employment among residents, employment/population, average earnings of employed residents, and poverty rate of residents
- Tract-by-year data, using person weights
- Focus on designated and eligible tracts that are LICs (by program criteria)
  - Fewer than 3% of designated tracts were not LICs
- ~7,600 OZ tracts, ~23,000 eligible but not designated tracts
OZ tracts have lower empl. and earnings and higher poverty than other LICs

<table>
<thead>
<tr>
<th></th>
<th>Treated Tracts (Opportunity Zone Tracts)</th>
<th>Potential Control Tracts (Other Low-Income Communities)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All Years (2013-2019)</td>
<td></td>
</tr>
<tr>
<td>Resident Employment Rate</td>
<td>0.52</td>
<td>0.56</td>
</tr>
<tr>
<td></td>
<td>(0.14)</td>
<td>(0.14)</td>
</tr>
<tr>
<td>Resident Poverty Rate</td>
<td>0.28</td>
<td>0.23</td>
</tr>
<tr>
<td></td>
<td>(0.17)</td>
<td>(0.16)</td>
</tr>
<tr>
<td>Resident Average Earnings</td>
<td>31,660</td>
<td>33,740</td>
</tr>
<tr>
<td></td>
<td>(13,600)</td>
<td>(12,950)</td>
</tr>
</tbody>
</table>
Empirical approach using all LICs as controls

- Begin with D-in-D model, similar to other recent papers

\[ y_{i,t} = \beta OZ_i \times Post_t + \gamma_i + \eta_t + \varepsilon_{i,t} \]

- Alternately treat Post as 2019, or 2018 and 2019 (OZs in effect for about half of 2018)

- Highly saturate model to include state x year, PUMA x year, or county x year fixed effects to control for differential changes in broader geographies containing the OZ tracts
  - Effectively narrows control tracts to those in the same geography
  - Extend to event study framework estimating treatment effects (including leads) by year

\[ y_{i,t} = \sum_l \{\beta OZ_i \times Post_l\} + \gamma_i + \eta_t + \varepsilon_{i,t} \]
Empirical approach matched LICs as controls

- Still concerned that OZ designation associated with underlying trends/changes
- Use propensity score matching
- Define pre to post change

\[(y_{i,2019} - y_{i,2017}) - (y_{i,2017} - y_{i,2013})\]

- Match on 2013-2017 levels of each outcome, based on nearest neighbor (closest propensity score)
  - Minimizes difference between treated and control tracts in terms of evolution of pre-treatment outcomes
  - Also estimate event study regressions for these matched tracts
- Provides more reliable causal estimates – and in this case it matters!
OZs appear to increase employment and reduce poverty of residents...

<table>
<thead>
<tr>
<th></th>
<th>Employment</th>
<th>Employment rate</th>
<th>Earnings</th>
<th>Poverty rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>OZ in 2019</td>
<td>26.02***</td>
<td>.007***</td>
<td>69.58</td>
<td>-0.012***</td>
</tr>
<tr>
<td></td>
<td>(8.83)</td>
<td>(0.002)</td>
<td>(170.8)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>OZ in 2018-19</td>
<td>21.21***</td>
<td>0.007***</td>
<td>227.0*</td>
<td>-0.011***</td>
</tr>
<tr>
<td></td>
<td>(6.62)</td>
<td>(0.001)</td>
<td>(129.7)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Tract FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>County-Year FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>
But apparent effects largely driven by prior trends
But apparent effects largely driven by prior trends

Employment rate

<table>
<thead>
<tr>
<th>Year</th>
<th>Baseline Model Point Estimates</th>
<th>Baseline Model 95% Confidence Interval</th>
<th>Saturated Model Point Estimates</th>
<th>Saturated Model 95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>2013</td>
<td>-0.01</td>
<td>-0.01 - 0.00</td>
<td>-0.005</td>
<td>-0.005 - 0.01</td>
</tr>
<tr>
<td>2014</td>
<td>-0.005</td>
<td>-0.01 - 0.00</td>
<td>0</td>
<td>0 - 0.01</td>
</tr>
<tr>
<td>2015</td>
<td>0</td>
<td>0 - 0.01</td>
<td>0.005</td>
<td>0.005 - 0.01</td>
</tr>
<tr>
<td>2016</td>
<td>0.01</td>
<td>0.005 - 0.01</td>
<td>0.01</td>
<td>0.01 - 0.02</td>
</tr>
<tr>
<td>2017</td>
<td>0.01</td>
<td>0.01 - 0.02</td>
<td>0.01</td>
<td>0.01 - 0.02</td>
</tr>
<tr>
<td>2018</td>
<td>0.01</td>
<td>0.01 - 0.02</td>
<td>0.01</td>
<td>0.01 - 0.02</td>
</tr>
<tr>
<td>2019</td>
<td>0.01</td>
<td>0.01 - 0.02</td>
<td>0.01</td>
<td>0.01 - 0.02</td>
</tr>
</tbody>
</table>
But apparent effects largely driven by prior trends

Earnings

Baseline Model Point Estimates
- Saturated Model Point Estimates

95% Confidence Interval
But apparent effects largely driven by prior trends
Matching estimates confirm there is little or no impact of OZs – D-in-D regressions

<table>
<thead>
<tr>
<th></th>
<th>Employment</th>
<th>Employment Rate</th>
<th>Avg. Earnings</th>
<th>Poverty Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>OZ</td>
<td>23.56</td>
<td>0.00387</td>
<td>434.9</td>
<td>-0.00654</td>
</tr>
<tr>
<td></td>
<td>(17.83)</td>
<td>(0.004219)</td>
<td>(353.2)</td>
<td>(0.004721)</td>
</tr>
<tr>
<td>Observations (Tracts)</td>
<td>15200</td>
<td>15200</td>
<td>15200</td>
<td>15200</td>
</tr>
</tbody>
</table>

SE’s larger, but employment and poverty rate estimates cut in half relative to standard D-in-D regressions.
Matching estimates confirm there is little or no impact of OZs – event study

Employment

Matching-Based Point Estimates
95% Confidence Interval
Matching estimates confirm there is little or no impact of OZs – event-study

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</tr>
</thead>
<tbody>
<tr>
<td>Estimate</td>
<td>Matching-Based Model Point Estimates</td>
<td>95% Confidence Interval</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>-0.01</td>
<td>-0.005</td>
<td>0</td>
<td>0.005</td>
<td>0.01</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Matching estimates confirm there is little or no impact of OZs – event-study.
Matching estimates confirm there is little or no impact of OZs – event-study

Poverty rate

Matching-Based Point Estimates

95% Confidence Interval

Year


Matching-Based Point Estimates

95% Confidence Interval
## Implications of magnitudes from matching estimates/confidence intervals

<table>
<thead>
<tr>
<th>Estimated effect</th>
<th>Employment</th>
<th>Employment Rate</th>
<th>Avg. Earnings</th>
<th>Poverty Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>No</td>
<td>23.6</td>
<td>0.4 p.p.</td>
<td>$434</td>
<td>-0.7 p.p.</td>
</tr>
<tr>
<td>Statistically significant?</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Rule out with 95% confidence</td>
<td>&gt; 59</td>
<td>&gt; 1.2 p.p.</td>
<td>&gt; $1,127</td>
<td>&lt; -1.6 p.p.</td>
</tr>
</tbody>
</table>
Conclusions/Discussion

- Limited or no statistical evidence of positive effects of OZs
- Estimates sufficiently precise to rule out substantial effects
- Methods matters – pre-trends badly contaminate evidence
- Contributes to mixed evidence; fuller picture needed
  - We will turn to other outcomes related to tracts, not just residents
- Evidence is “early,” but the pandemic is going to severely limit our ability to use more data to learn about the effectiveness of OZs
- My own view: we should focus on programs that more directly target incentives and resources on lower-skilled residents of disadvantaged areas
  - Two different approaches considered in recent *JPAM* exchange between me and Tim Bartik