

# **The Impact of Opportunity Zones on Zone Residents**

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**Matthew Freedman**

**Shantanu Khanna**

**David Neumark**

# 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)

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- 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

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- 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

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- 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

	Treated Tracts (Opportunity Zone Tracts)
	All Years (2013-2019)
Resident Employment Rate	0.52 (0.14)
Resident Poverty Rate	0.28 (0.17)
Resident Average Earnings	31,660 (13,600)
	Potential Control Tracts (Other Low-Income Communities)
Resident Employment Rate	0.56 (0.14)
Resident Poverty Rate	0.23 (0.16)
Resident Average Earnings	33,740 (12,950)

# 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

$$(y_{i,2019} - y_{i,2017}) - (y_{i,2017} - y_{i,2013})$$

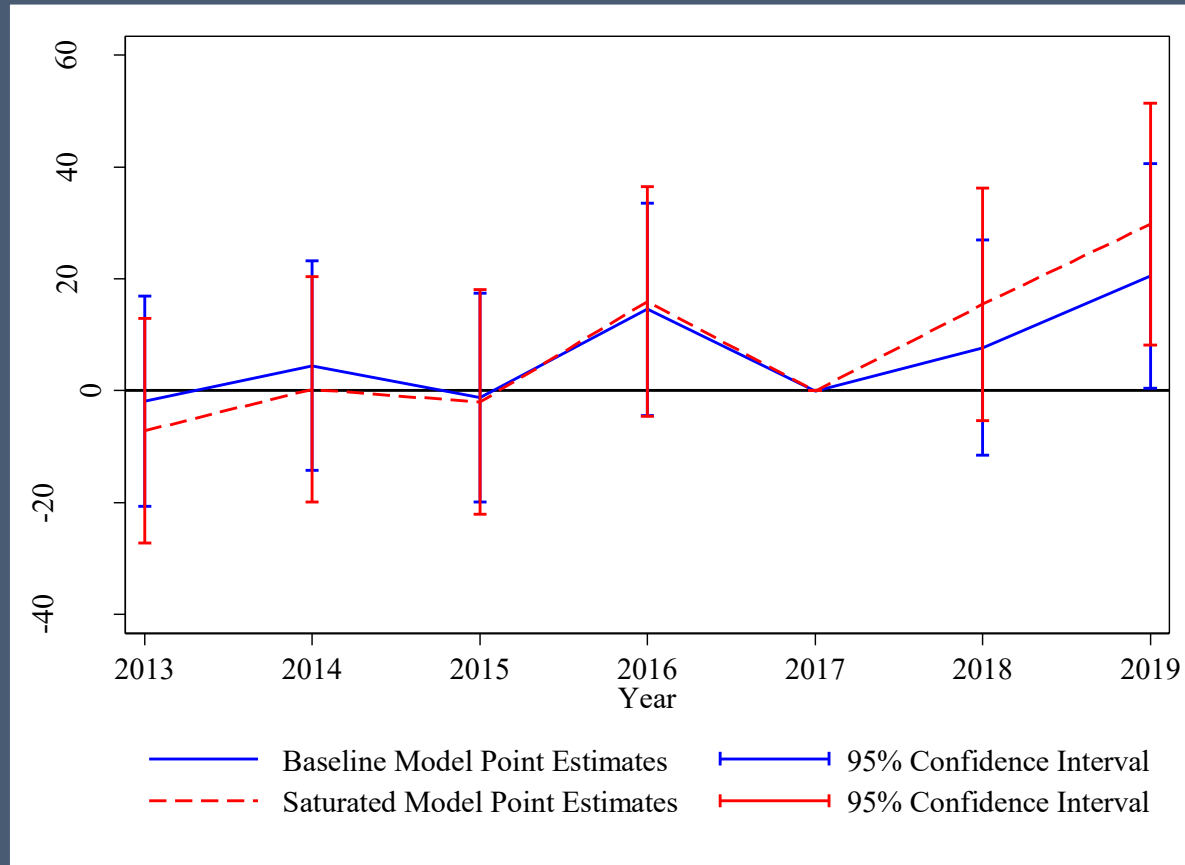
- Match on 2013-2017 levels of each outcome, based on nearest neighbor (closest propensity score)
  - Minimizes difference between treated and control tracts in terms of evolution of pre-treatment outcomes
  - Also estimate event study regressions for these matched tracts
- Provides more reliable causal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

# OZs appear to increase employment and reduce poverty of residents...

	Employment		Employment rate		Earnings		Poverty rate	
OZ in 2019	26.02***		.007***		69.58		-0.012***	
	(8.833)		(0.002)		(170.8)		(0.002)	
OZ in 2018-19		21.21***		0.007***		227.0*		-0.011***
		(6.62)		(0.001)		(129.7)		(0.002)
Tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

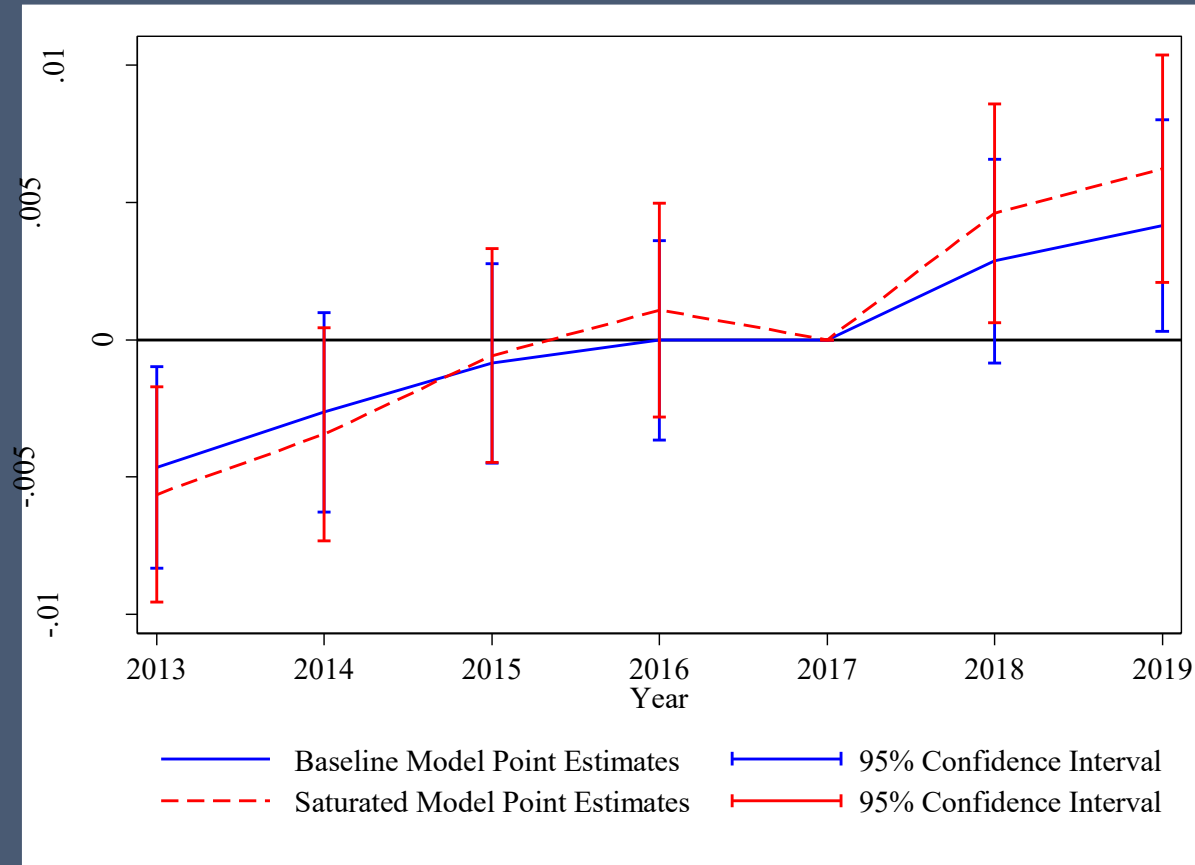
# But apparent effects largely driven by prior trends

## Employment



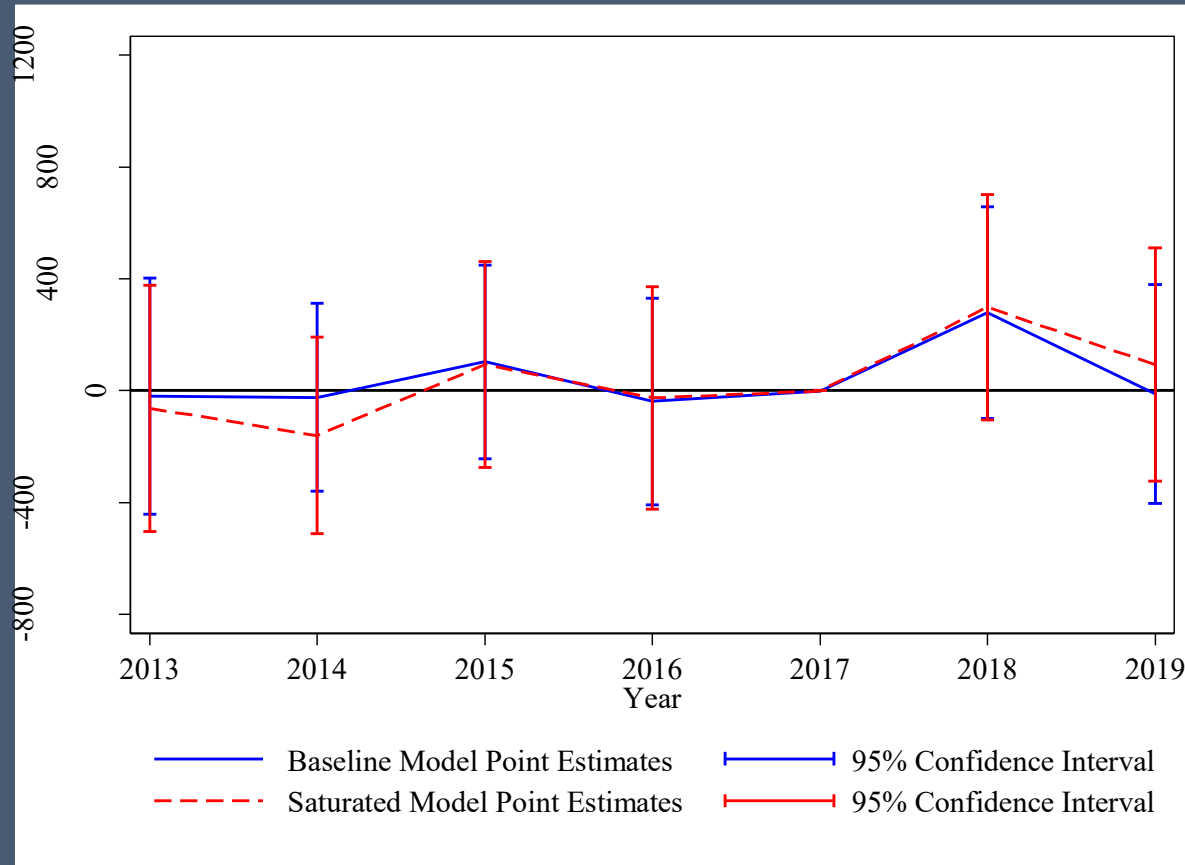
# But apparent effects largely driven by prior trends

## Employment rate



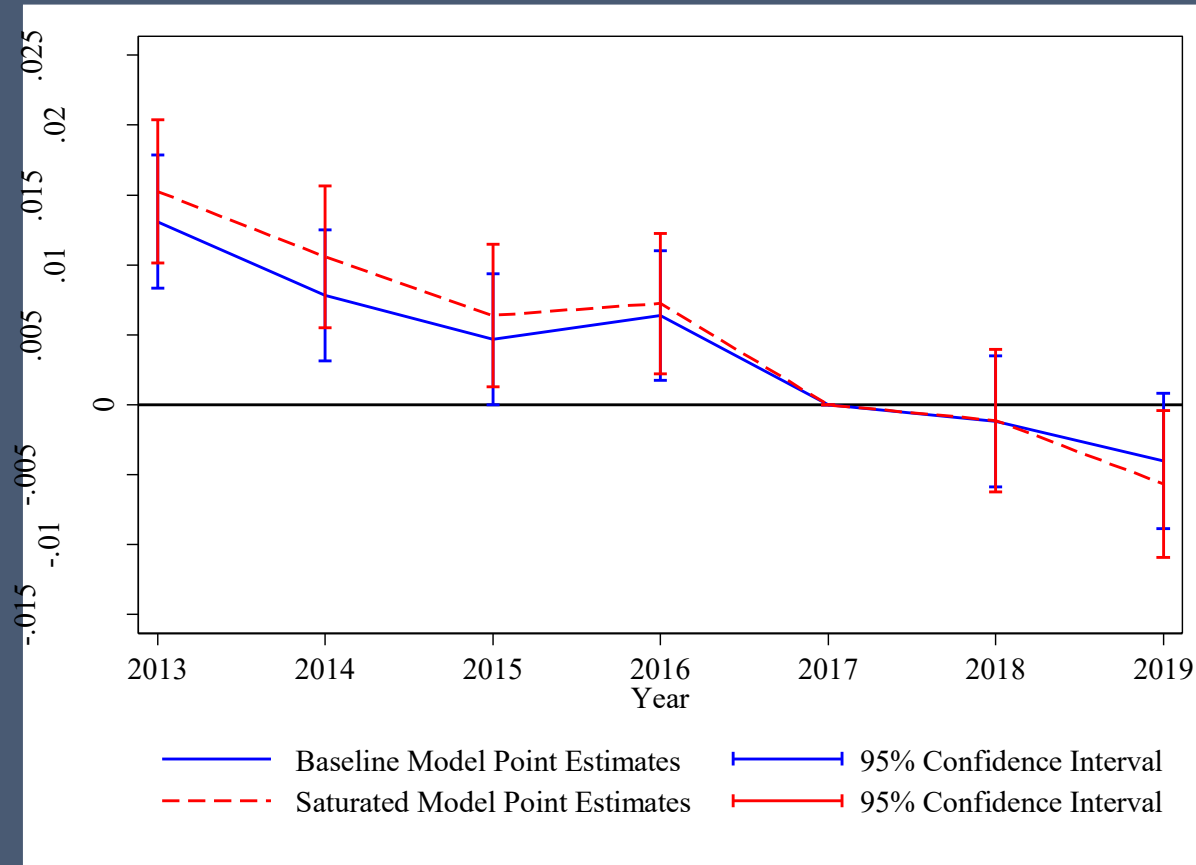
# But apparent effects largely driven by prior trends

## Earnings



# But apparent effects largely driven by prior trends

## Poverty rate



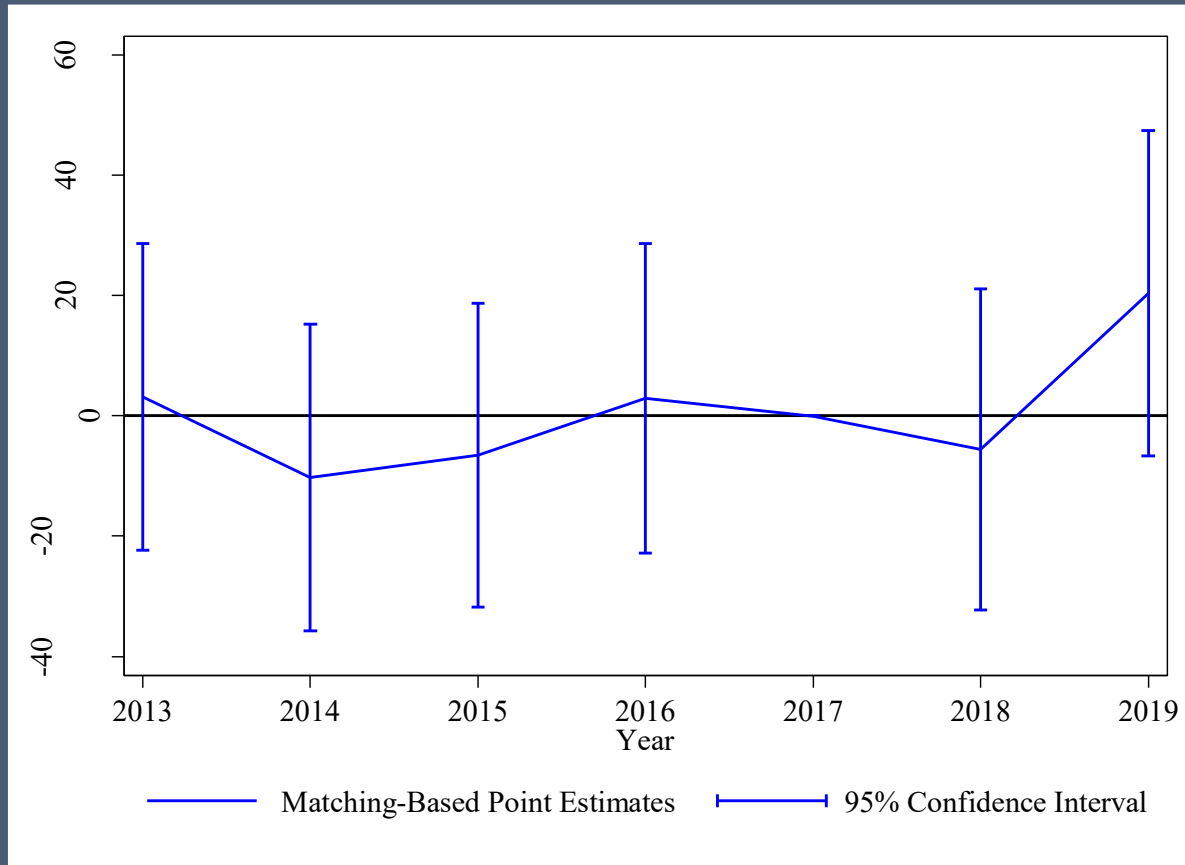
# Matching estimates confirm there is little or no impact of OZs – D-in-D regressions

	Employment	Employment Rate	Avg. Earnings	Poverty Rate
OZ	23.56	0.00387	434.9	-0.00654
	(17.83)	(0.004219)	(353.2)	(0.004721)
Observations (Tracts)	15200	15200	15200	15200

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

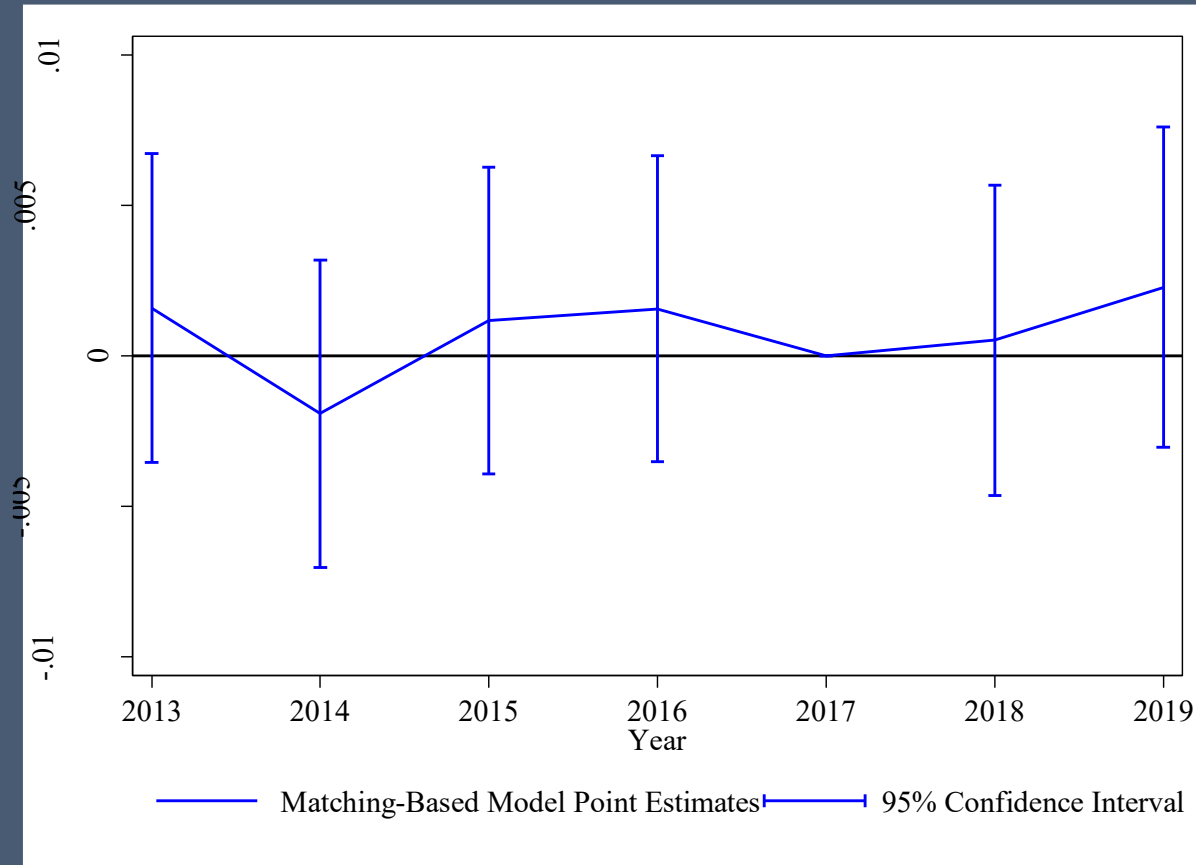
## Employment





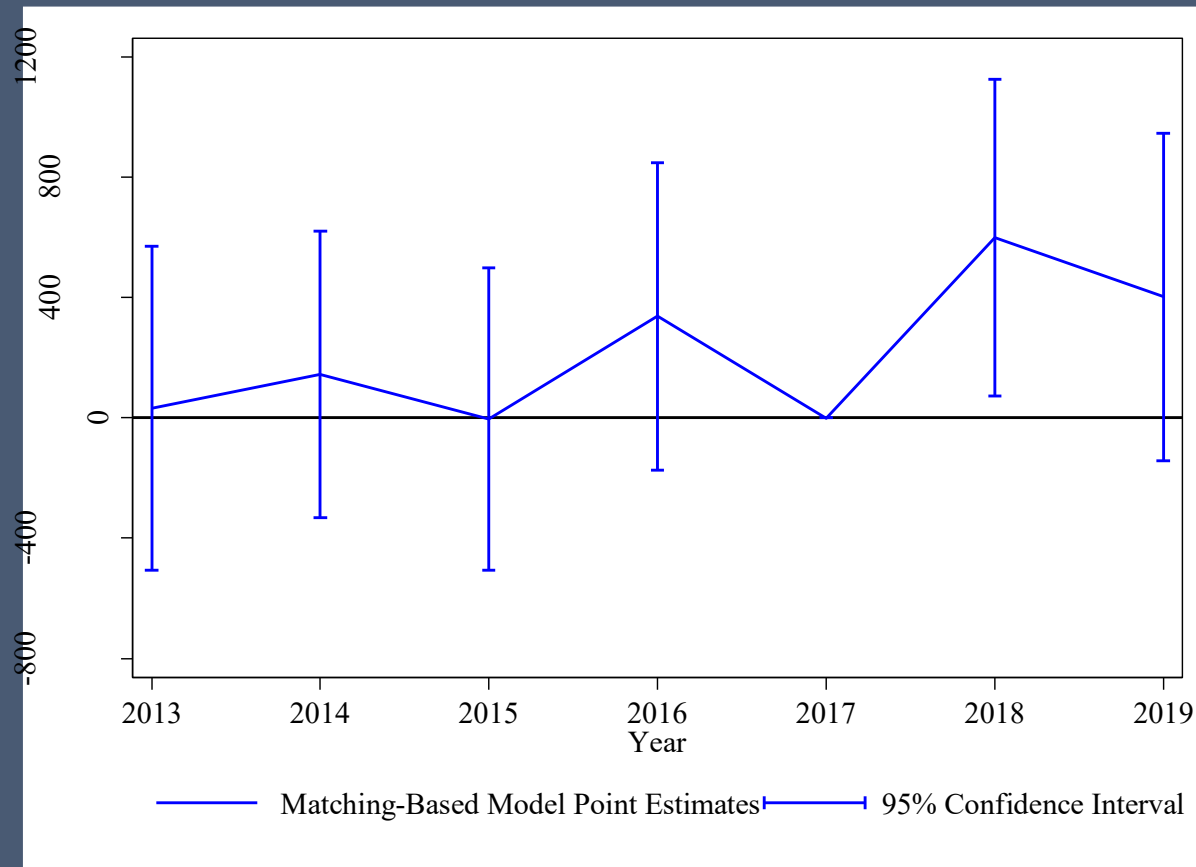
# Matching estimates confirm there is little or no impact of OZs – event-study

Employment rate



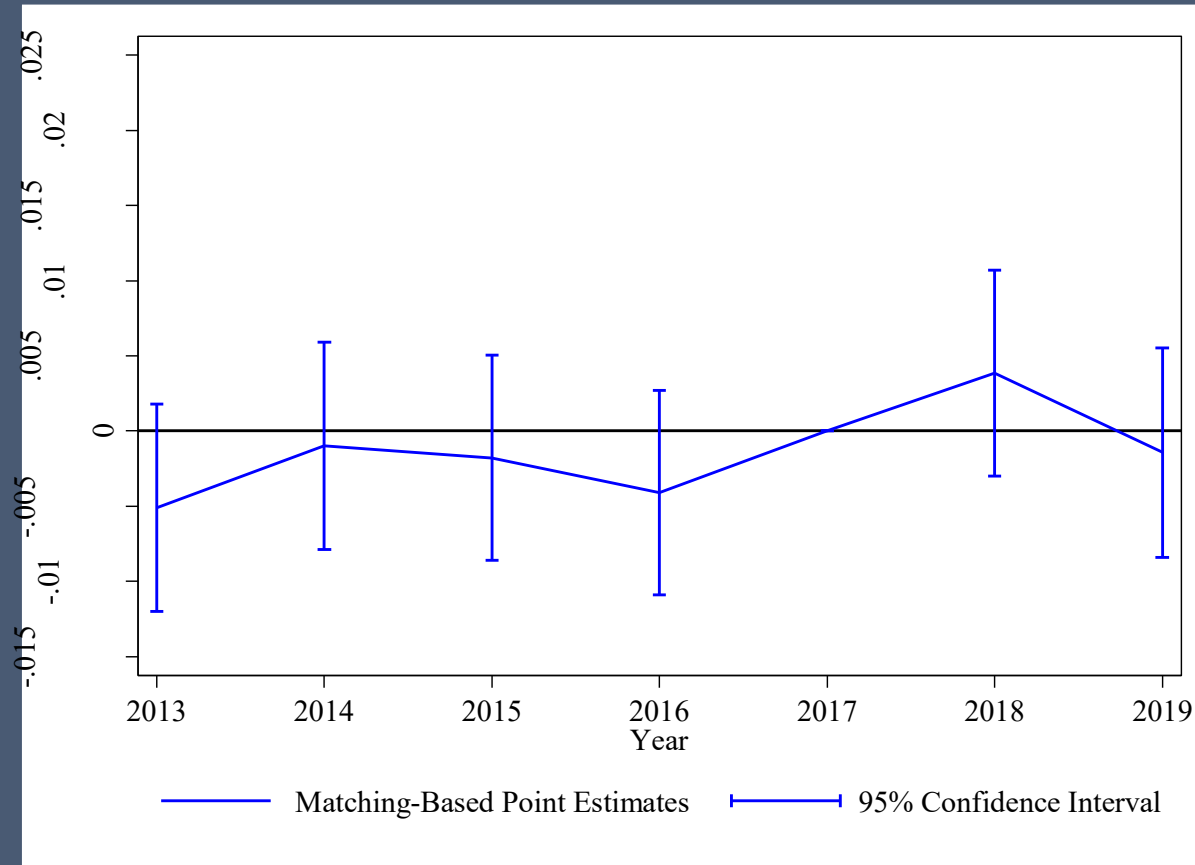
# Matching estimates confirm there is little or no impact of OZs – event-study

## Earnings



# Matching estimates confirm there is little or no impact of OZs – event-study

Poverty rate



# Implications of magnitudes from matching estimates/confidence intervals

	Employment	Employment Rate	Avg. Earnings	Poverty Rate
Estimated effect	23.6	0.4 p.p.	\$434	-0.7 p.p.
Statistically significant?	No	No	No	No
Rule out with 95% confidence	> 59	> 1.2 p.p.	> \$1,127	< -1.6 p.p.

# 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
  - <https://onlinelibrary.wiley.com/toc/15206688/2020/39/3>