What is the Impact of Opportunity Zones on Employment?

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“OZs chart a new course in Federal policy aimed at uplifting distressed communities…. OZs cut taxes to increase economic activity by spurring private sector investment, job creation, and self-sufficiency.”

-Economic Report of the President, 2021

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How we study the effect of OZs on employment

- Use Burning Glass job postings and posted wages (Jan 2015 – Dec 2020)
- Focus on zip codes for data reasons (next slide)
- Focus only on zip codes w/tracts that qualified as OZ via low-income status
  - Most direct way to assess efficacy of program in “uplifting distressed communities”
- Compare job vacancies and wages in “treated” zip codes to closely matched zip codes, pre and post OZ designation (pre Jan 2018 and post Dec 2018)
  - Also look at effects of Covid on OZs

Why we use Burning Glass data

- Burning Glass captures nearly the universe of job postings, and wages for many of these jobs
  - Though, missing wage data for 30-40% of vacancies
  - Data is better at the zip code level, not census tract
- The data is timely (monthly data, Jan 2015 – Dec 2020)
- Job posting data is a leading indicator of employment outcomes
  - Quarterly Census of Employment and Wages
  - Zip Code Business Pattern
- The data is reliable; growing use in academic papers (e.g., Acemoglu et al 2020, Azar et al, 2020, Forsythe et al 2020, Goldfarb et al, 2020)

Steps

- Selection
  - What are the characteristics of the census tracts designated as OZs?
- Creation of propensity score
  - For each state, predict census tract OZ designation; aggregate to zip code level; match to similar zip codes with no OZ tracts
- Employment outcomes
  - Panel data regression models comparing job postings and posted wages across treated and control zip codes
  - Use an additional selection approach to address missing posted wages data
- Robustness tests and treatment heterogeneity

OZ Selection (census tract; selected coefficients)

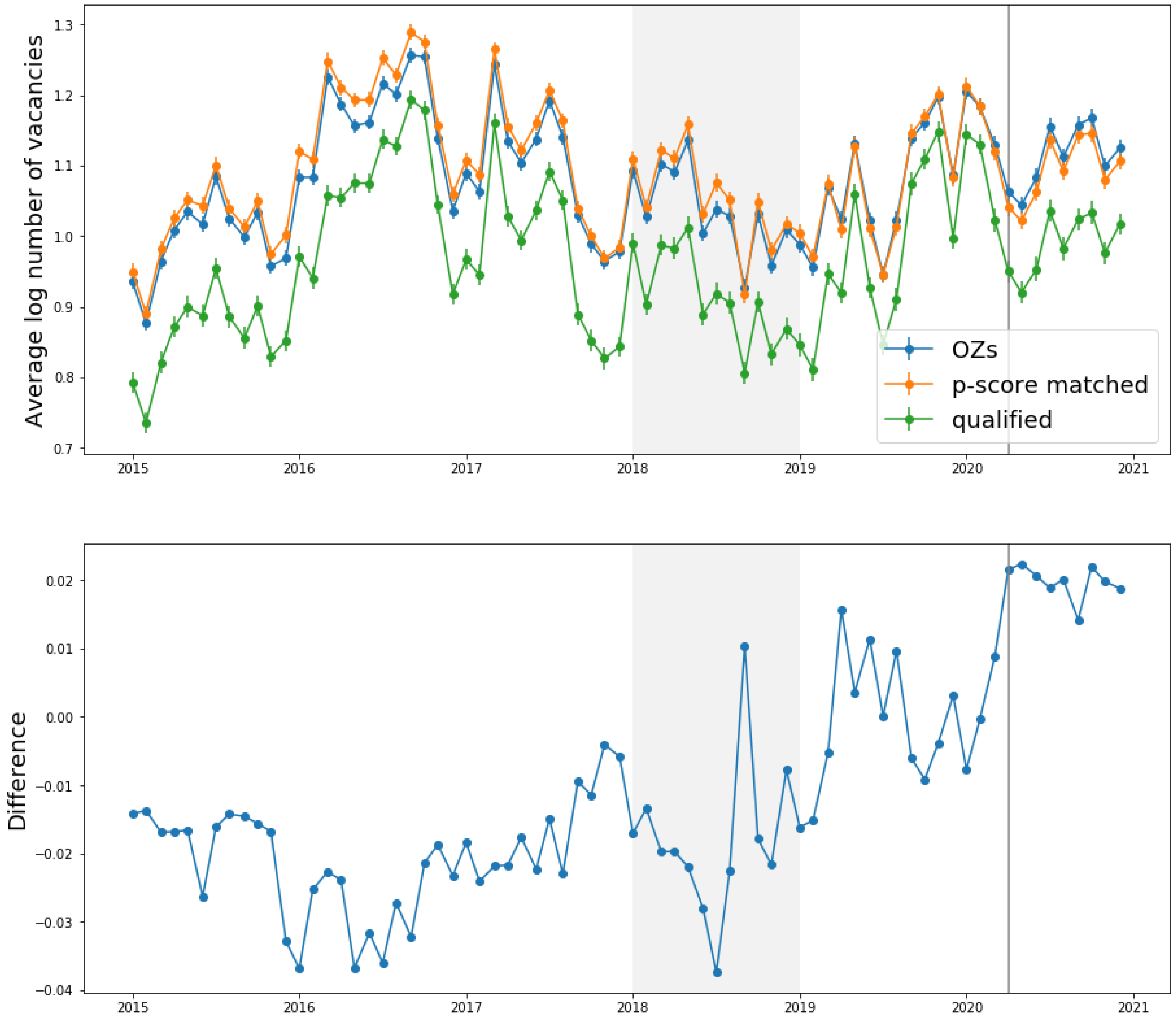
	(1) OZ dummy	(2) OZ dummy	(3) OZ dummy	(4) OZ dummy
income-qualified	0.102***			
	(0.00769)			
poverty-qualified	0.159***			
	(0.00545)			
percent-black		0.0409***	0.0374***	0.0629***
		(0.0109)	(0.0110)	(0.0121)
percent-hispanic		-0.135***	-0.137***	-0.117***
		(0.0147)	(0.0147)	(0.0154)
same-party (dem)				0.0127
				(0.00923)
same-party (rep)				0.0443***
				(0.00701)
income growth (YoY)			0.0773***	0.0745***
			(0.0211)	(0.0212)
other controls	Yes	Yes	Yes	Yes
State fe	Yes	Yes	Yes	Yes
N	32994	32803	32680	32501
adj. R^2	0.028	0.068	0.068	0.070
AIC	35736.8	34130.9	33968.9	33740.3

Controls include: percent-asian, percent-other-non-white, urban dummy, population, poverty, income-ratio, bachelors or higher, and pop growth (YoY).

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

OZ and Job Vacancies, Raw Data



Regressions

$$Y_{jt} = \alpha_0 + \sigma_j + \tau_t + \theta T_j \times I[t > 2018] + \gamma T_j \times I[t \geq 2020 March] + \epsilon_{jt},$$

job postings or posted wages for zip code *j* in month *t*

zip code *j* and month *t* fixed effects

role of OZ designation

role of Covid

clustered at zip code (and other levels)

OZ and Job Vacancies

	(1) N. of Vacancies	(2) N. of Vacancies	(3) N. of Vacancies	(4) N. of Vacancies
OZ × Post 2018	0.0299	0.0299	-0.000163	-0.000163
	(0.0350)	(0.0601)	(0.0337)	(0.0591)
OZ × Post-COVID			0.0821*	0.0821
			(0.0330)	(0.0436)
Year-month fe	Yes	Yes	Yes	Yes
Zipcode fe	Yes	Yes	Yes	Yes
Errors clustering	Zipcode	State	Zipcode	State
Estimation method	Poisson	Poisson	Poisson	Poisson
N	676560	676560	676560	676560
AIC	12703253.0	12703225.0	12686199.9	12686171.9

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OZ and Posted Wages

	(1) Avg. Hourly Wage	(2) Avg. Hourly Wage	(3) Avg. Hourly Wage	(4) Avg. Hourly Wage
OZ × Post 2018	0.0155***	0.0155*	0.0206***	0.0206**
	(0.00271)	(0.00675)	(0.00547)	(0.00722)
OZ × Post-COVID			-0.0131*	-0.0131
			(0.00577)	(0.00828)
Year-month fe	Yes	Yes	Yes	Yes
Zipcode fe	Yes	Yes	Yes	Yes
Errors clustering	Zipcode	State	Zipcode	State
Estimation method	OLS-Heckman	OLS-Heckman	OLS-Heckman	OLS-Heckman
N	396485	396485	396485	396485
adj. R^2	0.038	0.065	0.065	0.065
AIC	411722.6	411694.6	411712.3	411684.3

Standard errors in parentheses

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Additional results

- Variety of robustness tests
  - Cluster at different levels (results are somewhat sensitive to clustering)
  - Include additional time-varying controls (no difference)
  - Designate end of 2^{nd} quarter 2018 as time of treatment (no difference)
  - Compare treated zips to all qualified zips, rather than smaller control sample (sign flips for wage)
- Heterogeneous effects:
  - Results by state
  - Industry specific outcomes: Construction and Real Estate (no discernible difference)
  - Above and below median black population (no discernible difference)
  - Heavily vs less heavily treated zip codes (slightly stronger wage results for heavily treated)

Concluding thoughts

Interpretation

- Little evidence that OZ designation is associated with higher job postings in low-income OZ areas
- Some evidence that OZ designation effect on job postings is increasing over time, but not clear if due to OZ program or Covid-related policies
- Some evidence that OZ designation is associated with higher posted salaries
- Job postings are a good indicator of employment outcomes → no evidence that OZ has led to employment gains (yet)

Caveat

- OZs are relatively new; effect on employment could manifest in the future

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