Where is the Opportunity in Opportunity Zones? Early Indicators of the Opportunity Zone Program's Impact on Commercial Property Prices

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Abstract

In December 2017, the U.S. Congress passed into law the Opportunity Zone (OZ) program, offering significant tax benefits for property investments in designated low-income census tracts. As investors effectively gain from higher income, opportunity zones should affect property prices. In this study, we compare transaction prices of properties located in designated and eligible OZ census tracts, using a structural time series approach to estimate a hierarchical repeat sales price index. We find that OZ designation did not impact all properties prices, but resulted in a 14% price increase for "redevelopment" properties and a 20% price increase for vacant development sites. We do not find an expectation effect prior to designation. Our findings suggest that the OZ program has thus far primarily passed through the statutory tax benefits to existing land owners, with limited evidence of additional value creation.

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1. Introduction

In December 2017, the United States Congress passed the *Tax Cuts and Jobs Act of 2017*, including numerous widely publicized provisions to reduce corporate tax rates and modify income tax brackets for individuals. Many criticized the reform for increasing income inequality and deepening the US budget deficit.[1] At its heart comes a measure with unambiguous potential to stimulate low-income neighborhoods: Opportunity Zones (OZ). Meant as a development tool, the OZ program should spur local economic growth and job creation in distressed communities by offering location-based (census tract) tax breaks and deferrals to investors.

Following a selection process with strict eligibility requirements, such as poverty rates above 20% and median family income below 80% the metro or state average, approximately 9,000 census tracts across the US were officially designated as OZs between April and July 2018. OZs specifically target economically obsolete/heavily depreciated properties. To qualify for the tax incentive, properties must undergo a capital improvement at least equal to the initial acquisition expense within 30 months of purchase, thereby privileging new development and significant rehab. Acquisition of existing properties in designated OZs does not in and of itself qualify an investor to receive tax benefits.

Assuming that real estate markets are efficient, future OZ tax benefits should be priced into property transactions (Smith, 2009). The tax incentives themselves result in a direct increase in an investor's post-tax internal rate of return. In addition, investments could lead to increased productivity and land values in OZs, as well as spillover benefits.

This study focuses on the recognition of OZs among commercial property investors, examining the effect on commercial property prices. We test if the designation of OZs has an (positive) impact on commercial property prices and if

[1] Retrieved Spring 2019: `https://wapo.st/2XG5DWl`

so, how price effects compare to future tax benefits. To ensure a clean identification strategy, we use a difference-in-differences (DID) setup with propensity score matching (PSM), to explore property price differences between eligible and designated OZs, before and after designation.[2]

For our analysis, we use commercial real estate transactions data made available by Real Capital Analytics Inc (RCA), focusing on repeated sales of existing properties, repeated sales of "redevelopment properties", and pseudo-repeat sales of vacant land (sales that occur in the same census tract). However, as the OZ program started only several months ago and repeated-sales observations are generally difficult to obtain, we employ a structural time series hierarchical repeat sales model (Francke and Van de Minne, 2017), allowing us to simulate observational gaps. Similar to Geltner et al. (2017) we use a difference in differences specification of the model.

We find that while existing properties overall did not exhibit a significant increase in price after OZ designation, the prices of redevelopment properties (depreciated properties likely to be redeveloped) increase by 14.2%, and the prices of vacant land increase by 20.9%. We also test for an expectation effect for properties in eligible census tracts prior to OZ designation. While we do not find a statistically significant expectation effect, the results of the designation premium remained robust. We perform further robustness checks through a set of placebo experiments which show uniformly insignificant results for a placebo OZ designation coefficient.

Our finding that OZ designation significantly increased prices of redevelopment properties and vacant sites, but not existing properties, suggests that (some of) the tax benefit is priced into land sales. In the same vein, investors do not appear to have ascribed any future NOI growth to OZs resulting from the designation.

[2]As the OZ program was established only recently, it is too early to assess its long-term success on stimulating economic development at this point in time.

These findings call into question the capacity of the program to create value in low-income communities. If NOI were expected to grow in OZs, we could infer that the program demonstrated the potential to increase productivity in target areas. Rather, the program may instead be offering higher sale prices to existing OZ landowners for transactions that would have occurred in the absence of the program.

To our knowledge, this is the first academic paper estimating the effect of designating OZs on property prices. We are also among the first to show how tax incentives translate into commercial real estate property prices. Prior research on similar place-based tax incentive programs has primarily discussed second-order effects on socioeconomic indicators and residential housing prices growth rather than on changes in commercial real estate values (see Section 2).

2. Background and Theory

2.1. Location-based Tax Incentives

As a response to previous state and federal place-based tax incentives, yielding mixed results, Bernstein and Hassett (2015) first proposed the framework for the OZ program as an alternative. Prior and existing programs, such as state *enterprise zones* (EZ), the federal *Empowerment Zone/Enterprise Community* (EZ/EC) program and the federal *New Markets Tax Credit* (NMTC), have suffered from complex tax regulations and shallow subsidy levels, failing to sufficiently spur increased investment and employment in distressed communities.

The state EZ and federal EZ/EC programs are the most relevant predecessors to OZs. While the exact form of EZs and the magnitude of incentives differs measurably from state to state, they have all included some combination of wage tax credits for employees, capital investment tax credits (ITCs), property tax credits, and sales tax exemptions within a specific designated geographic region. While an EZ program existed in some incarnation within 75% of all states across

the country by 1990 (Peters and Fisher, 2002), incentives were smaller than those offered for OZs. Peters and Fisher (2004) note that the principal benefit of EZs, the wage tax credit, was often too small to matter, as a firm's wage expense was about 11 times the size of its tax expense. Tellingly, in an interim assessment of the federal EZ program, 65% of all businesses in EZs reported no noticeable benefits associated with being located in an EZ (Hebert et al., 2001).

Some studies analyzing state EZs and federal EZ/ECs show statistically significant positive effects on socioeconomic measures (employment, wages, firm starts) (see Busso et al., 2013; Hanson and Rohlin, 2011; Papke, 1993, 1994; Greenbaum and Engberg, 2004, among others), whereas others show limited impacts on similar outcomes (see Elvery, 2009; Neumark and Kolko, 2010; Engberg and Greenbaum, 1999, among others).[3] Unfortunately, fewer studies look at the impact of incentive programs on real estate, and none on commercial real estate to our knowledge. Krupka and Noonan (2009) do find that median home value price appreciation occurred 25% faster in federal EZs compared to what would have happened without the program. In contrast, Boarnet and Bogart (1996) find that New Jersey's state EZ program did not have any statistically significant impact on municipal property values.

While also restricted to low-income communities, the NMTC program differs somewhat from OZs and EZs, providing a capped allocation of tax credits which are competitively awarded to individual projects or companies. While much of the literature again looks at the program's impact on socioeconomic outcomes, such as employment or food access (see Harger and Ross, 2016; Freedman, 2018, among others), Freedman (2012) do find a 2% increase in median home values for every $1 million in NMTC investment in low-income neighborhoods.

Prior to being passed as part of the larger Tax Cuts and Jobs Act in December

[3]Boarnet (2001) suggests that findings diverge due to methodological inconsistency in addressing quasi-random designation of zones from a pool of eligible zones

2017, OZs were first formally introduced at the federal level within the Investing in Opportunity Act in February 2017.[4] Similarly to other federal tax incentives that leverage private sector capital to spur investment, such as the NMTC, OZs have significantly benefited from bipartisan support.

After the bill was passed, census tracts were first required to meet one of a number of eligibility requirements, specifically a poverty rate of greater than 20% or a tract median family income below 80% of that of the corresponding metro area or state. Based on the eligible tracts, state governors nominated up to 25% of the eligible census tracts in their respective states to be designated.[5] Tracts were designated in state-level cohorts between April and July of 2018.

While some states explicitly scored different census tracts for designation based on socioeconomic factors, others stated only that decisions were made based on recommendations from relevant stakeholders. For example, New Jersey calculated an index that took into account socioeconomic indicators such as poverty rate and unemployment, along with transit access and existing investments.[6] In contrast, New York designated tracts based on recommendations from the state economic development and housing agencies, along with regional councils.[7]

The OZ program offers three main incentives to investors, deploying capital through an Opportunity Fund (OF), an investment vehicle set up for making qualified investments in OZ census tracts. Investors are permitted to defer taxes on any capital gains invested until the earlier of 2026 or the date on which the investment in the OF is sold. This benefit is broader than, but in many ways similar to, the benefit provided through Section 1031 of the Internal Revenue Code, allowing for a deferral of capital gains taxes upon selling real property and

[4] https://eig.org/opportunityzones/history

[5] In addition, up to 5% of a given state's designated OZs were permitted to be simply contiguous with an eligible tract.

[6] https://www.state.nj.us/dca/

[7] https://esd.ny.gov/opportunity-zones

subsequently reinvesting proceeds within the same tax year in other real property. In contrast, OZ investors may defer any prior capital gains, such as from the sale of public equities, as opposed to only capital gains from the sale of real property.

In addition to deferred capital gains, OZ investors receive a reduction of 15% on the amount of prior capital gains tax when it finally comes due, provided the investment in the OF is held for more than 7 years (there is a 10% discount if the investment is held for between 5 and 7 years). If the investment is held for at least 10 years, the investor also receives an increase in tax basis equal to the investment's fair market value upon sale, effectively eliminating the exit tax due from any new capital gains generated by the OF's investment activities.

Investors may avail themselves of the aforementioned tax benefits only to the extent an OF successfully makes qualified investments in OZs. Most importantly for OF investments in real estate, properties must undergo a capital improvement at least equal to the OF's initial acquisition expense within 30 months of purchase, thereby privileging development and significant rehab over acquisition. The program allows for a wide range of asset classes without any blanket restrictions, and so can be used to finance industrial facilities, hotels, commercial space, and residential properties, to name a few.

In order to qualify for the benefit mechanically, a partnership or other investing vehicle needs only to self-certify to the IRS its status as an eligible OF concurrently with filing its federal tax return. As of December 2018, 53 legal entities across the country had certified as OFs, with total capitalization of nearly $15 billion.[8]

2.2. Theory - Opportunity Zones Investing

Applying an efficient market hypothesis to real estate, property transactions should capitalize future OZ statutory tax benefits (Smith, 2009). As a direct measure, OZ tax benefits can offer a significant increase in total post-tax cash

[8] *Opportunity Zone Fund Directory*, retrieved 2019 from `https://bit.ly/2VSLAGW`

flows and therefore post-tax internal rate of return (IRR) for development and redevelopment properties. Specifically, this increase should be capitalized into vacant land and depreciated property sales likely to be targeted for redevelopment.

As shown in Table 1, OZ tax benefits can offer a significant increase in both total post-tax cash flows and the post-tax internal rate of return (IRR) received by an investor. Based on an illustrative investment with a going-in 7% yield-on-cost and a 5% exit capitalization rate, the post-tax IRR could increase from 7.7% to 10.0%.[9] Based on an NPV analysis with an assumed discount rate of 10%, the increase in residual land value could be as high as 19.36% and the investor's return would be held constant. Alternatively, if the seller does not increase the price of the land or economically obsolete property at sale, the additional post-tax profit could accrue entirely to the company developing on the site (or redeveloping the economically obsolete property).

[Table 1 about here]

The underlying NPV formulas are presented in equation (1) and (2), showing a non-OZ and OZ investment with similar characteristics, respectively. In the equations, I represents the initial investment, t_i the income tax rate, $PTNOI$ the post-tax NOI, c the discount rate, and TV the terminal value. We assume the maximum capital gains tax discount of 15 percent.

$$NPV = -I(1+t_i) + \sum_{x=1}^{X} \frac{PTNOI_x}{(1+c)^x} + \frac{TV}{(1+c)^X} - \frac{(TV-I)t_i}{(1+c)^X} \tag{1}$$

$$NPV = -I + \sum_{x=1}^{X} \frac{PTNOI_x}{(1+c)^x} - \frac{0.85It_i}{(1+c)^{xi}} + \frac{TV}{(1+c)^X} \tag{2}$$

The expected increase in residual land value of investing into an OZ over a

[9] Assumes tax rate of 21% and 100% of invested capital constitutes capital gains from a prior transaction.

non-OZ census tract can de reduced to:

$$\Delta OZ = It_i(1 - \frac{0.85}{(1+c)^{xi}}) + \frac{(TV - I)t_i}{(1+c)^X} \tag{3}$$

Essentially, ΔOZ can therefore be explained by the reduction on initial capital gains tax, the deferral of initial capital gains tax, and the effective elimination of the exit tax on new capital gains. Considering ΔOZ as a percentage of the initial investment, the percentage gain for investors can be defined as:

$$pOZ = \frac{\Delta OZ}{I} = t_i(1 - \frac{0.85}{(1+c)^{xi}} - \frac{1}{(1+c)^X} + \frac{TV}{I(1+c)^X}) \tag{4}$$

Since TV can be defined as:

$$TV = \frac{NOI_l}{c_{ex}} = \frac{Iy_X}{c_{ex}} \tag{5}$$

where NOI_l is the last periods NOI and c_{ex} the exit capitalization rate. Assuming that NOIs are calculated as a percentage of the initial investment, as in our initial example, $NOI_l = Iy_X$, where y_X is the estimated yield in period X and substitution equation (5) into equation (4), the expected percentage gain of OZ investments is:

$$pOZ = \frac{\Delta OZ}{I} = t_i(1 - \frac{0.85}{(1+c)^{xi}} - \frac{1}{(1+c)^X} + \frac{y_X}{c_{ex}(1+c)^X}) \tag{6}$$

For our initial example, with a tax rate, t_i of 21 percent, a discount rate c of 10 percent, an exit capitalization rate c_{ex} of 5 percent, and a final yield y_X of 9.13 percent, assuming an investment period of 10 years X and an deferral of capital gains tax until 2026 ($xi = 8$), this leads to an investment gain of 19.36 percent.[10] Estimating the potential range for pOZ, we run a simple simulation, fixing all

[10] We assume a 3 percent NOI growth over time.

input parameters as above, and varying the yield-on-cost and discount rate. We test a yield-on-cost range between 3 and 10 percent and a discount rate of 5 to 12 percent. The results are shown in Figure 1, indicating a theoretical NPV gain of 6.12 to 29.67 percent.

[Figure 1 about here]

In addition to pure NPV incentives, the OZ program could also increase future productivity of OZs through investments, thereby resulting in increasing land values. An increase in the range of viable future options for development should increase the value of land in the short term (Titman, 1985).[11] Over the long term, an increase in commercial real estate uses within OZs could also lead to increased employment, which has been demonstrated to increase housing prices even at a granular geographic scale (Agnew and Lyons, 2018).

Finally, properties might benefit indirectly over time from renovated neighboring properties (Lin et al., 2009). The construction of new residential properties has been shown to increase the sales price of nearby housing by $670 per unit constructed (Simons et al., 1998). In New York City, in neighborhoods where new middle-income housing was constructed, price appreciation occurred at double the rate of other areas (DeSalvo, 1974).

Part of the goal of our study is to differentiate between these difference types of price increases. Specifically, we attempt to determine whether any observed price increase results from a tax benefit pass-through or a value-generating activity (increased land productivity or spillover amenity effects).

[11] Titman (1985) also notes that the uncertainty created by a program designated to encourage building activity can lead to a decrease in building activity during the short term.

3. Methodology

3.1. Repeat Sales Model

For modeling and tracking the prices of heterogeneous goods, such as real estate, a widely-used model is the hedonic pricing model (Rosen, 1974). As shown in equation (7), y is the (log) transaction price at time t of property i, X are observable characteristics, and Z are unobservable characteristics of property i, with parameters γ and ϱ, respectively. Controlling for cross-sectional differences in properties, parameter β gives the longitudinal price changes, i.e. the index, and residuals are captured by ϵ, assumed to be i.i.d.

$$y_{it} = \beta_t + \gamma X_{it} + \varrho Z_{it} + \epsilon_{it} \tag{7}$$

As the characteristics in Z are unobservable, they cannot be estimated and potentially affect and bias the residuals (Bailey et al., 1963; Deng and Quigley, 2008). This is problematic for commercial real estate data with a high degree of heterogeneity among properties, conjoined with few observable characteristics (Van de Minne et al., 2019). However, if repeated sales of the same property are available, it is possible to differentiate equation (7) into a repeat sales model.[12] For samples with missing controls in X, the repeat sales model is less vulnerable to mis-specification and omitted variable bias compared to the hedonic pricing model.

Differentiating equation (7), the resulting repeat sales model is illustrated in equation (8), where subscript s indicates the time of buy and t indicates the time of sell. Left hand side variable y_{ist} gives the (log) price return of property i. Parameter ω gives the effect of changing property characteristics on prices,

[12]The repeat sales model is a popular method to produce property price indexes, such as the House Price Index of the Federal Housing Finance Agency, based on Case and Shiller (1987), and the RCA price index for commercial real estate, based on Van de Minne et al. (2019).

but can only be identified if property characteristics X change over time ($X_{ist} = X_{it} - X_{is} \neq 0$). If there are no time-varying parameters, the model collapses to the standard Bailey et al. (1963) repeat sales model, eliminating X.[13]

$$y_{ist} = \beta_t - \beta_s + \omega X_{ist} + \epsilon_{ist} \tag{8}$$

We create an OZ location dummy x_{st}, indicating if property i is located in an designated OZ at time t. In the differentiated form, x_{ist} indicates if property i experiences a change in the OZ status between t and s. Thus, x_{ist} equals 0 if property i is bought and sold in a census tract with the same status and 1 otherwise.[14] It is theoretically possible, that properties are sold twice within an OZ ($x_{ist} = 0$), however, given the limited time that OZs are in place, we do not observe such cases. As the OZ location characteristic is the only changing property characteristic over time, we can reduce equation (8) to (9). Assuming parallel trends in β_t, parameter ω captures the price difference between properties in OZ and non-OZ census tracts.

$$y_{ist} = \beta_t - \beta_s + \omega x_{ist} + \epsilon_{ist} \tag{9}$$

3.2. Structural Time Series Modeling

A drawback of the repeat sale model is the loss of observation, significantly affecting commercial property transactions, generally transacting at lower frequencies. We therefore use structural time series modeling, which is used in many indexes, such as RCA's commercial property price indexes, Street Easy's local rent indexes and Propstack's Indian rent index (Bokhari et al., 2017; Francke and Van de Minne, 2017; Van de Minne et al., 2019). Structural time series models

[13] For identification we restrict $\beta_1 = 0$.
[14] Since we only observe OZ introductions, $x_{ist} \in [0, 1]$

like these are typically estimated using full Markov chain Monte Carlo (MCMC) simulations, although other Bayesian inferences, including empirical Bayes (i.e. Kalman filter), are used in the literature as well.

Following Van de Minne et al. (2019), we employ a structural time series for β_t, using a simple random walk with autoregressive structure.[15] We assume that the (log) price level in t, is approximately similar to the (log) price level in $t-1$ around some increment or a random effect, with estimated variance $\sigma_\rho^2 = \frac{\sigma_\zeta^2}{(1-\rho^2)}$. The time series structure is given by:

$$\Delta\beta_t = \rho\Delta\beta_{t-1} + \zeta_{t-1}, \qquad \zeta_{t-1} \sim N(0, \sigma_\rho^2), \tag{10}$$

To increase the sample size, we apply full Bayesian inference to derive the posterior marginal distributions for our parameters of interest (Betancourt and Girolami, 2015). We specify largely non-informative priors for all the (hyper)parameters (see Gelman, 2006, for a definition of "largely non-informative"). The prior on β and ω is normally distributed with mean zero and a standard error of 1. For the variance parameters we employ a half cauchy distribution with mean zero and standard error 1. In all models we center our parameters, as shown in Van de Minne et al. (2019).

In order to derive the marginal distributions of the parameters of interest we use Markov chain Monte Carlo (MCMC) techniques. We employ the No-U-Turn-Sampler (NUTS) developed by Hoffman and Gelman (2014), which is a generalization of the Hamiltonian Monte Carlo algorithm and converges quickly (especially compared to Gibbs sampling). With the NUTS algorithm and efficient

[15] Real estate returns are usually characterized by positive autocorrelation. This "inertia" is inherent to the price formation process in real estate and does not necessarily imply unexploited feasible arbitrage opportunities. More specifically: (1) Unique, whole assets are traded about which participants have incomplete information on the effect of news on the value of any one specific asset; (2) some period of costly search must be incurred by both buyers and sellers, due to the heterogeneity of real estate; (3) trades are decentralized, i.e. market prices are the outcome of pairwise negotiations; and (4) transaction costs are high relative to asset values.

re-parametrization of the model, we need a sample size of only $1,500$ times three (parallel) chains. We use half the sample size as a warm-up and we do not thin the series. The initial values are randomly (uniformly) selected with a value between -2 and +2.[16]

3.3. Difference-in-Differences Setup

In order to estimate the effect of OZs on property prices, we compare properties in eligible, but not designated census tracts, with designated OZs. From the approximately 42,000 eligible census tracts, state governors were given the opportunity to nominate up to 25% in their respective states to be designated as OZs.[17] Around 9,000 tracts were officially designated by the U.S. Treasury and Internal Revenue Service (IRS) between April and July 2018. On average, designated census tracts exhibit higher poverty rates and lower median family incomes than eligible census tracts, as shown by Theodos et al. (2018).

We control for potential group differences between properties in designated OZ and non-OZ census tracts using subtrends. Specifically, we relax the assumption of parallel trends between the two groups, and instead specify a hierarchical model with a common trend for all properties combined with random walk subtrends α^j, with $j = \{\text{non OZ census tract}, \text{OZ census tract}\}$. Francke and Van de Minne (2017) introduced this hierarchical specification of repeat sales models (the HRS). Note that due to variation in the OZ designation timing (between April and July 2018), we can distinguish the non-temporal price premium associated with OZs from other group-specific movements in the monthly subtrends. This model is

[16]Except for the variance parameters which have to be positive, and are thus initialized between 0 and +2.

[17]The eligibility criteria were a poverty rate greater than 20% or a median family income below 80% of the corresponding metro area or state.

given by:

$$y_{ist} = \beta_t - \beta_s + \sum_{j=1}^{J} d_i^j(\alpha_t^j - \alpha_s^j) + \omega x_{ist} + \epsilon_{ist},$$
$$\Delta\alpha_t = \varsigma_{t-1} \tag{11}$$

where ς is assumed to be normally distributed with mean zero and variance σ_ς^2. The selection row vector d_i^j has dimension n_j and consists of zeros and a one to select the appropriate element of cluster j for observation i. To get the log trend of opportunity zones, the estimated common trend and OZ subtrend have to be added together: $\hat{\beta}_t + \hat{\alpha}_t^{j=\mathrm{OZ}}$. We set both $\beta_1 = 0$ and $\alpha_1 = 0$ for identification purposes.

As equation (11) does not control for regional differences while our sample contains OZs from all over the US, capital price appreciation in one region might be different from other areas in the US, potentially introducing a sample selection bias. The HRS is therefore extended by an extra cluster of subtrends (λ^k), controlling for regional differences in dynamics. Based on our sample, we delineate 6 regions as defined by RCA and corresponding to NAREIT's regional classification: (1) Northeast, (2) Mid-Atlantic, (3) Midwest, (4) West, (5) Southwest and (6) Southeast. The two cluster hierarchical repeat sales model is given by:

$$y_{ist} = \beta_t - \beta_s + \sum_{j=1}^{J} d_i^j(\alpha_t^j - \alpha_s^j) + \sum_{k=1}^{K} d_i^k(\lambda_t^k - \lambda_s^k) + \omega x_{ist} + \epsilon_{ist},$$
$$\lambda_t = \lambda_{t-1} + \phi_{t-1}. \tag{12}$$

We omit most subscripts j and k throughout equation (12) for reading easiness. In both (11) and (12) the common trend β_t still follows the random walk with autoregression from equation (10). As an example, for the log price trend for OZs in the Northeast, we add the common trends with the corresponding subtrends, or in this case: $\hat{\beta}_t + \hat{\alpha}_t^{\mathrm{OZ}} + \hat{\lambda}_t^{\mathrm{Northeast}}$.

We apply the same set of equations for analyzing the impact of OZ designation on redevelopment properties, but update our sample set. We also apply the same equations for analysis of vacant land, but adopt a pseudo-repeat sales approach to form pairs using sales of different sites within the same census tract. Both modifications are discussed further in Section 4.

3.4. Propensity Score Matching

Based on the locations of our observed repeat sale transactions, we focus on 9,803 eligible census tracts across the entire US, of which 21% were actually designated as OZs by the corresponding state governments. Even though eligible, non-designated census tracts provide a control group of sufficient size, we question the randomness of designation process (on a state level). Approximately 57% of all US census tracts were eligible for the OZ program, fulfilling one of the two criteria.[18] However, since local income statistics differed widely among eligible tracts, the designation process was potentially not random, but favoring tracts with lower income statistics. We therefore use a nearest neighbor propensity score matching (PSM) among the control tracts, making groups more comparable.

We match eligible, non-designated census tracts to designated census tracts, using the eligibility criteria and estimating a logit model with OZ designation as the explained variable, and median household income and poverty rate as explanatory variables. We match only within RCA regions to avoid matches across the US, such as census tracts in NY with tracts in California. Even though the given regional subdivision is less granular than state boundaries (multiple states fit in one RCA "region"), this guarantees sufficient observations.

[18] `https://bit.ly/2ZFmU3R`

4. Data and Descriptive Statistics

4.1. Opportunity Zones

Illustrated in Figure 2, the locations of all eligible and designated census tracts across the U.S. (states and territories) are identified using data provided by the Community Development Financial Institutions (CDFI) Fund of the U.S. Treasury. We focus on census tracts with observed commercial real estate transactions only (see Section 4.2). This leaves us with a sample of 9,803 out of approximately 42,000 eligible census tracts. We further receive census-level median household income and poverty rate from American Community Survey data.

[Figure 2 about here]

Panel A in Table 2 provides descriptive statistics on median household income and poverty rate at the time of the Tax Cuts and Jobs Act of 2017, for our sample census tracts. The average median household income in eligible, non-designated census tracts is $44,854. In contrast, the median household income in designated census tracts is $ 35,675. Similarly, the average poverty rate is higher in designated zones (28 percent) compared to the eligible zones (20 percent). This indicates that the designation process was not completely random, but that census tracts with lower socio-economic status were favored by state governments.

Appendix Table A1 shows the regional logit model results, indicating that census tracts with higher (log) median household income have a lower probability to be designated OZs. For three of the six regions, higher poverty rates result in higher probability of OZ-designated status, while in the other three regions poverty rates show no significant effect. We match each treated unit (a designated OZ census tract with at least one repeat sale pair) to the control unit (an eligible non-OZ census tract with at least one repeat sale pair) with the most similar value of the estimated propensity score, known as nearest neighbor matching on the propensity score (Ho et al., 2007) Panel B in Table 2 provides summary statistics

of the “matched” census tract data, showing an equal number of designated and eligible opportunity zones. Both groups show a median household income close to $36,000 and a poverty rate of 28 percent.

[Place Table 2 about here]

4.2. Commercial Property Transactions

We utilize a (repeat sales) database provided by Real Capital Analytics (RCA), covering over $10 trillion of commercial real estate transactions across the United States, accessed as of the February 2019. RCA captures over 90% of all commercial real estate transactions in the institutional investor space. The data include 38,435 repeat sales transactions between January 2000 and February 2019 in eligible census tracts. Based on an address match, 7,839 transactions or 21% of the total sample are located in tracts that would eventually become designated OZs, and 599 transactions pairs (8% of the OZ designated sample) are formed after OZs were designated. These transactions include sales of residential, commercial office and retail, and industrial properties, but exclude vacant land sales.

Filtering the data for census tracts selected in the matching procedure, the sample is reduced to 14,871 repeat sales. Given that we filter only among eligible census tracts, the number of transactions in designated tracts remain the same. Since some census tracts have more transactions than others, 7,839 transactions in the OZ designated census tracts do not constitute exactly 50% of the total sample (actually 53%), as is the case in Table 2.

To define redevelopment properties, we adapt the research by Buechler and Van de Minne (2019), who use the same RCA data and estimate a hazard model in which properties exit the data after they get redeveloped. The authors find that for the first 60 years, the probability to redevelop an apartment building is approximately 7 percent, while after 60 years the probability of redevelopment

increases. For example, the redevelopment probability of 120-year old properties is over 50 percent.[19] We define redevelopment properties as apartments older than 60 years, and industrial/retail/office buildings older than 30 years, leaving us with 4,600 repeat sales, of which 161 are transacted in a designated OZ census tract.[20]

To measure the effect of OZ designation on (vacant) land prices, we construct a pseudo repeat sales sample from vacant land sales in the RCA data.[21] We control for all unobserved locational heterogeneity by creating pairs of land sales within the same census tract, thereby allowing us to compute actual (pseudo) repeat sales, even though vacant land - almost by definition - does not sell more than once. Compared to existing buildings, by definition vacant land exhibits significantly less heterogeneity, and therefore we need only to control for differences in size. Specifically, land returns are calculated on the difference in the price per square foot from one sale to the next. Additionally, as land sales generally follow the law of diminishing returns, we control for the (log) difference in square feet of parcels between sales (see e.g. Francke and van de Minne, 2017). For multiple transactions in a given census tract *at the same time*, we take the average price per square foot and average square foot size.

4.3. Descriptive Statistics

Table 3 offers descriptive statistics of existing properties and redevelopment properties, only. On average for existing properties, the realized annual property return is 10.8 percent annualized across both eligible and designated zones. Log annual return volatility is 0.384 (0.312) for designated zones (eligible zones). The PSM ensures that the number of transactions among designated and eligible OZs is similar throughout all regions, except the Southwest region, showing more transactions in designated OZs (62%). For both groups, we document similar holding

[19]Other property types have a considerably higher probability to be redeveloped.
[20]In the robustness section we also test other definitions of "typical redevelopment property".
[21]We consider only the same census tracts matched in Section 4.1.

periods, an important assumption of repeat sale models (Clapp and Giaccotto, 1999).[22]

For redevelopment properties, the average annual return of the indexes is 13.2 percent and 14.4 percent for non-OZ and OZ designated census tracts, respectively. Index volatility levels are similar to those of the previously estimated indexes. The higher returns could be explained by the fact that the Northeast region is the largest sub-group in the redevelopment sub-sample, whereas it is the West for all properties. The Northeast is highly supply constrained, and includes economically booming cities like Boston and New York.[23]

[Table 3 about here]

Table 4 provides descriptive statistics of the pseudo repeat sales. We document that the number of observations is lower (about 5 times) compared to data on existing properties in Table 3. The holding period is also significantly lower compared to the repeat sales data on existing and redevelopment properties. The average holding period for OZs and non-OZs is 2.5 years, with a mean log land size change between transactions of -0.046. Note that given the pseudo-repeat sale nature of the index, log returns are not meaningful before controlling for size in the repeat sales model and are therefore omitted here.

[Table 4 about here]

We estimate a simple index for eligible and designated OZs for a direct comparison, using the repeat sale model with a random walk as time structure (see

[22] Properties with longer (shorter) holding periods are by construction underrepresented (over-represented) in repeat-sales samples, particularly when the sample period is short. Homeowners and investors tend to sell "winners" – properties experiencing above-average price appreciation – more readily than 'losers', i.e. winners tend to have shorter holding periods, see Genesove and Mayer (2001); Bokhari and Geltner (2011).

[23] An alternative explanation could be that older properties' structure depreciated more, meaning the implicit land values are *relatively* higher. Given that land values tend to be more "risky" (or unpredictable) one would expect higher returns (e.g .see Jurado et al., 2015; Francke and van de Minne, 2017).

equation (8) – (10)). However, the models are estimated for both groups separately, as such we cannot identify the OZ premium. Figure 3 gives both log index levels. We denote this model as the Standard Repeat Sales model (SRS).

[Figure 3 about here]

The indexes for existing properties show significant co-movement. Even though the indexes diverge at the beginning of the sample, creating a persistent difference in index levels, correlation is 0.99. For a fairer comparison we examine index returns, documenting a correlation of 0.45 for monthly returns and 0.99 for yearly returns (Van de Minne et al., 2019; Guo et al., 2014). The average (log) index return is 5.0% and 5.5% for the OZ and non-OZ index, respectively.[24] We note that the OZ index seems to go down in the last months, after the designation of OZs. However, returns are not significantly different from each other in this specific period.

The index returns for redevelopment properties and vacant land are also highly correlated. Both showed a correlation of 0.99 on an annual basis, with average (log) index returns between 5.2% and 5.8%.

5. Results

5.1. Main Results

The parameter estimates and model diagnostics, with our main variable of interest $\omega^{\text{OZ Designation}}$, are shown in Table 5. Table 6 shows return statistics of indexes estimated from our models on all subsets of data. Figure 4 provides a graphical representation of the OZ and non-OZ indexes for the existing properties, redevelopment properties and vacant land, respectively.

[24]The average index return is considerably lower than the average "property return" given in Table 3, since the index is equally weighted over all periods, while in reality, prices and volume are heavily correlated over time (see van Dijk et al., 2018). As a result, fewer transactions are consummated when property values go down.

[Place Table 5 about here]

[Place Table 6 about here]

[Place Figure 4 about here]

Our main variable of interest ($\omega^{\text{OZ Designation}}$) indicates that the OZ designation has no effect on prices of existing properties, showing positive, but insignificant coefficients. However, the effect on typical redevelopment properties, and on the vacant land (for development) is statistically significant and economically considerable. The price jump in the month of OZ designation for typical redevelopment properties is (exp(0.133) - 1 =) 14.2%, and for vacant land (exp(0.190) - 1 =) 20.9%. These findings suggest that investors in OZ designated areas do not expect NOI growth. If the tax benefit would spur the local economy, one would expect price increases for *all* properties, not just the ones getting the actual tax benefit. Instead, we find that only properties that benefit from the tax break - redevelopment properties and vacant land - see their prices increase. The tax break is essentially factored into the land price.[25]

For the vacant land model, the difference in land size (ω^{Size}) is -0.046 and statistically significant, showing that land values decrease with size (square feet). We can therefore confirm a law of diminishing returns for land as documented by Francke and van de Minne (2017). The autoregressive parameter for the common trend is positive and significant for all models (ρ), confirming positively autocorrelated returns. Existing properties are the most predictable, showing the highest estimate for ρ. This is because the structure value component is relatively high for existing properties.[26] Land is more of an investment product, and therefore

[25]We also run the model using the inverse redevelopment properties, i.e. only younger properties, but find no significant coefficient on OZ designation.

[26]Structure values are consumed, and their prices are therefore relatively easy to forecast like any other consumption product.

behaves more like a random walk. Redevelopment and land properties are therefore riskier and harder to predict, and the variance parameters of the (sub)trends are higher ($\{\sigma_\zeta, \sigma_\varsigma, \sigma_\phi\}$), meaning higher (conditional) index volatility.

Figure 5 shows the regional subtrends coming from the HRS model for existing properties.[27] We document that most variability comes from the regional subtrends. The variance parameter for the subtrends (σ_ϕ) is relatively high and even the highest for the existing and redevelopment properties. In contrast, the difference in subtrends for OZ versus non-OZ properties (σ_ς) seems negligible. The noise is higher for land, meaning higher idiosyncratic risk. All parameters converge well, indicated by the low values of $\bar{R}$, and the effective sample size is sufficient to draw meaningful posteriors.

In line with previous findings, the indexes show that the redevelopment properties and the vacant land have been more “risky”. Both (unconditional) volatility, crash magnitude (the log drop in prices during the GFC), and index returns are higher compared to all properties. Since we do not add back the effect of OZ designation to these numbers, actual returns for OZ designated census tracts are a few basis points higher.[28] The correlations between the OZ and non OZ designated indexes are - again - relatively high. Given the low estimate of σ_ς (see Table 5), this can be expected. Other than the one time jump after OZ designation, there is no considerable difference in the price dynamics between these two types of census tracts.

The previous findings are further buttressed by eye-balling the indexes in Figures 4 – 5. The difference in index levels is indistinguishable between the OZ and non OZ census tracts many times. However, the difference in regions is quite large, see Figure 5. Even though there is some co-movement visible, especially

[27]Given that existing properties are the main focus of this research, results for redevelopment properties and vacant land are available upon request.

[28]This is except for all properties, where we find no significant effect of designation

during the GFC when all markets decreased, some time periods (like after the GFC) show very little correlation. Properties in the Northeast show the highest appreciation, whereas the Midwest performs the worse. Interestingly, the Southwest outperformed all indexes (+141%) after the GFC other than the Northeast (+212% since GFC).

[Place Figure 5 about here]

5.2. Anticipation Effect

Since it was known upfront that approximately 20 percent of all eligible census tracts would be designated, one might expect that part of the premium would be priced in after eligible zones were made public. This "jump" in prices would therefore be (incorrectly) "captured" by the price trends β and α. This would also mean that our previous estimates are actually an underestimation of the total effect of the OZ program on prices. Using the same methodology and model specifications, we therefore compare non-eligible (in lieu of eligible) census tracts with designated census tracts, again using PSM to ensure comparability.

[Place Table 7 about here]

[Place Figure 6 about here]

Panel A of Table 7 shows the statistics of these non-eligible census tracts, which can be compared to the designated and eligible census tracts in Table 2. Median income levels are considerably higher compared to those in designated census tracts (approximately twice as high). The poverty is rate is considerably lower, 7.3 percent for "non eligible" census tracts, compared to 28 percent for designated zones.

Appendix Table 7 shows the estimates of the second Logit model, comparing designated census tracts with non-eligible census tracts, compared to the previous

PSM analysis which compared designated with eligible.[29] Again, lower income and higher poverty will result in higher probability to have been designated. This is obviously not a surprise, given that the OZ program specifically targeted low income, high poverty areas. Even after the nearest neighbor propensity scoring, see Panel B of Table 7, income levels (higher) and poverty rates (lower) remain different from those of the designated OZs. Still, the estimated trends are nonetheless relatively parallel (results available upon request).

[Place Table 8 about here]

The main parameter results can be found in Table 8, showing that the designation effect remains robust. We find an insignificant effect for all properties, and a large significant effect on redevelopment properties and vacant land The other parameters remain similar as well; there is more serial autocorrelation in the existing properties' price trend compared to the others, and the most variability is in the regional subtrends. We do not find a significant effect of the announcement of the OZ program ($\omega^{\text{Eligibility}}$) on prices for typical redevelopment properties and vacant land. Figure 6 provides a graphical representation of the designated OZ and non-eligible indexes for the various property types.

We run a separate model (not shown here, but available upon request), where we also include an "anticipation" dummy, but only if the property was in a census tract that would in the end be designated. If this parameter would be significant, it could indicate that investors - a priori - knew which census tracts would be designated and which not. This parameter is also insignificant, indicating this was not the case. Another reason is that perhaps there simply was too much uncertainty surrounding the program when it was first announced, such that investors could not price the premium correctly at first.

[29]Census tracts that were made eligible, but did not get designated, were left out of this part of the analysis.

5.3. Alternative Specification & Placebo Effect

We re-estimate the HRS model with age data for existing properties. Previous results showed that the price effect of designation was insignificant. However, we add (log) age and introduce an interaction effect between (log) age and OZ designation to Eq. (12). A priori, we expect that age itself has a positive effect on price returns. Again, older properties have higher risk/return because of the relative high land value fraction. However, we also expect a (further) positive effect on the interaction term, meaning that older properties had higher price increases due to the OZ program compared to younger properties. A negative value indicates that young properties *decreased* in value at designation. Note that we cannot do this regression for the vacant land, given that the age of land is zero by default.

Secondly, we run multiple placebo models on the data for typical redevelopment properties and vacant land. As shown previously, these results show a considerable price increase after OZ designation. Even though we do allow for non-parallel trends, the underlying volatility of the subtrends might have changed over time. If we underestimated the standard deviation of the OZ trends at the end of the sample, high price increases (at the end of the sample) might be falsely "captured" by the OZ designation dummy. Part of the identification comes from the fact that the designation process was "fuzzy", meaning it was not done at the same time (although this might not have been enough.)

We omit all the data after January 2017, and "pretend" that the OZ designation happened in 2015 – 2016. We randomly assign OZ designation to properties that were sold in this time period and that are in census tracts that would eventually be designated after 2017. The odds of designation are similar to the probability of being sold as designated in a zone that would eventually be designated after 2017. The odds correspond to approximately 85% for the existing properties, and 60% for the vacant land. We redo this for the period 2015 – 2014 (and omit the

data after January 2016) and 2014 – 2013 (where we omit the data after January 2015). Information on the descriptives of this subset of data, fit statistics, and the estimated trends are available upon request. The parameter estimates of said models are in Table 9.

[Place Table 9 about here]

The left column of Table 9 shows that the OZ designation dummy is large and negative, but statistically insignificant. In line with previous results, this indicates that there was no price effect of OZ designation on young properties. Older properties have higher returns, which was expected a priori. Interestingly though, the interaction of age and designation is positive and significant (only at the 10% level though). At that rate a 20 year old property would have seen a 12% price increase due to designation, and a 50 year old property a 17% price increase, etc.[30] The placebo runs also show that the results are robust. The estimates remain relatively similar between the different runs and compared to the main findings in Table 5. Also (and more importantly) the placebo designation effect is statistically insignificant for all models.

6. Conclusion

It is perhaps surprising that most of the literature on place-based economic development policies to date has skirted the topic of commercial real estate given its obvious pertinence. Examining the OZ program, this paper provides the first empirical evidence on the impact of place-based policies on commercial real estate.

Despite limited time elapsed since the introduction of the OZ program, we are able to examine initial effects, simulating observational gaps through the use of structural hierarchical time series. We document that the OZ program leads to

[30]The WAIC of this model reveals a lower fit compared to the model without the interaction term, results are available upon request.

price premiums on redevelopment properties and vacant development sites, ranging from 14% to 20%. However, we document no significant impact on existing properties purchased for investment. Anticipation effects are not significant, showing that prices did not increase before the designation of OZs. The OZ designation price premium remained significant and consistent in the model specification with an added anticipation effect variable, and as expected, tests over three placebo time periods showed an insignificant effect for placebo designation.

There are some limitations to our research. The OZ designation happened only very recently and repeated sales are sparse to observe, leaving our sample with a relatively low number of observations in OZs. We therefore use structural time series modeling, negating this caveat to a large extent. Unfortunately, we cannot explore any decay for the documented OZ premium. Lastly, our sample might show a selection bias after OZ designation, resulting in an under-estimation of the effect of OZ designation, as we conflate this OZ designation with economic obsolescence.

Our findings cast doubt on the capacity of the OZ program to achieve its ostensible goal of creating value in low-income communities. As discussed in Section 2.2, the OZ program could potentially impact land values either due to a tax benefit pass-through or through value-creating activities in target neighborhoods, such as increased land productivity or a spillover amenity effect from improvements to depreciated properties.

However, our results suggest that the program has increased prices of only the properties that can benefit directly from OZ tax incentives. In addition, our empirically determined price increase is comparable to the increase in NPV of post-tax cash flows that we simulated in Table 1 based solely on tax incentives. If investors were pricing additional land productivity growth into transaction prices, we would expect the empirically determine price increase to be higher.

While beyond the scope of this current paper, the policy implications of this

finding warrant further attention as more transaction data becomes available. Whereas an increase in land productivity could produce benefits for residents of OZs, a pass-through of tax benefit will likely benefit only existing owners of commercial real estate in target neighborhoods.

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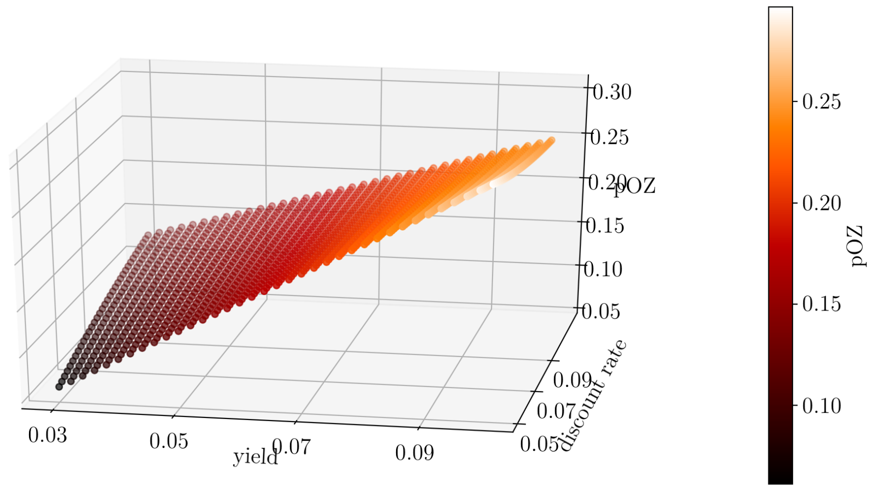
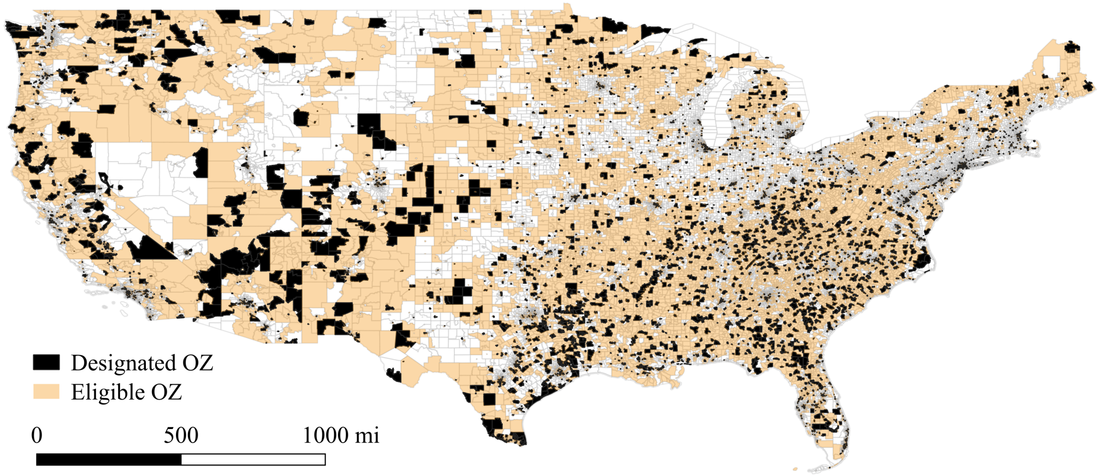
Figures

Figure 1: Theoretical NPV gain in opportunity zones



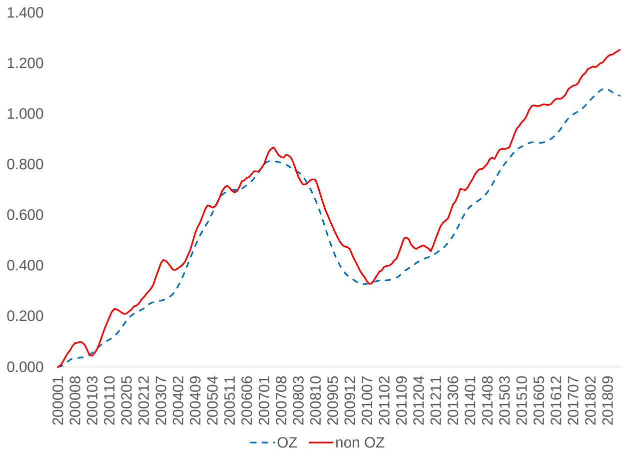
Notes: The graph shows the NPV difference of OZs over non-OZs as a percent of the initial investment (pOZ) as described in Section 2.2. We simulate potential advantages ad varying yields and discount rates.

Figure 2: Geographic distribution of opportunity zones (mainland US)

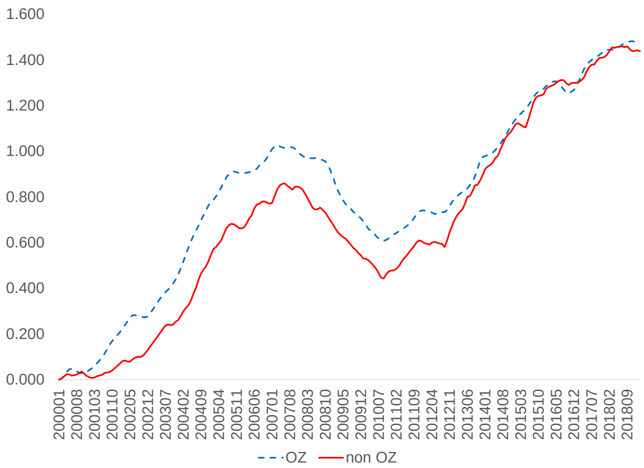


Notes: Black census tracts indicate opportunity zones, oragne census tracts eligible zones.

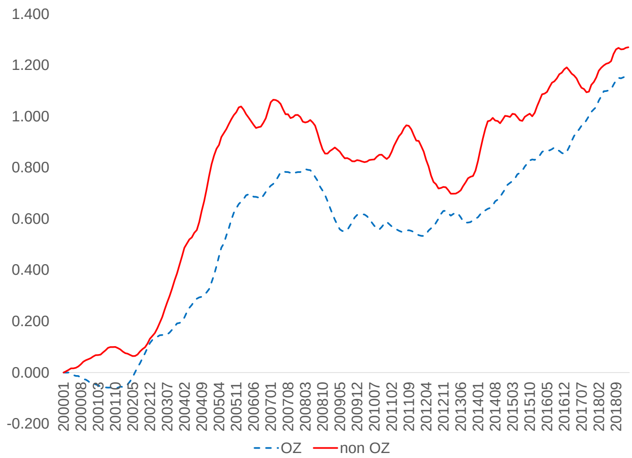
Figure 3: SRS model price indexes



(a) All properties



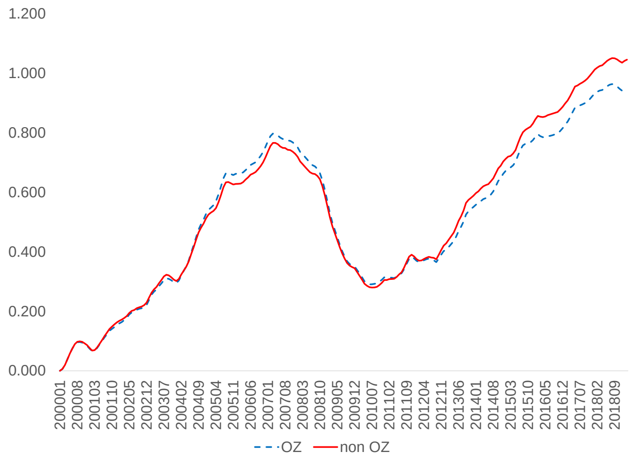
(b) Redevelopment properties only



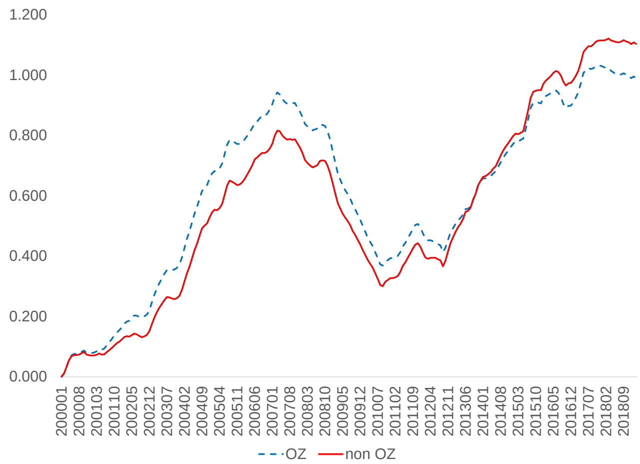
(c) Land price indexes

Notes: OZs (dashed blue) and non-OZs (solid red).

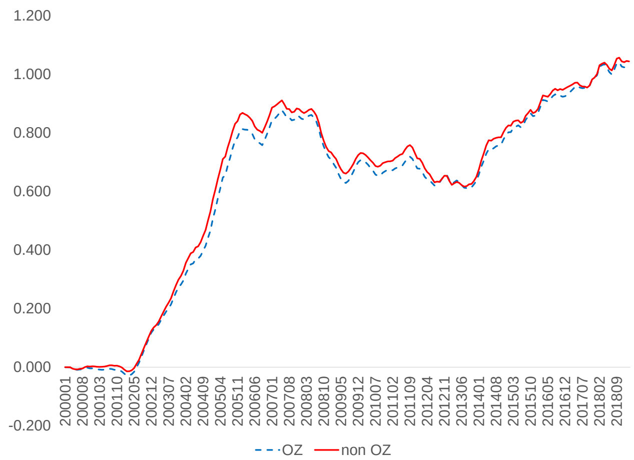
Figure 4: HRS model price indexes



(a) All properties



(b) Redevelopment properties only



(c) Land price indexes

Notes: Price indexes for OZs (dashed blue) and non-OZs (solid red), using the HRS model.

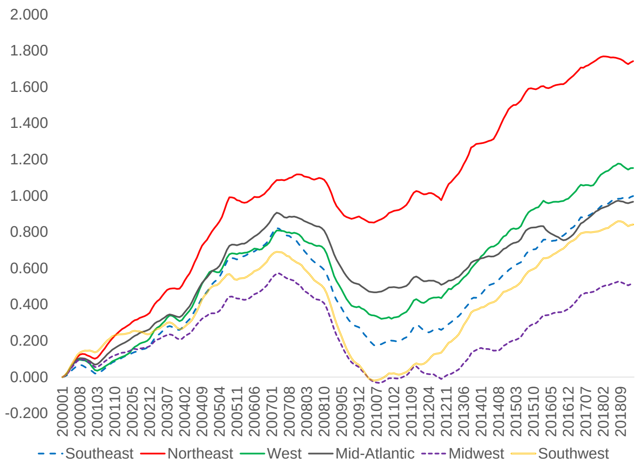
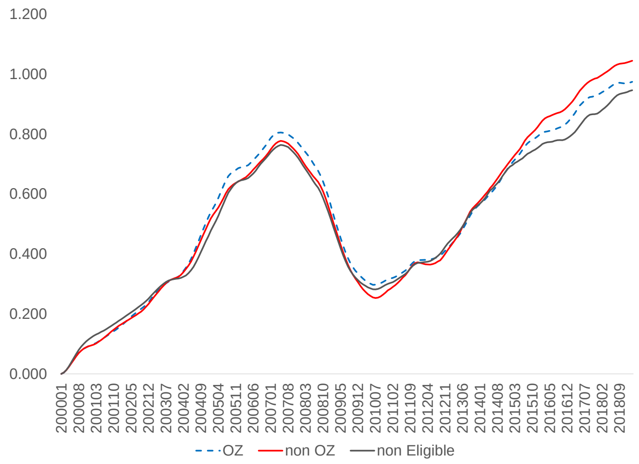
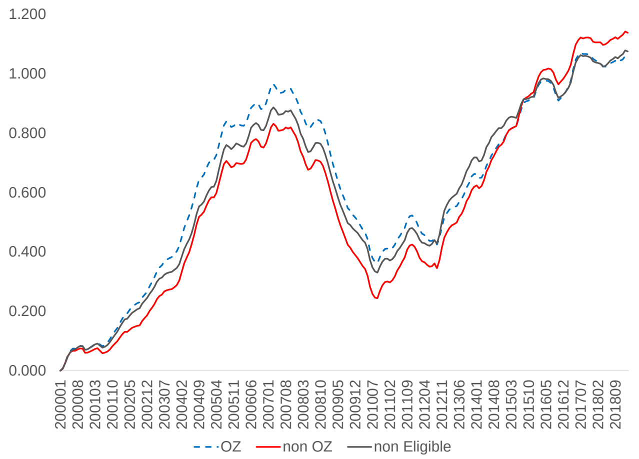


Figure 5: Regional indexes from the HRS model for existing properties.

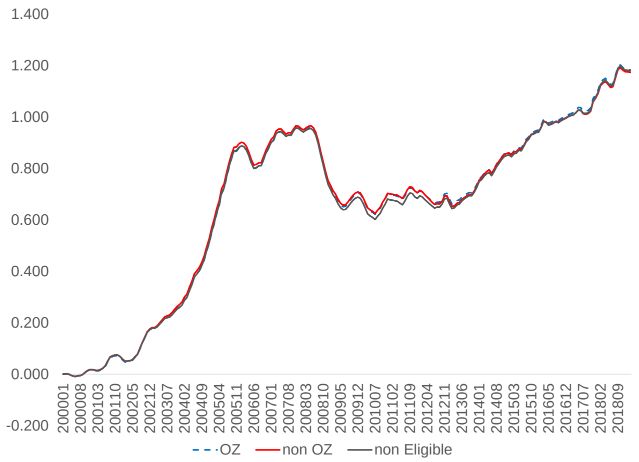
Figure 6: Anticipation effects



(a) All properties



(b) Redevelopment properties only



(c) Land price indexes

Notes: Log price trends of opportunity zones (OZ, solid red), eligible zones (non OZ, dashed blue) and the matched non eligible zones (non eligible, solid black).

Tables

Table 1: Opportunity Zone Cash Flows ($ millions).

	Opportunity Zone						
	Investment	t_p	**Income**	t_{income}	**Sale**	t_n	**Total**
2018	-10.0	0.0	0.0	0.0	0.0	0.0	-10.0
2019	0.0	0.0	0.7	-0.1	0.0	0.0	0.6
2020	0.0	0.0	0.7	-0.2	0.0	0.0	0.6
2021	0.0	0.0	0.7	-0.2	0.0	0.0	0.6
2022	0.0	0.0	0.8	-0.2	0.0	0.0	0.6
2023	0.0	0.0	0.8	-0.2	0.0	0.0	0.6
2024	0.0	0.0	0.8	-0.2	0.0	0.0	0.6
2025	0.0	0.0	0.8	-0.2	0.0	0.0	0.7
2026	0.0	-1.8	0.9	-0.2	0.0	0.0	-1.1
2027	0.0	0.0	0.9	-0.2	0.0	0.0	0.7
2028	0.0	0.0	0.9	-0.2	18.3	0.0	19.0
Total	-10.0	-1.8	8.0	-1.7	18.3	0.0	12.8
IRR							**10.0%**

	Non-Opportunity Zone						
	Investment	t_p	**Income**	t_{income}	**Sale**	t_n	**Total**
2018	-10.0	-2.1	0.0	0.0	0.0	0.0	-12.1
2019	0.0	0.0	0.7	-0.1	0.0	0.0	0.6
2020	0.0	0.0	0.7	-0.2	0.0	0.0	0.6
2021	0.0	0.0	0.7	-0.2	0.0	0.0	0.6
2022	0.0	0.0	0.8	-0.2	0.0	0.0	0.6
2023	0.0	0.0	0.8	-0.2	0.0	0.0	0.6
2024	0.0	0.0	0.8	-0.2	0.0	0.0	0.6
2025	0.0	0.0	0.8	-0.2	0.0	0.0	0.7
2026	0.0	0.0	0.9	-0.2	0.0	0.0	0.7
2027	0.0	0.0	0.9	-0.2	0.0	0.0	0.7
2028	0.0	0.0	0.9	-0.2	18.3	-1.7	17.3
Total	-10.0	-2.1	8.0	-1.7	18.3	-1.7	10.8
IRR							**7.7%**

Notes: All cash flows assume an initial outlay of $10 million in equity, with the assumption being that capital gains taxes due under the non-OZ scenario are paid from a separate source. t_p refers to taxes due for prior capital gains being invested and is calculated as 21% times the initial equity investment. t_{income} refers to taxes on annual taxable income (assumed to equate NOI in this unlevered scenario). t_n refers to capital gains taxes generated from the new investment (in an OZ or non-OZ) and is calculated as the difference between the terminal exit value and the initial equity outlay. Cash flows are unlevered for simplicity. Assumed yield-to-cost of 7% and exit cap rate of 5%, with annual NOI growth of 3%. Based on a discount rate of 10%, the difference in NPV of the non-OZ scenario and OZ scenario cash flows is 19.4% of the initial investment.

Table 2: Income and poverty statistics on eligible and designated opportunity zone census tracts.

	Panel A: Before Propensity Scoring		
	Census tract	**median income**	**poverty rate**
mean	Eligible	$ 44,854	0.197
	OZ	$ 35,675	0.280
std.	Eligible	$ 14,639	0.112
	OZ	$ 13,549	0.132
min	Eligible	$ 2,499	0.000
	OZ	$ 2,499	0.000
max	Eligible	$ 182,578	1.000
	OZ	$ 123,929	0.864
N	Eligible	7,742 (79%)	
	OZ	2,061 (21%)	

	Panel B: After Propensity Scoring		
	Census tract	**median income**	**poverty rate**
mean	Eligible	$ 35,883	0.275
	OZ	$ 35,675	0.280
std.	Eligible	$ 12,734	0.132
	OZ	$ 13,549	0.132
min	Eligible	$ 2,499	0.000
	OZ	$ 2,499	0.000
max	Eligible	$ 98,786	1.000
	OZ	$ 123,929	0.864
N	Eligible	2,061 (50%)	
	OZ	2,061 (50%)	

Notes: Socioeconomic data for designated and eligible census tracts before and after PSM was conducted. Includes only tracts where repeat sale pairs were observed.

Table 3: Summary Statistics of Repeat Sales Data

	Existing Properties			*Redevelopment Properties*		
	OZ	**non OZ**	**Total**	**OZ**	**non OZ**	**Total**
			log returns			
mean	0.249	0.288	0.267	0.341	0.381	0.362
Std.	0.585	0.539	0.564	0.612	0.533	0.572
Min.	-3.877	-3.102	-3.877	-3.261	-3.102	-3.261
Max.	4.699	3.850	4.699	3.007	3.334	3.334
			log returns/holding period (annual)			
mean	0.108	0.120	0.108	0.132	0.144	0.132
Std.	0.384	0.312	0.348	0.348	0.288	0.324
Min.	-7.512	-3.996	-7.512	-3.540	-3.996	-3.996
Max.	8.316	8.460	8.460	8.016	5.100	8.016
			holding period (in years)			
mean	5.190	5.155	5.174	5.220	4.850	5.027
Std.	3.458	3.455	3.457	3.461	3.199	3.332
Min.	0.083	0.083	0.083	0.083	0.083	0.083
Max.	17.833	17.917	17.917	16.917	16.083	16.917
			regional distribution			
Southeast	1,358	1,529	2,887	237	204	441
Northeast	1,438	1,387	2,825	1,010	1,106	2,116
West	2,972	2,686	5,658	637	842	1,479
Mid-Atlantic	415	385	800	100	101	201
Midwest	487	335	822	110	82	192
Southwest	1,169	710	1,879	106	65	171
Total	7,839	7,032	14,871	2,200	2,400	4,600

Notes: Descriptive statistics of existing property and redevelopment property repeat sale pairs.

Table 4: Summary Statistics - Vacant Land

	OZ	**non OZ**	**Total**
	holding period (in years)		
mean	2.451	2.477	2.464
std.	3.053	3.097	3.074
min.	0.083	0.083	0.083
max.	17.917	17.083	17.917
land size change (in log differences)			
mean	-0.043	-0.049	-0.046
std.	1.626	1.385	1.513
min.	-8.240	-5.161	-8.240
max.	8.472	11.057	11.057
regional distribution			
Southeast	344	382	726
Southwest	273	225	498
West	447	531	978
Northeast	343	246	589
Mid-Atlantic	104	81	185
Midwest	66	61	127
Total	1,577	1,526	3,103

Notes: Descriptive statistics of pseudo repeat sales data of vacant land.

Table 5: Parameter Estimates of Main Model

	Existing		**Redevelopment**		**Land**	
$\omega^{\text{OZ Designation}}$	0.041		0.133	**	0.190	***
ω^{Size}					-0.460	***
ρ	0.592	***	0.360	***	0.242	***
σ_ϵ	0.493	***	0.491	***	0.945	***
σ_ζ	0.010	***	0.023	***	0.033	***
σ_ς	0.005	***	0.009	***	0.011	***
σ_ϕ	0.018	***	0.032	***	0.024	***
Diagnostics						
waic	-10,662		-3,333		-4,253	
$\bar{R}$	1.001		1.001		1.001	
eff size (%)	0.444		0.451		0.430	

Notes: *** = significant within the 1% level, ** = significant within the 5% level.
waic = the Watanabe Akaike Information Criterium, see Watanabe (2010). Variable $\bar{R}$, also known as the Rubin-Gelman statistics test for convergence of parameters. Needs to be as close to 1 as possible; where values of less than 1.1 are seen as solid evidence for convergence. Eff size (%) is the effective sample size of the MCMC sampler divided by the total possible sample size (4,500 in our case). The $\bar{R}$ and effective sample size give the average over all parameters. See Lunn et al. (2013) for more details on said diagnostics.

Table 6: Return Statistics of Indexes

	OZ	non OZ
Existing		
return (annualized)	0.050	0.055
std. (annualized)	0.135	0.133
crash magnitude	-0.507	-0.486
correlation	0.993	
Redevelopment		
return (annualized)	0.052	0.058
std. (annualized)	0.168	0.162
crash magnitude	-0.574	-0.516
correlation	0.986	
Land		
return (annualized)	0.054	0.055
std. (annualized)	0.152	0.156
crash magnitude	-0.523	-0.518
correlation	0.988	

Notes: The crash magnitude is the min of the log index between 2004M6 and 2012M6 minus the max of the same period. It thus represent the total loss in asset value during the GFC, see Geltner and Van de Minne (2017). Y = yearly. Std.dev. = the standard deviations of the returns.

Table 7: Income and poverty statistics on the non-eligible and designated opportunity zone census tracts.

	Census tract	median income	poverty rate
	Panel A: Before Propensity Scoring		
mean	Not Eligible	$ 79,128	0.073
std.	Not Eligible	$ 26,557	0.049
min	Not Eligible	$ 9,750	0.000
max	Not Eligible	$ 250,001	0.540
N		7,995	
	Panel B: After Propensity Scoring		
	Census tract	**median income**	**poverty rate**
mean	Not Eligible	$ 54,891	0.124
std.	Not Eligible	$ 11,159	0.052
min	Not Eligible	$ 9,750	0.000
max	Not Eligible	$ 122,917	0.540
N		2,061	

Notes: Socioeconomic data for non-eligible census tracts before and after PSM was conducted with designated tracts. Includes only tracts where repeat sale pairs were observed. See Table 2 for equivalent data on designated tracts.

Table 8: Parameter Estimates of Anticipation Model

	Existing		**Redevelopment**		**Land**	
$\omega^{\text{Eligibility}}$	0.021		0.020		0.036	
$\omega^{\text{OZ Designation}}$	0.026		0.104	**	0.174	***
ω^{Size}					-0.449	***
ρ	0.876	***	0.323	***	0.241	***
σ_ϵ	0.502	***	0.503	***	0.939	***
σ_ζ	0.002	***	0.024	***	0.036	***
σ_ς	0.007	***	0.010	***	0.005	***
σ_ϕ	0.016	***	0.024	***	0.022	***
Diagnostics						
waic	-15,900		-4,557		-6,244	
$\bar{R}$	1.000		1.002		1.000	
eff size (%)	0.813		0.448		0.602	

Notes: *** = significant within the 1% level, ** = significant within the 5% level, waic = Watanabe Akaike Information Criterium, see Watanabe (2010).
Variable $\bar{R}$, also known as the Rubin-Gelman statistics test for convergence of parameters. Needs to be as close to 1 as possible; where values of less than 1.1 are seen as solid evidence for convergence. Eff size (%) is the effective sample size of the MCMC sampler divided by the total possible sample size (4,500 in our case). The $\bar{R}$ and effective sample size give the average over all parameters. See Lunn et al. (2013) for more details on said diagnostics.

Table 9: Parameter Estimates of the Robustness Models

	Existing		**Placebo (Redevelopment)**					
Start designation (Jan.)	-		2015		2014		2013	
End sample (Jan.)	-		2017		2016		2015	
$\omega^{\text{OZ Des.}}$	-0.120		-0.011		0.049		0.021	
$\omega^{\ln \text{Age}}$	0.062	***						
$\omega^{\text{OZ Des.}\times\ln \text{Age}}$	0.040	*						
ρ	0.573	***	0.449	***	0.345	***	0.279	***
σ_ϵ	0.477	***	0.492	***	0.493	***	0.485	***
σ_ζ	0.009	***	0.019	***	0.024	***	0.028	***
σ_ς	0.005	***	0.011	***	0.012	***	0.009	***
σ_ϕ	0.017	***	0.039	***	0.038	***	0.046	***
			Placebo (Land)					
$\omega^{\text{OZ Designation}}$			0.065		0.014		-0.085	
ω^{Size}			-0.467	***	-0.463	***	-0.453	***
ρ			0.256	***	0.258	***	0.251	***
σ_ϵ			0.955	***	0.970	***	0.992	***
σ_ζ			0.033	***	0.037	***	0.043	***
σ_ς			0.012	***	0.012	***	0.012	***
σ_ϕ			0.025	***	0.022	***	0.022	***

Notes: *** = significant within the 1% level, * = significant within the 10% level.

Appendix A. Logit Model for Propensity Score Matching

Table A1: Propensity Score Matching - Eligible zones vs. designated opportunity zones.

Region	**Intercept**	(ln) **median income**	**poverty rate**	**aic**	**N**
Mid-Atlantic	15.57***	-1.53***	-1.38	760	697
Midwest	17.28***	-1.78***	0.51	923	983
Northeast	5.83*	-0.70**	2.55***	1,488	1,344
Southeast	18.66***	-2.00***	2.35***	2,020	2,512
Southwest	9.34**	-1.09**	1.59	1,105	1,317
West	14.48***	-1.57***	4.16***	2,743	2,950

Notes: AIC = Akaike Information Criterium. *** = significant at the 1% level, ** = significant at the 5% level, and * = significant at the 10% level. We use a logit model with OZ designation (1/0) as explained variable.

Table A2: Propensity Score Matching - non-eligible zones vs. designated opportunity zones.

Region	**Intercept**	(ln) **median income**	**poverty rate**	**aic**	**N**
Mid-Atlantic	51.69***	-4.89***	8.92***	472	907
Midwest	72.60***	-7.07***	15.04***	359	1,385
Northeast	55.32***	-5.32***	14.95***	551	1,594
Southeast	61.81***	-6.20***	19.66***	581	2,175
Southwest	58.84***	-5.79***	14.49***	375	1,255
West	66.59***	-6.48***	18.95***	764	2,744

Notes: AIC = Akaike Information Criterium. *** = significant at the 1% level. We use a logit model with OZ designation (1/0) as explained variable.