CRE Development Potential and the Selection of Opportunity Zones*

David Glancy †1, Robert Kurtzman ‡1, and Lara Loewenstein§2

[1]Federal Reserve Board
[2]Federal Reserve Bank of Cleveland

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Abstract

Place-based policies are often caught between two potentially conflicting aims: (i) directing aid to needy communities and (ii) spurring investment. We study this tradeoff in the context of the Opportunity Zones (OZ) program. Leveraging unique phase-level microdata on commercial construction projects, we show that US state governors prioritized designating tracts where construction projects were already being planned. About two-thirds of the greater construction growth in OZs can be attributed to this selection. States prioritizing tracts with greater investment opportunities observed larger construction increases in designated tracts. We calibrate a structural model to quantify the effects of the program and examine counterfactuals under alternative preferences or eligibility criteria.

Keywords: opportunity zones, commercial real estate, construction, time-to-plan

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*The views expressed in this paper are solely those of the authors and do not necessarily reflect the opinions of the Federal Reserve Board or the Federal Reserve System.

†Federal Reserve Board, david.p.glancy@frb.gov
‡Federal Reserve Board, robert.j.kurtzman@frb.gov
§Federal Reserve Bank of Cleveland, lara.loewenstein@clev.frb.org

1. INTRODUCTION

Place-based policies often target distressed areas in the spirit of community redevelopment (Hanson et al., 2025). While such policies can be desirable on equity grounds (Gaubert et al., 2025), channeling aid to highly distressed regions may be hindered by a lack of viable investment opportunities in such neighborhoods (Glaeser and Gyourko, 2005). Policy makers thus face a trade-off between supporting areas that are highly distressed and those that are more likely to respond to program incentives. These considerations also complicate analysis of place-based policies since program effects need to be separated from selection effects (e.g., the designation of markets with severe distress or high economic potential).

The Opportunity Zones (OZ) program offers an illuminating case study of this tension. Enacted as part of the 2017 Tax Cuts and Jobs Act, the program allowed governors to designate up to 25 percent of eligible low-income or high-poverty census tracts for preferential capital gains tax treatment for qualifying investments.[1] Although the policy was intended to channel private capital toward distressed communities, state governors retained substantial discretion over which tracts to select from among those eligible. We study how tracts were selected in light of these tradeoffs, and the implications of this behavior for evaluating the program's effects.

The key challenge is that states potentially selected OZs partly based on difficult-to-observe factors related to construction potential. For example, Corinth and Feldman (2024) show that tax incentives are largest for projects that are profitable enough to occur without the program and Corinth et al. (2025) show that OZs attract more investment in high-growth regions. These factors might induce governors to designate tracts that would have had more activity even without the OZ program. However, absent the ability to measure this construction potential, it is difficult to quantify the extent to which such selection matters.

In this paper we conduct three pieces of analysis to overcome this difficulty and quantify

[1] Eligibility was defined by a poverty rate exceeding 20 percent or median income below 80 percent of the area median (the higher of the state or local MSA median income). Additionally, up to 5 percent of designated zones could be contiguous tracts that did not meet these criteria but bordered qualifying areas and had a median income not exceeding 125 percent of their designated neighbor. We refer the reader to Corinth and Feldman (2024) for a thorough discussion of the tax treatment of OZs.

the effects of OZ designation in the presence of selection. First, we analyze how OZs were selected and how construction activity responds to OZ designation using data that are uniquely suited to measuring development potential. Specifically, we leverage detailed project-level data from Dodge Data & Analytics (Dodge) that tracks commercial construction activity starting from early stages of the construction process. Critical to this study, the data includes projects in the planning phase—those where architects have been retained and designs are underway but before permits are filed—thus providing visibility into potential construction that is useful for distinguishing genuinely new investment stimulated by the OZ program from projects that were already underway.[2] We use this data to demonstrate that while census tracts designated as OZs had substantially more construction than other eligible tracts, the difference drops by nearly two-thirds (from 0.47 projects per tract to 0.17) when pre-existing planning activity is controlled for.

Second, we exploit cross-state variation in how OZs were selected to examine (i) how states balanced the trade-off between targeting areas with distress and those with development momentum and (ii) how differences in selection relate to program outcomes. We show that states that prioritized designating tracts with greater development potential—namely, those that disproportionately selected tracts with more pre-OZ planning activity or publicly indicated that development potential was an important consideration in designated tracts—observed larger construction gains in OZ-designated tracts. The predicted response of construction to OZ designation ranges from 0.06 projects in states that indicated that they only accounted for need-related factors in selecting OZs to 0.22 projects in states that only accounted for tracts' potential to attract investment. This difference in effects likely reflects a combination of heterogeneous treatment effects (investment-focused states selecting tracts that would respond more to the program) and selection effects (investment-focused states selecting tracts where more investment would occur without the program).

In the final part of the paper, we estimate a structural model of OZ selection that formalizes the tension between targeting poverty and maximizing development impact. Governors prefer to designate tracts that have more development potential and higher poverty, but differ in the relative preference for each. We jointly model OZ designation

[2]Dodge's data is the most comprehensive data that we are aware of on commercial construction projects, and is used by the Census in constructing their sampling frame for their commercial Construction Put in Place statistics. See Glancy et al. (2025) for more details on the data.

decisions and construction outcomes, accounting for the heterogeneous effects of OZ designation by development potential, cross-state variation in governor preferences, and unobserved variation in development potential.

The estimation of the model aligns closely with the empirical results, and yields several new insights. First, it allows us to estimate the effect of the OZ program accounting for selection on unobserved development potential. We estimate that OZ designation increased construction activity by about 12 percent in designated tracts. While this effect is economically meaningful, it is below the reduced form estimate, reflecting the effects of selection on unobservable development potential. Second, the model allows us to quantify the tradeoff between targeting areas with high poverty vs. high development potential. A change in preferences that causes states to designate tracts with an average poverty rate that is two percentage points higher reduces the effect of OZ designation by about 0.01 properties per designated tract, reflecting the shift in designation to tracts with fewer viable projects. Third, we use the model to examine the effect of changing eligibility criteria to the revised criteria used in the One Big Beautiful Bill Act (OBBBA). We show that imposing stricter tract income and poverty thresholds has a similar effect to increasing state prioritization of distressed tracts. In other words, OZs shift to higher poverty areas, but at the cost of lower program effects.

2. RELATED LITERATURE AND OUR CONTRIBUTION

A large and growing literature has emerged studying the OZ program; in this section, we review the findings in prior work and highlight our contribution where relevant.

Some prior research—including Corinth et al. (2025), Kennedy and Wheeler (2022) and Coyne and Johnson (2023)—has quantified investment into individual OZs using tax filings from Qualified Opportunity Funds (QOFs). All three of these studies found that within designated OZs, investment flowed more to tracts with specific characteristics. Corinth et al. (2025) found that OZs attracted more investment in areas with more pre-existing investment (as measured using data from Real Capital Analytics). Kennedy and Wheeler (2022) find that early OZ investment was concentrated in merely 16 percent of designated zones, predominantly in neighborhoods with pre-existing upward trends in population, income, and home values. Coyne and Johnson (2023) similarly found that investment flowed disproportionately to zones with higher median household incomes, educational attainment, and pre-existing growth trends, with tens of billions in qualified opportunity fund assets concentrated in areas already receiving investment. All three of these studies indicate the possibility that even within designated OZs, subsequent investment was correlated with pre-existing construction potential. Our work analyzes how states responded to the incentives created by this behavior. We find that investment responds more to OZ designation in states that prioritize investment potential more. Our model then allows us to quantify the tradeoff between aiding distressed areas and stimulating more construction in light of these heterogeneous responses.

Our work also provides additional support for the findings in some of the previous literature on the selection of OZs themselves. For example, Eldar and Garber (2023) found that governors selected tracts with higher distress levels but that were on upward trajectories, which is corroborated by our finding that development was already being planned prior to designation. Frank et al. (2022) demonstrate that states favored tracts whose representative's political affiliation matched that of the state's governor, noting that proportional allocation or local nomination mitigated this bias. While we do not add to the finding on favoritism, we do document clearly that designated tracts were already receiving higher rates of investment activity.

Estimates of the downstream treatment effects of OZs on outcomes such as consumer spending and employment have been mixed. Corinth and Feldman (2024) review much of the empirical work conducted. Their review includes Feldman and Corinth (2023); Freedman et al. (2021); Atkins et al. (2023) all of which found little downstream impact of OZ designation on consumer spending, employment or job postings. The exception is Arefeva et al. (2024) who find almost immediate sizable employment effects of OZ designation. We do not reconcile these disparate findings, but provide additional evidence as to why the downstream impacts may be limited.

We contribute most directly to the prior research on the impact of OZ designation on real estate investment. Real estate is particularly well-suited to OZ investment because of the clearer eligibility criteria and the fact that taxable returns are concentrated in capital gains, which receive favorable treatment by the program. In fact, real estate accounted for about 75% of OZ investment (Corinth et al., 2025). Most directly related to our work, Wheeler (2022) documents a roughly 20 percent increase in the probability of new development in designated zones in any given month. Though his estimate and our own are not directly comparable given the different outcome definitions and samples, our Poisson estimate (in Table 3) of 27 percent more construction starts in designated tracts, once we account for pre-existing planning, is broadly consistent with this finding. Another related paper is Glasner et al. (2025), who study the impact of OZs on the aggregate supply of housing units (both single family and multifamily) and attribute significant increases in all new housing units in OZs to the program. Our analysis does not incorporate single-family housing units, only multifamily and commercial buildings. When looking solely at multifamily buildings and controlling for pre-existing planned developments, we find OLS estimates of an increase of between 13 to 16 percent, depending on the specification (in Table A.5).

While our results indicate some response for planning starts, construction starts, and construction completions, this need not result in large responses in terms of property prices since the program could conceptually increase both the supply and demand for space. Our results therefore do not contradict previous research that has found little impact of OZ designation on property prices. These studies include Sage et al. (2023) who find positive property price appreciation in qualified properties and vacant land in designated tracts using commercial real estate transaction prices; Chen et al. (2023) who find a negligible impact of OZ designation on residential home prices, implying that even if commercial and residential investment was stimulated, the resulting investment was not capitalized into home prices; and Alm et al. (2024) who, looking only at Florida, also find limited to no impact of OZ designation on either commercial or residential real estate.

3. DATA AND SUMMARY STATISTICS

We start by discussing the tract-level data, including OZ status, construction and planning activity, and controls for tract level analysis. We then discuss state-level variables measuring differences in how states selected OZs.

3.1. Tract-level data

Our main data are project-level information from Dodge Data and Analytics, which we supplement with tract-level information from the American Community Survey (ACS).[3] The Dodge data provides comprehensive coverage of commercial construction projects across the United States, tracking projects from initial planning through completion (or abandonment if the project ends up being canceled). Critically for our analysis, Dodge captures projects at the planning stage—after an architect has been selected and design work has begun, but before building permits are filed. This early visibility into the development pipeline allows us to identify projects that were already being planned before OZ designation occurred, providing a unique measure of pre-existing development momentum that is unavailable in permit-based datasets. The data from Dodge also includes geographic information and information on the expected construction spending at the planning phase and then the construction spending at the start phase, as well as information on the property type and the building square footage.

Dodge tracks projects with a cost of construction of at least $500,000 with the exception of warehouses, which can have a lower construction cost. They track all construction projects that involve new construction, alterations, or repair work. In our analysis, we exclude projects that are purely alterations and repair work. Dodge does not collect information on single family home developments after the construction start. When we perform comparisons of aggregates for the various property types, we find that they are reasonably close to that of other sources such as Census and Costar (see Appendix Figures A.2 and A.3, which replicate figures from Glancy et al. (2025)).

We aggregate the Dodge project-level data, creating counts of planning starts, construction starts, and completions for both the pre-OZ period (2013Q1–2017Q4) and the post-OZ period (2018Q1-2023Q4). Planning starts represent projects entering the design phase, construction starts indicate ground-breaking, and completions mark project finalization. We also track project abandonments during the planning phase—instances where planned projects fail to proceed to construction—which provide insight into marginal projects that might benefit from additional incentives.

Tract demographics, including median income and the poverty rate used to determine

[3] Millar et al. (2016) and Glancy et al. (2025) provide further details on the data.

OZ eligibility, come from the 2015 5-year American Community Survey (ACS). Relative income is the eligibility criteria comparing the median tract income to the greater of the state or MSA median (i.e., the ratio of median income for a tract and that of the city or state). We also use ACS data on the share of occupied housing units that are renter occupied (Renter share) as a control since demand for multifamily housing might also contribute to designation decisions. We also include the natural log of the population as a control.

We obtain a list of designated and eligible tracts, including whether those eligible tracts are contiguous or independently eligible, from the IRS. Tracts are eligible to be an OZ if they (i) have a poverty rate of at least 20 percent (ii) have a relative income no greater than 0.8, or (iii) are contiguous with a designated tract meeting the first two criteria, and have a relative income under 1.25.

We also use information on 2018 employment counts by census tract from LODES workplace area characteristics, and a tract-level housing supply elasticity from Baum-Snow and Han (2024).[4] To avoid restricting the sample, we fill in missing housing supply elasticity information (typically for tracts outside of MSAs) using the sample mean, and include an indicator for whether the variable is missing in our analysis.

Table 1 contains tract-level summary statistics. Column (1) is limited to tracts that were not OZ-eligible, column (2) is limited to designated tracts, and column (3) includes tracts that are eligible, but were not designated. In column (4), we report the difference in means between columns (2) and (3). While OZs had more construction activity (about 0.8 more plan starts per tract, and about 0.4 more construction starts and completions), they also had many characteristics likely to be associated with activity independent of designation: more employment, more planning activity before the program started, and a higher share rental units (relevant since multifamily construction was a major component of OZ investing). To provide more clarity on the timing with which planning activity differed by OZ status, Figure A.4 show that flow planning starts were significantly higher in OZ designated tracts years before the program began, resulting in a large cumulative difference in previous planning activity by the start of the program (see Figure A.5).[5]

[4]We map the Baum-Snow and Han (2024) measures to 2010 tract definitions using the crosswalk from the Longitudinal Tract Database of Logan et al. (2014).

[5]Unlike with planning starts, differences in abandonment rates by OZ status are small (see Figure A.6).

The statistics in Table 1 also point to other potential motivations for designation besides development momentum. OZ tracts were more likely to have projects abandoned in the pre-OZ period, suggesting the presence of marginal projects that could benefit from extra inducements to go forward. Additionally OZs had higher poverty rates and lower relative incomes, suggesting a prioritization of areas in greater need of support.

3.2. State Heterogeneity in the Designation Decision

To understand heterogeneity in selection across states, we use three measures of the degree to which states strategically designated eligible tracts. Our first measure comes from Frank et al. (2022), and is an indicator for whether the state's selection process included some form of a proportional criteria (for example, proportionally across counties). States with proportional selection would have less discretion to allocate funds to areas with the greatest investment potential (for example, they could designate tracts within a county with greater potential, but not disproportionately designate tracts in faster growing counties). Table A.1 includes a list of states and an identifier for those that used proportional selection.

For our second measure, we impute the extent to which states targeted growing areas by estimating how much weight previous planning activity played in the selection decision. Specifically, we estimate a probit:

$$\Pr(\text{Designated}_i) = \Phi(\alpha_{s(i)} + \beta_{s(i)}\text{pre-OZ Plan Count}_i + \gamma X_i),$$

where i indexes tracts, and $\beta_{s(i)}$ is a state-specific sensitivity of selection to initial planning activity. We can think of this probit as a random utility model, where $\alpha_{s(i)}$ reflects (negatively) a state's reservation utility, and $\beta_{s(i)}$ reflects how much a governor values investment potential in designation. States that have a greater preference for investment potential in designation would be expected to have larger estimated responses to designation due to these selection effects being stronger. We refer to $\hat{\beta}_s$ as a state's planning sensitivity.

For our third measure, we construct an LLM estimate of how much states prioritized investment potential in designating tracts. Specifically, we had GPT-5 (from OpenAI) analyze the factors different states considered in designating OZs and score states from

1–5 on how much they considered investment opportunities in designating tracts. More detail regarding the collection of information on states' reported OZ selection criteria and the specific prompt used to generate the index are provided in Appendix B. The specific text used to assess states' selection criteria and the sources for that text are provided in the supplemental materials. To provide a couple of examples of how states scored, Texas scored a 1 as they cited weighing "1. Areas of chronic unemployment; 2. Areas with lower population density; [and] 3. Areas experiencing significant economic disruptors such as natural disasters within the past two years."[6] Indiana had a score of 5 because OZs "were selected based on a combination of factors including existing economic development programs and local coordination, economic and community data, likelihood of attracting short- and long-term investment, and growing industry sectors within the community."[7] Figure A.1 shows that states with an above the median planning sensitivity mostly had high reported investment preferences (4s or 5s), and states below the median in planning sensitivity mostly had low investment prioritization scores (3 or below).

4. EMPIRICAL RESULTS

Section 4.1 presents findings predicting tract-level OZ designation decisions and post-OZ construction activity. Section 4.2 examines how patterns differ by state selection criteria.

4.1. Tract-level determinants of OZ designation and construction

Table 2 presents our core empirical analysis of how pre-existing planning activity and other tract characteristics relate to OZ designation and subsequent construction activity. The sample includes low income communities (LICs)—tracts eligible to be OZs based on income or poverty limits—but results are nearly identical when including contiguous tracts in the sample (see Table A.4). The table reveals two key findings: first, that selection into the OZ program was systematically related to pre-existing development potential, and second, that controlling for this selection significantly reduces the estimated program effect. All specifications include state fixed effects, so estimates reflect differences in either the probability of OZ selection or the number of construction starts in OZs relative

[6] See: https://dallascityhall.com/government/Council%20Meeting%20Documents/edh_4_dallas-opportunity-zones-briefing_040119.pdf.

[7] See: https://iedc.in.gov/program/indiana-opportunity-zones/overview.

to other OZ-eligible tracts in the same state. Standard errors in the remainder of the empirical work are clustered at the state level to account for heteroskedasticity from state-specific selection processes.

Column (1) estimates a probit model for the probability of designation among eligible tracts. The results confirm that governors selected tracts strategically along multiple dimensions. An increase in pre-OZ planning activity increased the probability of designation, as did greater employment, and more elastic housing supply. Simultaneously, governors also prioritized designating areas facing economic distress; tracts with lower relative income and higher poverty rates were more likely to be chosen to be OZs.

Columns (2) through (5) present OLS estimates predicting tract-level construction starts after the implementation of the OZ program. The key result is the stark difference between specifications with and without controls for pre-existing planning activity. Without controls (column 2), designated tracts show 0.47 more construction starts than non-designated eligible tracts. Given that eligible, non-designated tracts only experienced 0.61 construction starts on average, this difference implies roughly 75% more construction starts in designated tracts.

However, this predicted effect falls to 0.17 when we control for pre-OZ planning activity (column 3) and further to 0.15 with the full set of controls (column 4). These results indicate that selection on observables—most prominently, the selection of tracts where more projects were planned in the pre-OZ period—accounts for about two-thirds of the greater construction in OZ designated tracts. The coefficient on pre-OZ planning activity remains large and highly significant across specifications, with each additional planned project before designation associated with 0.21 additional construction starts afterward.

Finally, in column (5) we expand the sample to include all tracts rather than only tracts that were eligible to be OZs. The coefficient on OZ Designation is broadly unchanged from column (4), which is expected: since no ineligible tracts could be designated, the added observations shift only the estimates for the controls, not the identification of the OZ effect itself. That the key control—pre-OZ planning—has nearly identical coefficients across the two samples (0.21 vs. 0.20) confirms that the pass-through of pre-existing development activity to post-program construction is not specific to low-income and high-poverty tracts. This extrapolation to the broader universe of tracts will be useful in the next section when we examine counterfactual eligibility criteria in the structural model.

Robustness We present robustness exercises, where we (1) run our main analysis using Poisson regressions, (2) extend the analysis to additional outcome measures, and (3) look at cuts of the analysis excluding 2020:Q2–2021:Q4 to assess the extent to which the pandemic may be affecting our analysis.

Table 3 presents estimates from Poisson regressions predicting the number of construction starts in a census tract. The model estimates the expected number of construction starts as:

$$\mathbb{E}[\text{Construction Starts}_i] = \exp\big(\alpha_{s(i)} + \delta \text{OZ Designation}_i + \beta \ln(\text{Pre-OZ Planning}_i) + \gamma X_i\big),$$

where $\alpha_{s(i)}$ is a state-specific intercept and X_i is the set of tract level controls including the same controls as in Table 2 and an indicator for whether Pre-OZ Planning$_i = 0$ (in which case we set $\ln(\text{Pre-OZ Planning}_i)$ to 0).[8] This specification allows us to examine proportional changes in construction activity allowing for the presence of 0s.

Without controls (column 1), OZs show 77 percent higher expected construction (exp(0.57) - 1), but this falls to 27 percent (exp(0.24)-1) with planning controls (column 2) and 23 percent (exp(0.21)-1) with full controls (column 3)—a proportional reduction similar to our linear specifications.

Table A.2 extends the analysis on the relationship between construction starts, OZ designation, pre-OZ planning, and controls presented in Table 2 to alternative outcome measures: planning starts and construction completions. For new planning starts (columns 1-3), the OZ effect falls from 0.87 to 0.27 with full controls. For construction completions (columns 4-6), the reduction is from 0.42 to 0.11. The consistency across different stages of the development process strengthens our conclusion that selection on pre-existing development activity accounts for the majority of observed differences between designated and non-designated tracts.

[8]We replace the pre-OZ Planning variable with the logarithm of pre-OZ Planning since we would expect a linear rather than exponential relationship between plan starts and construction starts. The variable No Pre-OZ planning$_i$ captures differences between tracts with no planned projects and tracts with one.

Table A.3 excludes the 2020:Q2–2021:Q4 from the analysis. The main takeaway is the same as from Table 2: the estimated effect of OZ designation still falls by about two-thirds when controlling for Pre-OZ planning. The estimates are smaller overall, as there are fewer years over which construction starts can occur, resulting in a proportional drop in the effect on starts relative to the main results. These results suggest a fairly symmetric relationship between the outcome variables of interest during and outside the pandemic.

4.2. Heterogeneity by State

This section demonstrates that states varied considerably in how they balanced the competing objectives of targeting distressed areas versus areas with development potential, and these differences influence the predicted effect of OZ designation on construction starts. We first validate that OZ designation decisions are aligned with the proxies discussed in Section 3.2. Namely, states with proportional allocation or a low stated prioritization of investment opportunities were less likely to designate tracts with greater planning activity as OZs. We then show that states that prioritized investment potential observed a greater increase in investment in OZs.

Differences in how states selected tracts Table 4 tests whether our state-level measures correlate with states' actual OZ designation decisions. Each specification repeats the analysis from the probit in Table 2, but interacts Pre-OZ Planning$_i$ with a state-level measure pertaining to how a particular state allocated OZs.[9]

Column (1) shows that proportional selection states were about 20 percent less responsive to Pre-OZ planning when designating tracts (a coefficient of 0.008 compared to 0.010 for non-proportional selection states). However, the difference is statistically insignificant.

Column (2) instead interacts Pre-OZ planning$_i$ with Investment Opportunity Prioritization$_i$, the 1–5 index measuring the extent to which states indicated that investment opportunity was an important consideration in designating tracts. The findings show that states with a higher stated prioritization of investment opportunity indeed disproportionately selected tracts with greater development potential as OZs. The point estimates imply that a state at the lowest value for the index (Investment Opportunity Prioritization$_i = 1$)

[9] We omit the State Planning Sensitivity measure from this analysis because it mechanically relates to states' tendencies to designate areas with high planning activity.

is less likely to designate tracts with more Pre-OZ planning as OZs, consistent with those states prioritizing areas with more economic stress that might otherwise struggle to attract investment. In contrast, a state with the highest value of the index is estimated to be over three times as responsive to Pre-OZ planning as in the baseline estimates not accounting for state-by-state heterogeneity. Column (3) shows that differences by investment opportunity prioritization are similar controlling for whether the state has a proportional selection criteria.

Columns (4) and (5) replicate specifications (2) and (3), but replace Investment Opportunity Prioritization$_i = 1$ with an indicator for whether it is above 3 (labeled as High Investment Opportunity Prioritization$_i = 1$). Findings are similar with this discrete measure; states with a low investment opportunity prioritization generally did not favor tracts with more pre-OZ planning. The relationship between planning and designation decisions is almost entirely driven by states that indicated that they accounted for development potential in selecting OZs.

Differences in the predicted effects of OZ designation Table 5 presents results replicating the specification shown in column (4) of Table 2, but interacting OZ designation with the three state-level selection criteria.

Column (1) shows that states with proportional allocation rules—which limited discretion to concentrate designations in high-growth areas—saw OZ effects roughly half as large as states without such constraints (0.09 vs. 0.20 more construction starts). This difference is consistent with the flexibility to strategically select zones being crucial for generating sizable construction effects, though the question remains whether the results reflect stronger construction effects due to the selection of more responsive markets (heterogeneous effects) or a stronger response due to the selection of tracts that would have had more construction anyway (selection bias).

Column (2) shows similar results for State Planning Sensitivity. A one standard deviation increase in this measure of a state's tendency to select high planning activity tracts (.03) raises the predicted construction response by .018 projects, a roughly 13 percent larger effect than for states that do not prioritize high planning activity tracts at all. Though the effect is statistically insignificant, it is important to point out that the specification controls for Pre-OZ Planning. Consequently, the results do not reflect higher planning activity in designated tracts, but instead reflect the fact that states that selected tracts with greater planning activity likely also prioritized tracts with greater development potential on unobserved margins. We will account for such selection on unobserved characteristics in the model in the next section.

The most direct measure of how states prioritized investment potential is likely the GPT-5-generated evaluation of how states indicated that they prioritized investment potential, which is reported in column (3). Each one-point increase in investment prioritization is predicted to yield an additional 0.04 projects. States that indicated taking only need-related factors into consideration (according to the evaluation) are predicted to have 0.06 more construction starts if designated as an OZ, while states only considering investment potential have a predicted response of 0.22.

Column (4) presents a horse race specification that includes the three interaction terms jointly. The results confirm that both proportional selection rules and low investment prioritization independently dampen the predicted effects of OZ designation. The state-specific planning sensitivity measure switches sign, indicating that the effect is successfully captured by the investment opportunity prioritization measure .

Table 6 provides easier interpretation by using binary measures for planning sensitivity and investment prioritization (i.e., high and low value states). Results are qualitatively similar. States above the median planning sensitivity see nearly twice as much of a construction response in designated tracts (0.19 starts vs. 0.11 starts). Effects are similar with the investment prioritization measure: states with scores above 3 see 0.22 more construction starts in designated tracts, while those at 3 or below see effects of 0.12. These effects are insignificant when those variables are included jointly due to the high correlation between the planning sensitivity and investment opportunity measures (see Figure A.1).

4.3. *Discussion*

To summarize the reduced form findings, we show that areas designated as OZs saw much more commercial construction than other eligible but not-designated tracts, but a large portion of this difference reflects the selection of tracts with greater development potential as OZs. States that appeared to prioritize development potential more observed larger predicted construction responses to OZ designation.

While these results highlight that selection is important, several questions remain. First, what about selection on unobservables? Though controlling for pre-OZ planning reduces the estimated effects of OZ designation, we still find about 25 percent more construction in OZs controlling for this variable. The true treatment effect of OZ designation is likely smaller to the extent that states designate areas with investment potential on unobserved margins as OZs. Second, why do states see heterogeneous responses to designation? The larger predicted construction response in states prioritizing the selection of markets with development potential could reflect either stronger selection bias or the strategic selection of tracts with a stronger genuine response to designation. Third, what are the tradeoffs in trying to target higher poverty areas? Designating a moderately stressed tract might be more desirable than a severely distressed tract if the latter would have little construction activity regardless of OZ status. Evaluating this tradeoff requires knowledge of how construction might decline if OZs were redirected to higher-poverty tracts. In the next section we present a model of OZ selection and construction activity to address these questions.

5. STRUCTURAL FRAMEWORK

Our reduced-form estimates identify the role of pre-existing development activity in driving measured effects of OZ designation. In this section, we estimate a structural model of OZ designation and subsequent construction activity to provide further context to these estimates and perform relevant counterfactuals.

5.1. *Theoretical framework*

5.1.1. *OZ designation decisions*

Consider the problem of a state governor designating OZs. Governors care about addressing location-specific stresses; they thus want to designate areas with high poverty or low incomes, but they also want to designate areas that will respond to the program with additional construction. Governors select OZs from a fixed, state-specific pool of eligible tracts. They thus solve the following maximization problem:

$$\max_{\{D_i\}} \sum_{i \in I_s} D_i \cdot (V_i + \varepsilon_i) \quad \text{s.t.} \quad \sum_{i \in I_s} D_i \leq Q_s, \tag{1}$$

where D_i is an indicator for whether tract i is designated, I_s is the set of eligible tracts in state s, and Q_s is the number of tracts states can select (roughly $0.25 \times |I_s|$, though we take the observed number of tracts selected if it differs). $\varepsilon_i \sim N(0,1)$ reflects unobserved preferences for tract i, and V_i is the expected utility from designating tract i based on observed factors, which takes the form:

$$\begin{aligned} V_i = & (1 - \theta_{s(i)}) \left[\rho \cdot \text{Poverty}_i + \zeta \cdot \text{Relative Income}_i\right] \\ & + \theta_{s(i)} \cdot \kappa \cdot \text{DevPotential}_i + \gamma \cdot \text{Contig}_i. \end{aligned} \tag{2}$$

The parameters ρ, ζ and κ reflect the baseline preference for designating tracts with high poverty (Poverty), income (Relative Income), or development potential (DevPotential), respectively. Poverty and relative income are measured as before (ζ should be negative given governors' preferences for designating low income tracts). The details regarding measuring the tract's development potential are laid in the next subsection. θ_s is the relative weight the governor in state s places on development opportunity versus revitalization (i.e., supporting areas with high poverty or low incomes). θ_s is therefore the analog of Investment Opportunity Prioritization in the empirical work. We also include a control for contiguous tracts as a reduced form way of accounting for additional restrictions to designating such tracts.

This framework allows us to give a random utility interpretation to our earlier reduced-form probit (Table 2), where the coefficient estimates on planning activity reflect preferences for development potential and those on poverty and income reflect preferences for addressing distress.

We next endogenize development potential using the Poisson framework from Table 3; this approach effectively microfounds the heterogeneous treatment effects of OZ designation that underlie the preference for areas with higher planning activity.

5.1.2. *Endogenizing development potential*

Suppose that the count of construction starts in tract i, denoted Y_i, follows a negative binomial process, with an expected number of construction starts:

$$\mathbb{E}[Y_i \mid X_i, D_i, e_i] \equiv \mu(X_i, D_i, e_i) = \exp\left(\beta_{\text{plan}}^{\top} X_i + \delta \cdot D_i + e_i\right), \tag{3}$$

where X_i is a vector of variables related to development potential (e.g., previous planning activity), $e_i \sim \mathcal{N}(0, \sigma_y^2)$ is an unobserved development factor that accounts for governors potentially designating tracts with unobserved development potential, and δ is the proportional treatment effect of OZ designation. We use a negative binomial process rather than Poisson process to account for overdispersion: $\text{Var}(Y_i) = \mu_i(1 + \alpha\mu_i)$, allowing for $\alpha > 0$ (whereas it would be 0 for a Poisson process). Accounting for this additional dispersion in construction starts reduces the risk of construction starting being attributed to dispersion in unobserved development potential and causing us to overstate the importance of selection on unobservables.[10]

We define development potential as the construction that would be expected to occur without OZ designation:

$$\text{DevPotential}_i = \exp\left(\beta_{\text{plan}}^{\top} X_i + e_i\right). \tag{4}$$

Our approach is agnostic as to whether states choose tracts with high development potential for reasons of actually stimulating more additional projects or so that more projects are more likely to go forward that would have gone forward anyway. Note that the true treatment effect of OZ designation is $\left(e^{\delta} - 1\right) \cdot \text{DevPotential}$. If states had different preferences for designating tracts with more marginal construction or more construction

[10] Though we work with this specification, it is relevant to note that our empirical results are nearly identical with Poisson and negative binomial regressions.

in general (call these parameters κ_{new} and κ_{old}, respectively), then this would affect the interpretation of the κ coefficient but not the structure of preferences:

$$\kappa \cdot \text{DevPotential} = \kappa_{\text{new}} \cdot \left(e^{\delta} - 1\right) \cdot \text{DevPotential} + \kappa_{\text{old}} \cdot \text{DevPotential}$$

for $\kappa = \kappa_{\text{new}}\left(e^{\delta} - 1\right) + \kappa_{\text{old}}$. Consequently, the model cannot distinguish between why states prefer tracts with development potential, but it can account for both motivations.

We use this structure to estimate the treatment effect of designating an OZ, accounting for selection on both observed (X_i) and unobserved margins (e_i). We additionally use the model to evaluate counterfactual effects of the OZ program under different preferences for development potential relative to economic distress.

5.2. *Estimation Strategy and Results*

We estimate the parameters of the model to maximize the joint likelihood of observing the number of construction starts (Y_i) and designation decisions (D_i) in the data.

Note that the probability of designating a tract as an OZ is:

$$\pi_i(e_i) = \begin{cases} \Phi\Big(V_i - v_{s(i)}\Big), \text{ if eligible} \\ 0, \text{ if ineligible,} \end{cases}$$

where $v_{s(i)}$ is the reservation utility for designating a tract as an OZ in state s. In equilibrium, this is the utility corresponding with the Q_s^{th} highest tract. In the estimation procedure, we treat this as a parameter to be estimated (as a state-specific intercept in the probit), but in counterfactuals we account for reservation utility being endogenous and adjust it to maintain the same number of designated tracts.

The likelihood of getting the observed construction activity comes from the pmf of a negative binomial distribution (parameterized by its mean and overdispersion), which we denote $f_{\text{NB2}}\big(Y_i \mid \mu(X_i, D_i, e_i), \alpha_{\text{NB}}\big)$.

Combining these two expressions provides the likelihood of getting the data for a given unobserved development potential:

$$\mathcal{L}_i(e_i) = \Big(f_{\text{NB2}}\big(Y_i \mid \mu(X_i, D_i = 1, e_i), \alpha_{\text{NB}}\big)\pi_i(e_i)\Big)^{D_i} \\ \times \Big(f_{\text{NB2}}\big(Y_i \mid \mu(X_i, D_i = 0, e_i), \alpha_{\text{NB}}\big)(1 - \pi_i(e_i))\Big)^{(1-D_i)}.$$

Integrating over e_i then gives the likelihood for an individual tract: $\mathcal{L}_i \equiv \int \mathcal{L}_i(e)\phi(e; 0, \sigma_y^2)de$. We approximate the integral over e by Gauss–Hermite quadrature.

One problem with maximizing the Likelihood function directly is that state-specific estimates of investment prioritization may be noisy for states with fewer eligible tracts. To address this issue, we impose a prior over the distribution of θ_s. Specifically, we assume that θ_s comes from a beta distribution with shape parameters a_θ and b_θ ($\sim \beta(a_\theta, b_\theta)$). This assumption restricts each $\hat{\theta}_s$ to be between 0 and 1 and, by penalizing deviation from typical investment prioritization, limits the extent to which we attribute extreme values to areas with less information on preferences. An additional benefit to the prior is that it parameterizes the distribution of θ_s, which allows us to consider the effects of resampling preferences rather than taking state-specific estimates for θ as given. For example, we can consider the effects of counterfactual eligibility criteria without assuming that individual states have the same preferences as before.

We estimate parameters to maximize the posterior log-likelihood function:

$$\max_{\beta_{\text{plan}}, \delta, \rho, \zeta, \kappa, \gamma, \{\theta_s\}, \{v_s\}, \sigma_y, \alpha_{\text{NB}}, a_\theta, b_\theta} \quad \sum_i \log \mathcal{L}_i \; + \; \sum_s \log \text{Beta}\big(\theta_s; a_\theta, b_\theta\big),$$

where Beta is the pdf of a beta distribution.

Parameter estimates Table 7 provides the estimated parameters. The main parameter of interest is δ, which estimates the causal effect of being designated as an OZ on construction. The value of 0.12 means that the effect of being designated as an OZ is a roughly 13 percent increase in expected construction starts. By comparison, the reduced form Poisson regressions estimated about 23 percent expected higher construction. The difference in these estimates is due to the e_i term in the model. Tracts with high unobserved construction potential were more likely to be designated as OZs and would have had higher construction than otherwise similar tracts even if they were not selected. In the estimated model, this bias accounts for a bit less than half of the estimated effect of OZ designation in the reduced form analysis. However, the estimate is imprecise; the 95% confidence interval runs from about 0.01 (virtually no effect of OZs) to 0.23 (the reduced form estimate for the most part not addressing selection on unobservables).[11]

The estimated treatment effect is highly sensitive to the dispersion in unobserved development potential (σ_y). A lower σ_y means that unobserved factors are comparatively less important and estimates for δ are closer to that in the reduced form analysis. This relationship is plotted in Figure 1. Each point corresponds to the estimated effect of OZ designation when we impose a particular value of σ_y ($\sigma_y = 0.67$ corresponds to situation where σ_y is estimated in Table 7). When $\sigma_y = 0$, there is no selection on unobservables, and the estimate for δ reproduces what we found in the reduced form Poisson regression. As σ_y rises, the unobserved component of development potential becomes more important and the estimated δ falls (i.e., it takes a smaller treatment effect to rationalize the difference in construction outcomes for designated and non-designated tracts). $\hat{\delta}$ falls to around 0 for a σ_y slightly above 1.

The other parameters are broadly in line with the reduced form findings. The parameters related to construction starts are similar to the estimates from the Poisson regressions. The parameters governing the distribution of θ_s imply that states on average placed about a 75 percent weight on development potential ($\frac{a_\theta}{a_\theta+b_\theta} \approx 0.74$). At this mean θ, the state preference parameter estimates imply that a state would require a development potential that was 0.1 expected starts higher to compensate for a poverty rate that was 1 percentage point lower. Table A.7 also demonstrates that we get broadly similar estimates to those in Table 2 when we repeat the probit and OLS analysis on model-generated data.[12]

[11] Standard errors are based on 200 bootstrap replications, resampling states with replacement for each replication.

[12] The probit estimates differ slightly from those reported in Table 2, because we do not include all of the controls in the model as in the empirical work; however, the estimates are nearly identical to what we get from an identical specification with the observed data. In the model-generated data, controlling for Pre-OZ planning reduces the estimated treatment effect from 0.50 to 0.27, less than the decline from 0.47 to 0.17 in the empirical work. In the model generated data, the effect falls further when controlling for true development potential, demonstrating that selection on unobservables likely inflates the reduced form estimates.

5.3. *Counterfactuals*

We now use the estimated model to investigate several counterfactuals that are useful for investigating the open questions discussed in Section 4.3. The main results are in Table 8. The first three columns show the averages for poverty rates, relative income, and the Pre-OZ Planning count for OZ designated tracts. The last two columns show the average effect of OZ designation (construction starts caused by the program) in OZ designated tracts, and the raw difference in average construction starts in OZ and eligible, non-OZ tracts. The top line presents averages from the data (excluding treatment effects, which are unobserved) while the rest present results from the model for various OZ selection processes, averaging results over 100 simulations.[13]

Baseline The first three rows show that the model is able to reproduce key patterns in the data. The data generating process in the model produces an average 30% poverty rate in OZ-designated tracts and an income that is 60% of that of the broader area, both of which are within one percentage point of the values observed in the data. The average Pre-OZ Plan count in the model is 3.82, a touch below the value of 3.94 found in the data. The difference in construction between designated and non-designated areas is 0.40 in the model and 0.35 in the data.[14] Averages are also reasonably close to the data if we resample $\{\theta_s\}$ using the estimated distribution of θ across states instead of the state-specific estimates (the third row). With redrawn state preferences, we get an average poverty rate of 29%, relative income of 61% and Plan Count of 3.91, similar to the observed values of 31%, 59% and 3.94.

[13]Each simulation makes independent draws for every tract's unobserved development potential (e_i), idiosyncratic utility from being selected (ε_i), and draw from a negative binomial distribution with expectation $\mu(X_i, D_i, e_i)$ where $D_i = 1$ if ε_i is such that V_i is in the $Q_{s(i)}$ highest for the state. In some simulations we resample θ_s in addition to D_i, in which case we additionally pull new state investment preferences from Beta distribution with the estimated shape parameters.

[14]This alignment between the data and model is to be expected: maximizing the probit likelihood effectively targets differences in average poverty, relative income, and plan counts by OZ status, and the negative-binomial regression effectively targets differences in construction starts by OZ status.

Counterfactual preferences The middle three rows present results for counterfactual state preferences. Each row presents model outcomes if all states have the same investment prioritization of θ =0, 0.5 or 1.0. These counterfactuals achieve two main goals. First, they quantify the cost in terms of construction activity of shifting OZ tax incentives to more highly-distressed regions. The counterfactuals imply that if governors ignored investment potential in designating tracts ($\theta = 0$), they would have designated tracts with a 37% average poverty rate. If they fully-prioritized investment potential ($\theta = 1$), the average poverty rate in designated tracts would have only been 26%. This shift towards high poverty markets comes at a cost though; the average effect of OZ designation falls from 0.15 projects for $\theta = 1$, to 0.09 for $\theta = 0$. This result mimics the empirical results in Table 5, which predict that the effect of OZ designation ranges from 0.06 to 0.22 projects for states at the bottom and top of the range of the investment opportunity prioritization index, respectively. The wider range of treatment effect estimates in the empirical results is consistent with some of that variation reflecting differences in their selection on unobserved characteristics (i.e., Pre-OZ Planning being an imperfect control for DevPotential).

Figure 2 plots the relationship between poverty rate and investment response as θ changes more generally, thus tracing out the policy frontier. The figure shows that increasing the average poverty rate by about 1 percentage point results in a construction response that is about 0.005 projects lower.

The counterfactuals also shed light on the greater response to OZ designation in high investment prioritization states (since θ_s is the theoretical analogue of the Investment Opportunity Prioritization$_s(i)$ in the empirical work). Conceptually, this response differential could be attributed to either greater selection bias or a larger treatment effect. The model allows us to decompose this difference.

The last column shows the raw differences in construction between eligible and designated tracts (the sum of selection and treatment effects), while the second-to-last column isolates the treatment effect. The results indicate that most of the difference in outcomes for high and low θ reflect selection rather than heterogeneous treatment effects. While going from the lowest to highest prioritization raises the raw difference in construction by 0.58 projects, the treatment effect only goes up by about 0.06. As long as the data generating process in the model truly aligns well with that of the data, these results indicate that much of the stark difference in the predicted response of construction to OZ designation reflects greater selection bias in high investment prioritization states. The results also point to potential negative selection bias in areas most focused on targeting poverty: the treatment effect is greater than the raw difference in construction (0.09 vs. 0.03) when $\theta = 0$. Consequently, the low predicted response of construction to designation in low investment prioritization states found in Section 4.2 should not necessarily be taken as indicating that OZs were ineffective in those states. Instead, states may have designated tracts that would have had less construction independent of the OZ program.

Alternative eligibility rules The final counterfactual we consider is changing tract eligibility criteria to have more stringent income and poverty thresholds. If national policymakers are more focused on poverty relief than those who designate which eligible tracts are selected, these counterfactuals reflect the ability of policy makers to shift activity to more stressed tracts by changing the menu of eligible tracts. For this counterfactual, we take the revised OZ eligibility criteria in the OBBBA (which moved the income threshold from 80% to 70% of the area median, excluded high poverty tracts if income exceeded 125%, and removed eligibility for contiguous tracts). We then re-simulate outcomes keeping preferences and construction processes the same, but narrowing the set of tracts governors can choose from.

Directionally, the effects of more stringent eligibility criteria are similar to the effects of reducing θ. Relative to the baseline model outcomes, the average poverty rate in designated tracts rises two or three percentage points and the average treatment effect declines by .01 or .02 projects. However, the decline in treatment effects for a given increase in poverty targeting is larger than from reducing θ. Intuitively, a change in preferences to focus more on poverty targeting still allows governors to designate some moderately distressed tracts if their development potential is high enough, while a change in eligibility criteria would remove such tracts from consideration entirely.

6. CONCLUSION

This paper leverages microdata on pre-existing commercial construction planning activity to show that approximately two-thirds of the observed construction boost in OZs reflects selection of areas with pre-existing development momentum rather than genuine program impact. Our analysis highlights a difficult choice that states faced between targeting truly distressed areas and achieving measurable program results. States where governors prioritized economic need over development potential saw a smaller response of construction to designation, likely reflecting a combination of reduced selection bias and smaller treatment effects.

We estimate a model of how construction activity is shaped by the OZ program, accounting for the endogenous selection of tracts as OZs and the presence of unobserved tract-level development potential and state-level preferences for OZ designation. We then use the model to disentangle selection effects from treatment effects, and investigate several counterfactuals pertaining to program priorities or eligibility criteria.

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Table 1: Summary Statistics

	Not Eligible (1)	**Designated** (2)	**Not Designated** (3)	**Designated - Not designated** (4)
pre-OZ Plan Count	3.45	3.97	2.58	1.39**
	(6.28)	(6.69)	(4.95)	(0.08)
post-OZ Construction Starts	0.77	1.07	0.61	0.46**
	(1.95)	(2.17)	(1.58)	(0.03)
post-OZ Plan Count	1.67	2.11	1.26	0.85**
	(3.82)	(3.86)	(3.10)	(0.05)
post-OZ Construction Completions	0.75	1.00	0.59	0.41**
	(1.85)	(2.06)	(1.54)	(0.03)
Renter Share	0.26	0.56	0.49	0.07**
	(0.17)	(0.22)	(0.22)	(0.00)
ln(Employment)	6.71	6.94	6.42	0.53**
	(1.24)	(1.30)	(1.30)	(0.02)
Housing Supply Elasticity (BH 2024)	0.19	0.10	0.10	-0.01*
	(0.21)	(0.17)	(0.18)	(0.00)
Missing Supply Elasticity	0.20	0.28	0.23	0.05**
	(0.40)	(0.45)	(0.42)	(0.01)
Prior Abandonment	0.21	0.23	0.16	0.07**
	(0.41)	(0.42)	(0.37)	(0.01)
Relative Income	1.21	0.58	0.65	-0.07**
	(0.37)	(0.21)	(0.20)	(0.00)
Poverty	0.09	0.31	0.26	0.06**
	(0.05)	(0.13)	(0.12)	(0.00)
ln(Tract Population)	8.32	8.17	8.19	-0.03**
	(0.53)	(0.54)	(0.52)	(0.01)
Proportional Selection State	0.47	0.47	0.48	-0.00
	(0.50)	(0.50)	(0.50)	(0.01)
State Planning Sensitivity	0.02	0.01	0.01	-0.00
	(0.04)	(0.04)	(0.03)	(0.00)
State Investment Opportunity Prioritization	3.06	2.97	2.98	-0.01
	(1.28)	(1.31)	(1.30)	(0.02)
Democratic Governor	0.42	0.40	0.40	-0.01
	(0.49)	(0.49)	(0.49)	(0.01)
Observations	42,055	7,584	23,252	30,836

Note: Columns (1), (2), and (3) present the mean and standard deviation (in parentheses) of various tract characteristics for tracts that were not eligible for OZ designation, tracts that were eligible and designated, and tracts that were eligible but not designated, respectively. Column (4) presents the difference in means, and standard error of the difference, between columns (2) and (3), reflecting differences in tracts that were chosen to be designated vs. those that were not. Relative income is the ratio of the census tract median income to the higher of the relevant MSA or state median income according to the 2015 5-year ACS. $^{+}$, *, and ** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively.
Source: Authors' calculations using Dodge Data and Analytics, information on OZ designation from the IRS, ACS, LODES workplace area characteristics, and Baum-Snow and Han (2024).

Table 2: Relationship between OZ Designation, Planning Activity, and Construction Starts

	Designated Probit	**Construction Starts** OLS			
	(1)	(2)	(3)	(4)	(5)
OZ Designation		0.47**	0.17**	0.15**	0.14**
		(0.08)	(0.04)	(0.04)	(0.04)
Pre-OZ Planning	0.01**		0.21**	0.21**	0.20**
	(0.00)		(0.01)	(0.02)	(0.01)
Renter Share	0.13			0.27*	0.36**
	(0.11)			(0.13)	(0.13)
ln(Employment)	0.22**			0.03	0.04^{+}
	(0.03)			(0.03)	(0.02)
Housing Supply Elasticity (BH 2024)	0.37^{+}			0.23*	0.45**
	(0.21)			(0.09)	(0.13)
Missing Supply Elasticity	0.43**			-0.13**	-0.12**
	(0.05)			(0.03)	(0.03)
Prior Abandonment	0.06**			-0.13*	-0.14**
	(0.02)			(0.06)	(0.04)
Relative Income	-0.70**			-0.10	-0.06
	(0.14)			(0.09)	(0.03)
Poverty	2.08**			0.03	-0.07
	(0.35)			(0.14)	(0.16)
ln(Tract Population)	-0.13**			0.01	0.07*
	(0.04)			(0.03)	(0.03)
R^2_a		0.055	0.458	0.459	0.450
Observations	30,485	30,836	30,836	30,485	61,374
State FE	✓	✓	✓	✓	✓

Note: Column (1) presents probit estimates of the relationship between OZ designation and tract characteristics, and columns (2)–(5) present OLS estimates predicting tract construction starts based on whether the tract was designated as an OZ, the number of projects planned before the OZ program started, and other tract characteristics. In columns (1)–(4) the sample is tracts that were eligible to be OZs, and column (5) includes the full sample of tracts (thus comparing OZ designated tracts to all other tracts, rather than tracts that were eligible but not chosen). Standard errors are clustered at the state level. $^{+}$, *, and ** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively.
Source: Authors' calculations using Dodge Data and Analytics, information on OZ designation from the IRS, ACS, LODES workplace area characteristics, and Baum-Snow and Han (2024).

Table 3: Poisson Estimates for Construction Starts

	Construction Starts			
	(1)	(2)	(3)	(4)
OZ Designation	0.57**	0.24**	0.21**	0.19**
	(0.09)	(0.04)	(0.03)	(0.03)
ln(Pre-OZ Planning)		0.90**	0.79**	0.79**
		(0.02)	(0.04)	(0.04)
No Pre-OZ Planning		-0.82**	-0.70**	-0.71**
		(0.08)	(0.08)	(0.05)
Renter Share			0.49**	0.51**
			(0.15)	(0.13)
ln(Employment)			0.10*	0.13**
			(0.05)	(0.04)
Housing Supply Elasticity (BH 2024)			0.39**	0.63**
			(0.10)	(0.12)
Missing Supply Elasticity			-0.45**	-0.32**
			(0.06)	(0.05)
Prior Abandonment			-0.05	-0.04
			(0.04)	(0.04)
Relative Income			-0.04	-0.06
			(0.05)	(0.04)
Poverty			0.07	-0.17
			(0.14)	(0.16)
ln(Tract Population)			0.06**	0.13**
			(0.02)	(0.01)
R^2_p	0.078	0.362	0.371	0.375
Observations	30,836	30,836	30,485	71,617
State FE	✓	✓	✓	✓

Note: Each column presents Poisson estimates of the relationship between construction starts and tract characteristics. Columns (1)–(4) include the same variables as Columns (2)–(5) in Table 2 but with a Poisson regression rather than OLS. The only change is that the pre-OZ plan starts is replaced with two variables: the logarithm of pre-OZ plan starts and an indicator for whether there were no pre-OZ plan starts (in which case we set the logarithm to 0). Standard errors are clustered at the state level. $^+$, *, and ** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively.
Source: Authors' calculations using Dodge Data and Analytics, information on OZ designation from the IRS, ACS, LODES workplace area characteristics, Frank et al. (2022), and Baum-Snow and Han (2024).

Table 4: OZ Designation by State Selection Characteristics

	Designated				
	(1)	(2)	(3)	(4)	(5)
Pre-OZ Planning	0.010**	-0.030**	-0.036**	-0.001	-0.003
	(0.002)	(0.004)	(0.004)	(0.002)	(0.003)
...×Proportional Selection	-0.002		0.008*		0.004
	(0.003)		(0.003)		(0.003)
...×Investment Opportunity Prioritization		0.013**	0.013**		
		(0.001)	(0.001)		
...×High Investment Opportunity Prioritization				0.026**	0.026**
				(0.003)	(0.003)
R^2_a					
Observations	30,485	30,485	30,485	30,485	30,485
Controls	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓

Note: This table repeats the probit from specification (1) from Table 2, but interacts Pre-OZ planning with state characteristics pertaining to how tracts within a state were designated. Column (1)'s state measure (Proportional Selection) is the interaction with whether states used a proportional allocation to designate tracts. Column (2)'s state measure (Investment Opportunity Prioritization) is a score (from 1 to 5) indexing how much a state took into account investment potential in designating tracts (as formed by GPT-5's scoring of public comments regarding allocation decisions). Column (3) presents results with both measures included simultaneously. Columns (4) and (5) repeat the specifications of (2) and (3), respectively, but using an indicator for whether the Investment Opportunity Prioritization score is above 3 in place of the continuous measure. The same controls as in Table 2 are included in all specifications, but not displayed. Standard errors are clustered at the state level. $^+$, *, and ** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively.
Source: Authors' calculations using Dodge Data and Analytics, information on OZ designation from the IRS, ACS, LODES workplace area characteristics, Frank et al. (2022), and Baum-Snow and Han (2024).

Table 5: Differential Construction Response by State Selection Characteristics

	Construction Starts			
	(1)	(2)	(3)	(4)
OZ Designation	0.20**	0.14**	0.02	0.07
	(0.02)	(0.02)	(0.04)	(0.05)
...×Proportional Selection	-0.11**			-0.09**
	(0.03)			(0.04)
...×State Planning Sensitivity		0.59		-0.56
		(0.49)		(0.62)
...×State Investment Opportunity Prioritization			0.04**	0.05**
			(0.01)	(0.02)
Pre-OZ Planning	0.21**	0.21**	0.21**	0.21**
	(0.00)	(0.00)	(0.00)	(0.00)
Renter Share	0.27**	0.27**	0.27**	0.27**
	(0.05)	(0.05)	(0.05)	(0.05)
ln(Employment)	0.03**	0.03**	0.03**	0.03**
	(0.01)	(0.01)	(0.01)	(0.01)
Housing Supply Elasticity (BH 2024)	0.23**	0.23**	0.24**	0.23**
	(0.05)	(0.05)	(0.05)	(0.05)
Missing Supply Elasticity	-0.13**	-0.13**	-0.13**	-0.13**
	(0.02)	(0.02)	(0.02)	(0.02)
Prior Abandonment	-0.13**	-0.13**	-0.13**	-0.13**
	(0.02)	(0.02)	(0.02)	(0.02)
Relative Income	-0.10*	-0.10*	-0.10*	-0.11*
	(0.05)	(0.05)	(0.05)	(0.05)
Poverty	0.04	0.03	0.04	0.04
	(0.08)	(0.08)	(0.08)	(0.08)
ln(Tract Population)	0.01	0.01	0.01	0.01
	(0.02)	(0.02)	(0.02)	(0.02)
R^2_a	0.459	0.459	0.459	0.459
Observations	30,485	30,485	30,485	30,485
State FE	✓	✓	✓	✓

Note: This table repeats specification (4) from Table 2, but interacts the OZ Designation indicator with state characteristics pertaining to how tracts within a state were designated. Column (1) adds an interaction with whether states used a proportional allocation to designate tracts. Column (2) adds an interaction with the imputed weight that a state placed on initial planning activity in selecting tracts, namely the state specific coefficient estimate on Pre-OZ Planning when the specification from Column (1) of Table 2 is expanded to the interaction of Pre-OZ Planning with state indicator variables. Column (3) adds the score indexing how much a state took into account investment potential in designating tracts (as formed by GPT-5's scoring of public comments regarding allocation decisions). Column (4) presents results with all three interactions included simultaneously. Standard errors are clustered at the state level. $^+$, *, and ** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. *Source:* Authors' calculations using Dodge Data and Analytics, information on OZ designation from the IRS, ACS, LODES workplace area characteristics, Frank et al. (2022), and Baum-Snow and Han (2024).

Table 6: Differential Construction Response by State Selection Characteristics, Discrete Measures

	Construction Starts			
	(1)	(2)	(3)	(4)
OZ Designation	0.20**	0.11**	0.12**	0.16**
	(0.02)	(0.02)	(0.02)	(0.03)
...×Proportional Selection	-0.11**			-0.10**
	(0.03)			(0.04)
...×High Planning Sensitivity		0.08*		0.03
		(0.03)		(0.04)
...×High Investment Opportunity Prioritization			0.10**	0.07
			(0.04)	(0.04)
Pre-OZ Planning	0.21**	0.21**	0.21**	0.21**
	(0.00)	(0.00)	(0.00)	(0.00)
Renter Share	0.27**	0.27**	0.27**	0.27**
	(0.05)	(0.05)	(0.05)	(0.05)
ln(Employment)	0.03**	0.03**	0.03**	0.03**
	(0.01)	(0.01)	(0.01)	(0.01)
Housing Supply Elasticity (BH 2024)	0.23**	0.23**	0.23**	0.23**
	(0.05)	(0.05)	(0.05)	(0.05)
Missing Supply Elasticity	-0.13**	-0.13**	-0.13**	-0.13**
	(0.02)	(0.02)	(0.02)	(0.02)
Prior Abandonment	-0.13**	-0.13**	-0.13**	-0.13**
	(0.02)	(0.02)	(0.02)	(0.02)
Relative Income	-0.10*	-0.10*	-0.10*	-0.11*
	(0.05)	(0.05)	(0.05)	(0.05)
Poverty	0.04	0.04	0.04	0.04
	(0.08)	(0.08)	(0.08)	(0.08)
ln(Tract Population)	0.01	0.01	0.01	0.01
	(0.02)	(0.02)	(0.02)	(0.02)
R^2_a	0.459	0.459	0.459	0.459
Observations	30,485	30,485	30,485	30,485
State FE	✓	✓	✓	✓

Note: This table repeats specification (4) from Table 2, but interacts the OZ Designation indicator with an indicator for whether state characteristics pertaining to how tracts within a state were designated (as described in Section 3 and shown in Table A.1) above (denoted as "High") their median value. Column (1)'s state measure (Proportional Selection) is whether states used a proportional allocation to designate tracts. Column (2)'s state measure (Investment Opportunity Prioritization) is the imputed weight that a state placed on initial planning activity in selecting tracts, namely the state specific coefficient estimate on Pre-OZ Planning when the specification from Column (1) of Table 2 is expanded to include the interaction of Pre-OZ Planning with state indicator variables. Column (3)'s state measure (Investment Opportunity Prioritization) is a score (from 1 to 5) indexing how much a state took into account investment potential in designating tracts (as formed by GPT-5's scoring of public comments regarding allocation decisions); for this measure, the value is denoted as High if its value is above 3. Column (4) presents results with all three measures included simultaneously. Standard errors are clustered at the state level. $^+$, *, and ** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. *Source:* Authors' calculations using Dodge Data and Analytics, information on OZ designation from the IRS, ACS, LODES workplace area characteristics, Frank et al. (2022), and Baum-Snow and Han (2024).

Table 7: Estimated Parameters

Parameter	Description	Estimate	Std. Error
Construction parameters			
δ	Proportional Effect of Designation	0.12	0.06
β_0	Intercept	-1.57	0.06
β_1	Coefficient on ln(Pre-OZ Planning)	0.92	0.01
β_2	Coefficient on No Pre-OZ Planning	-0.88	0.05
Selection parameters			
ρ	Poverty Preference	5.61	0.20
ζ	Income preference (rel. income)	-1.56	0.16
κ	Development Preference	0.17	0.06
γ	Contiguous tract preference	-1.07	0.09
Distributional parameters			
σ_y	SD of unobserved development factor	0.67	0.05
α_{NB}	NB overdispersion	0.22	0.04
a_θ	First shape of state prioritization prior $\theta_s \sim \text{Beta}(a_\theta, b_\theta)$	2.39	0.26
b_θ	Second shape of state prioritization prior $\theta_s \sim \text{Beta}(a_\theta, b_\theta)$	0.82	0.13

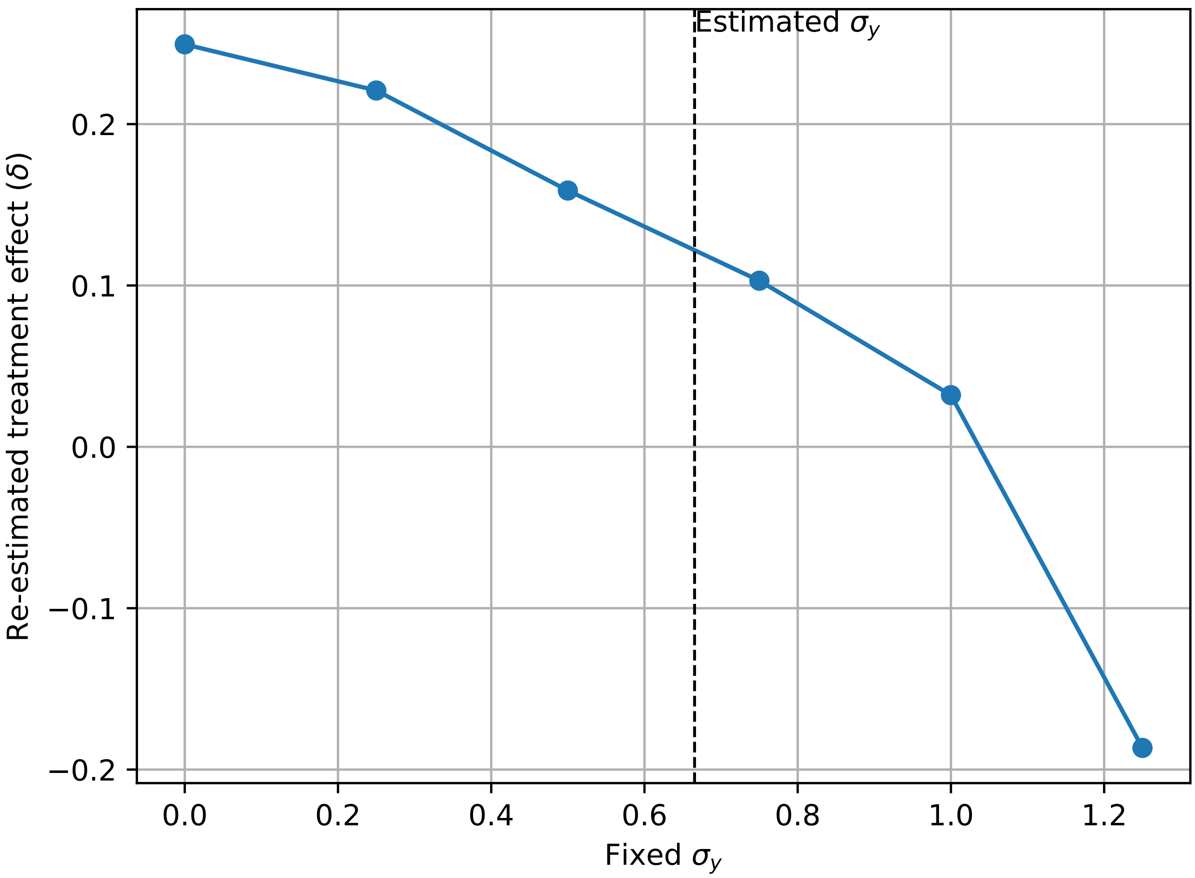
Note: The table shows parameter estimates and standard errors from the model presented in Section 5. Bootstrapped standard errors are clustered by state, with 200 replications.

Table 8: Counterfactual Outcomes

Scenario	Avg. Poverty	Avg. Rel. Income	Avg. Plan Count	Treatment on Treated	Raw Diff. Construction
Observed data	0.31	0.59	3.94		0.35
Model DGP (estimated params)	0.30	0.60	3.82	0.13	0.40
Model DGP (redrawn θ_s)	0.29	0.61	3.91	0.13	0.44
Counterfactual Investment Prioritization (θ)					
$\theta_s \equiv 0$	0.37	0.50	2.97	0.09	0.03
$\theta_s \equiv 0.5$	0.33	0.56	3.54	0.11	0.29
$\theta_s \equiv 1$	0.26	0.66	4.31	0.15	0.61
Counterfactual Eligibility Criteria					
Alt. eligibility rule	0.32	0.56	3.58	0.11	0.29
Alt. eligibility (redrawn θ_s)	0.32	0.57	3.62	0.12	0.31

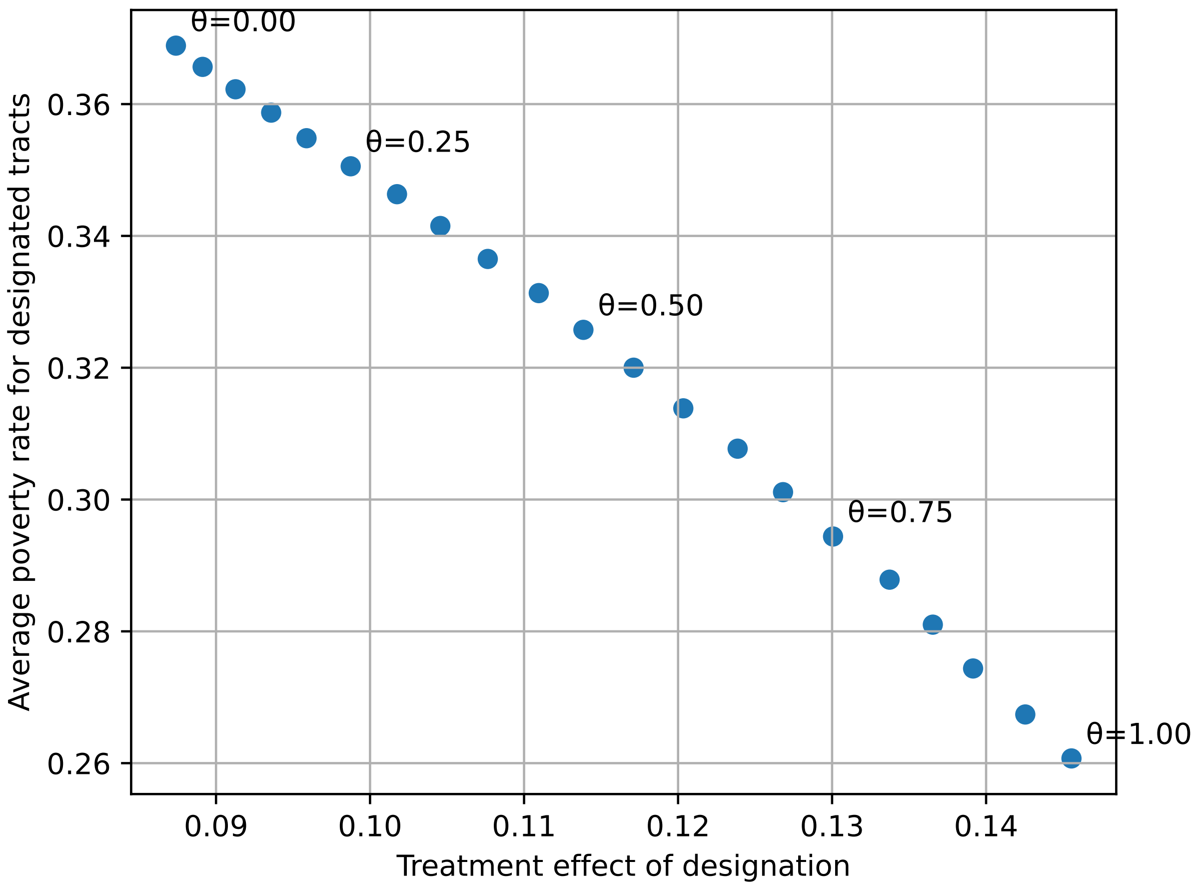
Note: Each row gives the average poverty rate in designated tracts, the average relative income in designated tracts, the average Pre-OZ Plan Count in designated tracts, the causal effect of OZ designation (in construction start counts), and the raw difference in construction starts between designated and non-designated tracts for a given scenario. The top set of rows provide averages in the observed data (where available), the averages from the data generating process implied by the model at the estimated values of $\{\theta_s\}$, and the model when θ_s are redrawn from the estimated distribution. The next block presents counterfactuals when governors have uniform preferences with $\theta = 0$, $\theta = .5$, and $\theta = 1$. The last block presents counterfactuals for the revised income and poverty eligibility criteria in the OBBBA.
Source: Authors' calculations using Dodge Data and Analytics and estimates from the simulated model described in Section 5.

Figure 1: Sensitivity of $\hat{\delta}$ to σ_y



Note: This is a plot of estimates of the proportional effect of OZ designation ($\hat{\delta}$) conditional on the volatility of unobserved development potential (σ_y). Each point gives the $\hat{\delta}$ estimate when σ_y is set to the value on the x-axis rather than estimated. Besides fixing σ_y, the estimation procedure is the same as in Section 5. The vertical line denotes the estimate for σ_y in the baseline model. *Source:* Authors' calculations from the simulated model described in Section 5.

Figure 2: Aid vs. Investment Tradeoffs



Note: This is a plot of the tradeoff between designating tracts with high poverty vs. designating tracts that will respond more to OZ designation. Each point gives the counterfactual average poverty rate in designated areas (y-axis) and treatment effect of OZ designation in designated areas (x-axis) when states have different uniform prioritization of investment (θ). Dots move down and to the right (lower poverty and higher investment response) as θ rises. *Source:* Authors' calculations from the simulated model described in Section 5.

A. ADDITIONAL TABLES AND FIGURES REFERENCED IN THE MAIN TEXT

Table A.1: Measures of State OZ Selection Criteria

State	Proportional Selection	Planning Sensitivity	Investment Opportunity Prioritization
Alabama	1	.041	4
Alaska	0	-.02	3
Arizona	1	.036	5
Arkansas	0	.008	5
California	1	-.004	2
Colorado	0	.008	3
Connecticut	0	.059	5
Delaware	0	.051	3
Florida	1	-.013	1
Georgia	0	-.035	1
Hawaii	0	.186	4
Idaho	0	-.011	4
Illinois	1	-.048	2
Indiana	0	.021	5
Iowa	0	-.003	3
Kansas	1	.048	3
Kentucky	1	0	3
Louisiana	0	.032	3
Maine	0	.027	5
Maryland	1	.036	5
Massachusetts	0	.008	3
Michigan	1	.039	4
Minnesota	0	.002	3
Mississippi	0	.054	3
Missouri	1	.053	3
Montana	0	-.118	5
Nebraska	0	.127	4
Nevada	0	.06	3
New Hampshire	0	.014	5
New Jersey	1	.072	4
New Mexico	0	.056	3
New York	0	.024	5
North Carolina	1	.005	2
North Dakota	0	-.006	3
Ohio	0	.028	4
Oklahoma	0	.04	3
Oregon	0	.086	3
Pennsylvania	0	.018	3
Rhode Island	0	.078	5
South Carolina	1	-.006	3
South Dakota	0	.031	5
Tennessee	0	.004	4
Texas	0	-.033	1
Utah	0	.02	3
Vermont	0	.181	4
Virginia	1	.037	3
Washington	1	.006	3
West Virginia	0	.084	4
Wisconsin	0	.051	4
Wyoming	0	.094	3

Note: This table presents measures of state OZ selection criteria. Proportional Selection is whether states used a proportional allocation to designate tracts. Planning Sensitivity is the imputed weight that a state placed on initial planning activity in selecting tracts, namely the state specific coefficient estimate on Pre-OZ Planning when the specification from Column (1) of Table 2 is expanded to include the interaction of Pre-OZ Planning with state indicator variables. Investment Opportunity Prioritization is a score (from 1 to 5) indexing how much a state took into account investment potential in designating tracts (as formed by GPT-5's scoring of public comments regarding allocation decisions).
Source: Authors' calculations using data from Dodge Data and Analytics, information on OZ designation from the IRS, ACS, LODES workplace area characteristics, Frank et al. (2022), Baum-Snow and Han (2024), and GPT-5.

Table A.2: Relationship between OZ Designation, Planning Activity, and Planning Starts or Construction Completions

	Planning Starts			**Construction Completions**		
	(1)	(2)	(3)	(4)	(5)	(6)
OZ Designation	0.87**	0.36**	0.27**	0.42**	0.12**	0.11**
	(0.14)	(0.07)	(0.06)	(0.08)	(0.03)	(0.03)
Pre-OZ Planning		0.36**	0.34**		0.21**	0.21**
		(0.02)	(0.02)		(0.01)	(0.02)
Renter Share			0.14			0.32*
			(0.15)			(0.14)
ln(Employment)			0.17**			0.01
			(0.02)			(0.03)
Housing Supply Elasticity (BH 2024)			0.76**			0.17*
			(0.23)			(0.07)
Missing Supply Elasticity			-0.30**			-0.09**
			(0.06)			(0.03)
Prior Abandonment			-0.01			-0.14**
			(0.10)			(0.05)
Relative Income			-0.45**			-0.05
			(0.16)			(0.10)
Poverty			0.05			-0.02
			(0.21)			(0.15)
ln(Tract Population)			0.06			-0.00
			(0.04)			(0.03)
R_a^2	0.052	0.390	0.393	0.055	0.496	0.497
Observations	30,836	30,836	30,485	30,836	30,836	30,485
State FE	✓	✓	✓	✓	✓	✓

Note: Columns (1)–(3) replicate Columns (2)–(4) in Table 2 but for a new dependent variable: planning starts. Columns (4)–(6) perform a similar exercise for a new dependent variable: construction completions. Standard errors are clustered at the state level. $^+$, *, and ** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively.
Source: Authors' calculations using Dodge Data and Analytics, information on OZ designation from the IRS, ACS, LODES workplace area characteristics, and Baum-Snow and Han (2024).

Table A.3: Relationship between OZ Designation, Planning Activity, and Construction Starts Excluding the Covid Period (2020:Q2—2021:Q4)

	Designated	Construction Starts			
	Probit	OLS			
	(1)	(2)	(3)	(4)	(5)
OZ Designation		0.32**	0.11**	0.10**	0.09**
		(0.06)	(0.02)	(0.02)	(0.03)
Pre-OZ Planning	0.01**		0.15**	0.15**	0.15**
	(0.00)		(0.01)	(0.01)	(0.01)
Renter Share	0.13			0.25*	0.29*
	(0.11)			(0.10)	(0.11)
ln(Employment)	0.22**			0.01	0.03
	(0.03)			(0.02)	(0.02)
Housing Supply Elasticity (BH 2024)	0.37^{+}			0.20**	0.33**
	(0.21)			(0.07)	(0.10)
Missing Supply Elasticity	0.43**			-0.07**	-0.06**
	(0.05)			(0.02)	(0.02)
Prior Abandonment	0.06**			-0.11**	-0.12**
	(0.02)			(0.04)	(0.03)
Relative Income	-0.70**			-0.05	-0.04
	(0.14)			(0.07)	(0.02)
Poverty	2.08**			-0.05	-0.12
	(0.35)			(0.10)	(0.12)
ln(Tract Population)	-0.13**			0.01	0.04*
	(0.04)			(0.02)	(0.02)
R^2_a		0.053	0.437	0.438	0.424
Observations	30,485	30,836	30,836	30,485	61,374
State FE	✓	✓	✓	✓	✓

Note: This table replicates the analysis in Table 2 except it excludes all observations from 2020:Q2 to 2021:Q4. Column (1) presents probit estimates of the relationship between OZ designation and tract characteristics, and columns (2)–(5) present OLS estimates predicting tract construction starts based on whether the tract was designated as an OZ, the number of projects planned before the OZ program started, and other tract characteristics. In columns (1)–(4) the sample is tracts that were eligible to be OZs, and column (5) includes the full sample of tracts (thus comparing OZ designated tracts to all other tracts, rather than tracts that were eligible but not chosen). Standard errors are clustered at the state level. $^{+}$, *, and ** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. Data from 2020Q2 on was excluded.
Source: Authors' calculations using Dodge Data and Analytics, information on OZ designation from the IRS, ACS, LODES workplace area characteristics, and Baum-Snow and Han (2024).

Table A.4: Relationship between OZ Designation, Planning Activity, and Construction Starts Including Contiguous Tracts

	Designated Probit	**Construction Starts** OLS			
	(1)	(2)	(3)	(4)	(5)
OZ Designation		0.46**	0.17**	0.15**	0.14**
		(0.09)	(0.04)	(0.04)	(0.04)
Pre-OZ Planning	0.01**		0.21**	0.21**	0.20**
	(0.00)		(0.01)	(0.01)	(0.01)
Renter Share	0.16			0.34*	0.38**
	(0.12)			(0.13)	(0.13)
ln(Employment)	0.21**			0.03	0.04*
	(0.03)			(0.02)	(0.02)
Housing Supply Elasticity (BH 2024)	0.40*			0.25*	0.43**
	(0.19)			(0.11)	(0.13)
Missing Supply Elasticity	0.41**			-0.10**	-0.10**
	(0.05)			(0.03)	(0.03)
Prior Abandonment	0.06**			-0.13**	-0.14**
	(0.02)			(0.05)	(0.04)
Relative Income	-0.66**			-0.05	-0.05
	(0.13)			(0.08)	(0.04)
Poverty	2.08**			0.01	-0.10
	(0.35)			(0.15)	(0.16)
Contiguous Tract	-0.96**			0.06**	0.02
	(0.10)			(0.02)	(0.02)
ln(Tract Population)	-0.14**			0.02	0.06*
	(0.04)			(0.03)	(0.03)
R_a^2		0.047	0.457	0.459	0.452
Observations	40,728	41,085	41,085	40,728	71,617
State FE	✓	✓	✓	✓	✓

Note: This is the same as Table 2 except that contiguous tracts are included in the analysis. Column (1) presents probit estimates of the relationship between OZ designation and tract characteristics, and columns (2)–(5) present OLS estimates predicting tract construction starts based on whether the tract was designated as an OZ, the number of projects planned before the OZ program started, and other tract characteristics. In columns (1)–(4) the sample is tracts that were eligible to be OZs, and column (5) includes the full sample of tracts (thus comparing OZ designated tracts to all other tracts, rather than tracts that were eligible but not chosen). Standard errors are clustered at the state level. $^+$, *, and ** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively.
Source: Authors' calculations using Dodge Data and Analytics, information on OZ designation from the IRS, ACS, LODES workplace area characteristics, and Baum-Snow and Han (2024).

Table A.5: Relationship between OZ Designation, Planning Activity, and Construction Starts for Multifamily Properties

	Designated Probit	**Construction Starts** OLS			
	(1)	(2)	(3)	(4)	(5)
OZ Designation		0.30**	0.16**	0.13**	0.13**
		(0.05)	(0.03)	(0.03)	(0.03)
Pre-OZ Planning	0.02**		0.26**	0.26**	0.25**
	(0.00)		(0.01)	(0.01)	(0.01)
Renter Share	0.11			0.24**	0.23**
	(0.11)			(0.08)	(0.05)
ln(Employment)	0.23**			0.02	0.03*
	(0.03)			(0.01)	(0.01)
Housing Supply Elasticity (BH 2024)	0.38+			0.02	0.08+
	(0.21)			(0.04)	(0.04)
Missing Supply Elasticity	0.42**			-0.08**	-0.09**
	(0.05)			(0.02)	(0.02)
Prior Abandonment	0.01			-0.16**	-0.17**
	(0.03)			(0.05)	(0.05)
Relative Income	-0.70**			-0.14**	-0.05
	(0.13)			(0.05)	(0.03)
Poverty	2.07**			-0.00	-0.00
	(0.36)			(0.09)	(0.09)
ln(Tract Population)	-0.13**			0.01	0.03+
	(0.04)			(0.02)	(0.01)
R_a^2		0.074	0.440	0.444	0.418
Observations	30,485	30,836	30,836	30,485	61,374
State FE	✓	✓	✓	✓	✓

Note: This table repeats the analysis in Table 2 for multifamily properties. Column (1) presents probit estimates of the relationship between OZ designation and tract characteristics, and columns (2)–(5) present OLS estimates predicting tract construction starts based on whether the tract was designated as an OZ, the number of projects planned before the OZ program started, and other tract characteristics. In columns (1)–(4) the sample is tracts that were eligible to be OZs, and column (5) includes the full sample of tracts (thus comparing OZ designated tracts to all other tracts, rather than tracts that were eligible but not chosen). Standard errors are clustered at the state level. $^+$, *, and ** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively.
Source: Authors' calculations using Dodge Data and Analytics, information on OZ designation from the IRS, ACS, LODES workplace area characteristics, and Baum-Snow and Han (2024).

Table A.6: State Characteristics by Investment Rating

Rating	1	2	3	4	5
Num. of States	3	3	22	11	11
Democratic Governor (%)	0.00	66.67	36.36	18.18	36.36
Supply Elasticity (%)	18.26	14.50	16.60	16.95	16.48

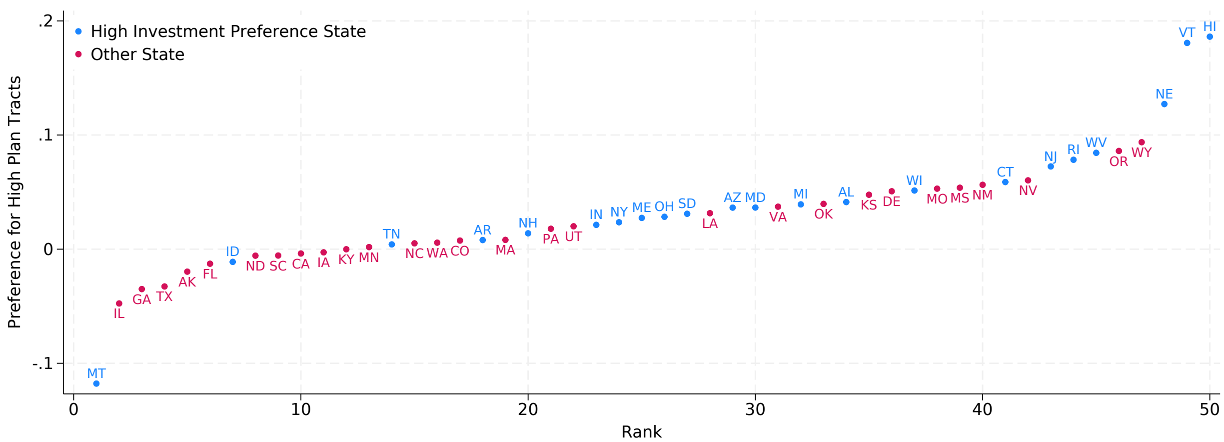
Note: This table includes information on correlates with the ChatGPT-generated investing rating. The top row indicates the rating, with 5 indicating highest preference for favoring tracts with investment potential. The lower rows include the number of states in each rating category, the percent of those states with a democratic governor, and the average supply elasticity within the state according to Baum-Snow and Han (2024).
Source: Authors' calculations using Dodge Data and Analytics, information on OZ designation from the IRS, Frank et al. (2022), and Baum-Snow and Han (2024).

Table A.7: Relationship between OZ Designation, Planning Activity, and Construction Starts in Model-Generated Data

	Designated Probit		**Construction Starts** OLS		
	(1)	(2)	(3)	(4)	(5)
OZ Designation			0.50	0.27	0.10
			(0.04)	(0.03)	(0.02)
Pre-OZ Planning	0.02	0.00		0.20	-0.00
	(0.00)	(0.00)		(0.01)	(0.01)
Poverty	1.78	1.78			-0.02
	(0.08)	(0.08)			(0.09)
Relative Income	-0.45	-0.45			-0.01
	(0.06)	(0.06)			(0.07)
Development Potential		0.11			1.08
		(0.01)			(0.07)
State FE	✓	✓	✓	✓	✓

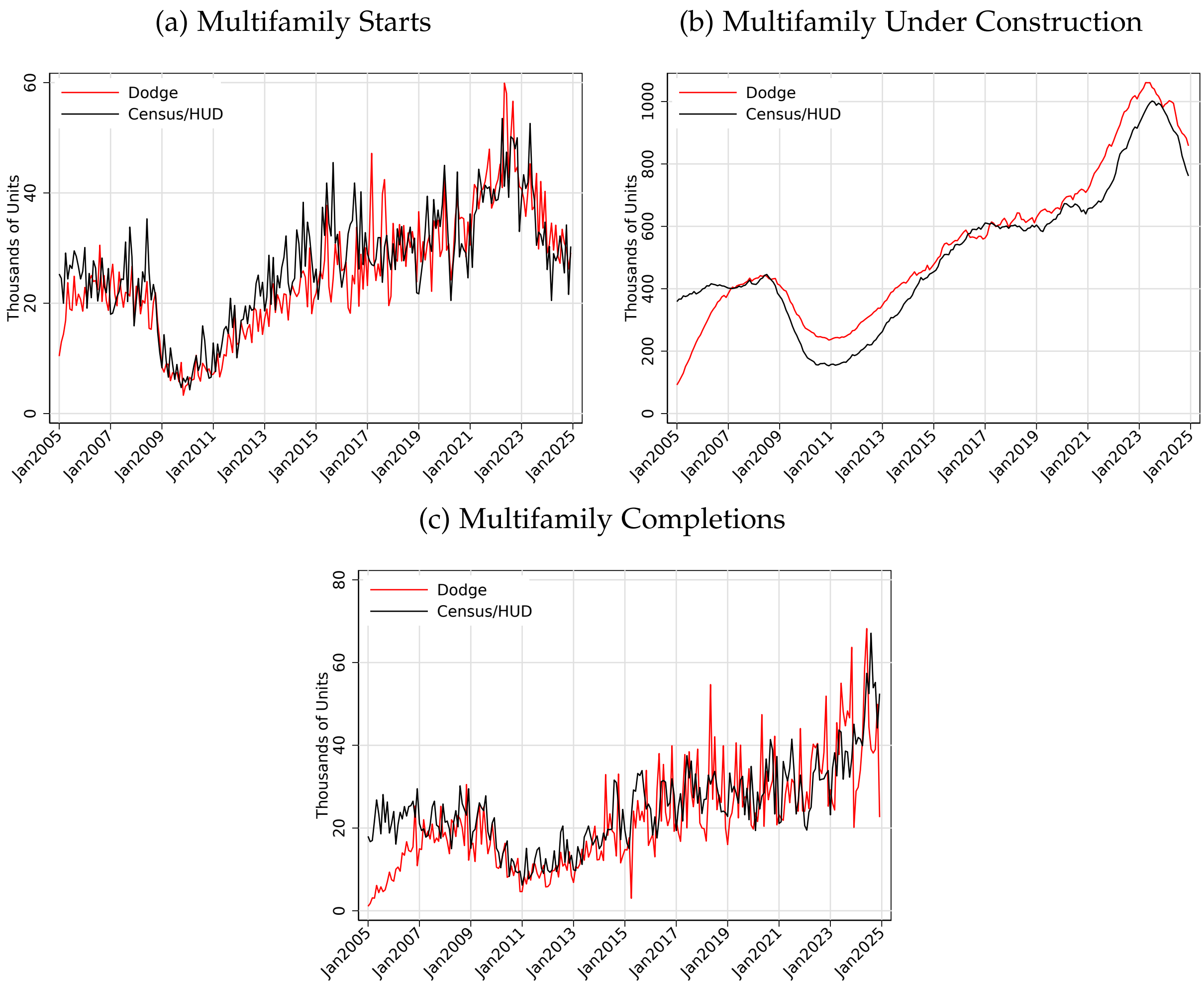
Note: This table repeats analysis from Table 2 with model-generated data (averaging over 100 simulations using parameters from the baseline model). Each cell reports the average point estimate from either a probit predicting OZ designation (columns 1 and 2) or a regression predicting construction starts (columns 3–5), with the standard deviation of the point estimate across simulations in parenthesis. Pre-OZ Planning, Poverty and Relative Income are observed tract-level data, while OZ designation, construction starts, and Development Potential are simulated. Columns (2) and (5) show the effects of controlling for development potential, which is unobservable in the actual data.
Source: Authors' calculations using Dodge Data and Analytics, information on OZ designation from the IRS, ACS, and the simulated model described in Section 5..

Figure A.1: State Planning Sensitivity



Note: This figure plots the state-specific coefficient estimate on Pre-OZ Planning when the specification from Column (1) of Table 2 is expanded to the interaction of Pre-OZ Planning with state Planning Sensitivity. Planning Sensitivity is the imputed weight that a state placed on initial planning activity in selecting tracts, namely the state specific coefficient estimate on Pre-OZ Planning when the specification from Column (1) of Table 2 is expanded to include the interaction of Pre-OZ Planning with state indicator variables. Investment Opportunity Prioritization is a score (from 1 to 5) indexing how much a state took into account investment potential in designating tracts (as formed by GPT-5's scoring of public comments regarding allocation decisions). High Investment Opportunity Prioritization states are denoted by blue dots with labels above markers, while other states are denoted by red dots, with labels below the markers.
Source: Authors' calculations using Dodge Data and Analytics, information on OZ designation from the IRS, ACS, LODES workplace area characteristics, and Baum-Snow and Han (2024).

Figure A.2: Multifamily Housing Statistics.



(a) Multifamily Starts

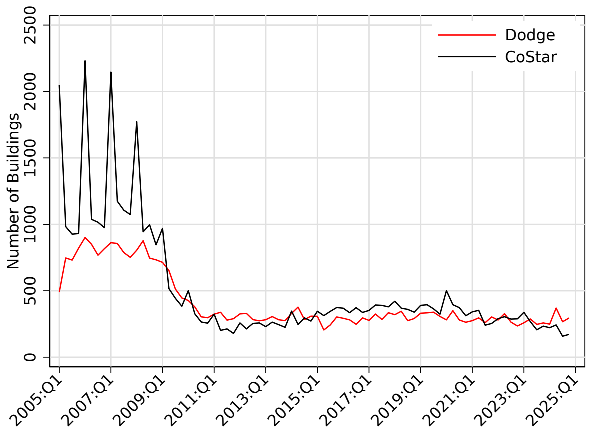
(b) Multifamily Under Construction

(c) Multifamily Completions

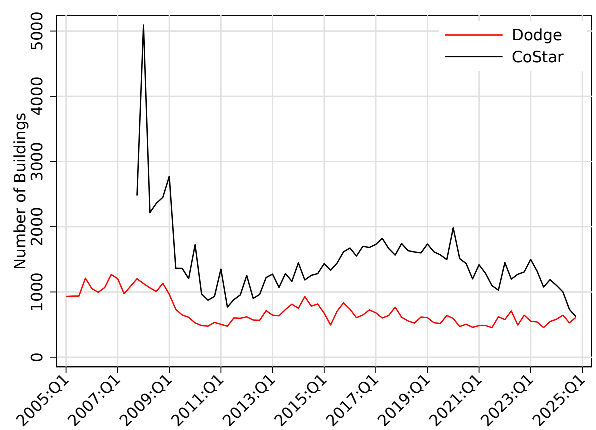
Note: We compare data in implied unit starts, units under construction, and unit completions from the Dodge data to reported statistics for buildings with five or more units from the U.S. Census and the Department of Housing and Urban Development.
Source: Authors' calculations using data from Dodge Data & Analytics, Inc. and the U.S. Census and the Department of Housing and Urban Development, retrieved from Haver Analytics.

Figure A.3: Comparison of Completions in Dodge Real Estate Analyzer to CoStar.

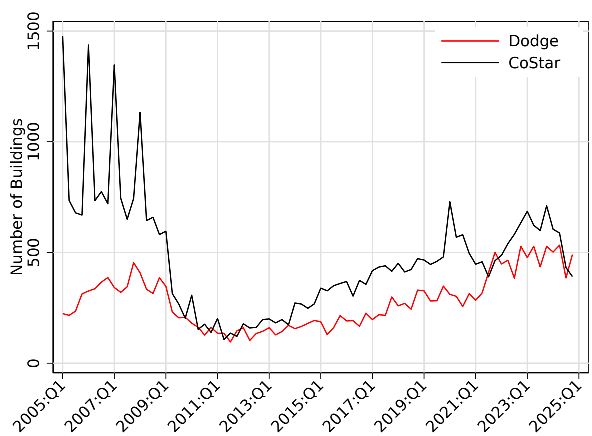
(a) Office Completions



(b) Retail Completions



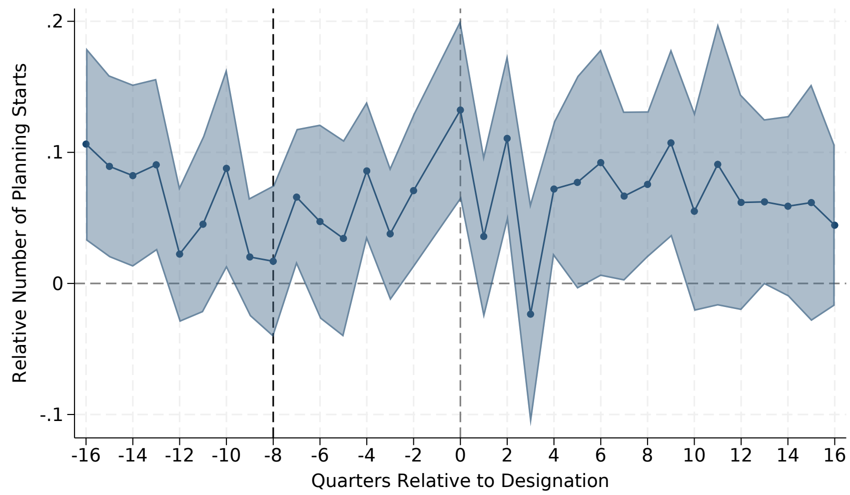
(c) Warehouse Completions



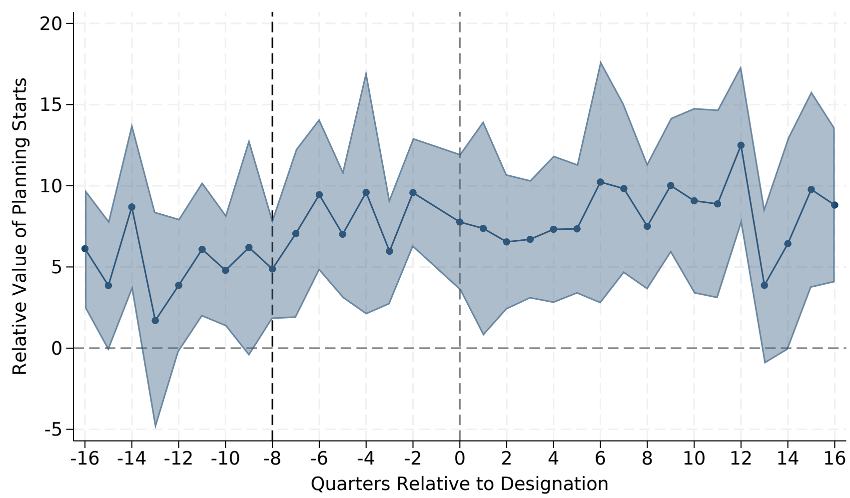
Note: Warehouses are compared to logistical industrial properties from CoStar. *Source:* Authors' calculations using data from Dodge Data & Analytics, Inc. and CoStar Suite (US).

Figure A.4: PLANNING STARTS OVER TIME.

(a) Number of Planning Starts



(b) Value of Planning Starts

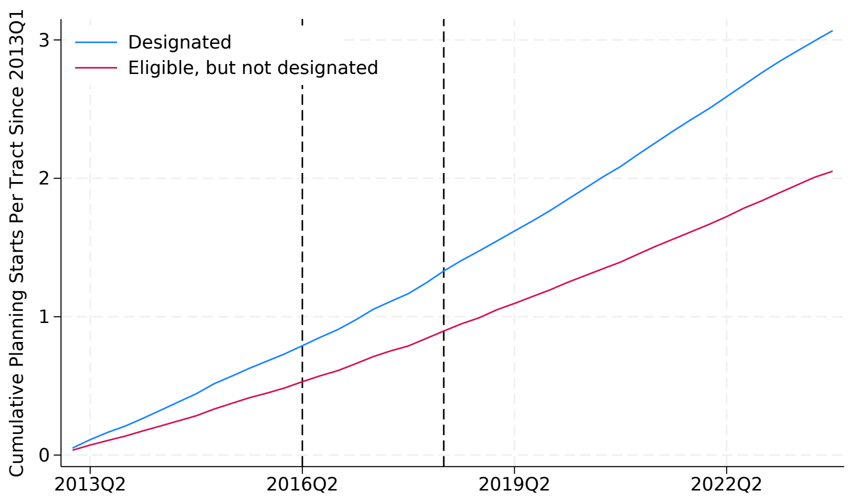


Note: These graphs plot estimates from:

$$\text{Plan Start}_{i,t} = \beta_t \text{OZ Designation}_i + \epsilon_{i,t}$$

where $\hat{\beta}_t$ estimates the difference in planning start counts (top figure) or the value of planning starts millions of 2012 USD (bottom figure) in designated vs. eligible but not designated tracts in quarter t. The vertical dashed line at zero is the time of designation in the second quarter of 2018. The vertical dashed line at -8 is when OZ legislation was first introduced in the second quarter of 2016. We also include a horizontal dashed line at zero as a reference point. Contiguous tracts are excluded and standard errors are clustered by state.
Source: Authors' calculations using the data from Dodge Data and Analytics and information on OZ designation from the IRS.

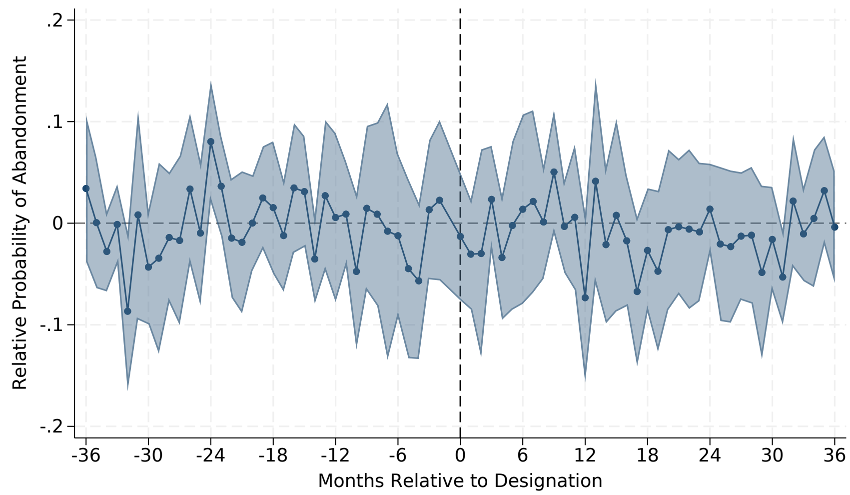
Figure A.5: Cumulative Planning Starts by OZ Status



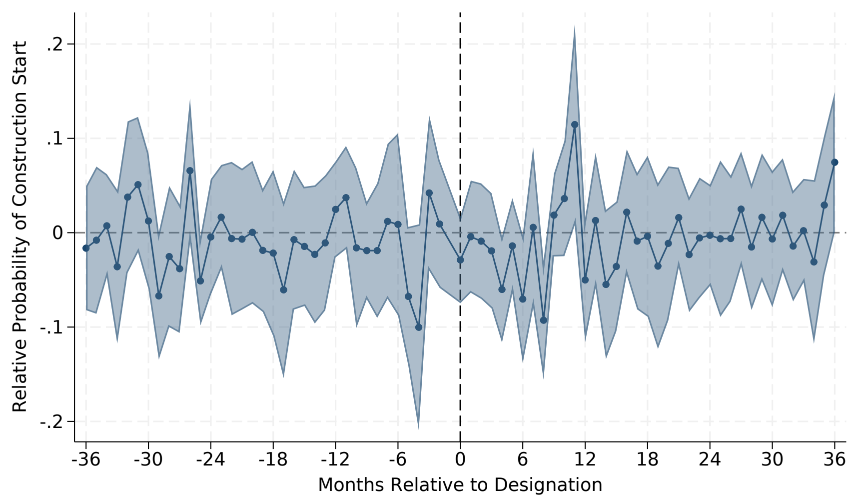
Note: This graphs plots the cumulative number of plan starts since the start of 2013, averaging over tracts that were designated as OZs (blue), and tracts that were eligible but not designated as OZs (red). The vertical dashed lines denotes when OZ legislation was first introduced (2016:Q2) opportunity zones designations were made (2018:Q2). Contiguous tracts are excluded.
Source: Authors' calculations using the data from Dodge Data and Analytics and information on OZ designation from the IRS.

Figure A.6: Relative Probability of Project Abandonment and Construction Start in Designated versus Eligible Tracts.

(a) Relative Abandonment Rate



(b) Relative Construction Start Rate



Note: These graphs plot estimates from:

$$\text{Transition}_{i,t} = \beta_t \text{OZ Designation}_i + \epsilon_{i,t}$$

where $\hat{\beta}_t$ estimates the difference the probability that a project in planning gets abandoned (top figure) or transitions to being under construction (bottom figure) in designated vs. eligible but not designated tracts in month t. The sample includes projects that were in planning in the previous month. The vertical dashed line at zero is the time of designation in the second quarter of 2018. We also include a horizontal dashed line at zero as a reference point. Contiguous tracts are excluded and standard errors are clustered by state.

Source: Authors' calculations using the data from Dodge Data and Analytics and information on OZ designation from the IRS.

B. CONSTRUCTION OF STATE INVESTMENT OPPORTUNITY PRIORITIZATION INDEX

The investment prioritization index is formed by a three-step process. First, we compiled sources on how OZs were selected based on ChatGPT deep research requests and the sources/text reported by Frank et al. (2022). Second, we reviewed the information from those sources to extract text pertaining to how states selected which tracts to designate as OZs, excluding information not coming from primary sources (e.g., news articles making inferences about the selection processes based on the characteristics of selected tracts). Third, we had ChatGPT-5 assess states on how much they prioritized investment potential based on those text excerpts.[15] We did this in "Temporary Chat" so that memory from previous activity would not contaminate results. This process allowed us to vet materials used for characterizing investment prioritization to ensure that measures were based on states' reported selection criteria rather than inferences based on ex-post construction activity in OZs (a potential source of reverse causality).

The specific prompt used was as follows:

> I have attached an ods file with state names in column A, and statements about how states selected OZs in column B. Some states have multiple entries, corresponding with different information sources. For each state and DC, read through all of the content for a given state, and extract information on what criteria were used to select OZs or what data were collected to support those decisions. Sort these factors based on whether they reflect measures of investment potential, whether they reflect need for revitalization, or whether they are neutral or ambiguous. Ignore statements about program eligibility (poverty rate of at least 20 percent or a median family income less than 80 percent of the reference area) even though they relate to income and poverty, I am interested in how states selected among eligible tracts. Based on that set of factors, rate the state on a scale of 1 to 5 based on how much it prioritized the potential of a tract to generate new investment or development. 5 should indicate that states predominantly selected tracts based on economic potential, 3 should indicate either a balanced approach with need

[15] Specifically, we used GPT-5.2 Extended Thinking

and economic potential weighed evenly or insufficient information to make an assessment, and 1 should indicate that states predominantly prioritized designating areas of high need. Start by undertaking this exercise for the first 10 states+DC alphabetically, then ask if I would like to proceed with the next 10 states, grading with the same rubric.