

# 20-opportunity-zone-evaluation

January 4, 2026

**DATA PROVENANCE:** Real FRED unemployment data + Simulated OZ designation & outcomes | See Hybrid Data Structure Notice

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## 1 Opportunity Zone Policy Evaluation

### 1.1 KASS Notebook 20 | Applied Econometrics Series

KRL Suite v2.0 | Tier: Professional | Data: FRED County Economics

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#### 1.1.1 Overview

This notebook demonstrates **place-based policy evaluation** using the 2017 Tax Cuts and Jobs Act Opportunity Zone (OZ) program as a case study. We apply quasi-experimental methods to estimate the impact of OZ designation on local economic outcomes.

#### 1.1.2 Learning Objectives

After completing this notebook, you will be able to:

1. **Selection Analysis** - Understand how tracts were designated as Opportunity Zones
2. **Difference-in-Differences** - Apply DiD to estimate OZ treatment effects
3. **Propensity Score Methods** - Account for selection on observables
4. **Spatial Econometrics** - Model spillover effects to neighboring tracts
5. **Displacement Analysis** - Test for adverse effects on residents

#### 1.1.3 Key Methods

Method	Purpose	KRL Component
Difference-in-Differences	Estimate treatment effect	<code>TreatmentEffectEstimator</code>
Propensity Score Weighting	Balance treated/control	<code>sklearn LogisticRegression</code>
Spatial DiD	Capture spillovers	<code>SpatialDiD</code> (Pro tier)
Event Study	Validate parallel trends	Custom implementation

#### 1.1.4 Policy Context

The Opportunity Zone program designated ~8,700 low-income census tracts for tax-advantaged investment. Key policy questions:

1. Did OZ designation increase investment flows?
2. Did investment translate to improved economic outcomes for residents?
3. Did investment displace existing residents (gentrification)?
4. What are the spillover effects on non-designated neighbors?

#### 1.1.5 Prerequisites

- Python 3.9+
- KRL Suite Professional Tier (for spatial analysis)
- FRED API key
- Understanding of difference-in-differences methodology

#### 1.1.6 Estimated Time: 35-45 minutes

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**Causal Inference Note:** This notebook makes causal claims under stated identifying assumptions. The parallel trends assumption is critical and testable. See the Identification Strategy and Limitations sections for validity assessment.

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## 1.2 HYBRID DATA STRUCTURE NOTICE

### CRITICAL DATA DISCLOSURE:

This notebook uses a **hybrid real/simulated data structure**:

Component	Source	Provenance
Unemployment rates (2016, 2022)	REAL	FRED LAUCN series for PA counties
OZ designation	SIMULATED	Based on <code>selection_score</code> with 50% probability
Home values	SIMULATED	Correlated with unemployment + random noise
Investment flows	SIMULATED	Lognormal draw conditional on designation
Poverty, income, education	SIMULATED	Derived from unemployment with noise

**Pre-programmed effects:** - Home value OZ effect: 8% (`oz_effect_pct = 0.08`) - Investment premium: Lognormal(14,1) vs Lognormal(12,1)

**Implication:** The DiD effect on home values is an **artifact of the data generation process**, not an empirical finding. Unemployment outcome analysis uses real data but with simulated treatment assignment.

**For actual OZ evaluation:** - Real OZ tract designations: <https://www.cdfifund.gov/opportunity-zones> - QOF investment data: Treasury Form 8996 filings - Tract-level outcomes: Census ACS 5-year estimates

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### 1.3 Motivation

#### 1.3.1 The Place-Based Policy Challenge

Place-based economic development policies—programs that target specific geographic areas for investment—face fundamental evaluation challenges:

- 1. Selection Bias** - Areas are selected based on observed characteristics (poverty, unemployment) - Selected areas may have different trajectories regardless of treatment - Simple before/after comparisons confound treatment with selection
- 2. Spatial Interdependence** - Treated areas interact with untreated neighbors - Investment may spill over or displace - SUTVA (Stable Unit Treatment Value Assumption) may be violated
- 3. Multiple Outcomes** - Investment metrics (QOF fund flows) - Economic outcomes (employment, income) - Resident welfare (housing costs, displacement) - May show positive effects on some outcomes but harm on others

#### 1.3.2 The Opportunity Zone Natural Experiment

The 2017 OZ program offers unique evaluation opportunities:

**Eligibility-Based Designation:** - Governors selected ~25% of *eligible* low-income tracts - Creates natural comparison group: eligible but not designated - Selection decision somewhat discretionary, creating variation

**Staggered Rollout:** - Initial designations in April 2018 - Investment flows ramp up through 2019-2021 - Allows event study analysis of dynamic effects

**Observable Selection Criteria:** - Low-income census tract status is deterministic - Can construct similar eligible comparison tracts - Propensity score methods address remaining selection

#### 1.3.3 Research Questions

This notebook addresses four policy questions:

Question	Method	Outcome
1. Did OZ increase investment?	DiD	QOF fund flows
2. Did investment improve outcomes?	DiD with weighting	Unemployment rate
3. Did OZ displace residents?	DiD	Housing costs, poverty
4. Did benefits spill to neighbors?	Spatial DiD	Neighbor outcomes

#### 1.3.4 Prior Literature

Key findings from existing OZ research:

- Chen, Glaeser & Wessel (2019): Early evidence of modest investment effects
- Arefeva et al. (2021): OZ increased property values, mixed employment effects
- Freedman et al. (2021): Some evidence of gentrification in certain markets
- Sage et al. (2022): Heterogeneous effects by urban/rural status

Our contribution: Demonstrating KRL Suite methods with real FRED county data.

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*This notebook uses Pennsylvania county data as an OZ-style evaluation. For tract-level analysis, connect to CDFI Fund QOF data.*

## 1.4 1. Environment Setup

```
[ ]: # =====
# Opportunity Zone Evaluation: Environment Setup
# =====

import os
import sys
import warnings
from datetime import datetime
from dotenv import load_dotenv

# Load environment variables
_env_path = os.path.expanduser("~/Documents/GitHub/KRL/Private IP/krl-tutorials/
˓.env")
load_dotenv(_env_path)

# Add KRL package paths
_krl_base = os.path.expanduser("~/Documents/GitHub/KRL/Private IP")
for _pkg in ["krl-open-core/src", "krl-model-zoo-v2-2.0.0-community",
            "krl-causal-policy-toolkit/src", "krl-geospatial-tools/src",
            "krl-data-connectors/src"]:
    _path = os.path.join(_krl_base, _pkg)
    if _path not in sys.path:
        sys.path.insert(0, _path)

import numpy as np
import pandas as pd
from scipy import stats
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
import matplotlib.pyplot as plt
import matplotlib.patches as mpatches
import seaborn as sns
import plotly.express as px
import plotly.graph_objects as go
from plotly.subplots import make_subplots
```

```

from krl_core import get_logger
from krl_policy.estimators.treatment_effect import TreatmentEffectEstimator

# Import Professional FRED connector
from krl_data_connectors.professional.fred_full import FREDFullConnector
from krl_data_connectors import skip_license_check

warnings.filterwarnings('ignore')
logger = get_logger("OpportunityZoneEvaluation")

# Visualization settings
plt.style.use('seaborn-v0_8-whitegrid')

# Color palette
COLORS = ['#0072B2', '#E69F00', '#009E73', '#CC79A7', '#56B4E9', '#D55E00']

print("=="*70)
print(" Opportunity Zone Policy Evaluation")
print("=="*70)
print(f" Execution Time: {datetime.now().strftime('%Y-%m-%d %H:%M:%S')}")
print(f"\n Analysis Components:")
print(f"    • Selection Analysis (Real County Data)")
print(f"    • Investment Flow Tracking")
print(f"    • Difference-in-Differences Impact")
print(f"    • Spatial Spillover Effects")
print(f"\n Data Source: FRED Professional (County Economics)")
print("=="*70)

```

## 1.5 2. Fetch Real County Economic Data from FRED

We use real unemployment and economic data to evaluate Opportunity Zone-style policies. Counties are classified as OZ-eligible based on high unemployment rates.

```

[ ]: # =====
# Fetch Real County Economic Data from FRED
# =====

# Initialize FRED connector with Professional tier license skip
fred = FREDFullConnector(api_key="SHOWCASE-KEY")
skip_license_check(fred)
fred.fred_api_key = os.getenv('FRED_API_KEY')
fred._init_session()

# Pennsylvania county FIPS codes with geographic info
# These counties will form our "Opportunity Zone" evaluation area
pa_counties = {

```

```

'001': ('Adams', -77.22, 39.87), '003': ('Allegheny', -79.98, 40.47),
'005': ('Armstrong', -79.47, 40.81), '007': ('Beaver', -80.35, 40.68),
'009': ('Bedford', -78.49, 39.99), '011': ('Berks', -75.93, 40.42),
'013': ('Blair', -78.35, 40.48), '015': ('Bradford', -76.51, 41.79),
'017': ('Bucks', -75.11, 40.34), '019': ('Butler', -79.91, 40.91),
'021': ('Cambria', -78.72, 40.49), '023': ('Cameron', -78.20, 41.44),
'025': ('Carbon', -75.71, 40.92), '027': ('Centre', -77.82, 40.92),
'029': ('Chester', -75.75, 39.97), '031': ('Clarion', -79.42, 41.19),
'033': ('Clearfield', -78.47, 41.00), '035': ('Clinton', -77.64, 41.23),
'037': ('Columbia', -76.40, 41.05), '039': ('Crawford', -80.11, 41.68),
'041': ('Cumberland', -77.26, 40.16), '043': ('Dauphin', -76.79, 40.41),
'045': ('Delaware', -75.40, 39.92), '047': ('Elk', -78.65, 41.42),
'049': ('Erie', -80.09, 42.12), '051': ('Fayette', -79.65, 39.91),
'053': ('Forest', -79.23, 41.51), '055': ('Franklin', -77.72, 39.93),
'057': ('Fulton', -78.11, 39.93), '059': ('Greene', -80.22, 39.85),
'061': ('Huntingdon', -77.99, 40.42), '063': ('Indiana', -79.15, 40.62),
'065': ('Jefferson', -78.99, 41.13), '067': ('Juniata', -77.40, 40.53),
'069': ('Lackawanna', -75.61, 41.44), '071': ('Lancaster', -76.25, 40.04),
'073': ('Lawrence', -80.33, 41.00), '075': ('Lebanon', -76.45, 40.37),
'077': ('Lehigh', -75.61, 40.61), '079': ('Luzerne', -76.05, 41.17),
'081': ('Lycoming', -77.06, 41.34), '083': ('McKean', -78.56, 41.81),
'085': ('Mercer', -80.26, 41.30), '087': ('Mifflin', -77.62, 40.61),
'089': ('Monroe', -75.33, 41.06), '091': ('Montgomery', -75.36, 40.21),
'093': ('Montour', -76.66, 41.03), '095': ('Northampton', -75.31, 40.75),
'097': ('Northumberland', -76.71, 40.85), '099': ('Perry', -77.26, 40.40),
'101': ('Philadelphia', -75.16, 39.95), '103': ('Pike', -75.03, 41.33),
'105': ('Potter', -77.90, 41.74), '107': ('Schuylkill', -76.22, 40.71),
'109': ('Snyder', -77.08, 40.77), '111': ('Somerset', -79.03, 40.01),
'113': ('Sullivan', -76.51, 41.45), '115': ('Susquehanna', -75.80, 41.82),
'117': ('Tioga', -77.25, 41.77), '119': ('Union', -77.06, 40.96),
'121': ('Venango', -79.76, 41.40), '123': ('Warren', -79.30, 41.81),
'125': ('Washington', -80.25, 40.19), '127': ('Wayne', -75.30, 41.65),
'129': ('Westmoreland', -79.47, 40.31), '131': ('Wyoming', -76.01, 41.52),
'133': ('York', -76.73, 39.92)
}

# Fetch unemployment data for 2016 (pre-OZ) and 2022 (post-OZ)
print(" Fetching PA county unemployment data from FRED...")
records = []

for county_code, (county_name, lon, lat) in pa_counties.items():
    try:
        series_id = f'LAUCN42{county_code}0000000003A'
        series_data = fred.get_series(series_id, start_date='2016-01-01', end_date='2022-12-31')

        if series_data is not None and not series_data.empty:

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        series_data.index = pd.to_datetime(series_data.index)

        # Get 2016 and 2022 annual averages
        ur_2016 = series_data[series_data.index.year == 2016]['value'].
        ↪mean()
        ur_2022 = series_data[series_data.index.year == 2022]['value'].
        ↪mean()

        if not (pd.isna(ur_2016) or pd.isna(ur_2022)):
            records.append({
                'tract_id': f'PA_{county_code}',
                'county_name': county_name,
                'longitude': lon,
                'latitude': lat,
                'unemployment_rate_2016': float(ur_2016),
                'unemployment_rate_2022': float(ur_2022)
            })
        except Exception as e:
            pass

print(f"    Retrieved data for {len(records)} PA counties")

# Create base dataset
oz_data = pd.DataFrame(records)

# Define OZ eligibility: counties with unemployment > 6% in 2016 are "eligible"
state_median_ur = oz_data['unemployment_rate_2016'].median()
oz_data['eligible'] = (oz_data['unemployment_rate_2016'] > state_median_ur).
    ↪astype(int)

# Simulate OZ designation: ~50% of eligible counties were designated as OZ
np.random.seed(42)
n_eligible = oz_data['eligible'].sum()
designation_prob = 0.5

# Selection based on unemployment severity (higher unemployment = more likely to
    ↪be designated)
eligible_mask = oz_data['eligible'] == 1
oz_data['selection_score'] = 0.0
oz_data.loc[eligible_mask, 'selection_score'] = (
    oz_data.loc[eligible_mask, 'unemployment_rate_2016'] /
    oz_data.loc[eligible_mask, 'unemployment_rate_2016'].max()
)
oz_data['designation_prob'] = oz_data['selection_score'] * designation_prob
oz_data['designated_oz'] = (
    (np.random.uniform(0, 1, len(oz_data)) < oz_data['designation_prob']) &
    (oz_data['eligible'] == 1)
)

```

```

).astype(int)

# Create derived economic indicators
oz_data['employment_rate_2016'] = 100 - oz_data['unemployment_rate_2016']
oz_data['employment_rate_2022'] = 100 - oz_data['unemployment_rate_2022']
oz_data['employment_change'] = oz_data['employment_rate_2022'] - oz_data['employment_rate_2016']

# Simulate investment and home values based on real unemployment patterns
# Higher unemployment areas assumed to have lower base home values
oz_data['home_value_2016'] = 150000 + (100 - oz_data['unemployment_rate_2016']) * 15000 + np.random.normal(0, 20000, len(oz_data))
oz_data['home_value_2016'] = oz_data['home_value_2016'].clip(50000, 500000)

# Home value appreciation: base appreciation + OZ effect
base_appreciation = 0.20 # 20% base appreciation 2016-2022
oz_effect_pct = np.where(oz_data['designated_oz'] == 1, 0.08, 0) # 8% OZ premium
oz_data['home_value_2022'] = oz_data['home_value_2016'] * (1 + base_appreciation + oz_effect_pct + np.random.normal(0, 0.05, len(oz_data)))

# Investment flows (simulated based on OZ designation)
oz_data['investment_post_2018'] = np.where(
    oz_data['designated_oz'] == 1,
    np.random.lognormal(14, 1, len(oz_data)), # Higher investment in OZ
    np.random.lognormal(12, 1, len(oz_data)) # Lower in non-OZ
)
oz_data['qof_investment'] = np.where(oz_data['designated_oz'] == 1, oz_data['investment_post_2018'] * 0.5, 0)

# Additional covariates (simulated for propensity score)
oz_data['poverty_rate_2016'] = 10 + oz_data['unemployment_rate_2016'] * 1.5 + np.random.normal(0, 3, len(oz_data))
oz_data['median_income_2016'] = 60000 - oz_data['unemployment_rate_2016'] * 2000 + np.random.normal(0, 5000, len(oz_data))
oz_data['education_pct'] = 30 - oz_data['unemployment_rate_2016'] * 0.5 + np.random.normal(0, 5, len(oz_data))
oz_data['transit_access'] = np.random.uniform(0.2, 0.9, len(oz_data))
oz_data['vacancy_rate'] = 5 + oz_data['unemployment_rate_2016'] * 0.5 + np.random.normal(0, 2, len(oz_data))

print(f"\n Opportunity Zone Dataset (Real FRED Data)")
print(f"  • Total counties: {len(oz_data)}")
print(f"  • Eligible counties (UR > median): {oz_data['eligible'].sum()}")
print(f"  • ({oz_data['eligible'].mean()*100:.1f}%)")

```

```

print(f" • Designated OZ counties: {oz_data['designated_oz'].sum()}")
    ↪({oz_data['designated_oz'].mean()*100:.1f}%)")
print(f" • Avg 2016 unemployment (designated):"
    ↪{oz_data[oz_data['designated_oz']==1]['unemployment_rate_2016'].mean():.
    ↪1f}%"")
print(f" • Avg 2022 unemployment (designated):"
    ↪{oz_data[oz_data['designated_oz']==1]['unemployment_rate_2022'].mean():.
    ↪1f}%"")
oz_data.head()

```

## 1.6 Identification Strategy

### 1.6.1 Causal Estimand

We seek to estimate the **Average Treatment Effect on the Treated (ATT)** of Opportunity Zone designation:

$$\tau^{ATT} = E[Y_{i,post}(1) - Y_{i,post}(0)|D_i = 1]$$

where: -  $Y_{i,post}(1)$ : Outcome for tract  $i$  in post-period if designated (observed) -  $Y_{i,post}(0)$ : Outcome for tract  $i$  in post-period if *not* designated (counterfactual) -  $D_i = 1$ : Tract was designated as Opportunity Zone

### 1.6.2 Difference-in-Differences Specification

We estimate the ATT using the canonical two-period DiD model:

$$Y_{it} = \alpha + \beta_1 \cdot \text{Treated}_i + \beta_2 \cdot \text{Post}_t + \tau^{DiD} \cdot (\text{Treated}_i \times \text{Post}_t) + \epsilon_{it}$$

The DiD estimator is:

$$\hat{\tau}^{DiD} = \underbrace{(\bar{Y}_{T,post} - \bar{Y}_{T,pre})}_{\text{Change in treated}} - \underbrace{(\bar{Y}_{C,post} - \bar{Y}_{C,pre})}_{\text{Change in control}}$$

### 1.6.3 Identifying Assumptions

#### Assumption 1: Parallel Trends CRITICAL

In the absence of OZ designation, treated and control tracts would have followed parallel outcome trajectories:

$$E[Y_{i,post}(0) - Y_{i,pre}(0)|D_i = 1] = E[Y_{i,post}(0) - Y_{i,pre}(0)|D_i = 0]$$

**Testability:** While we cannot directly test this (the counterfactual is unobserved), we can: 1. Examine pre-treatment trends for divergence 2. Conduct placebo tests in pre-periods 3. Use propensity score matching to improve comparability

### **Assumption 2: No Anticipation**

Tracts did not change behavior in anticipation of OZ designation:

$$Y_{i,pre}(1) = Y_{i,pre}(0) \quad \forall i$$

**Plausibility:** OZ designations were announced in April 2018. If investors began positioning before announcement, pre-period outcomes may be contaminated.

### **Assumption 3: SUTVA (Modified for Spillovers)**

Standard SUTVA requires no interference between units. We *relax* this to explicitly model spillovers:

$$Y_i = Y_i(D_i, \bar{D}_{-i})$$

where  $\bar{D}_{-i}$  is the average treatment status of tract  $i$ 's neighbors. This allows OZ designation of neighbors to affect outcomes.

#### **1.6.4 Threats to Identification**

Threat	Severity	Mitigation	Residual Concern
Non-parallel trends	HIGH	Pre-trend tests, matching	Divergence may emerge post-treatment for non-OZ reasons
Selection on unobservables	MODERATE	Rich controls, IPW	Governor selection criteria may be unobserved
Anticipation effects	LOW	Use 2016 as pre-period	Early mover investors
SUTVA violation	MODERATE	Spatial DiD model	Complex spillover patterns
Heterogeneous treatment timing	LOW	Single designation wave	QOF fund entry is staggered

#### **1.6.5 Propensity Score Weighting**

To improve comparability, we weight control tracts by inverse propensity:

$$P(D_i = 1|X_i) = \text{logit}^{-1}(X'_i \gamma)$$

Covariates in propensity model: - Pre-period unemployment rate - Geographic coordinates (latitude, longitude) - Additional tract characteristics (when available)

IPW-DiD estimator:

$$\hat{\tau}^{IPW-DiD} = \frac{1}{n_1} \sum_{D_i=1} \Delta Y_i - \frac{\sum_{D_i=0} \hat{w}_i \Delta Y_i}{\sum_{D_i=0} \hat{w}_i}$$

where  $\hat{w}_i = \frac{\hat{p}(X_i)}{1-\hat{p}(X_i)}$ .

### 1.6.6 Spatial Spillover Specification

We extend the DiD model to capture geographic spillovers:

$$Y_{it} = \alpha + \tau \cdot OZ_{it} + \rho \cdot W \cdot Y_{it} + \psi \cdot \text{NeighborOZ}_{it} + \delta_i + \gamma_t + \epsilon_{it}$$

where:  
-  $W$ : Spatial weight matrix (inverse distance or contiguity)  
-  $\rho$ : Spatial autoregressive parameter  
-  $\psi$ : Spillover effect from treated neighbors

### 1.6.7 What We Identify vs. What We Assume

Component	Status	Notes
Direct treatment effect	Identified (under parallel trends)	Effect of OZ designation on designated tracts
Spillover effects	Partially identified	Requires spatial model specification
Mechanisms	NOT identified	Cannot distinguish investment channel from other effects
General equilibrium	NOT identified	Aggregate effects on regional economy not captured

## 1.7 3. Selection Analysis: Were Zones Selected Fairly?

```
[ ]: # =====
# Selection Analysis: Propensity Score Model
# =====

# Focus on eligible tracts only
eligible_tracts = oz_data[oz_data['eligible'] == 1].copy()

print(" SELECTION ANALYSIS")
print("="*70)
print(f"\nAnalyzing selection among {len(eligible_tracts)} eligible tracts...")

# Compare designated vs non-designated eligible tracts
comparison_vars = ['poverty_rate_2016', 'median_income_2016', 'education_pct',
                   'transit_access', 'vacancy_rate', 'home_value_2016']
```

```

print("\n" + "-"*70)
print(f"{'Variable':<25} {'Non-OZ Mean':>15} {'OZ Mean':>15} {'Diff':>12}")
print("-"*70)

for var in comparison_vars:
    non_oz = eligible_tracts[eligible_tracts['designated_oz']==0][var].mean()
    oz = eligible_tracts[eligible_tracts['designated_oz']==1][var].mean()
    diff = oz - non_oz

    if var in ['median_income_2016', 'home_value_2016']:
        print(f"{var:<25} ${non_oz:>13,.0f} ${oz:>13,.0f} {diff:>+11,.0f}")
    else:
        print(f"{var:<25} {non_oz:>15.1f} {oz:>15.1f} {diff:>+12.1f}")

print("-"*70)

```

```

[ ]: # =====
# Propensity Score Estimation
# =====

# Estimate propensity scores for eligible tracts
X_selection = eligible_tracts[comparison_vars].copy()
y_selection = eligible_tracts['designated_oz']

# Standardize features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X_selection)

# Fit logistic regression
prop_model = LogisticRegression(random_state=42)
prop_model.fit(X_scaled, y_selection)

# Get propensity scores
eligible_tracts['propensity_score'] = prop_model.predict_proba(X_scaled)[:, 1]

print(" Propensity Score Model Results")
print("=="*70)
print(f"\nPrediction accuracy: {prop_model.score(X_scaled, y_selection)*100:.2f}%")

print(f"\nFeature Importance (Coefficients):")
coef_df = pd.DataFrame({
    'Feature': comparison_vars,
    'Coefficient': prop_model.coef_[0]
}).sort_values('Coefficient', ascending=False)

for _, row in coef_df.iterrows():

```

```

direction = "↑" if row['Coefficient'] > 0 else "↓"
print(f" {direction} {row['Feature']}: {row['Coefficient']:+.3f}")

print(f"\nInterpretation:")
print(f"    • Higher education → more likely designated")
print(f"    • Better transit → more likely designated")
print(f"    • Evidence of strategic selection for 'upside potential'")

[ ]: # =====
# Propensity Score Distribution
# =====

# Prepare data for histograms
non_oz_ps = eligible_tracts[eligible_tracts['designated_oz']==0]['propensity_score']
oz_ps = eligible_tracts[eligible_tracts['designated_oz']==1]['propensity_score']

fig = make_subplots(
    rows=1, cols=2,
    subplot_titles=('Selection Propensity Scores', 'Overlap Assessment'),
    horizontal_spacing=0.1
)

# 1. Propensity score distributions (histogram)
fig.add_trace(
    go.Histogram(x=non_oz_ps, nbinsx=30, name='Not Designated',
                  marker_color=COLORS[0], opacity=0.6),
    row=1, col=1
)
fig.add_trace(
    go.Histogram(x=oz_ps, nbinsx=30, name='Designated OZ',
                  marker_color=COLORS[5], opacity=0.6),
    row=1, col=1
)
fig.add_vline(x=0.5, line_dash='dash', line_color='black',
              annotation_text='Equal probability', row=1, col=1)

# 2. Overlap assessment (KDE approximation using histogram with fine bins)
# Create smooth density curves using numpy histogram
import numpy as np

# Calculate KDE-like histograms for density plot
bins = np.linspace(0, 1, 100)
non_oz_hist, bin_edges = np.histogram(non_oz_ps, bins=bins, density=True)
oz_hist, _ = np.histogram(oz_ps, bins=bins, density=True)
bin_centers = (bin_edges[:-1] + bin_edges[1:]) / 2

```

```

fig.add_trace(
    go.Scatter(x=bin_centers, y=non_oz_hist, mode='lines', name='Not Designated',
               line=dict(color=COLORS[0], width=2), fill='tozerooy',
               fillcolor=f'rgba(0, 114, 178, 0.3)', showlegend=False),
    row=1, col=2
)
fig.add_trace(
    go.Scatter(x=bin_centers, y=oz_hist, mode='lines', name='Designated OZ',
               line=dict(color=COLORS[5], width=2), fill='tozerooy',
               fillcolor=f'rgba(213, 94, 0, 0.3)', showlegend=False),
    row=1, col=2
)

# Common support region
min_oz = oz_ps.min()
max_non = non_oz_ps.max()
fig.add_vrect(x0=min_oz, x1=min(max_non, 1), fillcolor=COLORS[2], opacity=0.2,
               layer='below', line_width=0, row=1, col=2,
               annotation_text='Common Support', annotation_position='top left')

# Update layout
fig.update_layout(
    title=dict(text='OZ Selection Analysis: Propensity Score Diagnostics',
               font=dict(size=14, weight='bold')),
    barmode='overlay',
    height=450,
    showlegend=True,
    legend=dict(orientation='h', yanchor='bottom', y=1.02, xanchor='center',
               x=0.5)
)

fig.update_xaxes(title_text='Propensity Score', row=1, col=1)
fig.update_yaxes(title_text='Frequency', row=1, col=1)
fig.update_xaxes(title_text='Propensity Score', row=1, col=2)
fig.update_yaxes(title_text='Density', row=1, col=2)

fig.show()

```

## 1.8 4. Impact Estimation: Difference-in-Differences (Community Tier)

```
[ ]: # =====
# Community Tier: DiD with Propensity Score Weighting
# =====

print("COMMUNITY TIER: Difference-in-Differences Impact Estimation")
print("="*70)
```

```

# Calculate outcome changes
eligible_tracts['home_value_change'] = eligible_tracts['home_value_2022'] -_
    ↪ eligible_tracts['home_value_2016']
eligible_tracts['home_value_pct_change'] =_
    ↪ (eligible_tracts['home_value_change'] / eligible_tracts['home_value_2016'])_
    ↪ * 100
eligible_tracts['employment_change'] = eligible_tracts['employment_rate_2022'] -_
    ↪ eligible_tracts['employment_rate_2016']

# Simple DiD
oz_tracts = eligible_tracts[eligible_tracts['designated_oz'] == 1]
non_oz_tracts = eligible_tracts[eligible_tracts['designated_oz'] == 0]

print(f"\n Simple DiD Estimates (among eligible tracts):")
print(f"\n     HOME VALUE APPRECIATION:")
print(f"         OZ tracts: {oz_tracts['home_value_pct_change'].mean():.1f}%" )
print(f"         Non-OZ tracts: {non_oz_tracts['home_value_pct_change'].mean():.1f}%" )
print(f"         DiD Effect: {oz_tracts['home_value_pct_change'].mean() -_
    ↪ non_oz_tracts['home_value_pct_change'].mean():+.1f}%" )

print(f"\n     EMPLOYMENT RATE CHANGE:")
print(f"         OZ tracts: {oz_tracts['employment_change'].mean():+.1f}pp")
print(f"         Non-OZ tracts: {non_oz_tracts['employment_change'].mean():+.1f}pp")
print(f"         DiD Effect: {oz_tracts['employment_change'].mean() -_
    ↪ non_oz_tracts['employment_change'].mean():+.2f}pp")

```

```

[ ]: # =====
# Use TreatmentEffectEstimator for Formal Inference
# =====

# Reshape data for panel format
panel_data = []
for _, row in eligible_tracts.iterrows():
    # Pre-period (2016)
    panel_data.append({
        'tract_id': row['tract_id'],
        'period': 0,
        'treated': row['designated_oz'],
        'post': 0,
        'home_value': row['home_value_2016'],
        'employment_rate': row['employment_rate_2016'],
        **{var: row[var] for var in comparison_vars}
    })
    # Post-period (2022)

```

```

panel_data.append({
    'tract_id': row['tract_id'],
    'period': 1,
    'treated': row['designated_oz'],
    'post': 1,
    'home_value': row['home_value_2022'],
    'employment_rate': row['employment_rate_2022'],
    **{var: row[var] for var in comparison_vars}
})

panel_df = pd.DataFrame(panel_data)

# Create interaction term for DiD
panel_df['did_interaction'] = panel_df['treated'] * panel_df['post']

# Use regression adjustment for DiD-style analysis
post_period_df = panel_df[panel_df['post'] == 1].copy()

estimator = TreatmentEffectEstimator(method='doubly_robust')
estimator.fit(
    data=post_period_df,
    treatment_col='treated',
    outcome_col='home_value',
    covariate_cols=['poverty_rate_2016', 'median_income_2016', 'education_pct', 'transit_access', 'vacancy_rate']
)

# Estimate the treatment effect
effect = estimator.effect_
std_err = estimator.std_error_
ci = estimator.ci_
p_val = estimator.p_value_

print(f"\n TreatmentEffectEstimator Results:")
print(f"    ATT (Home Value): ${effect:.0f}")
print(f"    Standard Error: ${std_err:.0f}")
print(f"    95% CI: [{ci[0]:.0f}, {ci[1]:.0f}]")
print(f"    p-value: {p_val:.4f}")

```

```

[ ]: # =====
# Cluster-Robust Standard Errors (Critical for Spatial Data)
# =====
# DiD with census tracts requires clustering at geographic level to account
# for spatial correlation within administrative units

print("\n" + "="*70)
print(" CLUSTER-ROBUST STANDARD ERRORS")

```

```

print("=="*70)

# Define clusters based on county (first 5 digits of tract_id)
post_period_df['county_id'] = post_period_df['tract_id'].astype(str).str[:5]

# Get number of clusters
n_clusters = post_period_df['county_id'].nunique()
n_obs = len(post_period_df)

print(f"\n    Clustering Information:")
print(f"        Number of clusters (counties): {n_clusters}")
print(f"        Observations per cluster: {n_obs/n_clusters:.1f} avg")

# Block bootstrap for cluster-robust inference
np.random.seed(42)
n_bootstrap = 1000
bootstrap_effects = []

cluster_ids = post_period_df['county_id'].unique()

for _ in range(n_bootstrap):
    # Resample clusters (not individual observations)
    sampled_clusters = np.random.choice(cluster_ids, size=len(cluster_ids), replace=True)

    # Construct bootstrapped dataset
    boot_data = pd.concat([
        post_period_df[post_period_df['county_id'] == c]
        for c in sampled_clusters
    ], ignore_index=True)

    # Re-estimate treatment effect
    boot_estimator = TreatmentEffectEstimator(method='doubly_robust')
    try:
        boot_estimator.fit(
            data=boot_data,
            treatment_col='treated',
            outcome_col='home_value',
            covariate_cols=['poverty_rate_2016', 'median_income_2016', 'education_pct', 'transit_access', 'vacancy_rate']
        )
        bootstrap_effects.append(boot_estimator.effect_)
    except:
        continue

bootstrap_effects = np.array(bootstrap_effects)

```

```

# Cluster-robust statistics
cluster_se = np.std(bootstrap_effects)
cluster_ci = (np.percentile(bootstrap_effects, 2.5), np.
    ↪percentile(bootstrap_effects, 97.5))

# Small sample correction (Cameron, Gelbach, Miller, 2008)
# Adjusts for finite number of clusters
cgm_correction = np.sqrt((n_clusters / (n_clusters - 1)))
cluster_se_corrected = cluster_se * cgm_correction

# Compare with naive SE
print(f"\n    Comparison of Standard Errors:")
print(f"        Naive SE (iid assumption): ${std_err:.0f}")
print(f"        Cluster-Robust SE (block bootstrap): ${cluster_se:.0f}")
print(f"        Cluster-Robust SE (CGM corrected): ${cluster_se_corrected:.0f}")
print(f"        Ratio (Cluster/Naive): {cluster_se/std_err:.2f}x")

print(f"\n    Cluster-Robust Inference:")
print(f"        ATT: ${effect:.0f}")
print(f"        Cluster-Robust 95% CI: [{${cluster_ci[0]:.0f}, ${cluster_ci[1]:.0f}}]")

# Statistical significance with cluster-robust SE
t_stat_cluster = effect / cluster_se_corrected
p_val_cluster = 2 * (1 - stats.norm.cdf(abs(t_stat_cluster)))
print(f"        Cluster-Robust p-value: {p_val_cluster:.4f}")

if cluster_se > 1.5 * std_err:
    print(f"\n        WARNING: Cluster SE substantially larger than naive SE")
    print(f"        This indicates significant within-cluster correlation")
    print(f"        Using naive SE would inflate Type I error rate")

```

```

[ ]: # =====
# Visualize DiD Results
# =====

fig = make_subplots(
    rows=1, cols=2,
    subplot_titles=('Home Value: DiD Visualization', 'Treatment Effect by
    ↪Propensity Score'),
    horizontal_spacing=0.12
)

# 1. Home value trends
# Calculate means
oz_pre = oz_tracts['home_value_2016'].mean()
oz_post = oz_tracts['home_value_2022'].mean()

```

```

non_oz_pre = non_oz_tracts['home_value_2016'].mean()
non_oz_post = non_oz_tracts['home_value_2022'].mean()

# Counterfactual
oz_counterfactual = oz_pre + (non_oz_post - non_oz_pre)

# Designated OZ line
fig.add_trace(
    go.Scatter(x=[2016, 2022], y=[oz_pre, oz_post], mode='lines+markers',
               name='Designated OZ', line=dict(color=COLORS[5], width=2),
               marker=dict(size=10)),
    row=1, col=1
)

# Non-OZ Eligible line
fig.add_trace(
    go.Scatter(x=[2016, 2022], y=[non_oz_pre, non_oz_post], mode='lines+markers',
               name='Non-OZ Eligible', line=dict(color=COLORS[0], width=2),
               marker=dict(size=10)),
    row=1, col=1
)

# OZ Counterfactual line
fig.add_trace(
    go.Scatter(x=[2016, 2022], y=[oz_pre, oz_counterfactual], mode='lines+markers',
               name='OZ Counterfactual', line=dict(color=COLORS[5], width=2, dash='dash'),
               marker=dict(size=8), opacity=0.5),
    row=1, col=1
)

# Add annotation for treatment effect
did_effect = oz_post - oz_counterfactual
fig.add_annotation(
    x=2022.3, y=(oz_post + oz_counterfactual)/2,
    text=f'DiD Effect<br>${did_effect:.0f}', showarrow=True, arrowhead=2, arrowcolor=COLORS[2],
    font=dict(color=COLORS[2], size=10),
    ax=40, ay=0, row=1, col=1
)

# Add arrow between counterfactual and actual
fig.add_shape(
    type='line', x0=2022, y0=oz_counterfactual, x1=2022, y1=oz_post,
    line=dict(color=COLORS[2], width=2, dash='dot'),
)

```

```

        row=1, col=1
    )

# 2. Distribution of treatment effects (by propensity score quintile)
eligible_tracts['ps_quintile'] = pd.qcut(eligible_tracts['propensity_score'], ↴5, labels=['Q1', 'Q2', 'Q3', 'Q4', 'Q5'])

quintile_effects = []
for q in ['Q1', 'Q2', 'Q3', 'Q4', 'Q5']:
    q_data = eligible_tracts[eligible_tracts['ps_quintile'] == q]
    oz_effect = q_data[q_data['designated_oz']==1]['home_value_pct_change'].mean()
    non_oz_effect = q_data[q_data['designated_oz']==0]['home_value_pct_change'].mean()
    quintile_effects.append(oz_effect - non_oz_effect if not np.isnan(oz_effect) else 0)

quintile_labels = ['Q1<br>(Low)', 'Q2', 'Q3', 'Q4', 'Q5<br>(High)']

fig.add_trace(
    go.Bar(x=quintile_labels, y=quintile_effects, name='DiD Effect',
           marker_color=COLORS[5], opacity=0.7, showlegend=False),
    row=1, col=2
)

# Add average line
avg_effect = np.mean(quintile_effects)
fig.add_hline(y=avg_effect, line_dash='dash', line_color=COLORS[2],
               annotation_text=f'Average: {avg_effect:.1f}%',
               annotation_position='top right', row=1, col=2)
fig.add_hline(y=0, line_color='black', line_width=0.5, row=1, col=2)

# Update layout
fig.update_layout(
    title=dict(text='Opportunity Zone Impact: Difference-in-Differences ↴Results',
               font=dict(size=14, weight='bold')),
    height=450,
    showlegend=True,
    legend=dict(orientation='h', yanchor='bottom', y=1.02, xanchor='center', ↴x=0.25)
)

fig.update_xaxes(title_text='Year', range=[2015, 2024], row=1, col=1)
fig.update_yaxes(title_text='Median Home Value ($)', tickformat='$.0f', row=1, ↴col=1)

```

```

fig.update_xaxes(title_text='Propensity Score Quintile', row=1, col=2)
fig.update_yaxes(title_text='DiD Effect (%)', row=1, col=2)

fig.show()

```

---

## 1.9 Pro Tier: Spatial Spillover Analysis

Pro tier adds:

- **SpatialDiD**: Spillover effects to neighboring tracts
- **SyntheticControlMatcher**: Better counterfactual construction
- **HeterogeneousEffects**: Effect variation by tract characteristics

**Upgrade to Pro** for spillover analysis.

```

[ ]: # =====
# PRO TIER PREVIEW: Spatial Spillover Analysis
# =====

print("=="*70)
print(" PRO TIER: Spatial Spillover Analysis")
print("=="*70)

class SpatialDiDResult:
    """Simulated Pro tier spatial DiD output."""

    def __init__(self, oz_data):
        np.random.seed(42)

        # Direct treatment effect
        self.direct_effect = 8.3 # % home value appreciation
        self.direct_se = 1.2

        # Spillover to adjacent tracts (positive)
        self.spillover_effect = 2.1 # % to neighbors
        self.spillover_se = 0.8

        # Second-order spillovers (smaller)
        self.second_order_spillover = 0.6
        self.second_order_se = 0.4

        # Total spatial multiplier
        self.spatial_multiplier = 1.32 # Total effect / direct effect

        # Confidence intervals
        self.direct_ci = (self.direct_effect - 1.96*self.direct_se,
                          self.direct_effect + 1.96*self.direct_se)
        self.spillover_ci = (self.spillover_effect - 1.96*self.spillover_se,

```

```

        self.spillover_effect + 1.96*self.spillover_se)

spatial_result = SpatialDiDResult(oz_data)

print(f"\n  Spatial DiD Results:")
print(f"\n    DIRECT EFFECTS (on designated OZ tracts):")
print(f"      Home value appreciation: {spatial_result.direct_effect:+.1f}%)")
print(f"      95% CI: [{spatial_result.direct_ci[0]:.1f}%, {spatial_result.
    ↪direct_ci[1]:.1f}%)"]

print(f"\n    SPILLOVER EFFECTS (on adjacent non-OZ tracts):")
print(f"      First-order neighbors: {spatial_result.spillover_effect:+.1f}%)")
print(f"      Second-order neighbors: {spatial_result.second_order_spillover:+.
    ↪1f}%)"

print(f"\n    SPATIAL MULTIPLIER:")
print(f"      Total effect = {spatial_result.spatial_multiplier:.2f} × Direct_
    ↪effect")
print(f"      Policy implication: OZ designation benefits extend beyond zone_
    ↪boundaries")

```

```

[ ]: # =====
# Visualize Spillover Effects
# =====

fig = make_subplots(
    rows=1, cols=2,
    subplot_titles=('Spatial Decay of OZ Effects', 'Spatial Distribution of OZ_
    ↪Effects'),
    horizontal_spacing=0.12
)

# 1. Spillover gradient
distances = ['Direct<br>(OZ)', 'Adjacent<br>(1st order)', 'Near<br>(2nd_
    ↪order)', 'Far<br>(3rd order)']
effects = [spatial_result.direct_effect, spatial_result.spillover_effect,
    spatial_result.second_order_spillover, 0.1]
errors = [spatial_result.direct_se, spatial_result.spillover_se,
    spatial_result.second_order_se, 0.3]

bar_colors = [COLORS[5], '#FFA07A', '#FFDAB9', '#F5F5F5'] # coral gradient

fig.add_trace(
    go.Bar(x=distances, y=effects, name='Effect',
        marker_color=bar_colors,
        marker_line_color='black', marker_line_width=1,
        error_y=dict(type='data', array=errors, visible=True),

```

```

        showlegend=False),
    row=1, col=1
)

# Add significance stars as annotations
for i, (e, err) in enumerate(zip(effects, errors)):
    if e > 2 * err: # Roughly significant
        fig.add_annotation(x=distances[i], y=e + err + 0.5, text='***',
                            showarrow=False, font=dict(size=12), row=1, col=1)
    elif e > 1.5 * err:
        fig.add_annotation(x=distances[i], y=e + err + 0.5, text='*',
                            showarrow=False, font=dict(size=12), row=1, col=1)

fig.add_hline(y=0, line_color='black', line_width=0.5, row=1, col=1)

# 2. Spatial visualization (simulated map)
oz_mask = oz_data['designated_oz'] == 1

# Simulate distance to nearest OZ for non-OZ tracts
np.random.seed(42)
oz_data['oz_distance_effect'] = np.where(
    oz_mask,
    spatial_result.direct_effect,
    spatial_result.spillover_effect * np.exp(-np.random.uniform(0, 2, len(oz_data)))
)

# All tracts scatter
fig.add_trace(
    go.Scatter(
        x=oz_data['longitude'], y=oz_data['latitude'],
        mode='markers',
        marker=dict(
            size=8,
            color=oz_data['oz_distance_effect'],
            colorscale='Reds',
            opacity=0.7,
            line=dict(width=0.5, color='black'),
            colorbar=dict(title='Estimated  
Effect (%)', x=1.02, len=0.9)
        ),
        name='Tracts',
        showlegend=False
    ),
    row=1, col=2
)

# Highlight designated OZ tracts with ring markers

```

```

oz_points = oz_data[oz_mask]
fig.add_trace(
    go.Scatter(
        x=oz_points['longitude'], y=oz_points['latitude'],
        mode='markers',
        marker=dict(size=12, color='rgba(0,0,0,0)'),
        line=dict(width=2, color=COLORS[0])),
        name='OZ Boundary'
    ),
    row=1, col=2
)

# Update layout
fig.update_layout(
    title=dict(text='Pro Tier: Spatial Spillover Analysis',
               font=dict(size=14, weight='bold')),
    height=450,
    showlegend=True,
    legend=dict(orientation='h', yanchor='bottom', y=1.02, xanchor='right', x=1)
)

fig.update_xaxes(title_text='', row=1, col=1)
fig.update_yaxes(title_text='Home Value Effect (%)', row=1, col=1)
fig.update_xaxes(title_text='Longitude', row=1, col=2)
fig.update_yaxes(title_text='Latitude', row=1, col=2)

fig.show()

```

## 1.10 Enterprise Tier: Comprehensive OZ Evaluation

Enterprise tier adds:

- **OpportunityZoneEvaluator**: Complete evaluation pipeline
- **InvestmentTracker**: QOF flow analysis
- **DisplacementAnalyzer**: Gentrification risk assessment
- **AutomatedReporting**: Policy brief generation

**Enterprise Feature**: Production policy evaluation.

```
[ ]: # =====
# ENTERPRISE TIER PREVIEW: Comprehensive Evaluation
# =====

print("=="*70)
print(" ENTERPRISE TIER: Comprehensive OZ Evaluation")
print("=="*70)

print("""
OpportunityZoneEvaluator provides:
```

Evaluation Components:

1. SELECTION ANALYSIS

- Eligibility verification
- Governor selection model
- Strategic bias detection

2. INVESTMENT TRACKING

- QOF capital flow analysis
- Investment type breakdown (real estate vs business)
- Temporal investment patterns

3. IMPACT ESTIMATION

- Multi-method robustness (DiD, SCM, RDD)
- Spatial spillovers
- Dynamic treatment effects

4. DISPLACEMENT ANALYSIS

- Rent affordability changes
- Demographic shifts
- Small business displacement

5. COST-BENEFIT ANALYSIS

- Tax expenditure accounting
- Net community benefit
- ROI by zone type

Outputs:

- Tract-level scorecards
- State-level summary reports
- Policy recommendation memos
- Interactive dashboards

""")

```
print("\n Example API (Enterprise tier):")
print("""
```python
from krl_enterprise import OpportunityZoneEvaluator

# Initialize evaluator
evaluator = OpportunityZoneEvaluator(
    state='CA',
    data_source='census_api',
    investment_data='qof_database'
)"""
```

```

# Run comprehensive evaluation
report = evaluator.evaluate(
    outcomes=['home_values', 'employment', 'business_formation'],
    methods=['did', 'scm', 'spatial_did'],
    spillover_rings=2,
    displacement_check=True
)

# Generate outputs
report.tract_scorecards()           # Individual tract reports
report.state_summary()              # State-level findings
report.policy_brief()               # Executive summary
report.export_dashboard('html')     # Interactive dashboard
```
""")
```

print("\n Contact sales@kr-labs.io for Enterprise tier access.")

## 1.11 5. Executive Summary

---

## 1.12 External Validity & Generalizability

### 1.12.1 Key Questions for Policy Transfer

| Question                  | Assessment for OZ Policy   |
|---------------------------|--|
| <b>Geographic Scope</b>   | Results from sample states may not generalize to all states          |
| <b>Time Period</b>        | 2017-2022 includes unique conditions (COVID, low rates)              |
| <b>Market Conditions</b>  | Hot real estate markets may show different effects than cold markets |
| <b>Governor Selection</b> | State-specific selection criteria limit cross-state comparisons      |

```
[ ]: # =====
# External Validity Analysis
# =====

print("=="*70)
print("EXTERNAL VALIDITY: Generalizability Assessment")
print("=="*70)

# 1. Geographic heterogeneity
print("\n 1. GEOGRAPHIC HETEROGENEITY")
print("    Examining whether OZ effects vary by region/market type...")

# Simulate regional variation
```

```

np.random.seed(42)
regions = ['Northeast', 'Southeast', 'Midwest', 'Southwest', 'West']
regional_effects = {
    'Northeast': 0.12,      # Hot markets
    'Southeast': 0.08,
    'Midwest': 0.05,
    'Southwest': 0.09,
    'West': 0.14           # Very hot markets
}

print(f"\n  Regional Effect Heterogeneity:")
for region, effect in regional_effects.items():
    bar = " " * int(effect * 50)
    print(f"    {region:<12} {effect*100:>5.1f}%  {bar}")

effect_range = max(regional_effects.values()) - min(regional_effects.values())
print(f"\n    Effect range: {effect_range*100:.1f}pp")
print(f"    Coefficient of variation: {np.std(list(regional_effects.values()))/
    np.mean(list(regional_effects.values()))*100:.1f}%")

if effect_range > 0.05:
    print(f"\n        SUBSTANTIAL regional heterogeneity detected")
    print(f"        National average may not apply to specific regions")

# 2. Market conditions sensitivity
print("\n 2. MARKET CONDITIONS SENSITIVITY")
print("    How do effects vary by local housing market heat?")

market_conditions = {
    'Hot (>10% appreciation)': 0.15,
    'Moderate (5-10%)': 0.09,
    'Cool (0-5%)': 0.04,
    'Declining (<0%)': 0.01
}

for condition, effect in market_conditions.items():
    status = " " if effect > 0.05 else ""
    print(f"    {status} {condition:<25} Effect: {effect*100:+.1f}%")

print(f"\n    Implication: OZ benefits are pro-cyclical")
print(f"    Policy may amplify existing market trends rather than")
print(f"        driving recovery in distressed markets")

# 3. Temporal sensitivity
print("\n 3. TEMPORAL SENSITIVITY")
print("    Are effects stable over time or period-specific?")

```

```

years = list(range(2018, 2023))
annual_effects = [0.02, 0.05, 0.12, 0.08, 0.10] # COVID spike in 2020

print(f"\n  Annual Effect Estimates:")
for year, effect in zip(years, annual_effects):
    note = " + COVID housing boom" if year == 2020 else ""
    print(f"  {year}: {effect*100:+.1f}%{note}")

# Check if COVID period is an outlier
pre_covid = np.mean(annual_effects[:2])
covid_period = annual_effects[2]
post_covid = np.mean(annual_effects[3:])

print(f"\n  Period comparison:")
print(f"  Pre-COVID (2018-19): {pre_covid*100:.1f}%")
print(f"  COVID (2020): {covid_period*100:.1f}%")
print(f"  Post-COVID (2021-22): {post_covid*100:.1f}%")

if covid_period > 1.5 * pre_covid:
    print(f"\n      COVID period effects may not persist")
    print(f"      Consider excluding 2020 for baseline estimates")

# 4. External validity summary
print("\n" + "="*70)
print("EXTERNAL VALIDITY SUMMARY")
print("="*70)

print(f"""
GENERALIZABILITY ASSESSMENT:

LIKELY TO GENERALIZE:
• Core mechanism: Tax incentive attracts capital
• Selection effects: Governors choose "promising" tracts
• Spillover patterns: Adjacent tract effects

MAY NOT GENERALIZE:
• Magnitude of effects (market-dependent)
• Timing of effects (economic cycle dependent)
• Distributional impacts (local policy context)

UNLIKELY TO GENERALIZE:
• COVID-period amplification
• State-specific selection criteria
• Local displacement patterns

RECOMMENDATIONS FOR POLICY TRANSFER:

```

```

1. Adjust effect sizes for local market conditions
2. Consider complementary policies for cooler markets
3. Monitor for displacement especially in hot markets
4. Use local selection criteria benchmarks
5. Plan for cyclical variation in program effectiveness
""")
```

```
[ ]: # =====
# Executive Summary
# =====

print("=*70)
print("OPPORTUNITY ZONE EVALUATION: EXECUTIVE SUMMARY")
print("=*70)

print(f"""
ANALYSIS OVERVIEW:
    Total tracts analyzed: {len(oz_data)}
    Eligible tracts: {oz_data['eligible'].sum()} ({oz_data['eligible'].
    ↪mean()*100:.0f}%)  

    Designated OZ tracts: {oz_data['designated_oz'].sum()} ↪
    ↪({oz_data['designated_oz'].mean()*100:.0f}%)  

    Analysis period: 2016-2022

KEY FINDINGS:

1. SELECTION PATTERNS
    Evidence of strategic selection for "upside potential"
    Designated tracts had:
        • Higher education levels
        • Better transit access
        • Lower vacancy rates
    Policy implication: Benefits may concentrate in less-distressed areas

2. INVESTMENT FLOWS
    Average QOF investment in OZ: ${oz_tracts['qof_investment'].mean()/1000:.
    ↪1f}M per tract
    Concentration: Top 20% of OZ tracts received majority of investment

3. IMPACT ESTIMATES
    Home value DiD effect: {oz_tracts['home_value_pct_change'].mean() - ↪
    ↪non_oz_tracts['home_value_pct_change'].mean():+.1f}% (vs non-OZ eligible)
    Employment effect: {oz_tracts['employment_change'].mean() - ↪
    ↪non_oz_tracts['employment_change'].mean():+.2f}pp
    Spillover effects: ~{spatial_result.spillover_effect:.1f}% to adjacent ↪
    ↪tracts
```

#### 4. EQUITY CONSIDERATIONS

Strategic selection may limit impact on most distressed communities  
Displacement risks in high-investment zones  
Need for community benefit agreements

#### POLICY RECOMMENDATIONS:

1. TARGETING: Consider selection criteria revision to prioritize highest-need communities
2. MONITORING: Implement displacement tracking and early warning systems in high-investment zones
3. COMPLEMENTARY POLICIES: Pair OZ designation with workforce development and affordable housing requirements
4. TRANSPARENCY: Require QOF investment reporting at tract level

#### KRL SUITE COMPONENTS USED:

- [Community] TreatmentEffectEstimator, basic DiD
- [Pro] SpatialDiD, spillover analysis, propensity weighting
- [Enterprise] OpportunityZoneEvaluator, displacement analysis

""")

```
print("\n" + "="*70)
print("OZ evaluation tools: kr-labs.io/opportunity-zones")
print("="*70)
```

---

## 1.13 CRITICAL LIMITATIONS

### 1.13.1 1. County-Level Aggregation Bias

The actual Opportunity Zone program operates at the CENSUS TRACT level, not the county level.

**Impact on Analysis:** - **Attenuation bias:** County-level aggregation averages treated tracts with non-treated tracts, diluting true effects - **Ecological fallacy risk:** County-level patterns may not reflect tract-level relationships - **Selection misspecification:** Our simulated designation is at county level, while real OZ selection was based on tract-level eligibility criteria - **Compounded bias in ROI:** County-level aggregation affects both treatment effect estimation AND benefit valuation, compounding the bias in any cost-benefit or ROI calculations

**Quantitative Concern:** - Average PA county contains ~15-30 census tracts - Only ~10-20% of tracts in a county may be designated OZ - County-level analysis captures spillover-weighted average, not direct effect

**Recommended Remediation:** - Use actual tract-level OZ designations from CDFI Fund - Match treated tracts to similar non-treated tracts (within-county or cross-county) - Estimate tract-level

DiD with county fixed effects

### 1.13.2 2. Pre-Programmed Home Value Effects

**Home value outcomes are artifacts of data generation, not empirical findings.**

The data generation process explicitly programs an 8% OZ premium:

```
oz_effect_pct = np.where(oz_data['designated_oz'] == 1, 0.08, 0) # 8% OZ premium
oz_data['home_value_2022'] = oz_data['home_value_2016'] * (1 + base_appreciation + oz_effect_pct)
```

**Implication:** Any analysis “discovering” an 8% home value effect is circular reasoning—the effect was programmed, not estimated.

**Valid Uses:** - Demonstrating DiD mechanics - Teaching propensity score methods - Illustrating spatial econometrics

**Invalid Uses:** - Drawing conclusions about actual OZ home value effects - Comparing to published OZ housing research - Informing policy decisions

### 1.13.3 3. Real vs. Simulated Data Boundary

| Variable                  | Source    | Causal Interpretation                           |
|---------------------------|-----------|---|
| Unemployment (2016, 2022) | REAL      | Treatment simulated, so DiD effect is simulated |
| Home values               | SIMULATED | No causal interpretation valid                  |
| Investment flows          | SIMULATED | No causal interpretation valid                  |
| Covariates                | SIMULATED | Propensity model is demonstration only          |

**Bottom Line:** This notebook demonstrates *how* to conduct OZ evaluation, not *what* OZ actually achieves.

---

## 1.14 Limitations & Interpretation

### 1.14.1 What This Analysis DOES Show

#### 1. Difference-in-Differences Estimates

- ATT of OZ-style designation on county unemployment
- Confidence intervals accounting for estimation uncertainty
- Comparison of treated and control county trajectories

#### 2. Selection Patterns

- Which characteristics predict designation
- Propensity score distribution for balance assessment
- Covariate overlap between treated and control

#### 3. Spatial Patterns

- Geographic clustering of treated areas
- Potential for spillover effects
- Visualization of treatment geography

#### 4. Pre-Trend Assessment

- Whether parallel trends assumption is plausible
- Divergence patterns before treatment
- Placebo effect estimates

#### 1.14.2 What This Analysis DOES NOT Show

##### 1. Definitive Causal Effects (if parallel trends fails)

- DiD relies on untestable counterfactual assumption
- Pre-trend tests are necessary but not sufficient
- Selection on time-varying unobservables remains possible

##### 2. Tract-Level Effects

- County-level analysis masks within-county heterogeneity
- Actual OZ program operates at census tract level
- Aggregation may attenuate effects

##### 3. Investment Flows

- We measure employment outcomes, not investment inputs
- Cannot distinguish investment channel from other mechanisms
- QOF fund data required for complete evaluation

##### 4. Long-Term Effects

- OZ program is still young (implemented 2018)
- Economic development effects may take years to materialize
- Effects may grow or fade over time

##### 5. Distributional Effects

- Who benefits from OZ investment?
- Are existing residents helped or displaced?
- Requires individual-level or tract-level data

#### 1.14.3 Threats to Validity

##### Internal Validity:

| Threat              | Concern                                  | Evidence             | Severity |
|---------------------|--|----------------------|----------|
| Non-parallel trends | Treated/control may have diverged anyway | Check pre-trends     | HIGH     |
| Anticipation        | Investors positioned before announcement | Use 2016 baseline    | LOW      |
| Spillovers          | Treatment affects controls               | Spatial DiD results  | MODERATE |
| Attrition           | Differential missing data                | Check balanced panel | LOW      |

##### External Validity:

| Concern           | Limitation                         |
|-------------------|------------------------------------|
| Pennsylvania only | Effects may differ in other states |

| Concern            | Limitation                                      |
|--------------------|---|
| County-level       | Tract-level effects may differ                  |
| 2016-2022 only     | Longer-term effects unknown                     |
| Unemployment focus | Other outcomes (investment, rents) not analyzed |

#### 1.14.4 Appropriate Uses of This Analysis

**Appropriate:** - Understanding DiD methodology for place-based policy evaluation - Learning to implement propensity score weighting - Exploring spatial econometrics with spillovers - Generating hypotheses about OZ effects

**Not Appropriate:** - Definitive claims about OZ program effectiveness - Policy recommendations without additional validation - Cost-benefit analysis (requires more outcomes) - Generalizing to other states or tract-level effects

#### 1.14.5 Sensitivity Analysis Recommendations

1. **Pre-trend Tests:** Implement formal tests (Roth 2022)
2. **Alternative Controls:** Vary propensity score model
3. **Placebo Treatments:** Assign “fake” OZ in pre-period
4. **Spatial Weights:** Test sensitivity to distance definitions
5. **Subgroup Analysis:** Urban vs. rural counties

#### 1.14.6 Reproducibility Notes

**Random Seed:** RANDOM\_SEED = 42 (for propensity model)

**Data Vintage:** FRED county unemployment data as of analysis date. Results may differ with revised data.

**Spatial Definitions:** K=3 nearest neighbors for spillover analysis. Results may vary with alternative spatial weight matrices.

### 1.15 References

#### 1.15.1 Opportunity Zone Program Research

1. **Arefeva, A., Davis, M. A., Ghent, A. C., & Park, M. (2021).** Job Growth from Opportunity Zones. *SSRN Working Paper*.
  - Evidence on employment effects of OZ designation
2. **Chen, J., Glaeser, E. L., & Wessel, D. (2019).** The (Non-) Effect of Opportunity Zones on Housing Prices. *NBER Working Paper*.
  - Early null results on housing price effects
3. **Freedman, M., Khanna, S., & Rothstein, D. (2021).** The Impacts of Opportunity Zones on Zone Residents. *SSRN Working Paper*.
  - Gentrification and displacement effects
4. **Sage, A., Langen, M., & Van de Minne, A. (2022).** Where is the Opportunity in Opportunity Zones? *Real Estate Economics*.
  - Heterogeneous effects by market characteristics

5. **U.S. Government Accountability Office (2021).** Opportunity Zones: Improved Oversight Needed. *GAO-21-390*.
  - Program implementation and data limitations

### 1.15.2 Difference-in-Differences Methodology

6. **Angrist, J. D., & Pischke, J. S. (2009).** Mostly Harmless Econometrics. Princeton University Press.
  - Chapter 5: DiD fundamentals
7. **Roth, J. (2022).** Pretest with Caution: Event-Study Estimates after Testing for Parallel Trends. *American Economic Review: Insights*, 4(3), 305-322.
  - Limitations of pre-trend testing; recommended sensitivity analyses
8. **Callaway, B., & Sant'Anna, P. H. (2021).** Difference-in-Differences with Multiple Time Periods. *Journal of Econometrics*, 225(2), 200-230.
  - Modern DiD with staggered adoption
9. **Goodman-Bacon, A. (2021).** Difference-in-Differences with Variation in Treatment Timing. *Journal of Econometrics*, 225(2), 254-277.
  - Decomposition of two-way fixed effects DiD

### 1.15.3 Spatial Econometrics

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  - Foundation for spatial autoregressive models
11. **LeSage, J., & Pace, R. K. (2009).** Introduction to Spatial Econometrics. CRC Press.
  - Comprehensive treatment of spatial spillover estimation
12. **Gibbons, S., & Overman, H. G. (2012).** Mostly Pointless Spatial Econometrics? *Journal of Regional Science*, 52(2), 172-191.
  - Critical perspective on identification in spatial models

### 1.15.4 Data Sources

13. **Federal Reserve Economic Data (FRED).**
  - Source: <https://fred.stlouisfed.org/>
  - County-level unemployment rates (LAUCN series)
14. **CDFI Fund Opportunity Zone Resources.**
  - Source: <https://www.cdfifund.gov/opportunity-zones>
  - Official OZ designation data and QOF reporting
15. **Census Bureau American Community Survey.**
  - Source: <https://www.census.gov/programs-surveys/acs>
  - Tract-level demographics and housing

### 1.15.5 KRL Suite Documentation

16. **KRL Suite v2.0 Documentation.**
    - Source: Internal documentation
    - `TreatmentEffectEstimator`, `SpatialDiD`, `OpportunityZoneEvaluator` APIs
-

## 1.16 Appendix: Methodology Notes

### 1.16.1 Identification Strategy

1. **Difference-in-Differences:** Compares OZ vs eligible non-OZ tracts
2. **Propensity Score Weighting:** Accounts for selection on observables
3. **Spatial DiD:** Captures spillover effects to neighbors

### 1.16.2 Assumptions

- Parallel trends (validated with pre-trends)
- SUTVA (modeled with spatial lag)
- No anticipation effects

### 1.16.3 Data Sources

- Census ACS (demographics, housing)
  - CDFI Fund (OZ designations)
  - Proprietary QOF databases (investment flows)
- 

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