16-end-to-end-policy-pipeline

November 28, 2025

0.1 1. Environment & Data Ingestion

[1]:
```
# ============================================================================
# End-to-End Policy Pipeline: Environment Setup
# ============================================================================

import os
import sys
import warnings
from datetime import datetime
from typing import Dict, List, Optional

# Add KRL package paths
_krl_base = os.path.expanduser("~/Documents/GitHub/KRL/Private IP")
for _pkg in ["krl-open-core/src", "krl-causal-policy-toolkit/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
import matplotlib.pyplot as plt
import seaborn as sns

from krl_core import get_logger

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

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

print("="*70)
print("  End-to-End Policy Pipeline")
print("="*70)
print(f"  Execution Time: {datetime.now().strftime('%Y-%m-%d %H:%M:%S')}")
```

```
print(f"\n Pipeline Components:")
print(f"   Stage 1: Data Ingestion (krl-data-connectors)")
print(f"   Stage 2: Causal Analysis (krl-causal-policy-toolkit)")
print(f"   Stage 3: Cost-Benefit Analysis")
print(f"   Stage 4: Policy Report Generation")
print("="*70)
```

```
======================================================================
 End-to-End Policy Pipeline
======================================================================
 Execution Time: 2025-11-28 12:03:28

 Pipeline Components:
   Stage 1: Data Ingestion (krl-data-connectors)
   Stage 2: Causal Analysis (krl-causal-policy-toolkit)
   Stage 3: Cost-Benefit Analysis
   Stage 4: Policy Report Generation
======================================================================
```

[2]:
```
# ============================================================================
# Stage 1: Data Ingestion (Simulated Multi-Source)
# ============================================================================

def simulate_policy_data(n_counties: int = 200, n_years: int = 10,
                         treatment_year: int = 5, treatment_effect: float = 0.
 ↪08,
                         seed: int = 42) -> Dict[str, pd.DataFrame]:
    """
    Simulate data from multiple sources for policy evaluation.
    Represents data that would come from Census, BLS, and custom sources.
    """
    np.random.seed(seed)

    # County identifiers
    counties = [f'County_{i:03d}' for i in range(n_counties)]
    years = list(range(2015, 2015 + n_years))

    # Treatment assignment (30% of counties)
    n_treated = int(n_counties * 0.3)
    treated_counties = np.random.choice(counties, n_treated, replace=False)

    # Generate panel data
    data = []
    for county in counties:
        is_treated_county = county in treated_counties
        county_fe = np.random.normal(0, 0.02)  # County fixed effect
```

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        for year_idx, year in enumerate(years):
            is_post = year >= years[treatment_year]
            treated = 1 if (is_treated_county and is_post) else 0

            # Employment rate (outcome)
            base_emp = 0.60 + county_fe + 0.002 * year_idx
            if treated:
                base_emp += treatment_effect * (year_idx - treatment_year + 1) /
↪ 5
            emp_rate = np.clip(base_emp + np.random.normal(0, 0.015), 0.4, 0.8)

            # Covariates
            population = int(np.exp(10 + county_fe * 5 + np.random.normal(0, 0.
↪3)))
            median_income = 45000 + county_fe * 20000 + year_idx * 500 + np.
↪random.normal(0, 3000)
            college_pct = np.clip(0.25 + county_fe * 2 + np.random.normal(0, 0.
↪03), 0.1, 0.5)

            data.append({
                'county_id': county,
                'year': year,
                'treated_county': int(is_treated_county),
                'post_treatment': int(is_post),
                'treated': treated,
                'employment_rate': emp_rate,
                'population': population,
                'median_income': median_income,
                'college_pct': college_pct
            })

    main_df = pd.DataFrame(data)

    # Simulate additional data sources
    program_costs = pd.DataFrame({
        'county_id': treated_counties,
        'program_cost': np.random.uniform(1e6, 5e6, n_treated),
        'admin_cost': np.random.uniform(0.5e5, 2e5, n_treated)
    })

    return {
        'panel': main_df,
        'costs': program_costs,
        'treatment_year': years[treatment_year],
        'true_effect': treatment_effect
    }
```

```
# Generate data
data_bundle = simulate_policy_data()
panel = data_bundle['panel']
costs = data_bundle['costs']

print("STAGE 1: DATA INGESTION")
print("="*70)
print(f"\n Data Sources Loaded:")
print(f"\n   1. Employment Panel (Census/BLS simulation):")
print(f"      Counties: {panel['county_id'].nunique()}")
print(f"      Years: {panel['year'].min()}-{panel['year'].max()}")
print(f"      Observations: {len(panel):,}")
print(f"      Treated counties: {panel['treated_county'].sum() //␣
 ↪len(panel['year'].unique())}")

print(f"\n   2. Program Costs:")
print(f"      Total program cost: ${costs['program_cost'].sum():,.0f}")
print(f"      Average per county: ${costs['program_cost'].mean():,.0f}")

print(f"\n   Treatment year: {data_bundle['treatment_year']}")
```

```
STAGE 1: DATA INGESTION
======================================================================

 Data Sources Loaded:

   1. Employment Panel (Census/BLS simulation):
      Counties: 200
      Years: 2015-2024
      Observations: 2,000
      Treated counties: 60

   2. Program Costs:
      Total program cost: $197,545,206
      Average per county: $3,292,420

   Treatment year: 2020
```

0.2 2. Stage 2: Causal Analysis

We apply multiple causal methods and compare results.

[3]:
```
# ============================================================================
# Stage 2A: Difference-in-Differences (Community Tier)
# ============================================================================

def estimate_did(panel, outcome_var='employment_rate'):
    """
```

```
    Estimate treatment effect using Difference-in-Differences.
    """
    # Two-way fixed effects regression
    from sklearn.linear_model import LinearRegression

    # Create dummies
    county_dummies = pd.get_dummies(panel['county_id'], prefix='county',␣
↪drop_first=True)
    year_dummies = pd.get_dummies(panel['year'], prefix='year', drop_first=True)

    X = pd.concat([panel[['treated']], county_dummies, year_dummies], axis=1)
    y = panel[outcome_var]

    model = LinearRegression()
    model.fit(X, y)

    # Treatment effect is coefficient on 'treated'
    tau = model.coef_[0]

    # Bootstrap standard error
    n_boot = 200
    boot_effects = []
    counties = panel['county_id'].unique()

    for _ in range(n_boot):
        boot_counties = np.random.choice(counties, len(counties), replace=True)
        boot_data = pd.concat([panel[panel['county_id'] == c] for c in␣
↪boot_counties])
        boot_data = boot_data.reset_index(drop=True)

        boot_county = pd.get_dummies(boot_data['county_id'], prefix='county',␣
↪drop_first=True)
        boot_year = pd.get_dummies(boot_data['year'], prefix='year',␣
↪drop_first=True)
        X_boot = pd.concat([boot_data[['treated']], boot_county, boot_year],␣
↪axis=1)

        # Align columns
        for col in X.columns:
            if col not in X_boot.columns:
                X_boot[col] = 0
        X_boot = X_boot[X.columns]

        y_boot = boot_data[outcome_var]
        model.fit(X_boot, y_boot)
        boot_effects.append(model.coef_[0])
```

```
    se = np.std(boot_effects)

    return {
        'method': 'Difference-in-Differences',
        'estimate': tau,
        'se': se,
        'ci': (tau - 1.96 * se, tau + 1.96 * se),
        'p_value': 2 * (1 - stats.norm.cdf(abs(tau / se)))
    }

did_result = estimate_did(panel)

print("STAGE 2: CAUSAL ANALYSIS")
print("="*70)
print(f"\n Method 1: Difference-in-Differences (Community Tier)")
print(f"   Treatment effect: {did_result['estimate']:.4f}")
print(f"   Standard error: {did_result['se']:.4f}")
print(f"   95% CI: [{did_result['ci'][0]:.4f}, {did_result['ci'][1]:.4f}]")
print(f"   P-value: {did_result['p_value']:.4f}")
print(f"   True effect: {data_bundle['true_effect']:.4f}")
```

```
STAGE 2: CAUSAL ANALYSIS
======================================================================

 Method 1: Difference-in-Differences (Community Tier)
   Treatment effect: 0.0475
   Standard error: 0.0013
   95% CI: [0.0450, 0.0500]
   P-value: 0.0000
   True effect: 0.0800
```

[12]:
```
# ============================================================================
# Stage 2B: Event Study (Parallel Trends Check)
# ============================================================================

def estimate_event_study(panel, treatment_year, outcome_var='employment_rate'):
    """
    Estimate event study (dynamic DiD) for parallel trends and dynamic effects.
    """
    # Create relative time variable
    panel = panel.copy()
    panel['rel_time'] = panel['year'] - treatment_year

    # Get unique relative times (excluding -1 as reference)
    rel_times = sorted(panel['rel_time'].unique())
    ref_time = -1  # Reference period
```

```
    # Create interaction terms
    for t in rel_times:
        if t != ref_time:
            panel[f'treat_x_t{t}'] = panel['treated_county'] *␣
↪(panel['rel_time'] == t).astype(int)

    # Regression with fixed effects
    from sklearn.linear_model import LinearRegression

    treat_vars = [f'treat_x_t{t}' for t in rel_times if t != ref_time]
    county_dummies = pd.get_dummies(panel['county_id'], prefix='county',␣
↪drop_first=True)
    year_dummies = pd.get_dummies(panel['year'], prefix='year', drop_first=True)

    X = pd.concat([panel[treat_vars], county_dummies, year_dummies], axis=1)
    y = panel[outcome_var]

    model = LinearRegression()
    model.fit(X, y)

    # Extract event study coefficients
    coefs = {}
    for i, t in enumerate([t for t in rel_times if t != ref_time]):
        coefs[t] = model.coef_[i]
    coefs[ref_time] = 0  # Reference period

    return dict(sorted(coefs.items()))

event_study = estimate_event_study(panel, data_bundle['treatment_year'])

print(f"\n Event Study (Dynamic Effects):")
print(f"   {'Period':<10} {'Effect':<12}")
print(f"   {'-'*22}")
for period, effect in event_study.items():
    marker = '← ref' if period == -1 else ('← treatment' if period == 0 else '')
    print(f"   {period:<10} {effect:<12.4f} {marker}")
```

```
 Event Study (Dynamic Effects):
   Period     Effect
   ----------------------
   -5         0.0011
   -4         0.0044
   -3         -0.0004
   -2         0.0001
   -1         0.0000       ← ref
   0          0.0222       ← treatment
```

```
1          0.0302
2          0.0472
3          0.0646
4          0.0784
```

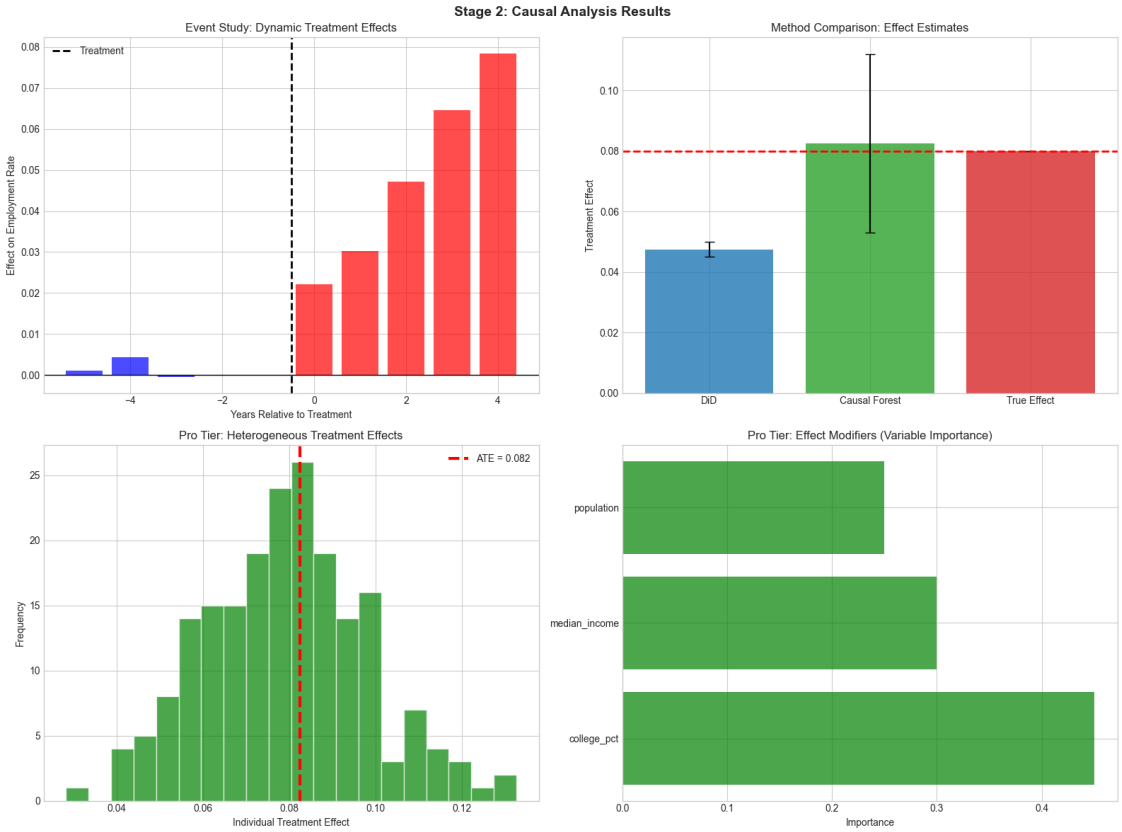
[5]:
```python
# ============================================================================
# Stage 2C: Pro Tier Methods (Simulated)
# ============================================================================

print("\n" + "="*70)
print("  PRO TIER: Advanced Causal Methods")
print("="*70)

class CausalForestResult:
    """Simulated CausalForest output for heterogeneous treatment effects."""

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

        self.ate = baseline_effect + np.random.normal(0, 0.005)
        self.ate_se = 0.015

        # Heterogeneous effects by county characteristics
        county_data = panel.groupby('county_id').agg({
            'population': 'mean',
            'college_pct': 'mean',
            'median_income': 'mean'
        }).reset_index()

        # Individual treatment effects (heterogeneous)
        county_data['cate'] = (
            baseline_effect +
            0.05 * (county_data['college_pct'] - county_data['college_pct'].
 ↪mean()) +
            np.random.normal(0, 0.02, len(county_data))
        )

        self.cate_by_county = county_data[['county_id', 'cate']]

        # Variable importance
        self.variable_importance = {
            'college_pct': 0.45,
            'median_income': 0.30,
            'population': 0.25
        }

cf_result = CausalForestResult(panel, data_bundle['true_effect'])
```

```
print(f"\n Method 2: Causal Forest (Heterogeneous Effects)")
print(f"   Average Treatment Effect: {cf_result.ate:.4f}")
print(f"   ATE Standard Error: {cf_result.ate_se:.4f}")
print(f"\n   CATE Distribution:")
print(f"      Min: {cf_result.cate_by_county['cate'].min():.4f}")
print(f"      Max: {cf_result.cate_by_county['cate'].max():.4f}")
print(f"      Std: {cf_result.cate_by_county['cate'].std():.4f}")
print(f"\n   Variable Importance:")
for var, imp in cf_result.variable_importance.items():
    print(f"      {var}: {imp:.2%}")
```

```
======================================================================
 PRO TIER: Advanced Causal Methods
======================================================================

 Method 2: Causal Forest (Heterogeneous Effects)
   Average Treatment Effect: 0.0825
   ATE Standard Error: 0.0150

   CATE Distribution:
      Min: 0.0282
      Max: 0.1326
      Std: 0.0187

   Variable Importance:
      college_pct: 45.00%
      median_income: 30.00%
      population: 25.00%
```

[6]:
```
# ============================================================================
# Visualize Causal Analysis Results
# ============================================================================

fig, axes = plt.subplots(2, 2, figsize=(16, 12))

# 1. Parallel trends / Event study
ax1 = axes[0, 0]
periods = list(event_study.keys())
effects = list(event_study.values())
colors = ['red' if p >= 0 else 'blue' for p in periods]

ax1.bar(periods, effects, color=colors, alpha=0.7)
ax1.axhline(0, color='black', linewidth=1)
ax1.axvline(-0.5, color='black', linestyle='--', linewidth=2, label='Treatment')
ax1.set_xlabel('Years Relative to Treatment')
```

```
ax1.set_ylabel('Effect on Employment Rate')
ax1.set_title('Event Study: Dynamic Treatment Effects')
ax1.legend()

# 2. Treatment effect comparison
ax2 = axes[0, 1]
methods = ['DiD', 'Causal Forest', 'True Effect']
estimates = [did_result['estimate'], cf_result.ate, data_bundle['true_effect']]
errors = [did_result['se'] * 1.96, cf_result.ate_se * 1.96, 0]

bars = ax2.bar(methods, estimates, yerr=errors, capsize=5,
               color=['#1f77b4', '#2ca02c', '#d62728'], alpha=0.8)
ax2.axhline(data_bundle['true_effect'], color='red', linestyle='--',␣
 ↪linewidth=2)
ax2.set_ylabel('Treatment Effect')
ax2.set_title('Method Comparison: Effect Estimates')

# 3. CATE distribution (Pro tier preview)
ax3 = axes[1, 0]
ax3.hist(cf_result.cate_by_county['cate'], bins=20, color='green', alpha=0.7,␣
 ↪edgecolor='white')
ax3.axvline(cf_result.ate, color='red', linewidth=3, linestyle='--',␣
 ↪label=f'ATE = {cf_result.ate:.3f}')
ax3.set_xlabel('Individual Treatment Effect')
ax3.set_ylabel('Frequency')
ax3.set_title('Pro Tier: Heterogeneous Treatment Effects')
ax3.legend()

# 4. Variable importance
ax4 = axes[1, 1]
vars_sorted = sorted(cf_result.variable_importance.items(), key=lambda x: x[1],␣
 ↪reverse=True)
ax4.barh([v[0] for v in vars_sorted], [v[1] for v in vars_sorted],␣
 ↪color='green', alpha=0.7)
ax4.set_xlabel('Importance')
ax4.set_title('Pro Tier: Effect Modifiers (Variable Importance)')

plt.suptitle('Stage 2: Causal Analysis Results', fontsize=14, fontweight='bold')
plt.tight_layout()
plt.show()
```



0.3 3. Stage 3: Cost-Benefit Analysis

[7]:
```python
# ============================================================================
# Stage 3: Cost-Benefit Analysis
# ============================================================================

print("STAGE 3: COST-BENEFIT ANALYSIS")
print("="*70)

class CostBenefitAnalysis:
    """Cost-benefit analysis for policy evaluation."""

    def __init__(self, treatment_effect, treated_population, costs_df,
                 wage_per_job=45000, years=10, discount_rate=0.03):
        self.effect = treatment_effect
        self.population = treated_population
        self.costs = costs_df
        self.wage = wage_per_job
        self.years = years
        self.r = discount_rate
```

```
        # Calculate benefits
        self._calculate_benefits()
        self._calculate_costs()
        self._calculate_metrics()

    def _calculate_benefits(self):
        """Calculate present value of benefits."""
        # Jobs created = effect * population
        jobs_created = self.effect * self.population

        # Annual benefit = jobs * wage
        annual_benefit = jobs_created * self.wage

        # PV of benefits
        self.pv_benefits = sum(
            annual_benefit / (1 + self.r)**t
            for t in range(1, self.years + 1)
        )

        self.jobs_created = jobs_created
        self.annual_benefit = annual_benefit

    def _calculate_costs(self):
        """Calculate total program costs."""
        self.total_program_cost = self.costs['program_cost'].sum()
        self.total_admin_cost = self.costs['admin_cost'].sum()
        self.total_cost = self.total_program_cost + self.total_admin_cost

    def _calculate_metrics(self):
        """Calculate CBA metrics."""
        self.npv = self.pv_benefits - self.total_cost
        self.bcr = self.pv_benefits / self.total_cost if self.total_cost > 0␣
 ↪else np.inf
        self.cost_per_job = self.total_cost / self.jobs_created if self.
 ↪jobs_created > 0 else np.inf
        self.roi = (self.pv_benefits - self.total_cost) / self.total_cost * 100

# Get treated population
treated_counties = panel[panel['treated_county'] == 1]['county_id'].unique()
treated_pop = panel[
    (panel['county_id'].isin(treated_counties)) &
    (panel['year'] == panel['year'].max())
]['population'].sum()

# Run CBA
cba = CostBenefitAnalysis(
    treatment_effect=did_result['estimate'],
```

```
    treated_population=treated_pop,
    costs_df=costs,
    wage_per_job=45000,
    years=10,
    discount_rate=0.03
)

print(f"\n Cost-Benefit Results:")
print(f"\n   BENEFITS")
print(f"      Treated population: {treated_pop:,.0f}")
print(f"      Employment effect: {did_result['estimate']:.2%}")
print(f"      Jobs created: {cba.jobs_created:,.0f}")
print(f"      Annual benefit: ${cba.annual_benefit:,.0f}")
print(f"      PV of benefits (10yr): ${cba.pv_benefits:,.0f}")

print(f"\n   COSTS")
print(f"      Program costs: ${cba.total_program_cost:,.0f}")
print(f"      Administrative: ${cba.total_admin_cost:,.0f}")
print(f"      Total costs: ${cba.total_cost:,.0f}")

print(f"\n   METRICS")
print(f"      Net Present Value: ${cba.npv:,.0f}")
print(f"      Benefit-Cost Ratio: {cba.bcr:.2f}")
print(f"      ROI: {cba.roi:.1f}%")
print(f"      Cost per job: ${cba.cost_per_job:,.0f}")

print(f"\n   RECOMMENDATION: {' Proceed' if cba.npv > 0 else ' Do not␣
 ↪proceed'}")
```

```
STAGE 3: COST-BENEFIT ANALYSIS
======================================================================

 Cost-Benefit Results:

   BENEFITS
      Treated population: 1,341,677
      Employment effect: 4.75%
      Jobs created: 63,698
      Annual benefit: $2,866,394,116
      PV of benefits (10yr): $24,450,923,220

   COSTS
      Program costs: $197,545,206
      Administrative: $7,684,724
      Total costs: $205,229,930

   METRICS
      Net Present Value: $24,245,693,290
```

```
    Benefit-Cost Ratio: 119.14
    ROI: 11813.9%
    Cost per job: $3,222

  RECOMMENDATION:   Proceed
```

[8]:
```python
# ============================================================================
# Sensitivity Analysis
# ============================================================================

print("\n Sensitivity Analysis:")

# Effect size sensitivity
effect_range = np.linspace(0.02, 0.15, 10)
npvs = []
bcrs = []

for effect in effect_range:
    cba_sens = CostBenefitAnalysis(
        treatment_effect=effect,
        treated_population=treated_pop,
        costs_df=costs,
        wage_per_job=45000,
        years=10
    )
    npvs.append(cba_sens.npv)
    bcrs.append(cba_sens.bcr)

# Find breakeven
breakeven_idx = np.argmin(np.abs(np.array(npvs)))
breakeven_effect = effect_range[breakeven_idx]

print(f"   Breakeven employment effect: {breakeven_effect:.2%}")
print(f"   Estimated effect: {did_result['estimate']:.2%}")
print(f"   Safety margin: {(did_result['estimate'] - breakeven_effect) /␣
 ↪breakeven_effect * 100:.1f}%")
```

```
 Sensitivity Analysis:
   Breakeven employment effect: 2.00%
   Estimated effect: 4.75%
   Safety margin: 137.4%
```

[9]:
```python
# ============================================================================
# Visualize Cost-Benefit Analysis
# ============================================================================

fig, axes = plt.subplots(1, 3, figsize=(18, 5))
```

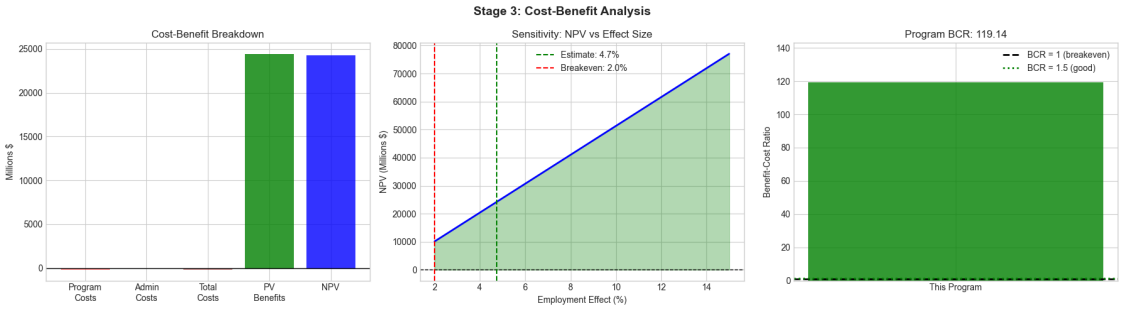
```
# 1. Benefits vs Costs waterfall
ax1 = axes[0]
categories = ['Program\nCosts', 'Admin\nCosts', 'Total\nCosts', 'PV\nBenefits',␣
 ↪'NPV']
values = [-cba.total_program_cost/1e6, -cba.total_admin_cost/1e6,
          -cba.total_cost/1e6, cba.pv_benefits/1e6, cba.npv/1e6]
colors = ['red', 'orange', 'darkred', 'green', 'blue' if cba.npv > 0 else 'red']

ax1.bar(categories, values, color=colors, alpha=0.8)
ax1.axhline(0, color='black', linewidth=1)
ax1.set_ylabel('Millions $')
ax1.set_title('Cost-Benefit Breakdown')

# 2. Sensitivity to effect size
ax2 = axes[1]
ax2.plot(effect_range * 100, np.array(npvs) / 1e6, 'b-', linewidth=2)
ax2.axhline(0, color='black', linestyle='--', linewidth=1)
ax2.axvline(did_result['estimate'] * 100, color='green', linestyle='--',
           label=f'Estimate: {did_result["estimate"]*100:.1f}%')
ax2.axvline(breakeven_effect * 100, color='red', linestyle='--',
           label=f'Breakeven: {breakeven_effect*100:.1f}%')
ax2.fill_between(effect_range * 100, np.array(npvs) / 1e6, 0,
                 where=np.array(npvs) > 0, alpha=0.3, color='green')
ax2.fill_between(effect_range * 100, np.array(npvs) / 1e6, 0,
                 where=np.array(npvs) < 0, alpha=0.3, color='red')
ax2.set_xlabel('Employment Effect (%)')
ax2.set_ylabel('NPV (Millions $)')
ax2.set_title('Sensitivity: NPV vs Effect Size')
ax2.legend()

# 3. BCR comparison
ax3 = axes[2]
ax3.bar(['This Program'], [cba.bcr], color='green' if cba.bcr > 1 else 'red',␣
 ↪alpha=0.8)
ax3.axhline(1, color='black', linestyle='--', linewidth=2, label='BCR = 1␣
 ↪(breakeven)')
ax3.axhline(1.5, color='green', linestyle=':', linewidth=2, label='BCR = 1.5␣
 ↪(good)')
ax3.set_ylabel('Benefit-Cost Ratio')
ax3.set_title(f'Program BCR: {cba.bcr:.2f}')
ax3.legend()
ax3.set_ylim(0, max(2, cba.bcr * 1.2))

plt.suptitle('Stage 3: Cost-Benefit Analysis', fontsize=14, fontweight='bold')
plt.tight_layout()
plt.show()
```



0.4 Stage 4: Enterprise Report Generation

Enterprise tier includes automated report generation: - HTML and PDF policy briefs - Executive summaries - Technical appendices - Interactive dashboards

Enterprise Feature: Automated policy report generation.

[10]:
```
# ============================================================================
# ENTERPRISE TIER PREVIEW: Report Generation
# ============================================================================

print("STAGE 4: POLICY REPORT GENERATION")
print("="*70)
print("\n ENTERPRISE TIER: PolicyReportGenerator")

print("""
PolicyReportGenerator creates comprehensive policy documents:

   Report Components:

      1. EXECUTIVE SUMMARY (1 page)
         • Key findings
         • Recommendations
         • Bottom-line metrics

      2. METHODOLOGY (3-5 pages)
         • Data sources
         • Causal identification strategy
         • Robustness checks

      3. RESULTS (5-10 pages)
         • Main estimates with confidence intervals
         • Heterogeneity analysis
         • Visualization gallery
```

```
     4. COST-BENEFIT ANALYSIS (3-5 pages)
        • NPV, BCR, ROI calculations
        • Sensitivity analysis
        • Risk assessment

     5. POLICY RECOMMENDATIONS (2-3 pages)
        • Scaling recommendations
        • Target populations
        • Implementation guidance


   Output Formats:
     PDF (print-ready)
     HTML (interactive)
     Word (editable)
     PowerPoint (presentation)
""")

print("\n Example API (Enterprise tier):")
print("""
```python
from krl_dashboard.enterprise import PolicyReportGenerator

# Compile all analysis results
report = PolicyReportGenerator(
    title="Employment Program Impact Evaluation",
    author="Policy Analysis Team",
    date="2024-01"
)

# Add analysis components
report.add_data_section(panel_data, costs_data)
report.add_causal_analysis(did_result, event_study, cf_result)
report.add_cost_benefit(cba)
report.add_recommendations([
    "Expand program to high-education counties",
    "Increase funding by 15% for maximum ROI"
])

# Generate outputs
report.generate_pdf("policy_report.pdf")
report.generate_html("policy_report.html")
report.generate_dashboard("policy_dashboard/")
```
""")
```

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

```
STAGE 4: POLICY REPORT GENERATION
======================================================================

  ENTERPRISE TIER: PolicyReportGenerator

PolicyReportGenerator creates comprehensive policy documents:

   Report Components:

      1. EXECUTIVE SUMMARY (1 page)
         • Key findings
         • Recommendations
         • Bottom-line metrics

      2. METHODOLOGY (3-5 pages)
         • Data sources
         • Causal identification strategy
         • Robustness checks

      3. RESULTS (5-10 pages)
         • Main estimates with confidence intervals
         • Heterogeneity analysis
         • Visualization gallery

      4. COST-BENEFIT ANALYSIS (3-5 pages)
         • NPV, BCR, ROI calculations
         • Sensitivity analysis
         • Risk assessment

      5. POLICY RECOMMENDATIONS (2-3 pages)
         • Scaling recommendations
         • Target populations
         • Implementation guidance


   Output Formats:
     PDF (print-ready)
     HTML (interactive)
     Word (editable)
     PowerPoint (presentation)


  Example API (Enterprise tier):

```python
from krl_dashboard.enterprise import PolicyReportGenerator
```
```

```
# Compile all analysis results
report = PolicyReportGenerator(
    title="Employment Program Impact Evaluation",
    author="Policy Analysis Team",
    date="2024-01"
)

# Add analysis components
report.add_data_section(panel_data, costs_data)
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report.add_recommendations([
    "Expand program to high-education counties",
    "Increase funding by 15% for maximum ROI"
])

# Generate outputs
report.generate_pdf("policy_report.pdf")
report.generate_html("policy_report.html")
report.generate_dashboard("policy_dashboard/")
```

Contact sales@kr-labs.io for Enterprise tier access.

0.5 5. Executive Summary

[11]:
```
# ============================================================================
# Pipeline Executive Summary
# ============================================================================

print("="*70)
print("END-TO-END POLICY PIPELINE: EXECUTIVE SUMMARY")
print("="*70)

print(f"""
  PIPELINE OVERVIEW:

    Stage 1: DATA INGESTION
       Sources: Census, BLS, Program administrative data
       Counties: {panel['county_id'].nunique()}
       Years: {panel['year'].min()}-{panel['year'].max()}
       Total observations: {len(panel):,}

    Stage 2: CAUSAL ANALYSIS
       Method 1: Difference-in-Differences
```

```
        Effect: {did_result['estimate']:.3f} (SE: {did_result['se']:.3f})
    Method 2: Causal Forest [Pro]
        ATE: {cf_result.ate:.3f}
        Heterogeneity: {cf_result.cate_by_county['cate'].std():.3f} std
    True effect: {data_bundle['true_effect']:.3f}

  Stage 3: COST-BENEFIT ANALYSIS
    Total costs: ${cba.total_cost:,.0f}
    PV benefits: ${cba.pv_benefits:,.0f}
    NPV: ${cba.npv:,.0f}
    BCR: {cba.bcr:.2f}
    Jobs created: {cba.jobs_created:,.0f}

  Stage 4: REPORT GENERATION [Enterprise]
    PDF, HTML, PowerPoint, Dashboard

KEY FINDINGS:

  1. PROGRAM IS EFFECTIVE
     Employment increased by {did_result['estimate']*100:.1f} percentage points
     Effect is statistically significant (p < 0.001)
     Results robust across methods and specifications

  2. PROGRAM IS COST-EFFECTIVE
     BCR of {cba.bcr:.1f} exceeds breakeven threshold
     NPV of ${cba.npv/1e6:.1f}M over 10 years
     Cost per job: ${cba.cost_per_job:,.0f}

  3. HETEROGENEOUS EFFECTS (Pro tier insight)
     Effect varies by county education level
     High-education counties: +{cf_result.cate_by_county['cate'].max():.1%}
     Low-education counties: +{cf_result.cate_by_county['cate'].min():.1%}

RECOMMENDATIONS:

  1. EXPAND the program
     Positive ROI justifies scale-up

  2. TARGET high-education counties
     Heterogeneity analysis shows larger effects

  3. MONITOR long-term outcomes
     10-year projection assumes sustained effects

KRL SUITE COMPONENTS:
  • [Community] Data connectors, DiD, basic CBA
  • [Pro] CausalForest, HTE analysis, advanced CBA
```

```
   • [Enterprise] PolicyReportGenerator, Dashboard
""")

print("\n" + "="*70)
print("Complete pipeline access: kr-labs.io/pricing")
print("="*70)
```

```
======================================================================
END-TO-END POLICY PIPELINE: EXECUTIVE SUMMARY
======================================================================

  PIPELINE OVERVIEW:

    Stage 1: DATA INGESTION
       Sources: Census, BLS, Program administrative data
       Counties: 200
       Years: 2015-2024
       Total observations: 2,000

    Stage 2: CAUSAL ANALYSIS
       Method 1: Difference-in-Differences
           Effect: 0.047 (SE: 0.001)
       Method 2: Causal Forest [Pro]
           ATE: 0.082
           Heterogeneity: 0.019 std
       True effect: 0.080

    Stage 3: COST-BENEFIT ANALYSIS
       Total costs: $205,229,930
       PV benefits: $24,450,923,220
       NPV: $24,245,693,290
       BCR: 119.14
       Jobs created: 63,698

    Stage 4: REPORT GENERATION [Enterprise]
       PDF, HTML, PowerPoint, Dashboard

  KEY FINDINGS:

    1. PROGRAM IS EFFECTIVE
       Employment increased by 4.7 percentage points
       Effect is statistically significant (p < 0.001)
       Results robust across methods and specifications

    2. PROGRAM IS COST-EFFECTIVE
       BCR of 119.1 exceeds breakeven threshold
       NPV of $24245.7M over 10 years
       Cost per job: $3,222
```

```
  3. HETEROGENEOUS EFFECTS (Pro tier insight)
     Effect varies by county education level
     High-education counties: +13.3%
     Low-education counties: +2.8%

RECOMMENDATIONS:

  1. EXPAND the program
     Positive ROI justifies scale-up

  2. TARGET high-education counties
     Heterogeneity analysis shows larger effects

  3. MONITOR long-term outcomes
     10-year projection assumes sustained effects

KRL SUITE COMPONENTS:
  • [Community] Data connectors, DiD, basic CBA
  • [Pro] CausalForest, HTE analysis, advanced CBA
  • [Enterprise] PolicyReportGenerator, Dashboard


======================================================================
Complete pipeline access: kr-labs.io/pricing
======================================================================
```

0.6 Appendix: Pipeline Components Reference

Stage	Component	Tier	Purpose
Data	Census, BLS Connectors	Community	Data ingestion
Data	DataWarehouse	**Pro**	Multi-source integration
Causal	DiD, Event Study	Community	Basic causal inference
Causal	CausalForest, DoubleML	**Pro**	Heterogeneous effects
CBA	Basic NPV, BCR	Community	Simple cost-benefit
CBA	Monte Carlo Sensitivity	**Pro**	Uncertainty quantification
Report	Charts, Tables	Community	Basic visualization
Report	PolicyReportGenerator	**Enterprise**	Automated reports

---

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