THE CAUSAL IMPACT OF NEW YORK CITY'S CONGESTION PRICING ON ROAD SPEED

A Comparative Event-Study Difference-in-Differences Analysis with Chicago

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BACKGROUND & MOTIVATION

Policy Background

New York City introduced congestion pricing in January 2025, applying a cordon toll on vehicles entering Manhattan’s Central Business District. The policy aims to reduce traffic congestion and improve travel speeds in one of the densest urban environments in the United States.

Causal Question

How did NYC's congestion pricing policy affect road speed relative to Chicago in the period following its implementation?

- Do drivers gain enough travel time savings to offset the toll payment?
- Are there spillover effects to nearby roads?

POLICY SIGNIFICANCE AND PRIOR EVIDENCE

Why This Study Matters

- Congestion pricing marks a major change in transportation policy and travel efficiency
- NYC’s rollout offers a unique real-world experiment on short-run mobility impacts

Most relevant prior work

- Cook et al. (2025): NYC’s pricing quickly improved mobility by raising speeds and cutting travel times
- Ostrovsky & Yang (2024): Fair and effective pricing requires equitable toll design
- Gibson & Carnovale (2015): Road pricing shifts driver behavior and reduces traffic and pollution

RESEARCH DESIGN, DATA, AND ESTIMAND

Treatment, Outcome & Unit Estimand

- Dataset: NYC Yellow Taxi data & Chicago Taxi Trips (2024/08-2025/05)
- Treatment (D): NYC × Post-January-2025 indicator (D_{it} = 1 if NYC and t ≥ implementation)
- Outcome (Y): Weekly traffic speed at the city-CBD level
- Unit of Analysis: City × week panel (NYC vs Chicago)
- Estimand: ATT via an event-study DID design

Covariates

- Weather: Daily temperature, precipitation, snow, wind, visibility (aggregated weekly)
- Gas Prices: Weekly retail gasoline prices, aligned to weekly panel
- Holidays: Federal holiday indicator to capture travel anomalies

DATA OVERVIEW

Data Structure

- 2 observational dataset (no randomized assignment)
  - Chicago
  - New York
- Time-series structure:
  - Data collected daily, aggregated to weekly for analysis

Variable	Unit	Meaning
CBD Speed	mph	Weekly avg speed for all taxi ride in CBD area
Precipitation	inches	Weekly avg precipitation in sample city
Snow	inches	Weekly avg snow in sample city
Windspeed	mph	Weekly avg windspeed in sample city
Visability	mi	Weekly avg horizontal visibility distance
Cloudcover	%	% of sky covered by clouds in weekly avg
Gasoline Price	dollar	Average weekly retail gasoline price

DATA HANDLING

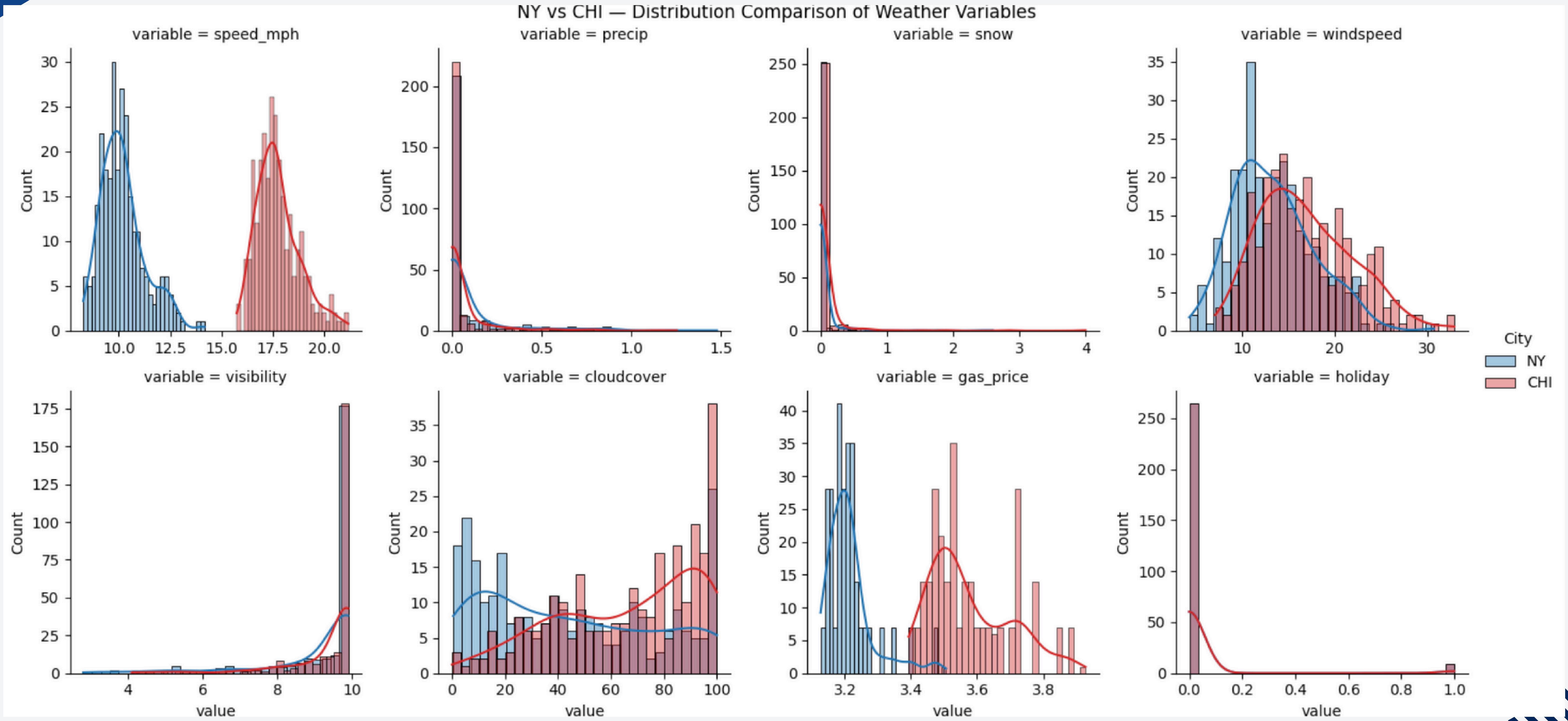
Chicago Dataset

- **Merge & Standardize Data:** Normalize column names, convert timestamps and numeric fields, remove invalid trips (0 miles/seconds), and prepare core variables
- **Filter & Clean:** Use shapely polygons to identify whether pickup or dropoff occurs inside the Chicago Loop and keep only Loop-related trips
- **Aggregate Daily Metrics:** Compute speed, trip minutes, and daily metrics, then group by date to generate cleaned daily summaries

New York Dataset

- **Merge & Standardize Data:** Load yellow/green NY trip files, select needed columns, rename datetime fields, and combine into one dataset
- **Filter & Clean:** Keep only Manhattan-zone trips, fix datetime formats, remove invalid distances/durations, and compute ride time & speed
- **Aggregate Daily Metrics:** Create date column and compute daily averages for speed, trip distance, ride time, and total amount

BASIC DESCRIPTIVE STATISTICS



METHODOLOGY

Identification Strategy: Difference-in-Differences

Treatment Group: NYC	Control Group: Chicago
• Affected by congestion pricing (Jan 5, 2025)	• NOT affected by any policy change • Provides counterfactual trend

$$\text{DiD Estimator} = \underbrace{(NYC_{post} - NYC_{pre})}_{\text{First Difference}} - \underbrace{(Chicago_{post} - Chicago_{pre})}_{\text{Second Difference}}$$

What DiD Controls For:

✓ Time-invariant city differences (NYC ≠ Chicago)
✓ Common time trends (seasons, economy, holidays)
✓ National shocks affecting both cities

Compare Casual Strategies:

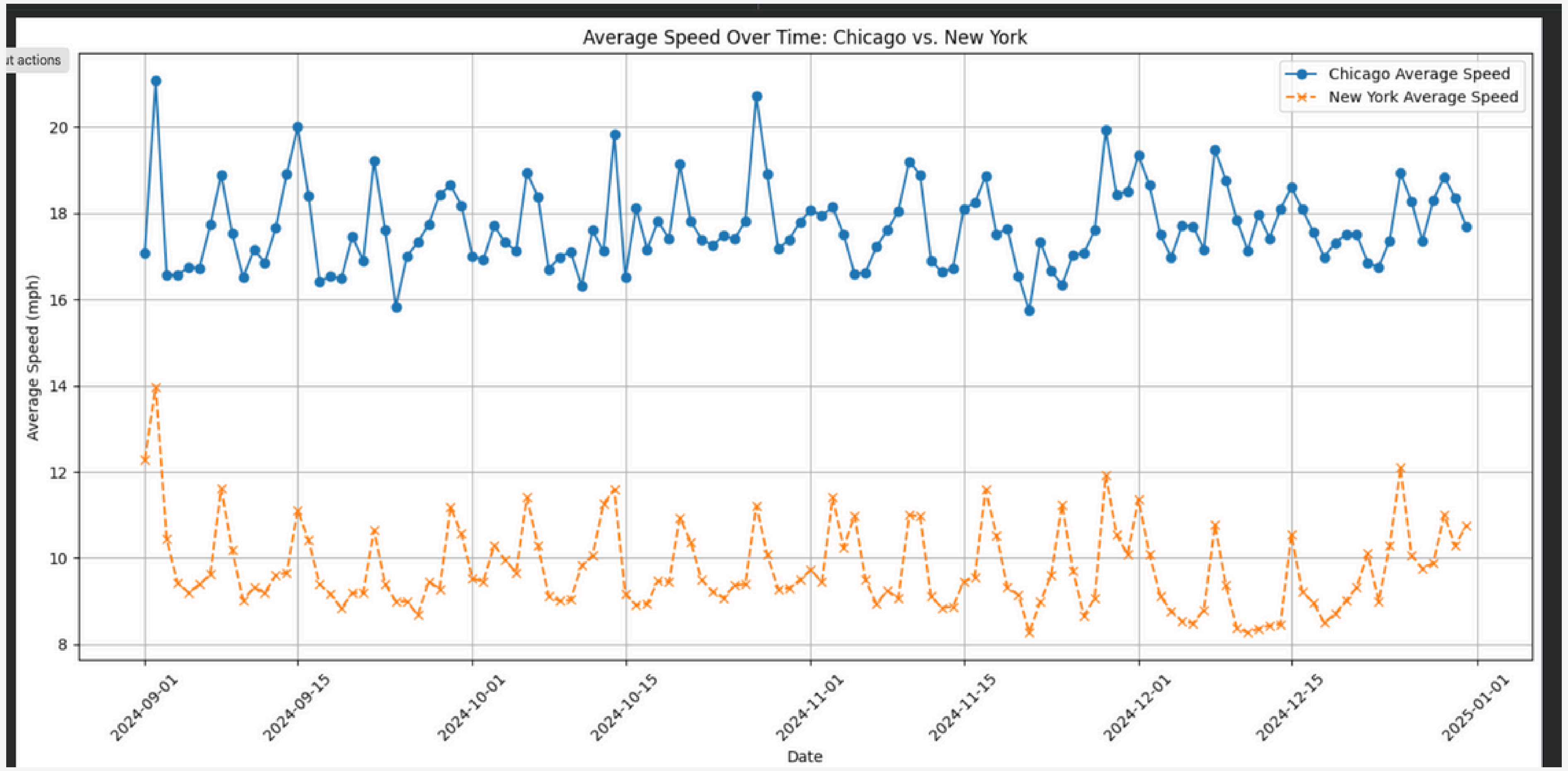
- Before-After Comparison: Co-founded by time trend (seasons, holidays..)
- Regression Discontinuity: No sharp cut-off (policy apply to entire CBD
- Instrumental Variables: No valid IV, policy not random

ASSUMPTION

Parallel Trends

Key assumptions: Absent treatment, NYC and Chicago would follow similar trajectories.

$$E[Y_{it}^0 | \text{NYC}] - E[Y_{it'}^0 | \text{NYC}] = E[Y_{it}^0 | \text{Chicago}] - E[Y_{it'}^0 | \text{Chicago}]$$



Conclusion: The difference between NYC and Chicago would remain a over time without the policy.

MODEL

Two-Way Fixed Effects (TWFE) Model

MODEL 1: BASIC TWFE

$$Y_{it} = \alpha_i + \gamma_t + \beta \cdot \mathrm{TreatPost}_{it} + \varepsilon_{it}$$

MODEL 2: TWFE + WEATHER

$$Y_{it} = \alpha_i + \gamma_t + \beta \cdot \mathrm{TreatPost}_{it} + \mathbf{X}'_{it}\delta + \varepsilon_{it}$$

MODEL 3: TWFE + CITY-SPECIFIC TRENDS

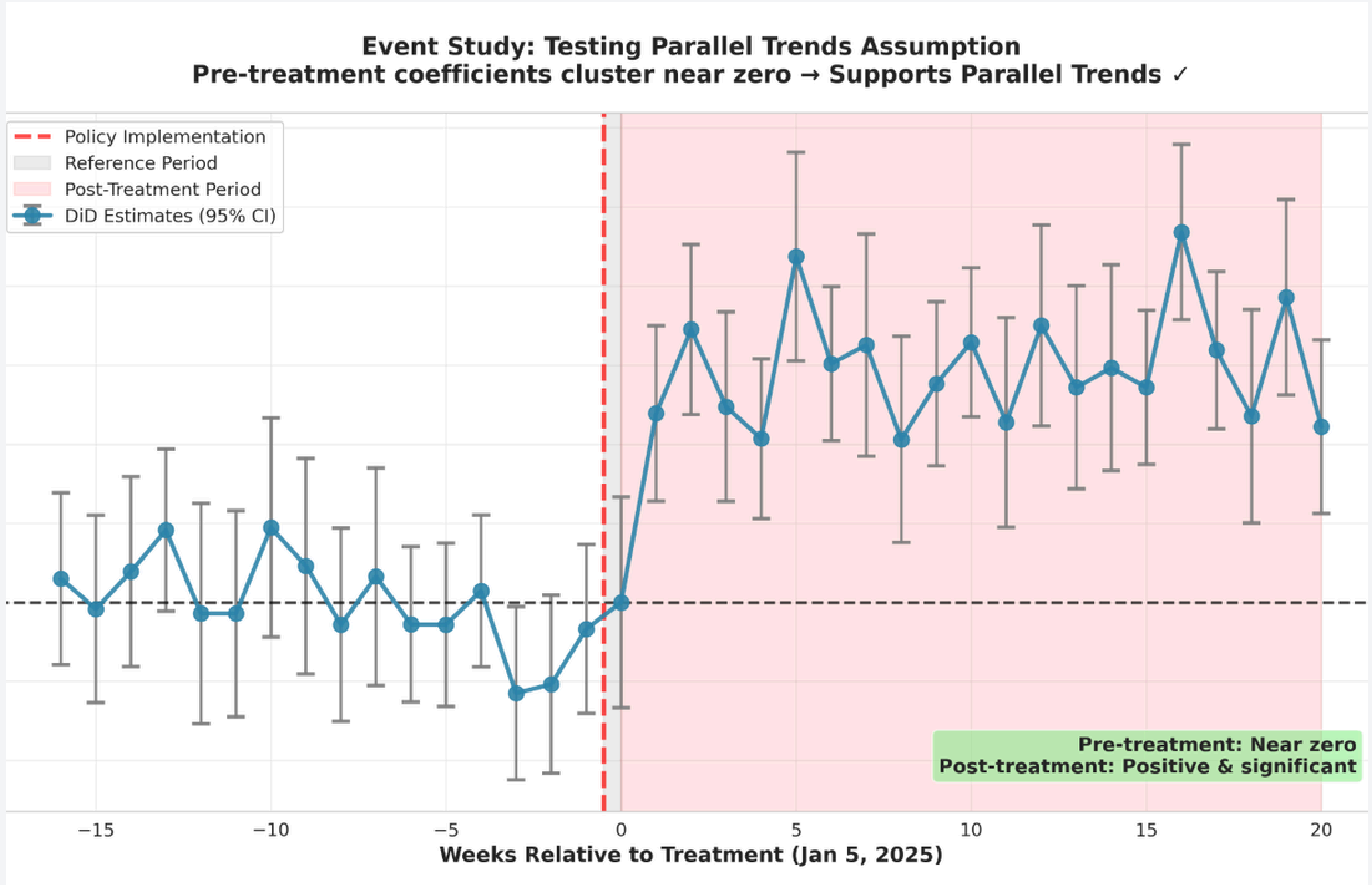
$$Y_{it} = \alpha_i + \gamma_t + \beta \cdot \mathrm{TreatPost}_{it} + \sum_i \delta_i \cdot \mathrm{time} \cdot \mathbb{1}\{i\} + \varepsilon_{it}$$

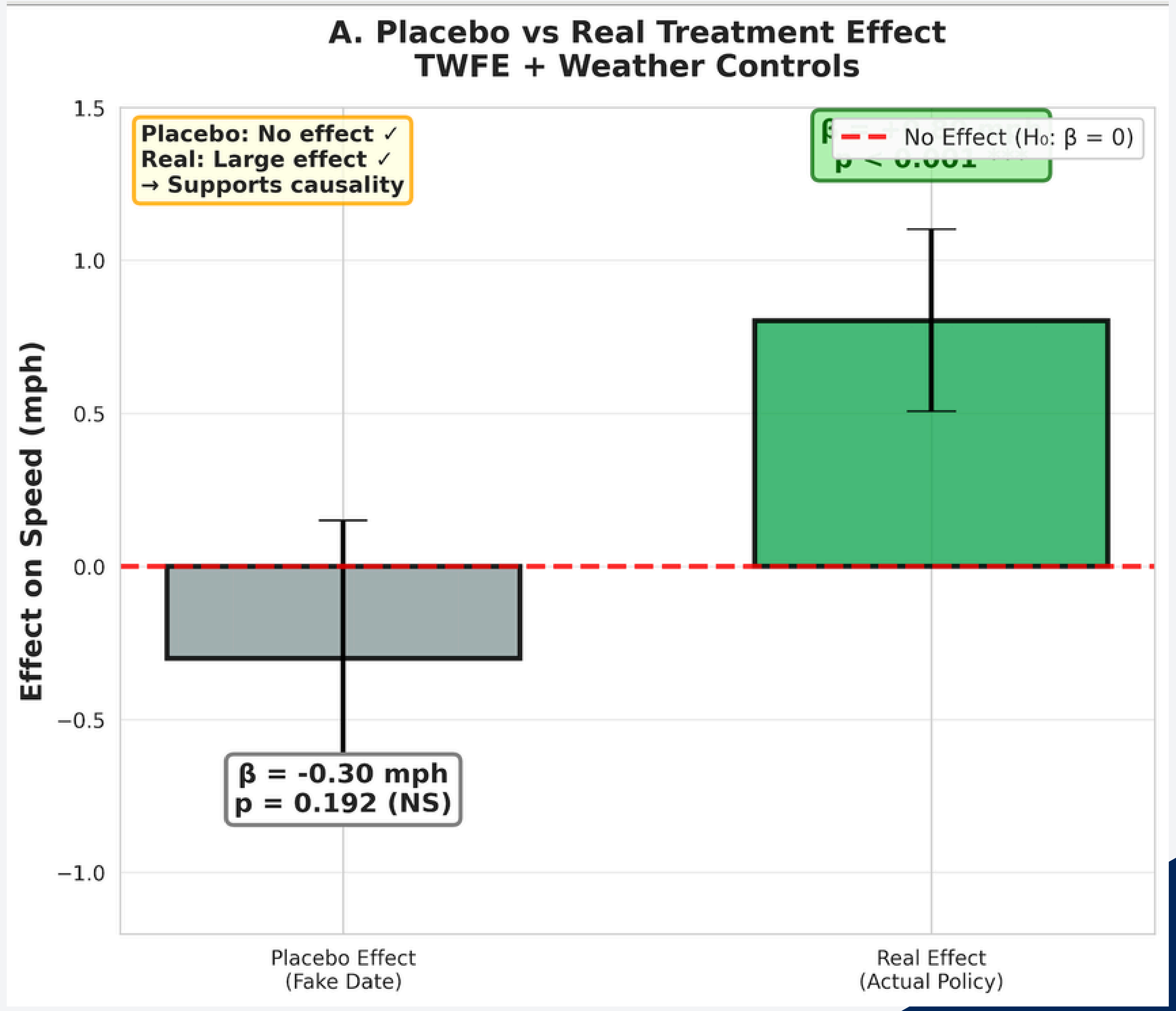
Variable	Model 1 (TWFE)	Model 2 (TWFE + Weather)	Model 3 (TWFE + Trends)
TreatPost (β)	0.7613*** (0.1677)	**0.8037*** (0.1514)	**5.7417*** (0.6030)
Temperature	—	-0.0072 (0.0063)	—
Precipitation	—	-0.5475** (0.2095)	—
Holiday	—	2.2637*** (0.3405)	—
City FE	Yes	Yes	No
Week FE	Yes	Yes	Yes
City Trends	No	No	Yes
N (observations)	546	546	546
R^2	941	951	954

ROBUSTNESS CHECK

Placebo Test

Results from Model 2 → Change the date to 11/06/2024

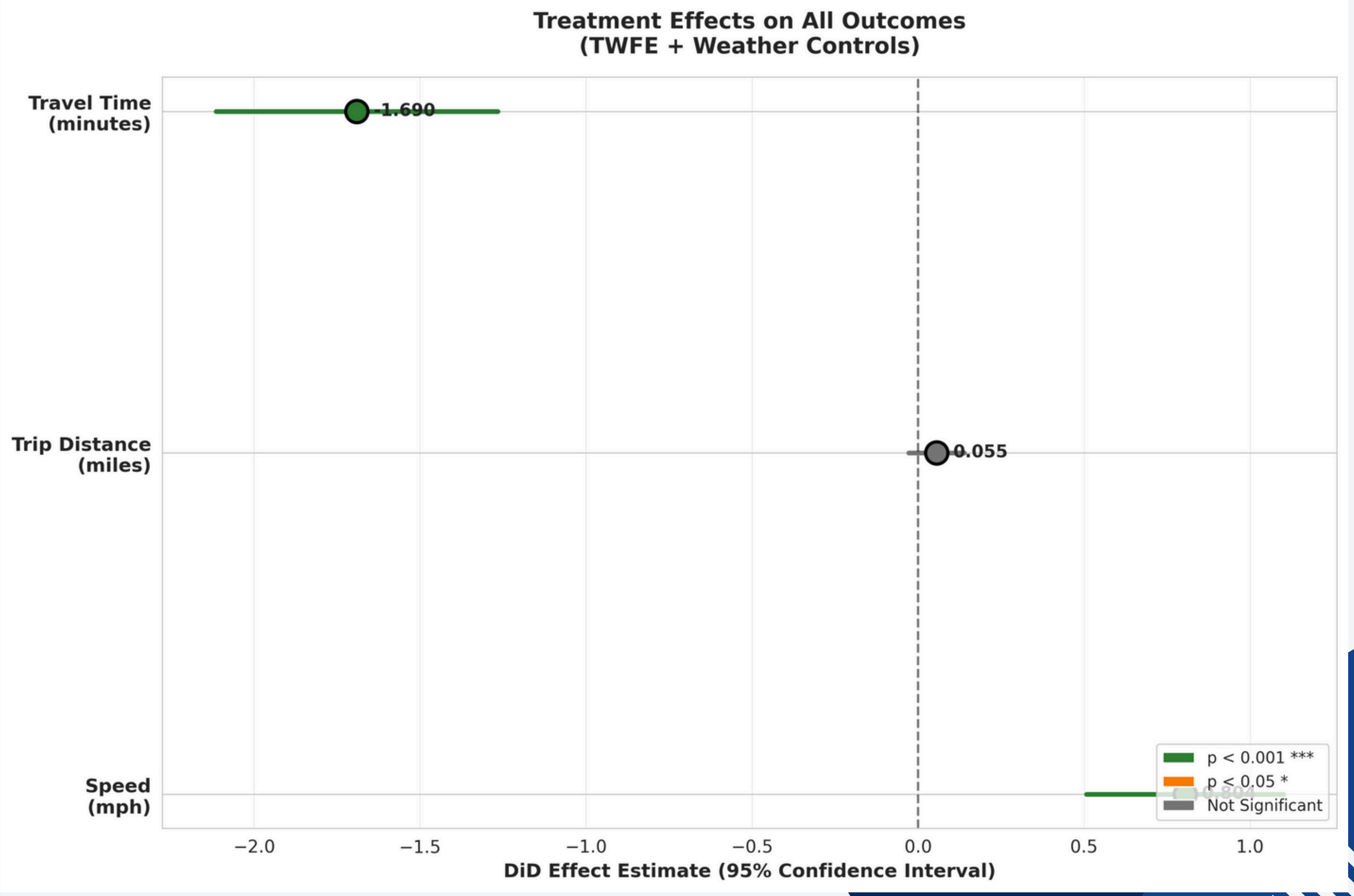




PHASE 1 RESULTS

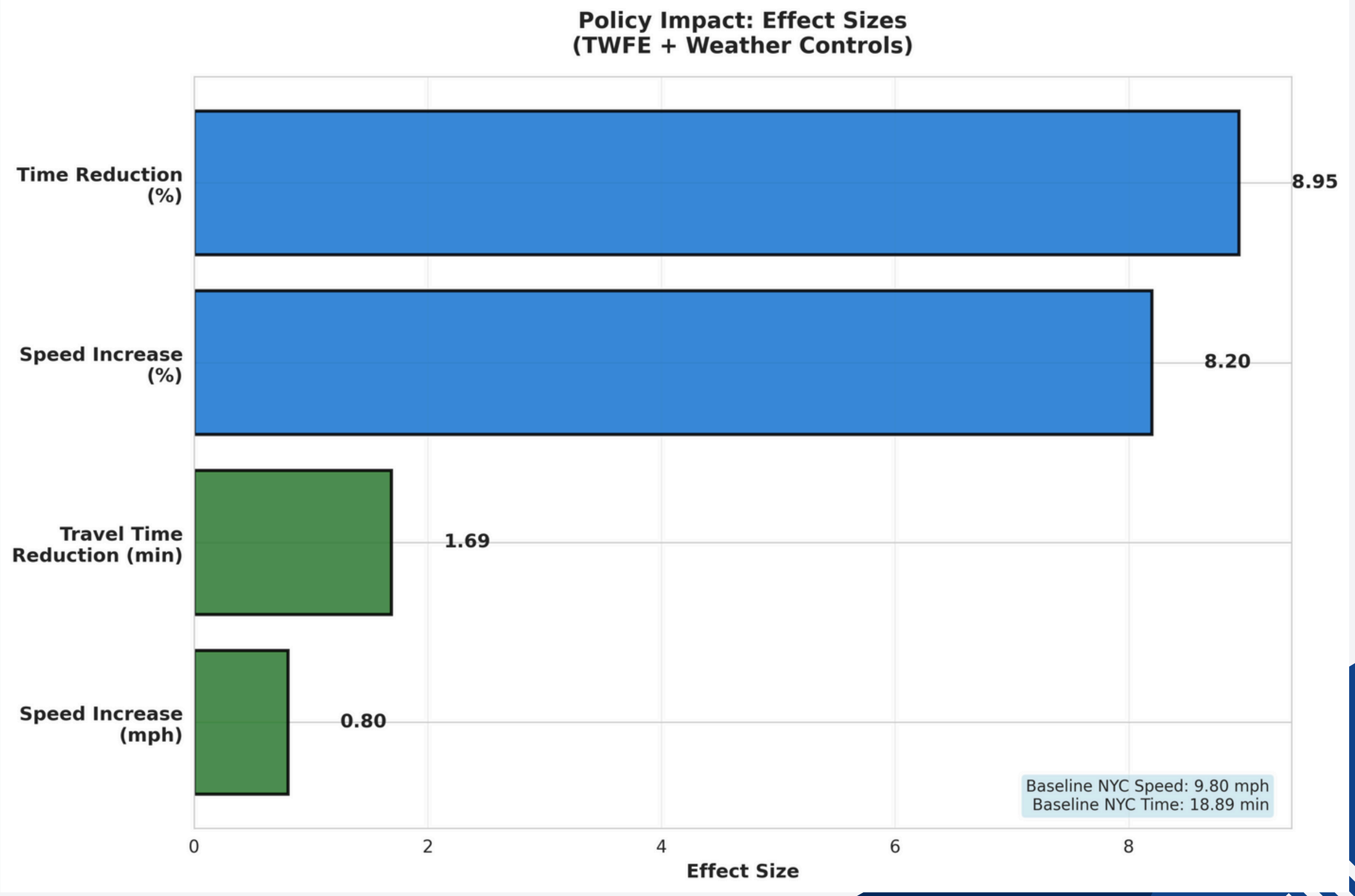
– Causal Evidence

- **Confirm statistical significance:** 95% confidence intervals for **Speed (positive)** and **Trip Time (negative)**
- **Validate robustness:** Significant causal effect persists after strictly controlling for weather and holiday confounders



PHASE 1 RESULTS
– Quantifying the Policy Impact

- **Observe** a **~8.2% increase in traffic speeds** relative to the Chicago Loop counterfactual
- **Translate** to a **~8.95% reduction in travel time** per trip
- Demonstrate that **pricing successfully internalized the externality, significantly reducing congestion friction in the CBD.**



NEXT STEP

Phase 2 – Driver Welfare Analysis

Assess the economic trade-off

Do the efficiency gains (time savings) justify the financial cost (toll) for the average driver?

Method & Formula

Calculate the Net Welfare Change using a DiD-based Consumer Surplus framework

$$\Delta \text{Welfare}_{trip} = [\text{VOTT} \times (\text{Time}_{pre} - \text{Time}_{post})] - \text{Toll Cost}$$

- VOTT: Value of Travel Time (calibrated to % of local hourly wage).
- Time Savings: Estimated directly from our DiD treatment effect.

Aggregation

Scale per-trip benefits by total trip volume to estimate the aggregate social surplus

NEXT STEP

Roadmap to Final Deliverable

Sensitivity Analysis (VOTT Robustness)	Since VOTT is subjective, we will recalculate welfare under different scenarios to ensure our conclusion holds regardless of the specific valuation of time
Heterogeneity Analysis (Peak vs. Off-Peak)	We will re-run the DiD model separately for Peak Hours (7-10 AM, 4-7 PM) and Off-Peak Hours to determine if the welfare gains are concentrated during specific times of day
Final Policy Recommendation	To prove: Does the congestion pricing policy **generate a net positive social surplus,** or does the toll burden outweigh the efficiency gains?

QNA
SESSION

THANK YOU