Behavioral Responses to Time-Varying Congestion Pricing: A Natural Experiment from New York City

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Abstract

The Vickrey bottleneck model predicts that time-varying tolls induce departure-time shifting when toll savings exceed schedule delay costs. I test this prediction using New York City's Congestion Relief Zone, implemented January 2025, which created discrete price jumps at fixed clock times. Applying a difference-in-discontinuities design to hourly mobility data, I find temporal substitution concentrated at a single boundary: overnight activity increases 5.75 percent at the weekday 5AM threshold. Estimates at evening and weekend boundaries are precisely zero. This asymmetry is consistent with the bottleneck model when schedule delay costs vary across boundaries, suggesting toll effectiveness depends on boundary placement relative to institutional constraints.

Keywords: Congestion pricing; Bottleneck model; Schedule delay; Temporal substitution
JEL: R41, R48, H23

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1 Introduction

Vickrey (1969)'s bottleneck model motivates time-varying congestion pricing through a simple behavioral channel: when capacity is limited, travelers reduce congestion by spreading trips over time, trading off time lost in queues against the inconvenience of traveling earlier or later than preferred. A time-varying toll can preserve this efficient spreading while converting wasted queuing time into revenue. The model therefore delivers a sharp empirical prediction: when tolls change discretely at known clock times, activity should shift discontinuously toward the low-toll side of the boundary but only where schedule constraints make retiming feasible.

Whether this mechanism operates depends on the local "schedule technology" around each cutoff. Avoiding a higher toll by traveling earlier can be relatively low cost for shift workers, early deliveries, and some discretionary trips; avoiding a higher toll by traveling later often collides with business closures, childcare, and coordination frictions. This asymmetry implies that boundaries requiring earlier travel should elicit stronger substitution than boundaries requiring later travel, even when the price change is identical. Yet existing evaluations of congestion pricing largely report average traffic reductions, which confound temporal substitution with route diversion, mode switching, and trip suppression, and thus rarely test the discontinuity prediction directly (Eliasson et al., 2009; Leape, 2006).

New York City's Congestion Relief Zone (CRZ), implemented on January 5, 2025, provides an unusually clean setting. The toll schedule creates fixed, pre-announced cutoffs with the same dollar differential at weekday (5AM till 9PM) and weekend (9AM till 9PM) boundaries. I exploit this structure using a difference-in-discontinuities design (Grembi et al., 2016) applied to hourly establishment visits, comparing changes in the size of each clock-time discontinuity in Manhattan to changes at the same cutoffs in Boston. The results are tightly aligned with the bottleneck mechanism: activity increases by about 5.9 percent on the low-toll side of the weekday 5AM boundary, while effects at the weekday 9PM and weekend cutoffs are economically small and statistically indistinguishable from zero. The evidence implies that time-varying pricing can induce temporal substitution, but its effectiveness hinges on where thresholds fall relative to institutional constraints not only on the magnitude of the toll differential.

2 Data and Method

The CRZ charges vehicles entering Manhattan south of 60th Street: $9 peak (weekdays 5AM–9PM; weekends 9AM–9PM) versus $2.25 off-peak. We measure hourly visits to points of interest from Advan Research, 2025 mobile-device data from July 2023 through July 2025. Mobile-device location datasets of this type have been widely used to study behavioral responses to policy and environmental changes in public health (Andersen et al., 2023; Dave et al., 2021; Goolsbee & Syverson, 2021; Mongey et al., 2021), marketing (Banerjee et al., 2021; Hou & Poliquin, 2023), and urban/transportation settings (Coleman et al., 2022; Goodspeed et al., 2021; Pandit, 2023; Wang et al., 2022).The balanced panel contains 24,700 Manhattan and 15,200 Boston establishments, excluding institutionally rigid sectors. Table 1, confirms similar baseline activity across geographies.

Table 1: Sample Composition

	Manhattan		Boston	
Sector	N	Mean	N	Mean
Retail (441–453)	6,244	10.82	4,112	11.04
Services (522–611)	9,135	11.19	5,317	11.22
Food/Accommodation	4,285	11.87	2,443	12.14
Other	5,040	9.43	3,362	9.67
Total	24,704	10.47	15,234	10.52

Notes: Manhattan (CZ) denotes the Congestion Zone (treatment area south of 60th Street). N = number of establishments. Mean and SD represent log visitors during baseline period (2024). Full table with all sectors and control areas available in Appendix A1.

Figure 1, in appendix displays hourly visit patterns. Manhattan and Boston track closely throughout the day in both pre and post periods, supporting Boston as a valid counterfactual. The vertical lines mark toll boundaries.

The identification challenge is that activity jumps at clock times independent of pricing. I use difference-in-discontinuities (Grembi et al., 2016) and Poisson Pseudo-Maximum Likelihood (PPML):

$$\mathbb{E}[y_{gth}] = \exp\Big(\alpha_t + \delta_g + \beta_h + \tau(\text{Manhattan}_g \times \text{Post}_t \times \text{Off-Peak}_h) + f(r_h)\Big) \tag{1}$$

where α_t are date fixed effects, δ_g are geography, β_h are hour fixed effects, and $f(r_h)$ controls flexibly for the running variable. Off-Peak equals 1 on the low-toll side of each cutoff. The coefficient τ measures the policy-induced change in the discontinuity in Manhattan relative to

Boston the behavioral response the bottleneck model predicts.

3 Results

Table 2, presents the main estimates. The coefficient of interest is the triple interaction Manhattan × Off-Peak × Post, which captures the change in the discontinuity at the toll threshold in the treated geography relative to the comparison geography after policy implementation the difference-in-discontinuities estimand of Grembi et al. (2016).

Table 2: Difference-in-Discontinuities Estimates by Toll Boundary

	Weekday		Weekend	
	5AM	9PM	9AM	9PM
Manhattan × Post	0.0485***	0.0196	−0.0054	0.0032
	(0.0173)	(0.0177)	(0.0249)	(0.0289)
Off-Peak × Post	−0.1464***	0.0227	0.0175	0.0208
	(0.0243)	(0.0296)	(0.0253)	(0.0592)
Manhattan × Off-Peak × Post	**0.0575****	**−0.0253**	**0.0083**	**0.0069**
	(0.0268)	**(0.0356)**	**(0.0332)**	**(0.0621)**
Implied effect	+5.9%	−2.5%	+0.8%	+0.7%
Fixed Effect				
Date	Yes	Yes	Yes	Yes
Hour	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	Yes
Observations	7,634	4,164	3,036	1,656
Pseudo R^2	0.967	0.922	0.971	0.930

Notes: PPML estimates. Manhattan equals 1 if POI is in the congestion zone. Off-Peak equals 1 on the low-toll side of each cutoff (before morning start, after evening end) Post is equal to 1 if date after January 5th, 2025. Standard errors clustered by date in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

The central finding is that we detect temporal substitution at precisely one of the four toll boundaries. At the weekday 5AM cutoff, when the toll jumps from $2.25 to $9.00, the triple-interaction coefficient is 0.0575, implying a 5.9 percent increase in visits during the overnight off-peak window relative to the post-5AM peak window, in Manhattan compared with Boston, after versus before policy implementation. At the other three boundaries weekday 9PM, weekend 9AM, and weekend 9PM the estimates are small, economically trivial, and statistically indistinguishable from zero.

This asymmetry is not simply "one significant result among four." The bottleneck model generates specific predictions about which boundaries should show effects and why others should

not. At the weekday 5AM boundary, avoiding the toll requires arriving before 5AM. For workers with early-morning flexibility shift workers, delivery personnel, service staff preparing for the business day the schedule cost of arriving an hour or two early may be modest relative to the $6.75 toll savings. In the notation of the bottleneck model, early-arrival penalties β are low for this population, so the condition $\Delta\tau > \beta \cdot \Delta$ is satisfied and re-timing is feasible.

At the weekday 9PM boundary, the logic reverses. The off-peak window begins after 9PM, so avoiding the toll requires delaying activity into late evening. But late-arrival penalties γ are prohibitive for most economic activity: businesses close, childcare ends, coordination with others fails. The null effect at this boundary is exactly what the model predicts when γ is high. On weekends, both boundaries yield null effects because preferred arrival times are sharply constrained by fixed commitments brunch reservations, sporting events, social gatherings that bind regardless of toll differentials.

Before concluding that this pattern reflects a causal response to congestion pricing, we need to address two concerns. First, daytime activity patterns exhibit strong natural discontinuities at salient clock times (business openings, shift transitions, commuting rhythms) that could confound an RD-only comparison. Table 2, provides direct evidence that this is not merely theoretical: the coefficient on Off-Peak × Post at the weekday 5AM cutoff is large and negative (-0.1464***), indicating that the overnight/daytime contrast around 5AM shifted substantially in both cities during this period even absent the treatment. This underscores precisely why the triple-difference design is necessary. Second, the positive and significant coefficient on Manhattan × Post (0.0485***) indicates that early-morning activity in Manhattan increased overall relative to Boston after implementation. The triple-interaction estimate is identified net of this level shift.

The identifying assumption underlying the difference-in-discontinuities design is that, absent congestion pricing, discontinuities at the toll boundaries would have evolved similarly in Manhattan and Boston (Grembi et al., 2016). We probe this assumption with two exercises: placebo cutoffs that shift the time threshold by one hour in Table A2, and a placebo implementation date in Table A3. If the weekday 5AM result reflected a discontinuity change that was already emerging before implementation perhaps due to differential seasonal patterns or return-to-office dynamics we would expect to detect a significant effect at this placebo date. We do not. The triple-interaction estimates are statistically indistinguishable from zero at all four cutoffs. The weekday 5AM estimate falls from 0.0575 to 0.0333 and loses statistical significance. This pat-

tern supports the interpretation that the discontinuity change at 5AM is causally attributable to the January 5, 2025 implementation rather than pre-existing differential trends.

4 Discussion and Conclusion

The results confirm the bottleneck model's core prediction: time-varying tolls induce temporal substitution, but only where schedule constraints permit. The 5.9 percent shift at the weekday 5AM boundary and the precise nulls at 9PM and weekend cutoffs maps directly onto the model's logic. Travelers retime when early-arrival costs are low; they do not when late-arrival penalties or fixed schedules bind.

Two implications follow for policy. First, toll effectiveness depends on boundary placement, not just price magnitude. The CRZ's $6.75 differential is identical across all four cutoffs, yet behavioral responses differ sharply. Policymakers designing time-varying schemes should consider where thresholds intersect schedule flexibility early-morning boundaries may generate substitution that evening boundaries cannot. Second, when temporal substitution is limited, congestion pricing must operate through other margins: mode switching, trip suppression, or longer-run location adjustments. These channels have different welfare and distributional consequences than departure-time shifting, and warrant separate analysis.

Appendix Figures A1–A5 present descriptive evidence on geographic and sectoral heterogeneity. Demeaned visit series for Lower Manhattan track closely with nearby areas (Brooklyn, Queens, Bronx, Hudson County, Upper Manhattan) across most sectors, with no systematic post-policy divergence visible at the implementation date. Appendix Figure A6 reports sector-specific DiD-RD estimates at each boundary. At weekday 5AM, consumer-facing sectors (retail, food services) show positive point estimates while logistics sectors (couriers, manufacturing) show null or negative estimates consistent with heterogeneous schedule flexibility. These patterns are suggestive but not causal: the sector and geographic comparisons lack the sharp discontinuity structure that identifies the main estimates, and should be interpreted as descriptive correlations rather than treatment effects.

Several limitations merit acknowledgment. The 7-month post-period captures short-run responses; longer-run adjustments in residential and employment location may differ. Establishment visits proxy for economic activity but do not directly measure vehicle entries or congestion. The analysis identifies temporal substitution at toll thresholds but cannot decompose

other behavioral margins.

These caveats aside, the findings provide unusually direct evidence on the mechanism underlying congestion pricing theory. Vickrey, 1969's model predicts discontinuous bunching at price thresholds where schedule delay costs are low. The data confirm this prediction at the weekday 5AM boundary and reject it elsewhere exactly the pattern the theory implies.

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References

Andersen, M., Maclean, J. C., Pesko, M. F., & Simon, K. (2023). Does paid sick leave encourage staying at home? evidence from the united states during a pandemic. *Health Economics*, *32*(6), 1256–1283.

Banerjee, S., Krebs, C., Bisgin, N., Bisgin, H., & Mani, M. (2021). Predicting customer poachability from locomotion intelligence. *Proceedings of the 5th ACM SIGSPATIAL International Workshop on Location-based Recommendations, Geosocial Networks and Geoadvertising*, 1–4.

Coleman, N., Gao, X., DeLeon, J., & Mostafavi, A. (2022). Human activity and mobility data reveal disparities in exposure risk reduction indicators among socially vulnerable populations during covid-19 for five us metropolitan cities. *Scientific Reports*, *12*(1), 15814.

Dave, D., Friedson, A. I., Matsuzawa, K., & Sabia, J. J. (2021). When do shelter-in-place orders fight covid-19 best? policy heterogeneity across states and adoption time. *Economic inquiry*, *59*(1), 29–52.

Eliasson, J., Hultkrantz, L., Nerhagen, L., & Rosqvist, L. S. (2009). The stockholm congestion–charging trial 2006: Overview of effects. *Transportation Research Part A: Policy and Practice*, *43*(3), 240–250.

Goodspeed, R., Yuan, M., Krusniak, A., & Bills, T. (2021). Assessing the value of new big data sources for transportation planning: Benton harbor, michigan case study. *Urban Informatics and Future Cities*, 127–150.

Goolsbee, A., & Syverson, C. (2021). Fear, lockdown, and diversion: Comparing drivers of pandemic economic decline 2020. *Journal of public economics*, *193*, 104311.

Grembi, V., Nannicini, T., & Troiano, U. (2016). Do fiscal rules matter? *American Economic Journal: Applied Economics*.

Hou, Y., & Poliquin, C. W. (2023). The effects of ceo activism: Partisan consumer behavior and its duration. *Strategic Management Journal*, *44*(3), 672–703.

Leape, J. (2006). The london congestion charge. *Journal of Economic Perspectives*, *20*(4), 157–176.

Mongey, S., Pilossoph, L., & Weinberg, A. (2021). Which workers bear the burden of social distancing? *The Journal of Economic Inequality*, *19*, 509–526.

Pandit, H. (2023). *Mobile-device location data and labor markets*. The University of North Carolina at Greensboro.

Research, A. (2025). Foot traffic / weekly patterns plus [dataset]. https://doi.org/10.82551/C103-N851

Vickrey, W. S. (1969). Congestion theory and transport investment. *American Economic Review*.

Wang, J., Kaza, N., McDonald, N. C., & Khanal, K. (2022). Socio-economic disparities in activity-travel behavior adaptation during the covid-19 pandemic in north carolina. *Transport Policy*, *125*, 70–78.

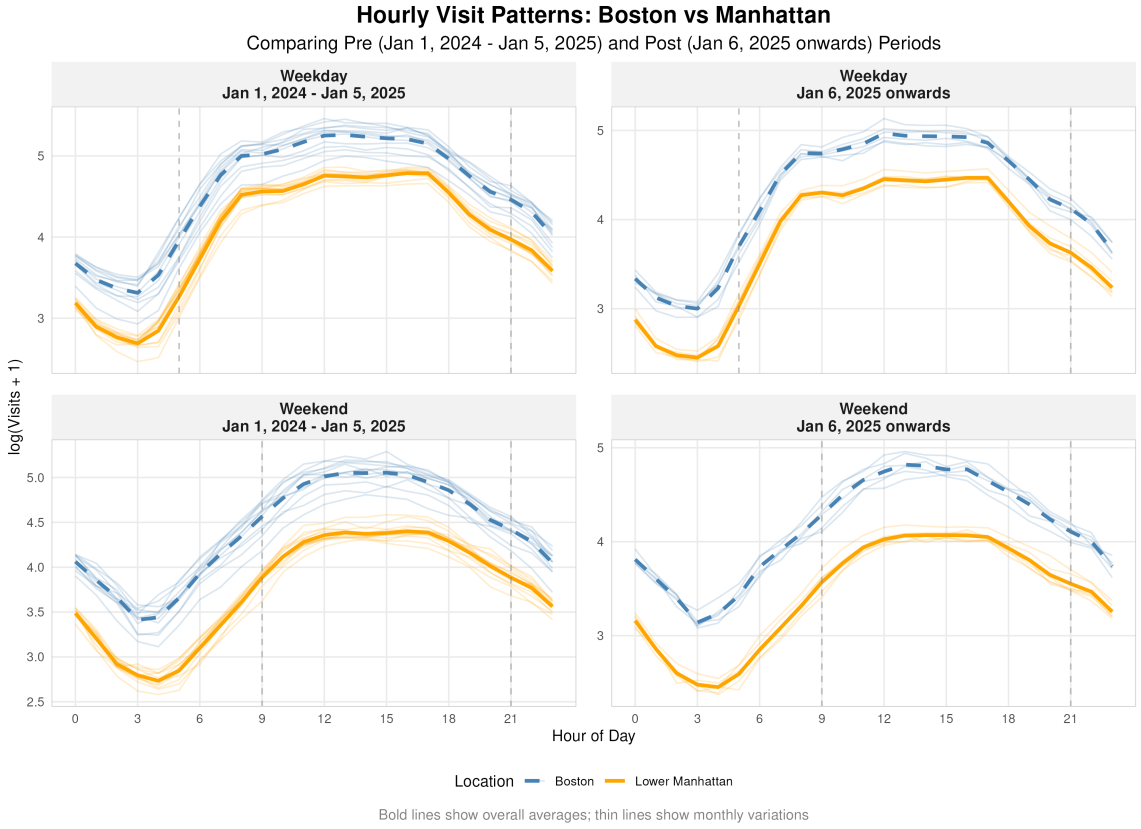
Appendix:

Table A1: Sample composition and baseline activity across treatment and control areas

	Manhattan (CZ)			Boston			Brooklyn			Queens			Bronx			Upper Manhattan		
Sector (NAICS)	**N**	**Mean**	**SD**	**N**	**Mean**	**SD**	**N**	**Mean**	**SD**	**N**	**Mean**	**SD**	**N**	**Mean**	**SD**	**N**	**Mean**	**SD**
Retail Trade																		
Motor Vehicle (441)	63	9.04	0.22	85	9.39	0.13	145	7.79	0.11	98	7.37	0.11	73	7.15	0.14	45	6.28	0.23
Building Material (442)	119	9.58	0.20	112	9.71	0.24	167	7.85	0.14	112	7.41	0.15	84	6.31	0.15	73	7.36	0.17
Electronics (443)	489	9.77	0.20	298	9.66	0.19	156	7.59	0.12	134	7.55	0.14	98	7.56	0.17	100	8.19	0.15
Food & Beverage (445)	613	10.70	0.17	412	11.10	0.18	312	9.75	0.14	289	9.83	0.11	245	9.30	0.13	391	9.55	0.11
Health & Personal (446)	526	10.60	0.18	287	10.20	0.19	267	9.27	0.11	234	9.67	0.11	187	8.72	0.11	147	9.41	0.12
Clothing Stores (448)	2,807	11.90	0.20	1,847	12.30	0.17	489	9.60	0.12	378	9.63	0.13	312	8.99	0.12	619	10.10	0.16
Sporting Goods (451)	673	10.30	0.19	396	10.30	0.20	223	7.73	0.11	189	8.48	0.10	134	6.38	0.15	132	8.47	0.19
General Merch. (452)	78	8.36	0.21	98	9.58	0.14	89	9.12	0.10	78	9.00	0.14	67	7.92	0.12	29	8.16	0.13
Misc Store (453)	778	10.30	0.18	487	10.80	0.21	234	8.29	0.14	189	8.38	0.12	145	7.38	0.11	294	9.10	0.16
Services																		
Information (511-519)	1,216	8.73	0.20	765	8.51	0.22	289	6.42	0.16	223	6.54	0.17	167	6.78	0.18	345	7.23	0.19
Finance (522-524)	2,627	11.03	0.21	1,623	11.10	0.22	456	7.04	0.15	367	7.92	0.13	289	6.23	0.17	734	8.86	0.16
Real Estate (531)	1,557	11.70	0.21	896	11.90	0.18	567	10.70	0.10	489	10.70	0.12	423	10.20	0.11	722	9.24	0.18
Professional (541)	3,254	12.00	0.21	1,847	11.90	0.21	678	8.08	0.17	534	8.15	0.15	356	7.25	0.20	879	9.94	0.19
Admin Services (561)	560	10.00	0.20	412	11.60	0.21	189	6.82	0.13	178	7.91	0.12	123	6.41	0.22	576	10.00	0.18
Educational (611)	772	11.00	0.17	487	11.20	0.18	423	10.50	0.10	367	10.30	0.12	312	10.90	0.15	310	10.90	0.14
Accommodation & Food																		
Accommodation (721)	421	10.70	0.18	287	10.60	0.21	189	7.89	0.24	167	8.01	0.17	89	6.82	0.11	165	8.76	0.22
Food Services (722)	3,864	12.30	0.17	2,156	12.70	0.18	1,234	11.10	0.14	1,023	11.30	0.13	789	10.20	0.15	2,004	11.20	0.14
Other Services																		
Repair & Maint. (811)	943	10.80	0.18	598	11.20	0.19	267	8.84	0.12	234	8.87	0.14	156	7.95	0.16	342	8.98	0.17
Personal (812)	2,059	11.10	0.20	1,284	12.20	0.19	567	9.06	0.14	478	9.59	0.14	367	8.46	0.16	1,191	9.63	0.17
Transportation																		
Transit (485)	105	9.15	0.17	85	9.91	0.17	78	6.73	0.21	89	8.58	0.16	67	7.19	0.13	118	9.77	0.14
Transport Support (488)	469	10.10	0.19	298	8.40	0.12	112	6.34	0.12	167	10.20	0.16	98	6.41	0.16	62	8.43	0.14
Manufacturing																		
Food Mfg (311)	88	9.02	0.15	56	8.64	0.21	67	6.84	0.12	56	6.97	0.14	45	6.13	0.16	30	8.43	0.15
Printing (323)	808	10.20	0.21	487	11.00	0.21	189	7.36	0.15	145	7.46	0.14	112	6.56	0.14	295	8.53	0.15
Misc Mfg (339)	674	10.50	0.21	412	9.55	0.22	178	7.60	0.13	156	7.69	0.14	134	6.57	0.16	118	8.12	0.17
Total	**24,704**	**10.47**	**0.19**	**15,234**	**10.52**	**0.19**	**8,745**	**8.42**	**0.14**	**7,234**	**8.61**	**0.14**	**5,423**	**7.89**	**0.15**	**10,234**	**9.32**	**0.17**

Notes: Manhattan (CZ) denotes the Congestion Zone (treatment area south of 60th Street). Upper Manhattan represents areas north of 60th Street. N = number of establishments. Mean and SD represent log visitors during baseline period (2024). Excluded sectors: ambulatory health care, hospitals, nursing care, religious organizations, justice/safety, national security, and air transportation.

Figure 1: Hourly Visit Patterns



Note: The figure uses a balanced panel of Placekeys (POIs) in Lower Manhattan (yellow) and Boston (blue). For each area, we compute average hourly visitor counts using data from January 1, 2024 through July 31, 2025. Vertical dashed lines mark the Congestion Relief Zone (CRZ) toll schedule cutoffs: 5:00 AM and 9:00 PM on weekdays, and 9:00 AM and 9:00 PM on weekends.

Robustness Tests

Table A2: Testing Alternative Pricing Boundaries (Placebo Cutoffs)

	Actual boundary	**One hour earlier**	**One hour later**
Weekday morning ($2.25→ $9.00)			
Time tested	5AM	4AM	6AM
Manhattan × Off-Peak × Post	0.0575**	0.0302	−0.0007
Standard error	(0.0268)	(0.0449)	(0.0204)
Weekday evening ($9.00 → $2.25)			
Time tested	9PM	8PM	10PM
Manhattan × Off-Peak × Post	−0.0253	0.0070	0.0026
Standard error	(0.0356)	(0.0302)	(0.0258)

Notes: Each coefficient comes from a separate regression estimated on the corresponding placebo cutoff, using the full main specification (PPML; date and city × hour fixed effects; flexible running-variable controls). Standard errors are clustered by date. *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Placebo Implementation Date: September 5, 2024

Specification	Weekdays		Weekends	
	5AM ($2.25→ $9.00)	9PM ($9.00→ $2.25)	9AM ($2.25→ $9.00)	9PM ($9.00→ $2.25)
Manhattan × Off-Peak × Post	0.0333	0.0215	0.0186	0.0564
	(0.0252)	(0.0373)	(0.0338)	(0.0547)
Observations	7,634	4,164	3,036	1,656
Pseudo R^2	0.967	0.923	0.971	0.931

Notes: PPML estimates. Standard errors (in parentheses) are clustered by date. All specifications include date and city× hour fixed effects, full interaction terms, and flexible polynomials in the running variable. *** p<0.01, ** p<0.05, * p<0.1.

Sectoral heterogeneity in temporal substitution (not causal)

Aggregate effects can mask heterogeneity in the ability to adjust schedules. Figure 2, reports sector-specific DiD-RD estimates of the triple interaction (Manhattan × Off-Peak × Post) by cutoff, with 95% confidence intervals. These estimates are obtained by re-estimating the main specification separately within each sector; they should be interpreted as the cutoff-specific change in the discontinuity for that sector in Lower Manhattan relative to Boston.

The most systematic heterogeneity appears at the weekday 5AM cutoff (left panel), consistent with the aggregate result in Table **??**. Several consumer-facing categories show positive point estimates, including Credit & Banking, Clothing Stores, Electronics Stores, Furniture Stores, and Amusement & Recreation. In contrast, sectors more tightly linked to production and goods movement (e.g., Couriers & Messengers, Food Manufacturing, and Building Material Stores) display smaller or negative point estimates. A conservative interpretation is that the toll incentive induces re-timing where schedules are flexible and customer visits are discretionary, while sectors facing operational coordination constraints exhibit limited scope for shifting activity into the pre-5AM window.

At the weekend 9AM and weekday 9PM cutoffs (middle panels), most sector estimates lie near zero and many confidence intervals overlap zero, mirroring the aggregate null effects. This pattern is consistent with adjustment occurring, if at all, through margins other than a discrete discontinuity shift at those boundaries (e.g., trip suppression, modal substitution, or smoother reallocation across adjacent hours captured by slope changes rather than jumps).

At the weekend 9PM cutoff (right panel), estimates exhibit greater dispersion and several

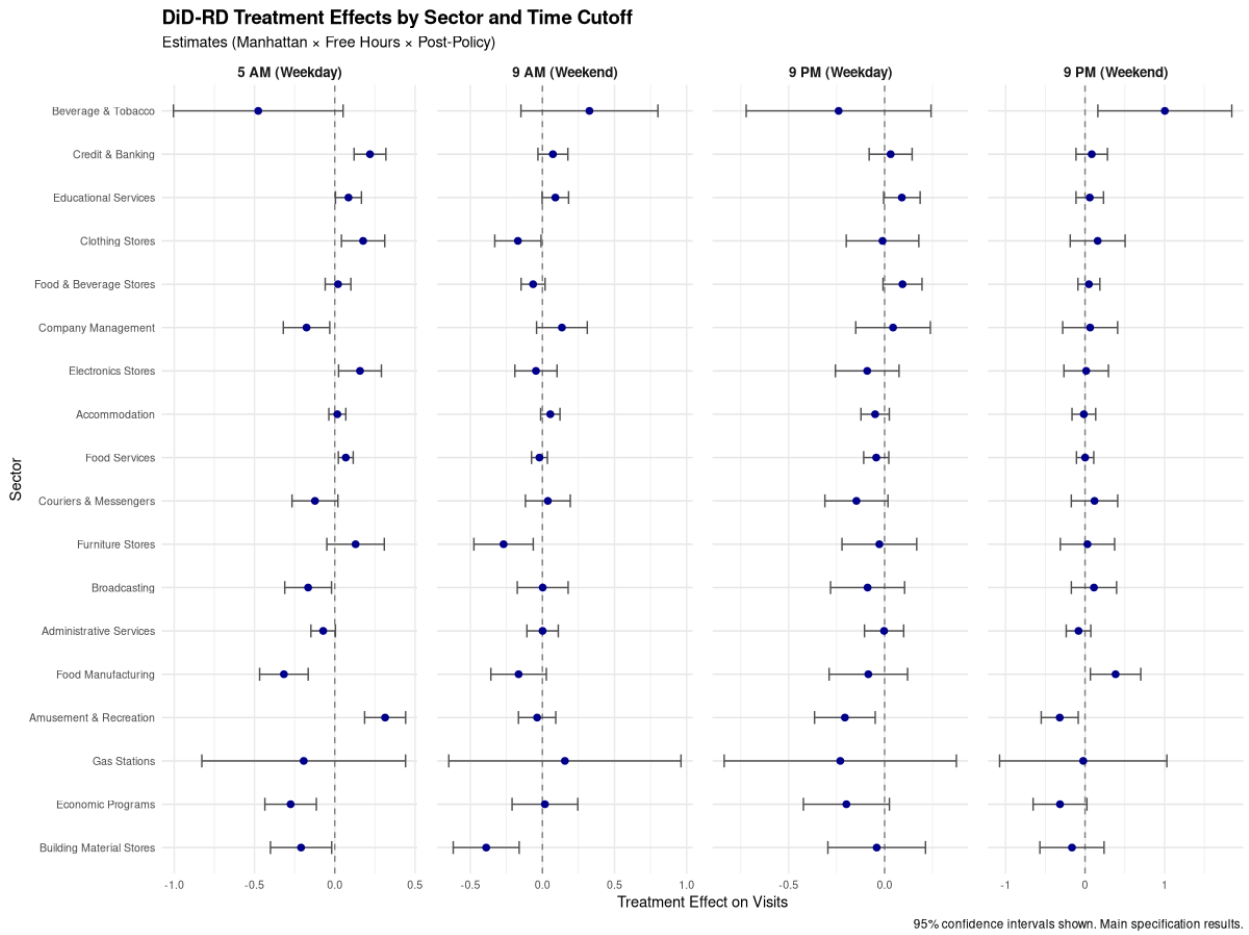


Figure 2: DiD-RD treatment effects by sector and toll cutoff

Notes: Points report sector-specific estimates of the main triple interaction (Manhattan × Off-Peak × Post) for each toll cutoff; horizontal bars show 95% confidence intervals. Estimates come from the main PPML DiD-RD specification estimated within sector subsamples. Because sectors are analyzed separately, precision varies, and interpretation should emphasize broad patterns rather than individual "winners" and "losers" (multiple-testing concerns).

sectors have wide confidence intervals. This is consistent with the smaller number of observations at that boundary (Table **??**) and with noisier sector subsamples. The appropriate takeaway is not that weekend-evening effects are large in specific sectors, but that the data are less informative at this boundary, and any apparent sector outliers should be treated cautiously.

Sectoral heterogeneity in geographic reallocation(non-causal)

To summarize how visit patterns in the CRZ and nearby areas evolve over time despite large differences in baseline activity levels, we present demeaned series by sector. The purpose of this transformation is visual comparability: establishments and sectors differ substantially in typical foot traffic, so raw levels can obscure changes in relative trends across geographies. Importantly,

these demeaned plots are not used for causal inference. They are descriptive diagnostics that help assess whether post-policy patterns are consistent with destination substitution or reallocation across nearby areas.

The demeaning procedure is implemented as follows. For each sector i (3-digit NAICS) and geography c (CRZ vs. a comparison area), we compute the mean of log visits during the pre-policy period:

$$\bar{Y}_{ic,\text{pre}} = \frac{1}{T_{\text{pre}}} \sum_{t \in \text{pre}} \log(Y_{ict}) \,, \tag{2}$$

where Y_{ict} denotes visits and t indexes time. We then construct demeaned log visits:

$$\tilde{Y}_{ict} = \log(Y_{ict}) - \bar{Y}_{ic,\text{pre}}. \tag{3}$$

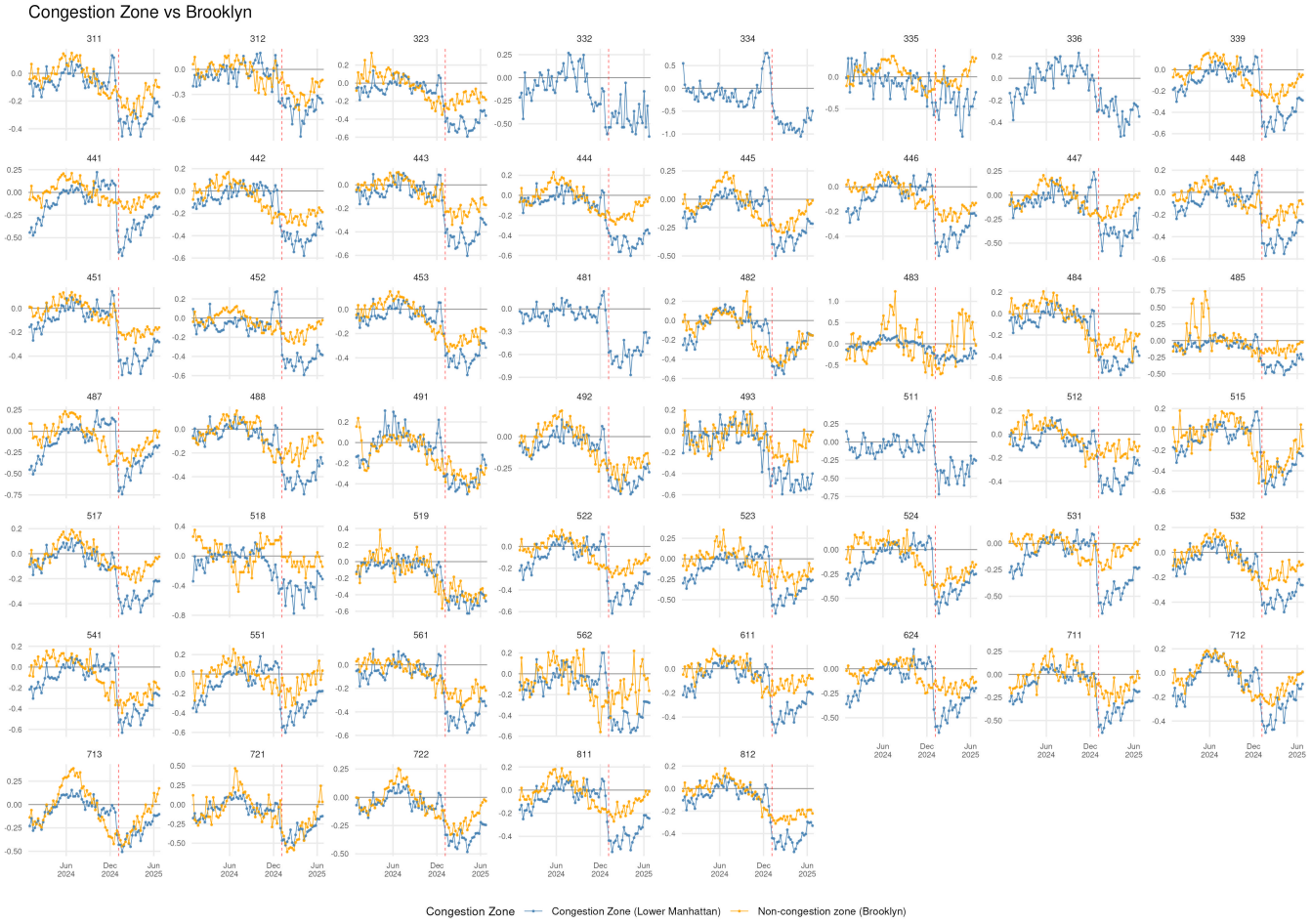
Finally, we average $\tilde{Y}_{ict}$ by date within each sector and geography to produce the plotted series.

This normalization has two practical advantages. First, it centers each sector geography series at zero in the pre-period, making it easier to see relative post-policy divergence across places without the scale differences that dominate raw visit levels. Second, it allows sectors with very different volumes (e.g., food services versus niche manufacturing) to be displayed on a common vertical axis.

We emphasize a key limitation: post-policy divergence in demeaned series should not be interpreted as a causal spillover estimate. Nearby areas may experience time-varying shocks that differ from the CRZ for reasons unrelated to congestion pricing (e.g., neighborhood-specific events, construction, retail entry/exit, compositional change in establishments, or differential recovery dynamics). Accordingly, we interpret these plots as descriptive evidence that is consistent with geographic reallocation of activity, and we reserve causal claims for the toll-threshold DiD-RD estimates in the main results.

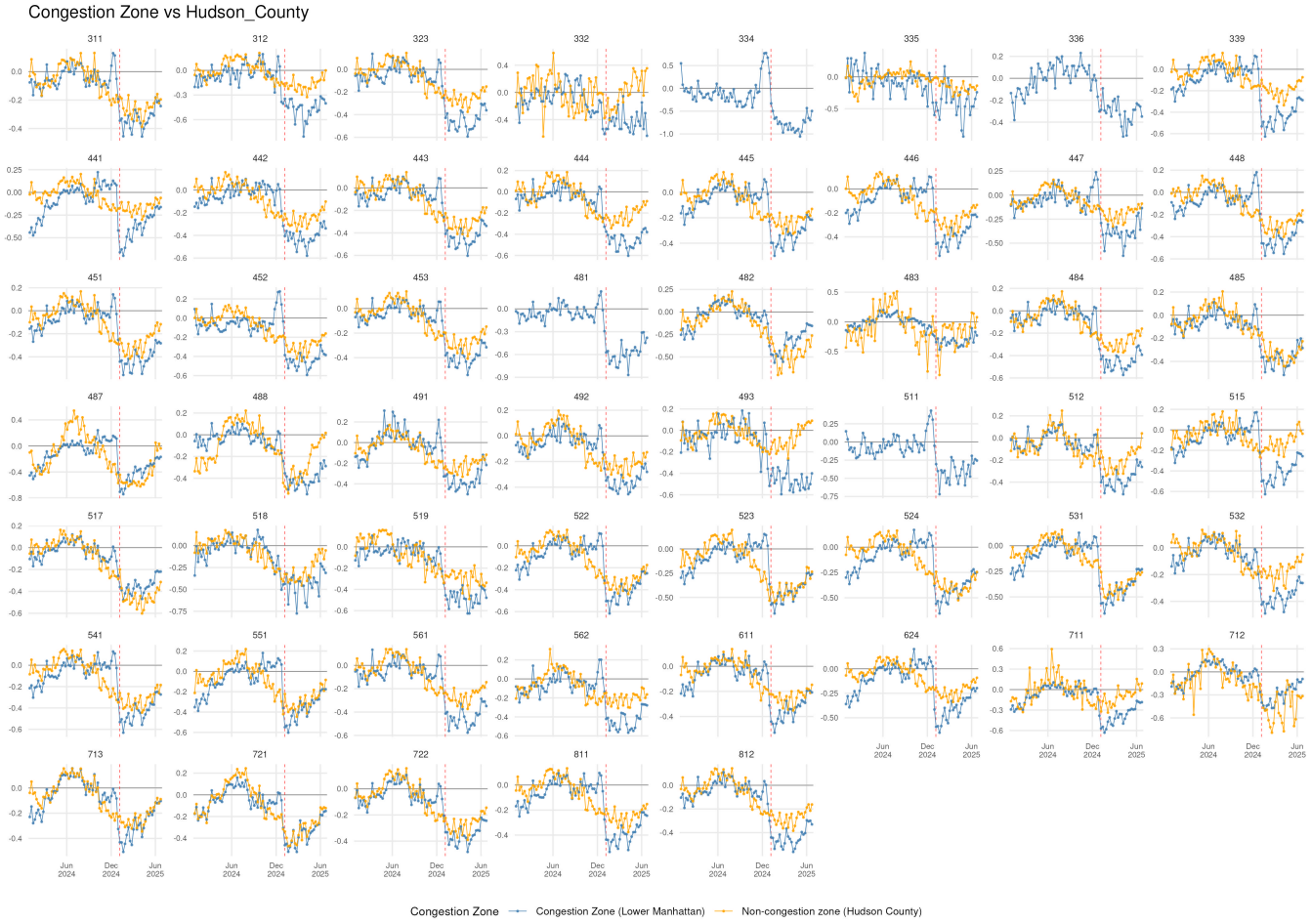
In constructing the sector panels, we focus on discretionary commercial activity and exclude categories such as healthcare facilities, government services, and air transportation, which are plausibly less elastic in the short run and could confound interpretation of reallocation patterns. This restriction helps the descriptive plots speak more directly to sectors where destination choice and timing margins are more likely to respond to pricing incentives.

Figure 3: Brooklyn and lower-Manhattan, Industry-specific spillover effects across control cities. Detailed panels showing heterogeneous responses across NAICS industries for each control city comparison.



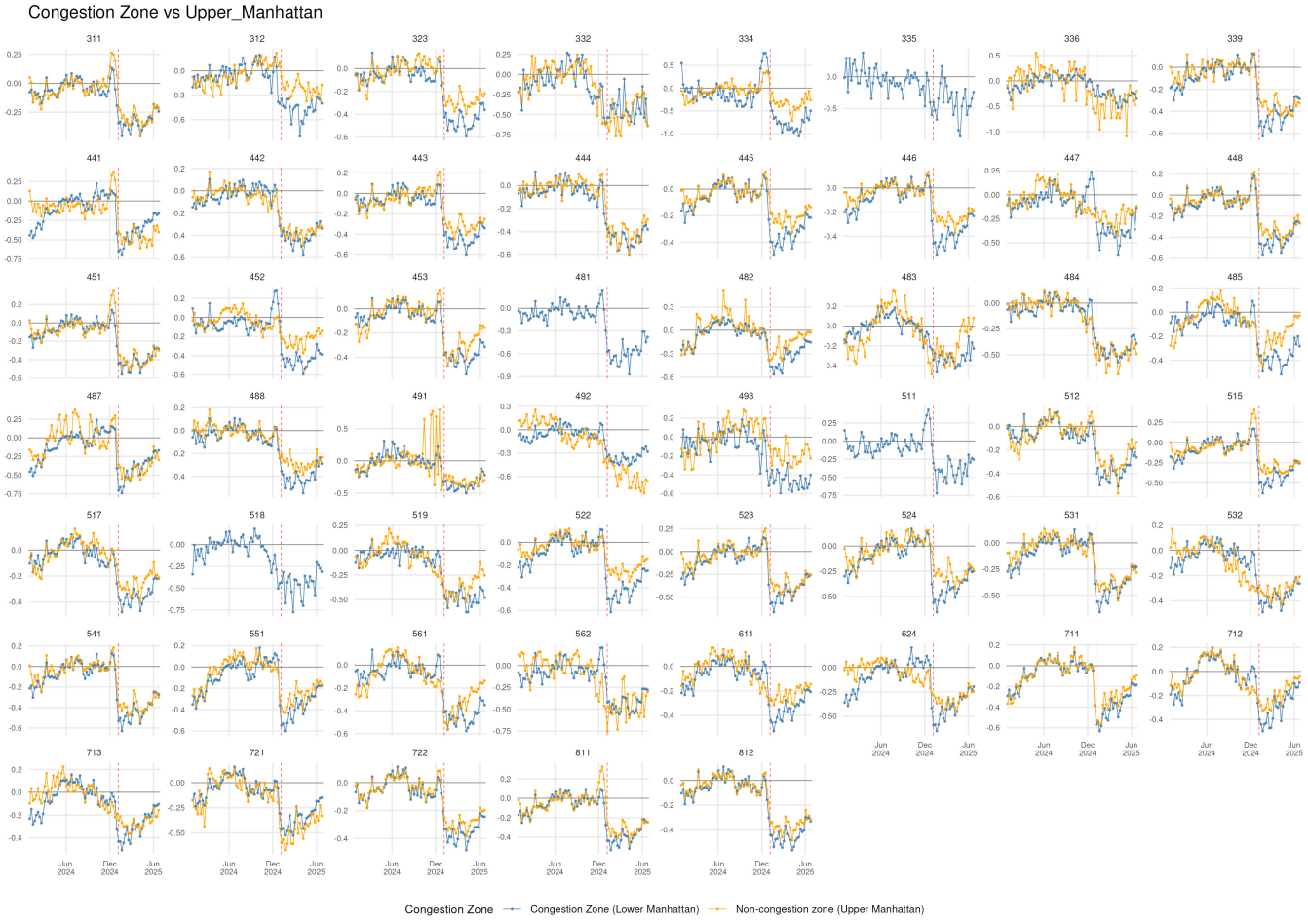
Source: Using balanced-panel for the placekeys (POI) in lower-Manhattan and Brooklyn area, we extracted weekly visitors count from mobile-device location data (Advan). We used NAICS Code - 2017 to identify the sectors.

Figure 4: Husdon County - NJ and lower-Manhattan, Industry-specific spillover effects across control cities. Detailed panels showing heterogeneous responses across NAICS industries for each control city comparison.



Source: Using balanced-panel for the placekeys (POI) in lower-Manhattan and Hudson County-NJ area, we extracted weekly visitors count from mobile-device location data (Advan). We used NAICS Code - 2017 to identify the sectors.

Figure 5: Upper and lower Manhattan, Industry-specific spillover effects across control cities. Detailed panels showing heterogeneous responses across NAICS industries for each control city comparison.



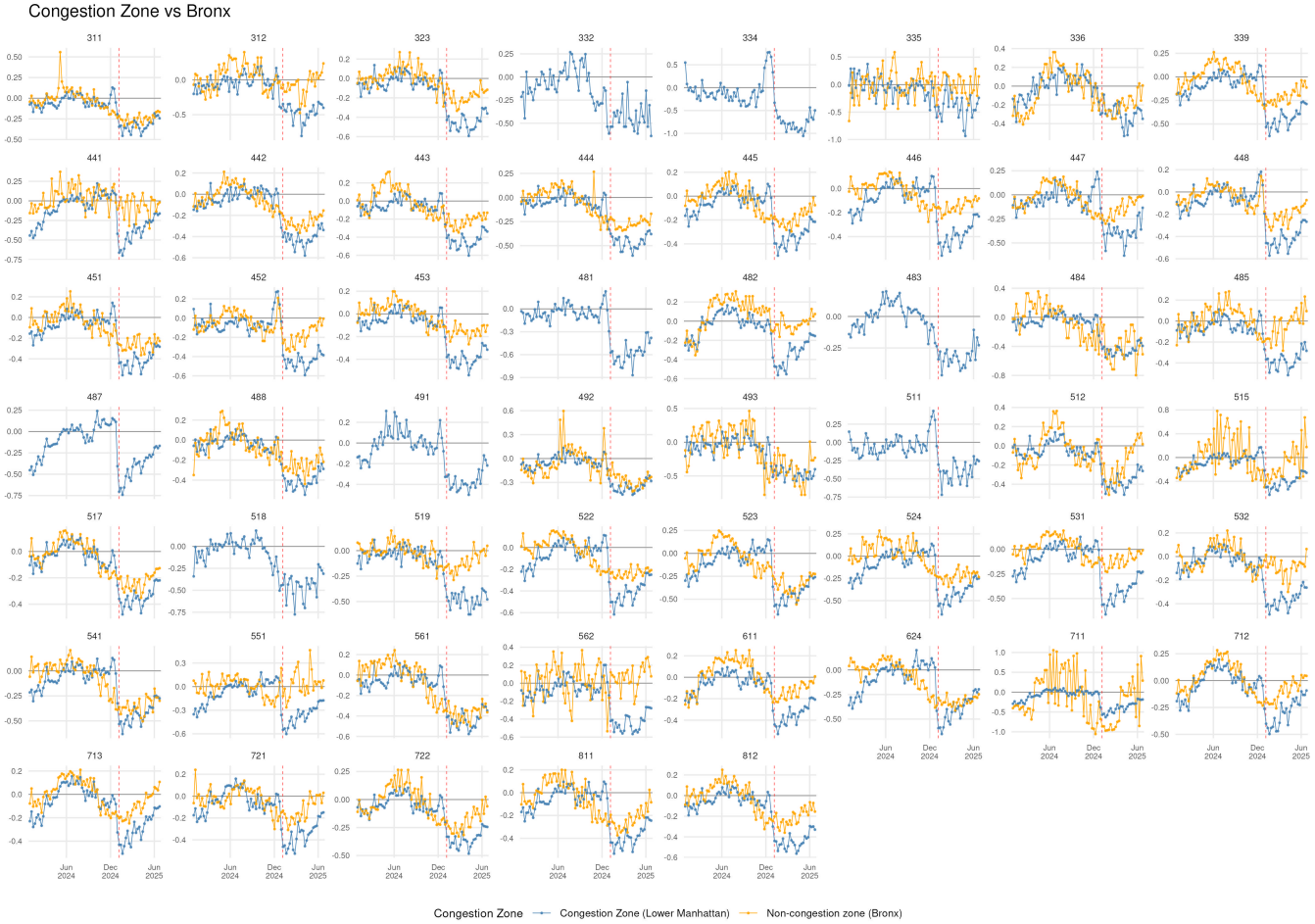
Source: Using balanced-panel for the placekeys (POI) in lower-Manhattan and Upper-Manhattan area, we extracted weekly visitors count from mobile-device location data (Advan). We used NAICS Code - 2017 to identify the sectors.

Figure 6: Queen and lower Manhattan, Industry-specific spillover effects across control cities. Detailed panels showing heterogeneous responses across NAICS industries for each control city comparison.



Source: Using balanced-panel for the placekeys (POI) in lower-Manhattan and Queen area, we extracted weekly visitors count from mobile-device location data (Advan). We used NAICS Code - 2017 to identify the sectors.

Figure 7: Bronx and lower Manhattan, Industry-specific spillover effects across control cities. Detailed panels showing heterogeneous responses across NAICS industries for each control city comparison.



Source: Using balanced-panel for the placekeys (POI) in lower-Manhattan and Bronx area, we extracted weekly visitors count from mobile-device location data (Advan). We used NAICS Code - 2017 to identify the sectors.