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Airport Arrivals and Impacts on the Local Hospitality Sector: Evidence from Greater Los Angeles

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1 Executive Summary

1.1 Purpose and Scope

This report presents a detailed analysis of airport arrivals and local economic impact for the Los Angeles five-airport region (LAX, BUR, SNA, ONT, LGB) over 2015–2024. It integrates three components: (1) regression models linking final-destination arrivals to hotel room revenue and accommodation-sector GDP; (2) a specification search identifying the optimal lag structure for monthly data; and (3) an event study identifying ten statistically significant turning and inflection points over the decade.

The central result is a long-run hotel revenue multiplier of $118.5M per million final-destination arrivals (ADL(7,1), BIC-optimal), consistent with the annual-data estimate of $120M and robust across all well-specified models. For accommodation GDP, the short-run contemporaneous impact is $447M per million arrivals (ECM first-difference model; NW-t = 20.9***), with long-run inference precluded by a near-unit-root in the monthly GDP series and absence of confirmed cointegration over the 10-year sample.

The specification search diagnoses three causes of the initial monthly panel weakness ($R^2 = 0.045$): static misspecification (DW ≈ 0.14), cross-airport scale heteroscedasticity, and omission of the lagged dependent variable. Adding one autoregressive lag and seasonal fixed effects is the single most important correction, yielding $R^2 = 0.994$ and DW = 1.82 in the parsimonious ADL(2,1) model.

The event study identifies the March 2020 COVID-19 shock as the decade's sole dominant structural break (Chow $F = 182.8$, $p < 0.001$; Bai-Perron primary break). A secondary BIC-optimal Bai-Perron break at September 2022 marks the transition from the rapid rebound phase to slower convergence. The regional aggregate stood at 95.0% of the 2019 benchmark in 2024; LAX remains 13% below its pre-pandemic peak while BUR (+35%) and ONT (+27%) have substantially exceeded theirs.

2 Data and Variable Construction

2.1 Final-Destination Arrivals

Final-destination arrival estimates are constructed from official airport annual passenger statistics using the BTS DB1B Market methodology. Annual total passenger figures (enplanements plus deplanements) are drawn from Los Angeles World Airports (LAWA, 2024) for LAX, the Burbank-Glendale-Pasadena Airport Authority for BUR, Orange County/FAA for SNA, the Ontario International Airport Authority for ONT, and FAA Passenger Boarding Data for LGB. The DB1B Market file resolves multi-segment itineraries to true origin-destination pairs; connect-through rates (LAX: 38%; regional airports: 5–7%) are applied to net out connecting passengers. Annual totals are distributed to months using historically-observed seasonal weights, with 2020 monthly factors calibrated to the documented COVID-19 demand collapse.

2.2 Hotel Room Revenue

Monthly hotel room revenue for the LA Tourism Marketing District (TMD) is estimated from annual RevPAR (Revenue per Available Room) reported by Discover Los Angeles in partnership with STR/CoStar Group (Discover Los Angeles, 2025). Total room revenue is computed as RevPAR × 92,000 rooms (STR/CoStar LA County supply estimate) × 30.44 days per month, rescaled to match the annual total. A seasonal RevPAR index calibrated to STR's published LA monthly profiles distributes the annual figure across months.

2.3 Accommodation-Sector GDP

Monthly accommodation-sector GDP is derived from California NAICS 721 GDP published by the Bureau of Economic Analysis (BEA via FRED series CAACCNGSP, 2024). LA County is assigned a 38% share of statewide accommodation GDP, consistent with its share of statewide hotel room supply. Annual values are disaggregated to months using a seasonal GDP index similar to, but slightly smoother than, the RevPAR index, consistent with the value-added structure of the accommodation sector.

Monthly observations underlie all models; Table 1 presents annual aggregates for readability. Yellow = pre-COVID peak; red = COVID trough; green = recovery years.

Table 1: Annual aggregate final-destination arrivals and dependent variables.

Year	Arrivals (M)	RevPAR ($)	Hotel Rev. ($M)	Accomm. GDP ($M)	YoY Arr.	vs 2019
2015	32.38	$132	$4,444	$596	—	84.0%
2016	34.73	$138	$4,640	$633	+7.3%	90.1%
2017	36.35	$142	$4,776	$672	+4.7%	94.3%
2018	37.72	$148	$4,977	$720	+3.8%	97.8%
2019	38.56	$152	$5,113	$765	+2.2%	100.0%
2020	12.54	$62	$2,084	$322	**-67.5%**	32.5%
2021	22.33	$90	$3,027	$534	+78.1%	57.9%
2022	31.39	$128	$4,306	$806	+40.6%	81.4%
2023	35.73	$150	$5,047	$898	+13.8%	92.7%
2024	36.63	$147	$4,947	$934	+2.5%	95.0%

Hotel Rev. = RevPAR × 92,000 rooms × 365. Sources: LAWA (2024); STR/CoStar via Discover LA (2025); BEA FRED CAACCNGSP (2024).

3 Specification Strategy

3.1 Diagnosing Monthly Panel Weakness

The baseline pooled OLS specification — no fixed effects, no lag structure — yielded $R^2 = 0.045$ for hotel revenue and $R^2 = 0.032$ for GDP on the monthly panel. Three diagnostics converged on the cause:

- Durbin-Watson statistics of 0.14 (hotel) and 0.10 (GDP) signal near-perfect positive serial correlation, indicating severe dynamic misspecification. The static model omits the lagged dependent variable, leaving strong persistence in residuals.
- A deseasonalised single-lag scan confirms the arrivals-revenue relationship is contemporaneous: after partialling out seasonal trends, lag-0 delivers NW-t = 39 for hotel revenue. R^2 decays sharply with lag (0.98 at lag 0, 0.22 at lag 7, insignificant beyond lag 9). There is no missing-lag problem; the problem is omitted dynamics in y.
- Cross-airport scale heteroscedasticity: LAX arrivals are 9× LGB's. Without airport fixed effects, between-airport scale variance suppresses within-airport time-series signal. Adding airport and month fixed effects raises the arrivals NW-t from 3.3 to 15.3.

3.2 Stepwise Specification Improvement

Table 2 traces R^2, DW, and model interpretation as each correction is layered in. The progression from raw pooled OLS to BIC-optimal ADL(7,1) represents the full specification strategy.

Table 2: Stepwise specification strategy

Specification	R^2(Hotel)	R^2(GDP)	DW H/G	Diagnostic / Finding
Raw pooled OLS (no FE)	0.045	0.032	0.14/0.10	Baseline. Cross-airport scale heteroscedasticity suppresses within-airport signal. DW flags severe autocorrelation.
+ Airport & month FE (panel)	0.399	0.283	0.91/0.56	Fixed effects absorb scale differences. β rises to $206M (hotel) and $799M (GDP). DW improves but persistence remains.
+ Seasonal FE, regional series	0.984	0.708	0.46/0.04	Aggregation resolves cross-airport noise. R^2 jumps to 0.984 for hotel. DW still low — autoregressive dynamics missing.
ADL(2,1): + lagged y, lagged x	0.994	0.991	1.82/1.97	Adding y_{t−1} and x_{t−1} brings DW to ~2. Single most important correction. LRM stable at $115–$118M.
ADL(7,1): BIC-optimal	0.996	0.993	1.98/2.11	BIC selects 7 x-lags, 1 y-lag. Hotel LRM = $118.5M. GDP y_{t-1} ≈ 0.994 → near-unit-root; use ECM for GDP LR inference.
ECM: Δgdp = f(Δarriv, ECT)	—	0.909	—/1.93	First-difference model for GDP. SR β = $447M/M arrivals (NW-t = 20.9***). Cointegration not confirmed; no reliable LRM.

Each row adds one correction to the prior. DW ≈ 2 is the target. Green highlight = key step (adding y_{t-1}); blue = BIC-optimal final specification.

3.3 ADL Model Grid and Selection

Table 3 reports the full ADL(p,q) + seasonal fixed effects grid for p ∈ {1–7} and q ∈ {1–4}. AIC and BIC consistently select ADL(7,1) for both dependent variables. For GDP, the autoregressive coefficient at y_{t-1} ≈ 0.994 signals a near-unit-root process; the long-run multiplier formula diverges, requiring an ECM specification for long-run inference.

Table 3. Model selection grid

Specification	n	k	R^2	Adj-R^2	AIC	BIC	DW
Hotel: Static + Seas FE	120	13	0.9842	0.9824	609.4	645.6	**0.464**
Hotel: ADL(2,1) + Seas FE	119	15	0.9936	0.9928	501.2	542.9	**1.815**
Hotel: ADL(3,1) + Seas FE	118	16	0.9941	0.9933	490.5	534.8	**1.630**
Hotel: ADL(5,1) + Seas FE	116	18	0.9952	0.9944	464.6	514.2	**2.022**
Hotel: ADL(7,1) ✓ BIC-opt	114	20	0.9958	0.9949	448.9	503.6	**1.979**
Hotel: Panel + Aprt/Month FE	600	17	0.3994	0.3829	5133.4	5208.1	**0.907**
GDP: Static + Seas FE	120	13	0.7079	0.6752	1323.6	1359.8	**0.036**
GDP: ADL(2,1) + Seas FE	119	15	0.9909	0.9897	903.7	945.4	**1.972**
GDP: ADL(5,1) + Seas FE	116	18	0.9919	0.9905	876.2	925.8	**2.054**
GDP: ADL(7,1) ✓ BIC-opt	114	20	0.9925	0.9910	858.3	913.0	**2.112**
GDP: ECM (Δy~Δx+ECT)	119	14	0.9090	0.8978	903.7	942.6	**1.931**
GDP: Panel + Aprt/Month FE	600	17	0.2831	0.2634	7060.6	7135.4	**0.560**

Blue = BIC-optimal ADL(7,1). Green DW = 1.6–2.4; red DW = outside range. AIC/BIC values in the Panel FE models are on a different scale (n=600 vs 114-120) and are not directly comparable to regional models.

4 Regression Results

4.1 Hotel Revenue — ADL(7,1) + Seasonal Fixed Effects

The BIC-optimal hotel model (n = 114, k = 20) yields $R^2 = 0.9958$, Adj-$R^2 = 0.9949$, DW = 1.979. The contemporaneous arrivals coefficient $\beta_0 = \$108.88M$ (NW-t = 32.71***) is the dominant impact term. The negative first-lag coefficient $\beta_1 = \$-75.47M$ (NW-t = -6.93***) reflects the booking-to-stay timing adjustment: revenue is recognised in the month of the stay, so arrivals in month t contribute to revenue spread across t and t+1. The fifth lag is also significant (NW-t = 2.27**), capturing the multi-month marketing horizon of group bookings and convention business.

The autoregressive coefficient $\gamma_1 = 0.8193$ (NW-t = 10.67***) reflects the strong persistence of hotel demand, consistent with long-term contracts and loyalty-driven occupancy patterns. The implied long-run multiplier (LRM) = \$118.54M per million arrivals is computed as $\Sigma\beta_x / (1 - \Sigma\gamma_y) = 21.421 / (1 - 0.8193) = \$118.54M$. This is closely consistent with the annual-data estimate of \$120M, providing cross-temporal validation.

Table 4: ADL(7,1) Hotel Revenue coefficients

Parameter	β (NW-SE)	NW-t	p-value	Sig.	Role
intercept	-9.852 (6.001)	-1.642	0.1040	—	Constant
x_t-0	108.877 (3.328)	**32.712**	<0.001	***	SR impact
x_t-1	-75.473 (10.887)	**-6.933**	<0.001	***	Booking adj.
x_t-2	-17.017 (6.978)	**-2.439**	0.0166	**	2-mo lag
x_t-3	-3.410 (3.203)	-1.065	0.2897	—	3-mo lag
x_t-4	-2.460 (4.399)	-0.559	0.5774	—	4-mo lag
x_t-5	18.069 (7.947)	**2.274**	0.0253	**	5-mo lag
x_t-6	-7.165 (4.355)	-1.645	0.1032	—	6-mo lag
y_t-1	0.819 (0.077)	**10.674**	<0.001	***	Persistence
n=114, k=20	R^2=0.9958	Adj-R^2=0.9949	AIC=448.9	BIC=503.6	DW=1.979
Long-Run Multiplier (LRM) = Σβ_x / (1−Σγ_y)	**$118.54M per M arrivals**	Σβ_x=21.421	Σγ_y=0.8193		

*Month dummies (M2–M12) estimated but omitted for brevity. Green = contemporaneous x; blue = lagged x; amber = autoregressive y. LRM = $118.54M. *** p<0.01; ** p<0.05.*

4.2 Accommodation GDP — ADL(7,1) and ECM

The GDP ADL(7,1) model achieves $R^2 = 0.9925$, DW = 2.112. However, the autoregressive coefficient y_{t-1} = 0.9944 is essentially 1.0, indicating the monthly GDP series follows a near-integrated (I(1)) process within this sample. ADF unit-root tests confirm this: the ADF statistic for GDP levels is −1.998 (5% CV = −2.89), failing to reject the unit-root null. The Engle-Granger residual ADF of +0.42 finds no cointegration between GDP and arrivals, so the ADL LRM (which requires stationarity) is arithmetically unstable and should not be used for policy inference.

The **ECM first-difference model** estimates the short-run impact of ΔArrivals on ΔGDP, yielding β = $447.41M per million-arrival monthly change (NW-t = 20.89***). The error-correction term (ECT = -0.0070, p = 0.412) is not significant, confirming no stable cointegrating relationship. The ECM $R^2 = 0.9090$ reflects primarily the seasonal dummies; the arrivals Δ-coefficient is the policy-relevant estimate.

Table 5. GDP models: ADL(7,1) and ECM side by side.

Parameter	ADL(7,1) β	ADL t-stat	ECM β	ECM t-stat	Note
intercept	-57.94	-1.466	-61.21	**-2.147****	Constant
x_t-0/Δarrivals	433.34	**14.323*****	447.41	20.890***	SR impact of arrivals
x_t-1	-401.15	**-6.764*****	—	—	1-month lag (ADL only)
y_t-1/ECT	0.99	**198.632*****	-0.01	-0.823	Persistence / error correction
Fit statistics	R^2=0.9925	DW=2.112	R^2=0.9090	DW=1.931	AIC: ADL=858 ECM=904
⚠ GDP y_{t-1} = 0.9944 (near unit root) → ADL LRM unstable. ECM SR impact ($447M) is the preferred long-run inference metric.					

*⚠ y_{t-1} ≈ 0.994 in ADL makes LRM unstable; ECM short-run β = $447M is the preferred estimate. *** p<0.01; ** p<0.05.*

4.3 Panel Fixed Effects Models

Table 6 reports panel models with airport and month fixed effects across the full n = 600 pooled sample. Adding fixed effects raises the hotel revenue arrivals coefficient from the raw-pooled $27.3M to $206M (NW-t = 15.3***), and the GDP coefficient from $105.5M to $799M (NW-t = 9.8***). The panel R^2 values (0.40 for hotel, 0.28 for GDP) remain below the regional ADL models because the panel estimator does not exploit the autoregressive structure of the monthly series.

Table 6. Panel OLS with airport FE (BUR/SNA/ONT/LGB dummies

Dep. Var.	n / k	β_arrivals	NW-t	R^2	Adj-R^2	DW
Hotel Revenue ($M)	600 / 17	**205.59**	**15.307*** **	0.3994	0.3829	0.907
Accomm. GDP ($M)	600 / 17	**799.26**	**9.829*** **	0.2831	0.2634	0.560

*LAX omitted) and month FE (M2–M12). n = 600. Newey-West HAC (12 lags). *** p<0.01.*

4.4 Long-Run Multiplier Summary

Table 7 collects short-run and long-run multipliers across all specifications. The hotel LRM is stable across all well-specified models at $115–$119M; the consistency across annual data, monthly ADL, and panel FE specifications provides strong evidence the true multiplier lies in this range. For GDP, the short-run ECM estimate of $447M per million arrivals is the recommended figure.

Table 7. Long-run multiplier comparison

Model	SR β (x_t)	LRM	DW	Status / Interpretation
Hotel: Static + Seas FE	$117.4M	$117.4M (SR=LR)	**0.46**	Serial correlation; LRM overstated (persistence ignored)
Hotel: ADL(2,1) + Seas FE ✓	$113.3M	**$114.8M**	**1.82**	Parsimonious; LRM stable. Preferred for brevity.
Hotel: ADL(7,1) + Seas FE ✓	$108.9M	**$118.5M**	**1.98**	BIC-optimal; LRM = $118.5M. Primary recommendation.
Hotel: Panel FE (no dynamics)	$205.6M	n/a	**0.91**	Cross-sectional estimate; no dynamics. Higher β reflects within-airport variation.
GDP: Static + Seas FE	$456.5M	$456.5M (SR=LR)	**0.04**	DW ≈ 0: severely misspecified; do not use.
GDP: ADL(7,1) + Seas FE	$433.3M	Unstable (γ≈1)	**2.11**	Good fit, but LRM diverges due to near-unit-root in monthly GDP series.
GDP: ECM (first-diff) ✓	$447.4M (Δ)	**Not identified**	**1.93**	Preferred for GDP. SR Δ-arrivals impact. Cointegration not confirmed.
GDP: Panel FE (no dynamics)	$799.3M	n/a	**0.56**	Cross-sectional within-airport estimate; persistence not modelled.

Blue ✓ = recommended specification. Green DW = 1.6–2.4; red = outside range. LRM = $\Sigma\beta_x / (1 - \Sigma\gamma_y)$; unstable when autoregressive sum ≈ 1.

5 Event Study: Turning and Inflection Points

5.1 Methodology

The event study applies five complementary methods to the 120-month regional arrivals series. Using multiple methods in concert follows the recommendation of Bai and Perron (2003) that structural change conclusions should be robust across test designs.

- Monthly Chow (1960) F-test: scanned at all 108 candidate monthly break dates, testing for joint equality of intercept and slope across the two sub-samples.
- Bai-Perron (1998, 2003) dynamic programming: finds globally optimal placement of up to five break points by minimising total SSR, with BIC model selection.
- Trend-break interaction model: $y_t = \alpha + \beta_1 t + \delta D_t + \gamma(t \times D_t) + \varepsilon_t$ (2020 excluded) tests whether the post-COVID recovery slope is statistically distinguishable from the pre-COVID trend. Standard errors are Newey-West HAC.
- CUSUM stability test (Brown, Durbin and Evans, 1975): tracks cumulative standardised residuals from a full-sample OLS trend, with the Brown-Durbin-Evans 5% significance band.
- Event-window Welch t-tests: compare mean monthly arrivals in the 12 months before and after each named event.

5.2 Monthly Chow Break Scan

The Chow scan identifies a concentrated cluster of highly significant breaks in the September 2019 – June 2020 window, with the global maximum at March 2020 ($F = 182.8$, $p < 0.001$). No break points outside this window enter the top ten, confirming that the COVID-19 shock is the sole dominant structural discontinuity in the decade. The F-statistic begins building from September 2019 onward, reflecting that the rolling pre-break sample was already showing growth deceleration before the acute shock arrived.

Table 8. Top 10 monthly Chow break points (out of 108 candidates scanned)

Rank	Date	F-stat	p-value	Interpretation
1	2019-10	60.18	<0.001***	Pre-COVID growth deceleration first becomes visible in rolling sample
2	2019-11	73.65	<0.001***	Sharpening deceleration; late-cycle demand softening at LAX
3	2019-12	84.49	<0.001***	Year-end 2019 — final pre-COVID month before structural collapse
4	2020-01	104.12	<0.001***	COVID anticipation; early booking cancellations begin
5	2020-02	136.60	<0.001***	Final month of near-normal travel; F-stat still building
6	**2020-03**	**182.80**	<0.001***	**PEAK F=182.8: federal emergency + travel shutdown. Dominant break.**
7	2020-04	149.63	<0.001***	Full lockdown; near-zero demand. F moderates as post-break sample grows
8	2020-05	90.16	<0.001***	Continued near-zero; F declining as shock becomes "priced in"
9	2020-06	61.61	<0.001***	Partial domestic recovery begins; break significance fading
10	2019-09	49.80	<0.001***	First month where deceleration is statistically detectable

*F-tests with k = 2 parameters. *** p < 0.001. All top-ranked breaks are concentrated in the Sep 2019 – Jun 2020 window.*

5.3 Bai-Perron Multiple Break Point Analysis

The BIC-optimal Bai-Perron model selects three break points: March 2020 (COVID onset), September 2022 (recovery plateau), and September 2023 (deceleration). The

two-break model (March 2020 only) is strongly preferred over the single-segment model (ΔBIC = +37.4 points). Adding a second break at September 2022 further improves BIC by 37.4 points, reflecting the genuine inflection between the rapid rebound and slower convergence phases. The third break (September 2023) provides only marginal additional improvement (+1.5 BIC points), suggesting a mild but detectable further deceleration entering 2024.

Table 9. Bai-Perron dynamic programming results

Breaks	Break Dates	SSR	BIC	Interpretation
0	None	∞	∞	Single regime — no significant break (BIC = ∞; unit-slope model undefined)
1	62	16.4955	-214.19	Primary COVID break at March 2020 only
2	62, 92	11.1527	-251.58	COVID break + recovery plateau at September 2022
3	**62, 92, 104**	10.1735	**-253.04**	**COVID + recovery plateau + deceleration (Sep 2022, Sep 2023) ← BIC optimal**
4	62, 80, 92, 104	9.5829	-250.64	Four breaks; diminishing marginal BIC improvement

Minimum segment length = 12 months. BIC = n×ln(SSR/n) + (2m+1)×ln(n). Amber = BIC-optimal (3 breaks).

5.4 Trend-Break Interaction Model

Excluding the acute 2020 shock (n = 108), the interaction model finds the pre-COVID monthly trend β_1 = -0.00060M/month is statistically indistinguishable from zero (NW-t = -0.087, p = 0.931), confirming that pre-COVID arrivals were in near-steady-state maturity at approximately 3.1–3.5M/month. The slope change γ = 0.02924M/month is highly significant (NW-t = 2.853***), yielding a post-recovery annualised slope of 0.3437M/yr — approximately 195% faster than the pre-COVID trend. The negative level shift δ = -3.023M captures the permanent demand deficit at the recovery onset.

Table 10. Trend-break interaction model

Parameter	Estimate	NW-SE	NW-t	p-value / sig.
Intercept (α)	2.93700	0.19227	**15.275**	**<0.001 *****
Pre-COVID monthly trend β_1	-0.00060	0.00689	-0.087	0.9309
Level shift δ (Apr 2021)	-3.02315	0.61964	**-4.879**	**<0.001 *****
Slope change γ (post-Apr 2021)	0.02924	0.01025	**2.853**	**0.0052 *****
Pre-COVID annualised slope	**-0.0072M/yr**	**Post-COVID annualised slope**	**0.3437M/yr**	

*D = 1 from 2021-05 onward. 2020 excluded. n = 108. Newey-West HAC (12 lags). *** p<0.01.*

5.5 CUSUM Parameter Stability

The CUSUM statistic first breaches the Brown-Durbin-Evans 5% significance band (±0.948) in August 2018 (CUSUM = 1.053), approximately 19 months before the dominant Chow break. This earlier signal reflects latent deceleration in growth momentum consistent with LAX approaching its practical capacity ceiling (88M total passengers in 2019). The CUSUM statistic peaks at 2.087 in mid-2020 and gradually reverts toward zero during the 2022–2024 recovery, indicating the post-COVID trajectory is not statistically inconsistent with the pre-COVID growth model — a permanent level shift but not a permanent trajectory change.

5.6 Event-Window Welch t-Tests

Table 11 reports Welch two-sample t-tests comparing mean monthly arrivals in 12-month windows before and after named events. Four events are significant at 5% or better; the ONT transfer is marginal at 10%. The 2019 LAX peak is not a discrete turning point — it was a continuation of an already-decelerating trend.

Table 11. Welch two-sample t-tests on 12-month windows

Event	Pre-mean	Post-mean	Change	% Change	p-val (Welch)	Sig.
COVID-19 onset	3.246	0.813	-2.433	**-75.0%**	<0.001	***
ONT local control	2.699	2.894	+0.195	**+7.2%**	0.0924	*
Phase I recovery	1.045	1.860	+0.816	**+78.1%**	0.0161	**
Phase II recovery	1.860	2.616	+0.755	**+40.6%**	<0.001	***
LAX 2019 peak	3.144	3.214	+0.070	+2.2%	0.5842	n.s.
Post-pandemic plateau	2.616	2.978	+0.362	**+13.8%**	0.0035	***

**** p<0.01; ** p<0.05; * p<0.10; n.s. = not significant. Green = positive significant shift; red = negative.*

5.7 Airport-Level Recovery

The aggregate 2024 regional total remains statistically below 2019 (gap = 0.161M/month, $p < 0.001$). However, the deficit is entirely concentrated at LAX. BUR and ONT have significantly exceeded their 2019 benchmarks, reflecting structural demand shifts toward less-congested regional airports during and after the pandemic. Table 12 provides the airport-level breakdown.

Table 12. Airport-level 2024 vs 2019 annual final-destination arrivals

Airport	2019 Arr. (M)	2024 Arr. (M)	% of 2019	Sig.	Notes
Los Angeles Intl.	27.30	23.74	**87.0%**	***	Largest volume deficit; international recovery lag + capacity ceiling
Hollywood Burbank	2.26	3.05	**135.4%**	***	+35% above 2019; Southwest/Avelo network expansion; new terminal underway
John Wayne (SNA)	4.88	4.99	**102.3%**	n.s.	Fully recovered; Orange County O&D demand restored
Ontario Intl.	2.65	3.37	**127.0%**	***	+27% above 2019; fastest-growing mid-size CA airport; Inland Empire demand
Long Beach	1.47	1.47	**100.0%**	n.s.	At parity; slot-constrained (58 flights/day cap); Southwest operational recovery

*Welch t-tests on 12 monthly obs per year. Green = significantly above 2019. *** p<0.01; n.s. = not significant.*

5.8 Ten Identified Turning Points

Table 13 presents all ten statistically identified turning and inflection points, combining evidence from the five methods. The March 2020 break is confirmed by three independent methods simultaneously.

Table 13. Ten turning/inflection points.

#	Date	Method(s)	Statistic	p	Description
1	2016-01	Event t-test	t=−1.73*	0.092	ONT transfer to local control (+7.2% mean monthly arrivals). Statistically marginal; marks start of Ontario's decade-long +67% growth trajectory.
2	2018-08	CUSUM breach	CUSUM=1.05	>0.948	First breach of Brown-Durbin-Evans 5% band. Latent deceleration ~19 months before COVID shock; consistent with LAX approaching 88M practical ceiling.
3	2019-09	Chow scan	F=49.80***	<0.001	First month where monthly Chow F exceeds 1% critical value. Statistical onset of pre-COVID growth exhaustion phase.
4	**2020-03**	Chow scan + Bai-Perron	**F=182.8*** **	<0.001	DOMINANT STRUCTURAL BREAK. COVID-19 travel restrictions: −75.0% mean monthly arrivals. Highest Chow F-stat; primary Bai-Perron break confirmed.
5	2021-02	Rolling 12M slope	Sign flip	—	Rolling annual slope turns positive for first time since COVID onset (from −0.80M/yr to +0.64M/yr). Onset of sustained recovery trajectory.
6	2021-01	Event t-test	t=−2.72**	0.016	Phase I recovery: mean monthly arrivals +78.1% vs 2020 trough window. Interaction model confirms recovery slope is +195% steeper than pre-COVID.
7	2022-01	Event t-test + Bai-Perron	t=−5.11***	<0.001	Phase II recovery acceleration (+40.6%). Most statistically robust non-COVID event. Bai-Perron secondary break at Sep 2022 marks end of rapid rebound.
8	2022-09	Bai-Perron (BIC optimal)	BIC break	—	Recovery plateau transition. BIC-optimal model identifies this as second break, separating the rapid rebound (2021–mid-2022) from slower convergence phase.
9	2023-01	Event t-test	t=−3.09***	0.004	Plateau growth: +13.8% arrivals vs 2022 window still significant. Continued but decelerating normalisation. Third Bai-Perron break at Sep 2023.
10	2024	Paired t-test	t=−31.1***	<0.001	2024 regional total statistically below 2019 (−5.0%, −0.161M/month). At post-COVID slope (+0.374M/yr), full recovery to 2019 projected for mid-2025.

Methods: Chow = monthly F-test scan; B-P = Bai-Perron; CUSUM = Brown-Durbin-Evans; t = Welch event-window; Momentum = rolling 12M slope sign change. Red = dominant shock; green = recovery acceleration.

6 Discussion

6.1 Economic Interpretation of the LRM

The hotel revenue LRM of $118.54M per million final-destination arrivals implies approximately $0.12 per individual arriving passenger, or roughly $200 per occupied hotel room-night at a 33% visitor-to-hotel capture rate and 1.8-night average stay. This is consistent with STR/CoStar-reported LA ADR of $180–$220 over 2022–2024 (Discover LA, 2025) and with the Los Angeles Tourism and Convention Board's estimate that approximately 35% of LA visitors stay in paid accommodation.

6.2 Structural Shifts and the Regional Airport Mix

The most economically significant finding of the event study is the permanent level shift in the monthly series: the interaction model estimates a level drop of 3.02M arrivals per month at the January 2021 recovery onset, which the steeper post-COVID growth slope is only gradually closing. Simultaneously, the composition of the regional market has shifted: BUR and ONT now handle a substantially larger share of regional arrivals than in 2019. Since these airports have lower RevPAR and accommodation GDP multipliers per arrival than the LAX corridor, the effective regional multiplier may be declining even as total arrivals recover.

6.3 Limitations

- The GDP series follows a near-unit-root process over 10 years of monthly data; long-run GDP multiplier inference is not possible from this dataset without a longer sample or instrument for cointegration.
- Endogeneity: hotel investment and capacity expansion may respond to arrivals growth, creating reverse causality. Instrumental variable approaches are not employed.
- The ADL models exploit within-year variation that includes the 2020 structural break. Excluding 2020 reduces both sample size and identification power; including it leverages the extreme variation as a quasi-experiment.
- Monthly arrival series are constructed from annual totals using seasonal weights; genuine month-level BTS T-100 data would sharpen the estimates.

7 References and Data Sources

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