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Year: 2025

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Political Sentiment and Flight Demand

Canada–U.S. Travel in 2025

Date of Submission: July 27, 2025

1 Introduction

Air travel demand serves as a powerful and dynamic indicator of global political, economic, and social sentiment. In normal conditions, it follows highly-regular seasonal patterns driven by widely-shared societal rhythms like school calendars, religious holidays, and climate preferences. These patterns allow analysts to benchmark expected behavior and to detect deviations with some confidence. Large-scale disruptions-such as the September 11 terrorist attacks, the 2008 financial crisis, and the COVID-19 pandemic-have left clear and lasting imprints on international travel flows. In each case, shifts in travel demand have reflected not only logistical constraints, but also deeper changes in public confidence, risk perception, and political alignment. Similarly, political events can shape travel behavior even when no direct travel restrictions are imposed. In this project, I report on an investigation into whether such a politically driven shift is observable in flight demand from Canada to the United States in the wake of Donald Trump's return to the U.S. presidency in January 2025.

The evidence for the political sentiment shift is clear, and unmistakably visible in the polling conducted during the course of Canada's most recent federal election campagin. Since May 2023 the Canadian Conservative party, which is ideologically closer to the Republican party in the US, had been taking a clear lead in the Canadian polling, and was widely expected to win the Prime Ministership in 2025. Donald Trump's election in the United States and his subsequent actions regarding the trade relationship along with his questioning of Canadas sovereignty rapidly and dramatically reversed this trend.

Polling reported by CBC News [6] in early January had the Conservatives at 44 percent while the Liberals languished at a mere 20 percent. By late March however the two parties were tied at 37 percent, and a month later, on election day, the Liberal party, which had campaigned on a strong theme of standing up for Canada in the face of U.S. hostility, actually won with 42 percent of the vote compared to the Conservatives' 39 percent. A graph depicting this shift in sentiment as reflected in polling trends can be seen in Figure 19 in the appendix.

Against this political backdrop, I seek to examine whether such shifts in public sentiment translated into measurable behavioral responses—specifically in the form of altered demand for international travel. The central question is as follows: *Is there evidence to support that a decline in Canadian-origin demand for flights to the United States is attributable to Trump's return to office in 2025? If so, what can be said about the direction and magnitude of this effect?* Answering this requires distinguishing between normal historical patterns, plausible counterfactual projections assuming no intervention, and the observed trajectory of travel behavior under the new administration.

To estimate the potential impact of the Trump administration's return, I apply an intervention analysis framework built on a Seasonal AutoRegressive Integrated Moving Average with eXogenous regressors (SARIMAX) model. This structure captures regular seasonal cycles and temporal dependencies in the data while allowing for the introduction of an intervention variable. Rather than assuming a discrete or instantaneous shift, I introduce a ramp function that begins in January 2025 and increases over time. This ramp is designed to reflect a gradual behavioral response, acknowledging that shifts in travel behavior may evolve as political developments unfold and public sentiment adapts. By incorporating this smoothly increasing function as an exogenous regressor in the SARIMAX model, I can assess statistically whether the observed trend in Canadian travel to the United States significantly deviates from historical expectations, and, if so, quantify that effect.

2 Literature Review

Understanding how external shocks influence economic behavior, and in this case, how political sentiment changes influence flight demand, requires some understanding of economic theory. This section is a review of key contributions that form the methodological and theoretical foundation of this study.

2.1 Box and Tiao (1975)

In "Intervention Analysis with Applications to Economic and Environmental Problems," [2] Box and Tiao pioneered the formal development of intervention analysis within the ARIMA framework. Their method allows researchers to isolate the impact of a known event (or "intervention") on a time series by introducing an exogenous variable representing the timing and form of the shock. Importantly, they distinguish between different types of interventions: step functions, pulse functions, and ramp functions. This framework is well-suited to situations where the timing of the intervention is known, but the magnitude or structure of its impact are uncertain.

2.2 Gilmour, Degenhardt, Hall, and Day (2006)

In their paper "Using intervention time series analyses to assess the effects of imperfectly identifiable natural events: A general method and example,"[5] Gilmour and others expanded on traditional intervention methods by addressing cases in which the effects of the intervention diffuse, are delayed, or poorly identified. They applied this modeling to overdose deaths in response to a suspected change in heroin supply. The intervention I focus on in my research (political sentiment shifts and tariffs) does not necessarily manifest in a single, discrete moment. The approach highlights the importance of flexible functional forms for intervention variables, such as ramp functions, which are especially useful when behavioral responses accumulate over time.

2.3 Carroll, Fuhrer, and Wilcox (1994)

The authors of "Does Consumer Sentiment Forecast Household Spending? If So, Why?" [4] provide empirical evidence that consumer sentiment indexes are powerful predictors of household consumption, even when controlling for income, interest rates, and other economic fundamentals. These findings support the use of non-financial variables such as political confidence or national identity as influences on discretionary spending. Given that international leisure travel is often discretionary, the inclusion of political sentiment as a latent explanatory variable is both intuitive and theoretically grounded.

2.4 Akerlof, and Shiller (2009)

The book “Animal Spirits: How Human Psychology Drives the Economy, and Why It Matters for Global Capitalism” [1] builds on Keynesian ideas to explore the role of emotions, confidence, and sentiment in driving macroeconomic outcomes. The authors argue that “animal spirits” like fear, trust, and fairness influence market behavior and economic trends. The psychological component of consumer behavior is essential for understanding the observed decline in Canada-U.S. travel. Political sentiment and perceived unfairness can lead to consumer backlash, especially in the face of policies like tariffs.

2.5 Seddighi, and Theocharous (2002)

In “A Model of Tourism Destination Choice: A Theoretical and Empirical Analysis" [7], Seddighi and Theocharous propose a model of tourist decision-making that incorporates perceptions of service quality, advertising effectiveness, and political instability. Unlike many prior models, their framework explicitly integrates political sentiment as a destination attribute, acknowledging its critical role in shaping travel intentions. Their empirical findings demonstrate that political instability exerts a significantly negative influence on destination choice, highlighting the importance of risk perceptions and political alignment in tourism behavior.

3 Economic Theory

The economic mechanisms by which an exogenous political shock may be analyzed include behavioral economics, consumer choice theory, and uncertainty-based consumption models. In this section, I outline the economic theoretical basis of my analysis.

3.1 Utility Maximization under Uncertainty

Under the standard microeconomic framework, individuals make consumption decisions by maximizing expected utility subject to a budget constraint. In this context, travel is a discretionary good that yields some utility. Political uncertainty such as volatile tariffs or international tensions may increase the perceived risk or lower the expected utility of travel. This leads to either postponement, substitution or outright cancellation.

Formally, let $U = U(C, T)$, where C is a vector of nondiscretionary consumption and T is a travel-related good. If the utility from T is a function of political sentiment s (with $\frac{\partial U_T}{\partial s} < 0$), a decline in s (for example, worsening political relations) reduces optimal demand for T even when prices remain constant.

3.2 Random Utility Models and Travel Demand

In transportation economics, discrete choice models like the Random Utility Model are widely used to explain/investigate travel destination selection. Each alternative destination yields a utility score $U_{ij} = V_{ij} + \epsilon_{ij}$, where V_{ij} is the logistic component (based on cost, distance, etc.) and ϵ_{ij} is the unobserved component. Political events can enter V_{ij} as a negative attribute for U.S. destinations, effectively reducing their likelihood of being chosen. This framework offers a lens for understanding how ideological preferences or political tensions can suppress travel demand to particular regions.

3.3 Political Economy and Retaliatory Consumption

Beyond individual choice, political economy models suggest that consumers may engage in "retaliatory consumption" as a symbolic act against foreign policy decisions. Travel demand may fall not just due to personal opinion, but as a deliberate political signal. In this framework, boycotting travel to the U.S. can be seen as a form of political action, not due to utility loss, but as a signal to show political opposition, similar to boycotts of U.S. products in Canadian supermarkets.

4 Data

In this study, two primary datasets were used to assess changes in Canadian travel behavior to the United States: the T100 Segment data from the U.S. Bureau of Transportation Statistics, and proprietary forward-looking airline booking data compiled by third-party distribution systems. Together, these sources provide a comprehensive view of both historical and developing travel demand.

4.1 T100 Segment Data

Published monthly by the Bureau of Transportation Statistics, the T100 dataset contains operational characteristics of commercial flights into and out of the United States. Each record in the dataset corresponds to a unique airline–route–month combination. Key fields include the flight month (`fltmth`), which indicates the calendar month of the flight (formatted as YYYY-MM-01), and passenger count (`psgr_cnt`), which I used as a proxy for travel demand. Flight origins and destinations are specified at both the airport level (`apt_fm` and `apt_to`) and the country level (`ctry_fm` and `ctry_to`), using IATA and ISO codes, respectively. The dataset further includes directional and non-directional airport and country pairs (`dir_apt_pair`, `dir_ctry_pair`, `ndir_apt_pair`, and `ndir_ctry_pair`), which allow for both direction-sensitive and non-direction-sensitive analysis.

This dataset, spanning from 2010-25, forms the foundation for measuring observed demand in the form of passenger count. By aggregating these values by month and filtering for relevant directional flows (specifically, from Canada to the U.S.), the data allow for the construction of a historical time series that reflects long-term trends, seasonal variation, and potential structural breaks in passenger flows.

4.2 Forward-Looking Booking Data

In addition to historical passenger counts, I incorporated proprietary forward-looking airline booking data. This dataset, compiled from global distribution systems used for airline and travel agency booking coordination, documents the number of passengers who have booked travel for a given future flight month as of a particular snapshot date. Each record specifies the month of intended travel (`fltmth`), the date on which the data was extracted (`snapshot_date`), the directional country pair of travel (`dir_ctry_pair`), the point-of-sale country (`pos_ctry`), and the number of passengers booked as of that date (`booked_pax`).

Unlike the T100 dataset, which reflects completed travel, this booking data serves as a real-time indicator of future travel intent. It spans from 2023-5 and is particularly valuable for measuring developing sentiment shifts in response to political events, since consumers often book their travel plans long before they actually depart. I leveraged these rich data to construct a time-series of daily bookings gained by finding the difference in total bookings each day. By capturing the daily trajectory of future travel demand at multiple points in time, the booking data allow for early detection of behavioral changes and provide a forward looking complement to the realized passenger data in T100. Both time series will be used to represent air travel demand as described in the empirical specification below.

5 Theoretical Model and Empirical Specifications

In this section, I outline the modeling framework used to identify and to estimate deviations in Canadian demand for air travel to the United States in response to political developments in 2025. The objective is to establish a counterfactual forecast of travel demand under normal conditions and evaluate the effect of the intervention using a formal statistical structure.

5.1 Understanding the Baseline

Air travel demand exhibits both long-term trends and strong seasonal patterns. Trends reflect gradual increases or decreases in passenger volumes, often driven by macroeconomic factors, population growth, or long-run structural changes such as recovery from COVID-19-related travel restrictions and sentiment changes. Seasonality captures predictable cyclical fluctuations such as increased traffic during holiday periods or school breaks that repeat at regular intervals.

To isolate these components, I used STL (Seasonal-Trend decomposition using LOESS), which separates the observed time series Y_t into the following three additive components:

$$Y_t = T_t + S_t + R_t \tag{1}$$

where T_t is the trend component, S_t is the seasonal component, and R_t is the residual component.

The trend component T_t is estimated using LOESS (Locally Estimated Scatterplot Smoothing), which fits localized regression curves across a moving window of the data. This approach allows the trend to adapt smoothly over time and capture gradual shifts. It is particularly well-suited for time-series data such as air passenger counts, where long-term trends may accelerate, plateau, or reverse due to external shocks such as political developments.

The seasonal component S_t is extracted by averaging the de-trended data over corresponding periods within each seasonal cycle (for example, monthly values across years). STL iteratively refines this seasonal pattern by removing the estimated trend and residual noise. The method is applied to both the historical T100 passengers-flown time-series and the forward-looking bookings-per-day time series, as well as COVID-adjusted iterations of the series.

ACF and PACF Diagnostics

To inform the appropriate lag structure of the forecasting model, I examined the autocorrelation function (ACF), and partial autocorrelation function (PACF) of the time series. The ACF measures the correlation between Y_t and its past values at lag k, while the PACF isolates the direct influence of Y_{t-k} on Y_t after controlling for the intermediate lags. These diagnostics guide the identification of autoregressive and moving-average terms in the model.

5.2 Forecasting Normal Conditions

To forecast what travel demand would have looked like in 2025 under normal conditions, I use a Seasonal Autoregressive Integrated Moving Average (SARIMA) model. This class of models accounts for both trend and seasonal autocorrelation to provide a strong baseline for constructing counterfactual extensions of the series. The general form of the SARIMA model is expressed as:

$$\Phi_P(B^s)\,\phi_p(B)(1-B)^d(1-B^s)^D Y_t = \Theta_Q(B^s)\,\theta_q(B)\,\varepsilon_t \tag{2}$$

Here, B denotes the backshift operator, such that $BY_t = Y_{t-1}$; p, d, and q refer to the order of the non-seasonal autoregressive, differencing, and moving average components, respectively, and P, D, and Q denote the seasonal analogs. The differencing terms $(1-B)^d$ and $(1-B^s)^D$ are used to remove trend and seasonal nonstationarity. The model is estimated using maximum likelihood.

The SARIMA model in the `statsmodels` package in Python uses the Kalman filter. The Kalman filter is a recursive algorithm for estimating hidden state variables in dynamic systems, which SARIMA uses to compute likelihood functions and generate optimal forecasts. The Kalman filter employs Bayesian updating to processes time series data by sequentially updating predictions as new observations arrive. In this context, the Kalman filter creates a smoothed trend forecast that accounts for both model uncertainty and observational noise.

5.3 Intervention Analysis

To evaluate whether the political developments in early 2025 caused a significant deviation from expected trends, I employ an interrupted time series design using a SARIMAX regression model. This extends the SARIMA framework by incorporating an exogenous intervention variable X_t that captures the political shock:

$$Y_t = \mu + \beta X_t + \text{SARIMA terms} + \varepsilon_t \tag{3}$$

In this model, μ is the intercept, β is the coefficient on the intervention variable, and ε_t is an error term. The intervention variable X_t models the response to the Trump administration and subsequent deterioration in U.S.–Canada relations.

Rather than assuming an immediate or discrete effect, I defined X_t as a ramp function which linearly increases from its beginning in January 2025. This form admits for a gradual response consistent with the notion that travel behavior adjusts progressively as sentiment shifts and the presidency continues. The ramp structure is informed by external evidence, including news timelines, booking data behavior, and polling data for the 2025 Canadian federal election.

The parameter β quantifies the marginal effect of the political event on passenger demand over time. A significantly negative β would indicate that the intervention has led to a sustained and accumulating decline in Canadian flight demand to the U.S..

6 Results

6.1 Baseline Demand Analysis

Figure 1 depicts the full T100 passenger count time-series from January 2012 through April 2025. A red vertical line marks the start of the intervention period in January 2025. The most visually striking feature is the abrupt and severe collapse in passenger volume in early 2020, coinciding with the onset of the COVID-19 pandemic and subsequent travel bans. This disruption is followed by a gradual recovery that persists through 2025. The objective of this figure is twofold: first, to establish a baseline understanding of long-term demand trends for flights to the U.S. and second, to contextualize any deviations from the post-COVID growth trajectory that may be emerging during the early months of Donald Trump's second presidential term. In particular, this graph is a clear signal that passenger counts are collapsing in 2025.

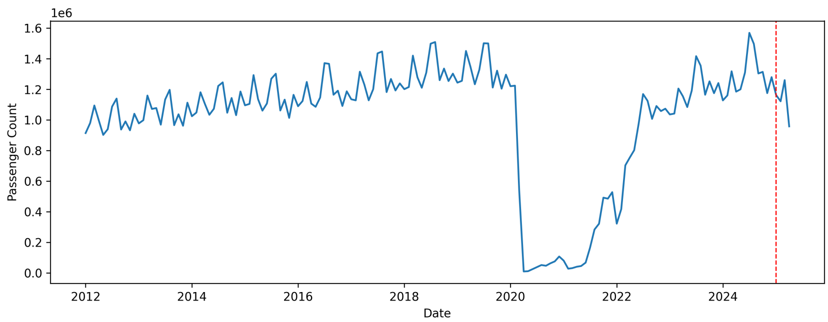

Figure 1: Full T100 Time-Series

Below, Figure 2 permits a closer look at the yearly seasonality in the Canada–U.S. air travel demand by illustrating the average monthly passenger volumes from 2012 through 2025. The series reveals a clear seasonal pattern, with fluctuations consistent with travel demand cycles. Notable is the peak observed in March, likely reflecting increased demand during the Canadian spring break period. This is followed by a springtime dip, which then gives way to a strong summer surge in July and August. For year-over-year percentage changes in passenger count from 2012 to 2025 see Figure 20 in the appendix.

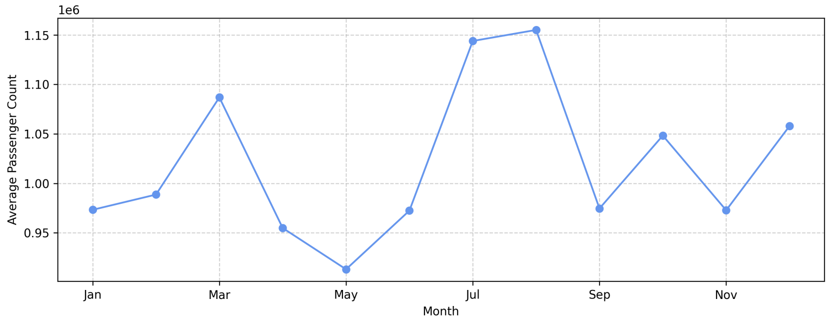

Figure 2: Average Yearly Seasonal Passenger Volume Pattern

My focus is on quanitfying the impact of Trump's second presidential term on Canada - U.S. travel, so I shall highlight the importance of Canada as the second largest source of international passengers to the U.S. in figure 3. Canada makes up nearly 12 percent of all flights coming into the United States. Given the substantial share, any disruption in this relationship is both economically and strategically important to monitor.

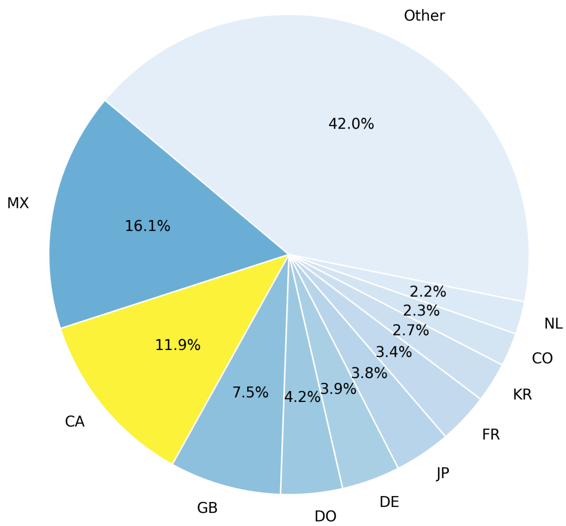

Figure 3: Percentage Share of International Flights into the United States by Country

6.2 T100 SARIMA Modeling

As outlined in the empirical specifications, SARIMA modeling requires careful selection of both non-seasonal and seasonal parameters, particularly the autoregressive (AR) and moving average (MA) components. To inform these choices, I examine the ACF and PACF of the T100 passenger count time series.

The ACF quantifies the correlation between the time series and its own lagged values across time. A slow, gradual decay in the ACF such as the one observed below often indicates a non-stationary process in the time series, and suggests the need for differencing. The PACF quantifies the correlation at each lag by removing the influence of intermediate lags. It is used to determine the number of autoregressive terms (AR).

In the case of the T100 series, both plots exhibit significant autocorrelation persisting across many lags. This supports the inclusion of differencing in the model ($d > 0$). The PACF cuts off sharply after the first lag, which implies the selection of a low-order AR component. Furthermore, the slowly declining ACF also suggests an AR proscess. Together, these diagnostics inform the parameter selection for creating the SARIMA models that will appropriately capture the dynamics of the time series.

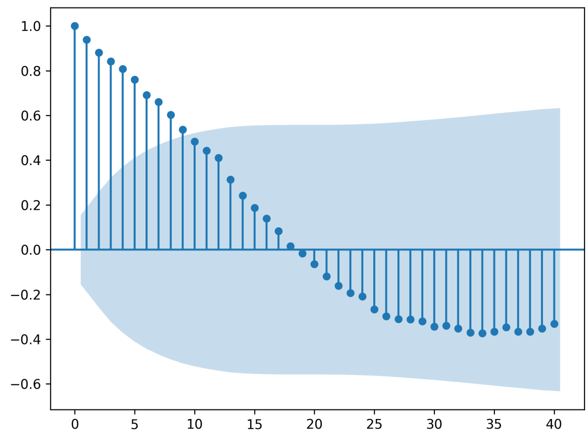

Figure 4: T100 Autocorrelation Function

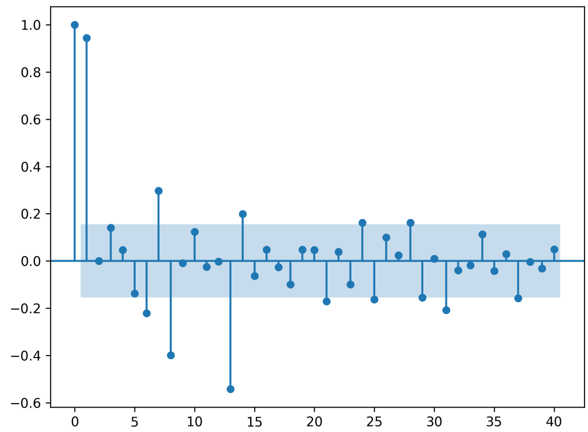

Figure 5: T100 Partial Autocorrelation Function

I now transition to a more statistically structured approach to the analysis. In Figure 6, I depict the T100 passenger time series, along with out-of-sample forecasts generated by a SARIMA model trained through January 2024 and projected through June 2025. The objective of this model is to estimate a counterfactual trajectory of what uninterrupted post-COVID growth in passenger demand may have looked like in the absence of external interventions.

To put the forecast in context, the graph begins in January 2019, capturing the pre-COVID trend in passenger volumes. Following the sharp collapse in early 2020, we observe a steady recovery trend that gradually approaches pre-pandemic levels over the course of five years. Notably, the model underpredicts the pace of recovery in early to mid-2024, suggesting stronger-than-expected demand during that period. This pattern reverses by late 2024, where the model begins to overpredict observed values. This may be a potential signal of early demand decreases coinciding with shifting political dynamics in the United States, namely the onset of Donald Trump's second presidential term.

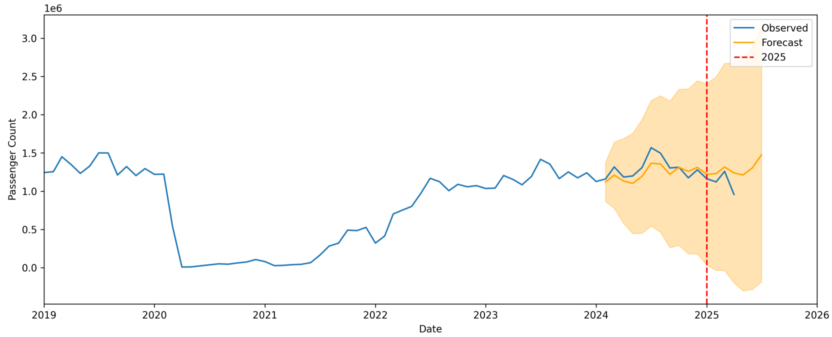

Figure 6: SARIMA Forecast Trained Until Januray 2024

Figure 7 provides a closer look on the residuals of the forecast in Figure 6. Residuals are calculated by subtracting the predicted values from the observed values. As described above, the predictions were below the observed values, suggesting an increasing recovery velocity. In October 2024 the residuals begin to dip below the predictions as observed demand crumbles. For a numerical analysis of the residuals in this graph see Table 21 in the appendix.

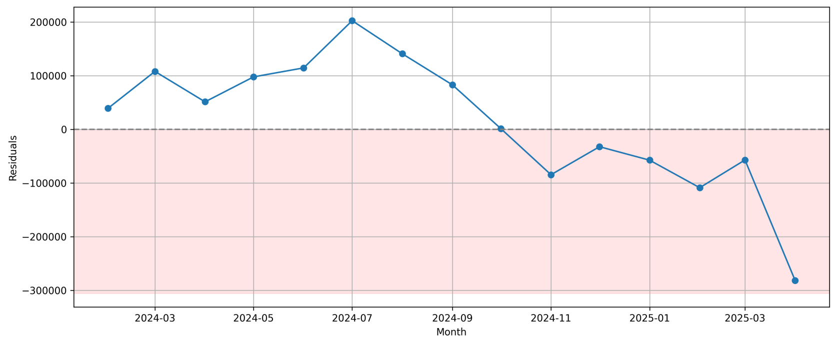

Figure 7: SARIMA Forecast Trained Until January 2024 Residuals

To account for the evolving trajectory of passenger demand following the Trump intervention, I estimated a second SARIMA model that incorporates all available data through March 2025, extending the forecast to January 2026. By including the most recent observations, this model captures the developing shifts in trend and level that may be associated with post-intervention dynamics. As a result, the updated forecast takes into account any structural changes that have begun to materialize during the early months of Trump's second term.

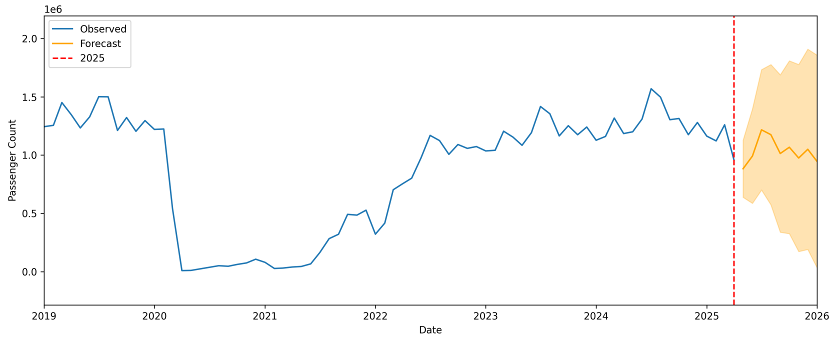

Figure 8: SARIMA Forecast Trained Until April 2025 (Trump-Effect forecast)

6.3 T100 SARIMAX Modeling

To advance the analysis and begin to quantify the direction and magnitude of the Trump effect statistically, I next incorporated SARIMAX regression modeling. Before doing so, it is useful to first visually and statistically deconstruct the passenger time series using Seasonal-Trend decomposition using LOESS (STL).

Figures 9 and 10 depicts STL decompositions of the full T100 time series and the no-COVID adjusted time series both filtered for Canada-U.S. passenegrs. The full series (which includes COVID years) show a sharp dip in the trend component beginning in early 2020 due to COVID. The residuals during this period are large and volatile, indicating that COVID introduced dramatic shocks not well captured by seasonal or trend patterns. In contrast, the no-COVID series (which interpolates through the pandemic disruption) exhibits a smoother trend trajectory and more consistent residuals. Notable is the dramatic downtrun in trend in 2025 shown in the No-COVID series, indicating a large structural shift. To evaluate how the time series behaves under different assumptions, I estimate SARIMAX models on both the raw time series and on the STL trend components from each version of the data.

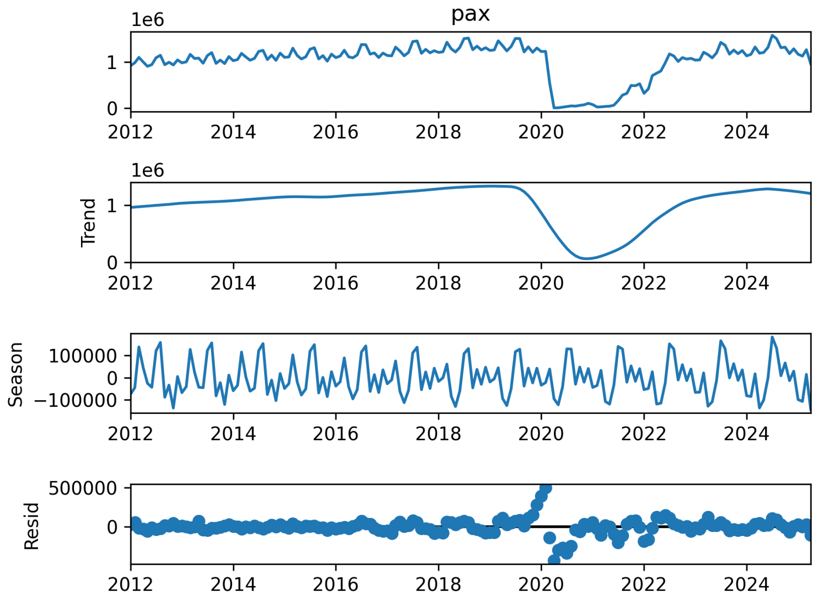

Figure 9: STL Decomposition of Full T100 Time-Series

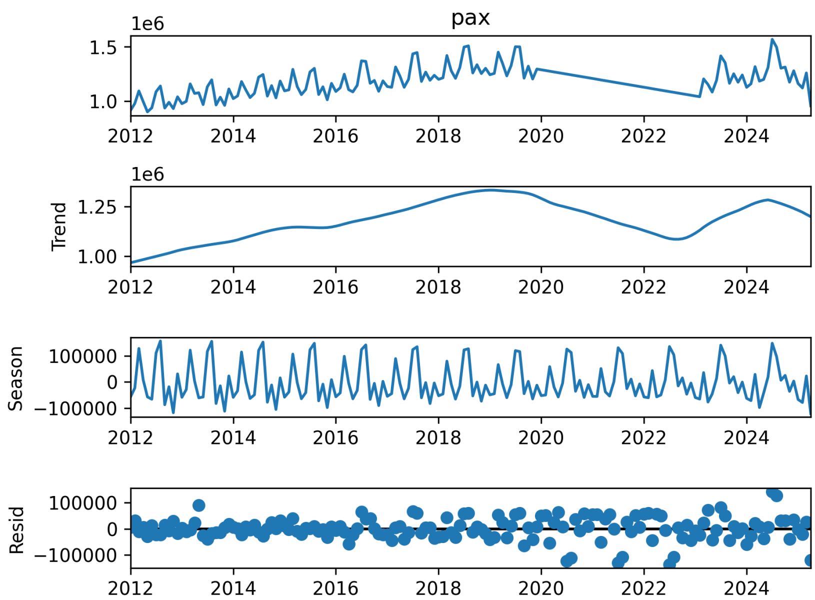

Figure 10: STL Decomposition of No-COVID T100 Time-Series

6.3.1 SARIMAX Statistical Outputs

When SARIMAX models are applied to an unadjusted time series, results are influenced by the presence of short-term noise, seasonal variation, and slight irregualrities. These elements increase variability in the data, and, rather than show the overall structural shift, show the raw impact on the time series given all the noise. In contrast, applying SARIMAX to the trend component extracted via STL decomposition shows the long term structural effect. This is because the trend is smoother, with noise and seasonality removed, allowing the model to better isolate and detect underlying structural patterns. Additionally, the assumptions of constant variance and uncorrelated errors tend to hold more closely in the trend series, improving the reliability of parameter estimates.

While the data show a small, lagged impact in the first quarter, and a dramatic drop in passengers in April as shown below in Figure 11, I used a linear ramp function beginning in January 2025 that increases uniformly over time to model the impact of the TrumpEffect on passenger volumes. The linear specification offers interpretability and stability, which proved essential given the limited post-intervention time frame. While I explored several nonlinear alternatives — including power, logarithmic, and piecewise ramp functions — each resulted in unstable or non-identifiable estimates. This instability was primarily due to the short post-intervention window and the dominance of the sharp decline observed in April.

	2024	2025	Diff	% Change
January	1127331.0	1162686.0	35355.0	3.1
February	1160073.0	1121615.0	-38458.0	-3.3
March	1317702.0	1259871.0	-57831.0	-4.4
April	1184688.0	957591.0	-227097.0	-19.2

Figure 11: Passenger Count Totals, Differences, and Percent Changes (2024-2025)

Table 1 presents the SARIMAX regression results for the full T100 time series (Canada–U.S.), including the COVID period, which I define as 2020-23. The TrumpEffect variable in this model is statistically insignificant, indicating that any effect is not distinguishable from noise in the unadjusted data. In contrast, Table 2 reports the results of the same model applied to the trend component of the series, with a negative and statistically significant coefficient.

Table 1: FULL T100 TIME SERIES SARIMAX

Variable	Coef	Std Err	95% CI
TrumpEffect	-6.647 $\times 10^4$	1.470 $\times 10^5$	[-3.540 $\times 10^5$, 2.210 $\times 10^5$]
ϕ_1	3.260 $\times 10^{-1}$	8.000 $\times 10^{-2}$	[1.690 $\times 10^{-1}$, 4.830 $\times 10^{-1}$]
Φ_1	-3.916 $\times 10^{-1}$	3.400 $\times 10^{-2}$	[-4.570 $\times 10^{-1}$, -3.260 $\times 10^{-1}$]
σ^2	1.556 $\times 10^{10}$	5.220 $\times 10^{-1}$	[1.560 $\times 10^{10}$, 1.560 $\times 10^{10}$]

AIC = 3.520 $\times 10^3$, RMSE = 1.462 $\times 10^5$

Table 2: FULL T100 TREND COMPONENT SARIMAX

Variable	Coef	Std Err	95% CI
TrumpEffect	-1.876 $\times 10^4$	4.056 $\times 10^3$	[-2.670 $\times 10^4$, -1.080 $\times 10^4$]
ϕ_1	9.861 $\times 10^{-1}$	1.600 $\times 10^{-2}$	[9.540 $\times 10^{-1}$, 1.018 $\times 10^0$]
Φ_1	-4.853 $\times 10^{-1}$	6.000 $\times 10^{-2}$	[-6.030 $\times 10^{-1}$, -3.680 $\times 10^{-1}$]
σ^2	7.779 $\times 10^7$	5.270 $\times 10^{-1}$	[7.780 $\times 10^7$, 7.780 $\times 10^7$]

AIC = 2.802 $\times 10^3$, RMSE = 1.021 $\times 10^5$

Next, I introduce the COVID-adjusted time series and its smoothed trend, in which data from 2020 to 2023 have been removed and interpolated over to smooth the pandemic disruption.

Table 3: No-COVID T100 TIME SERIES SARIMAX

Variable	Coef	Std Err	95% CI
TrumpEffect	-8.748 $\times 10^4$	3.010 $\times 10^4$	[-1.460 $\times 10^5$, -2.850 $\times 10^4$]
ϕ_1	-2.761 $\times 10^{-1}$	6.900 $\times 10^{-2}$	[-4.120 $\times 10^{-1}$, -1.400 $\times 10^{-1}$]
σ^2	3.682 $\times 10^9$	1.130 $\times 10^{-1}$	[3.680 $\times 10^9$, 3.680 $\times 10^9$]

AIC = 3.636 $\times 10^3$, RMSE = 1.112 $\times 10^5$

Table 4: No-COVID TREND T100 TIME SERIES SARIMAX

Variable	Coef	Std Err	95% CI
TrumpEffect	-1.925×10^{4}	5.654×10^{2}	$[-2.040 \times 10^{4}, -1.810 \times 10^{4}]$
ϕ_1	9.571×10^{-1}	2.600×10^{-2}	$[9.060 \times 10^{-1}, 1.008 \times 10^{0}]$
σ^2	4.437×10^{6}	1.360×10^{0}	$[4.440 \times 10^{6}, 4.440 \times 10^{6}]$

AIC = 2.655×10^{3}, RMSE = 1.032×10^{5}

The TrumpEffect variable manifests differently across the four SARIMAX models depending on whether the underlying series is trend-smoothed and whether the COVID period is included. In the SARIMAX model using the raw no-COVID series (Table 3), the TrumpEffect coefficient is –87,480 and statistically significant, but with a high standard error, reflecting uncertainty in how the model distributes the effect over time. Since the decline builds gradually and then drops sharply at the end, the linear ramp averages the total impact, causing the coefficient to absorb much of the April effect, even though earlier months exhibit minimal change. As shown in Table 11, the raw difference in passengers between April 2024 and April 2025 is -227,097, which aligns closely with the cumulative effect implied by the model: a coefficient of –87,480 multiplied by a ramp value of 3, yielding an estimated April drop of –262,440.

In contrast, the SARIMAX model applied to the STL-smoothed trend component produces a smaller and more precise coefficient of -19,250, capturing the underlying structural shift without the volatility present in the raw data. This trend-based model therefore offers a clearer view of the persistent decline in demand across this period, even as the bulk of the observed change remains concentrated in its final month. The trend models consistently suggest a decline of roughly 2 percent in Canada–U.S. passengers post-2025, relative to the pre-Trump baseline of approximately one million monthly passengers. The raw series outputs, however, suggest short-run impact is accelerating, even if the long-run trend evolves more gradually.

6.4 Booking Curves

The following section shifts focus to the forward-looking booking data, which provide valuable insight into how demand is evolving in real time. Figure 12 illustrates the development of bookings for travel in January of 2024, 2025, and 2026, plotted as a function of months prior to departure. The x-axis represents the number of months before January, while the y-axis indicates the cumulative volume of bookings recorded at each point in time. The 2024 and 2025 booking curves follow a similar trajectory, both showing a typical evolution in demand as the departure month approaches. The 2026 curve diverges notably in its slower growth and flatter slope which suggest dampening passenger demand. This emerging pattern may reflect declining economic confidence or deteriorating travel sentiment between Canada and the U.S..

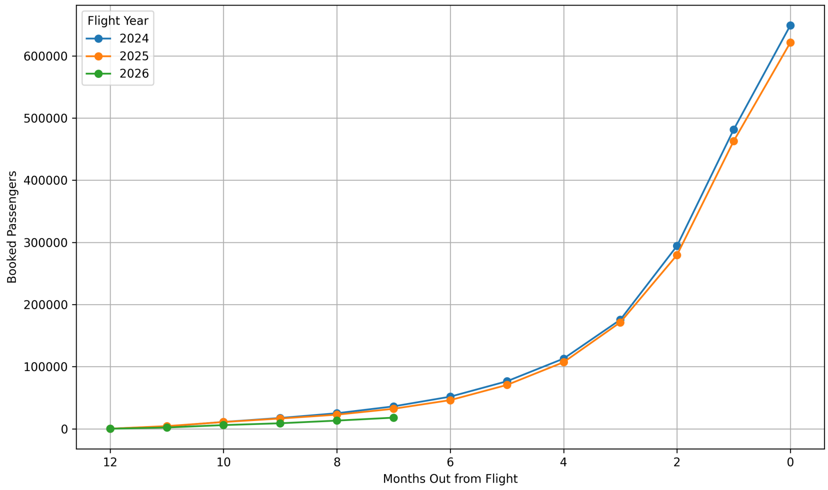

Figure 12: January Booking Curves

To emphasize the decline in passenger demand, Figure 13 depicts the booking curves for June of 2023, 2024, and 2025. Here, we see how the Trump effect is developing deeper into 2025. The 2025 booking curve is remarkably lower than those of 2023 and 2024, with a much lower realized June bookings count. From both graphs we see that the confidence and sentiment is deteriorating as time goes on. For a numerical analysis of these curves, see Tables 22 and 23 in the appendix.

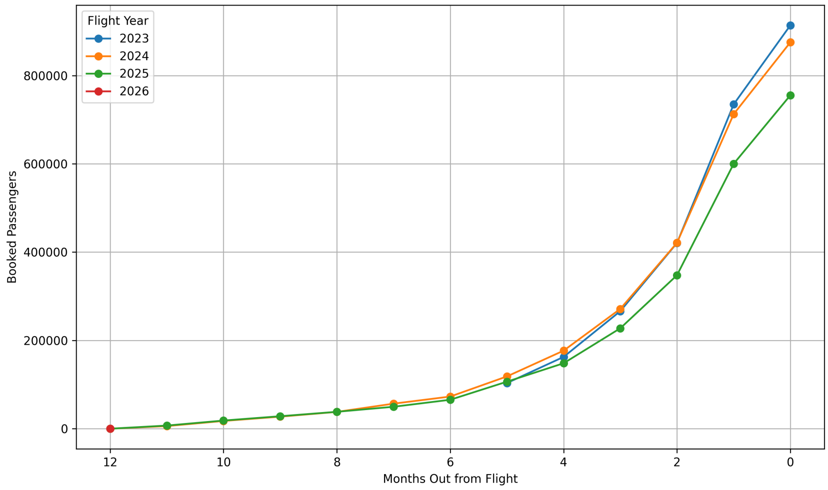

Figure 13: June Booking Curves

6.5 Canadian Bookings by Market Segment

After constructing the daily booking time series which spans from April 2024–July 2025, I filtered for Canadian-origin bookings and categorized them into three distinct market segments: domestic Canadian bookings (`Domestic CA`), bookings from Canada to the United States (`CA-US`), and all other international bookings (`Oth Intl`). Figure 14 depicts the total daily bookings by market segment, and figure 15 displays the seven-day moving average of daily bookings by market segment.

A notable feature of the series is the sharp decline in bookings across all segments in December 2024. This drop is typical of booking behavior for air travel, as holiday travel is often booked months in advance and general activity slows during the holiday season. The post-holiday recovery period in January 2025, however marks a meaningful turning point in terms of the Trump Effect. While `Domestic CA` and `Oth Intl` bookings rebound and even stabilize slightly above pre-holiday levels, `CA-US` bookings plummet at a persistent decline.

This divergence suggests that Canadian air travel demand remains robust overall, but that the United States has become a less preferred destination. In other words, Canadians are still flying—just not to the U.S..

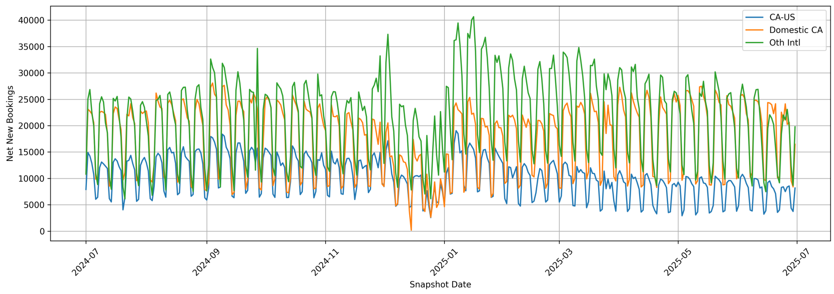

Figure 14: Total Bookings by Market Share.

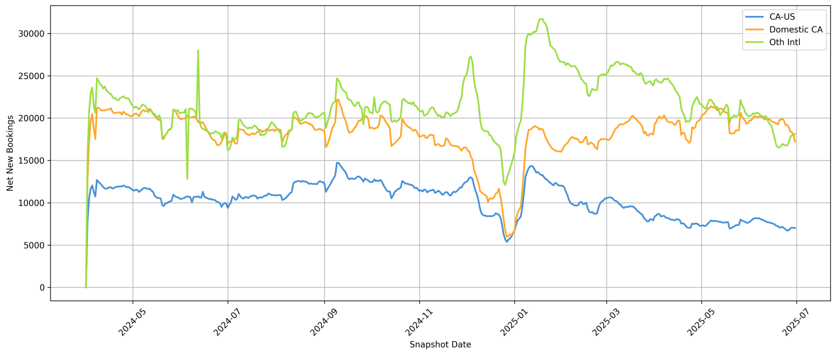

Figure 15: Seven-Day Moving Average by Market Share.

To illustrate this shift, Figure 16 depicts the average market share by segment before and after January 2025. The CA-US share of the pie has shrunk by 21.7 percent (from 22.6 percent to 17.7 percent), and the Domestic CA, and Other International shares have increased by 0.4 percent and 11.6 percent respectively. Notably, even with the sharp contraction in the `CA-US` segment, total net new bookings have increased by 3.4 percent in the post-Trump period. This reinforces the idea that the decline in Canada–U.S. air travel is not part of a broader demand collapse, but rather a targeted shift in destination preferences.

For additional context on weekly booking cycles, see Figure 24 in the appendix. Note how bookings tend to drop over the weekend and spike during weekdays.

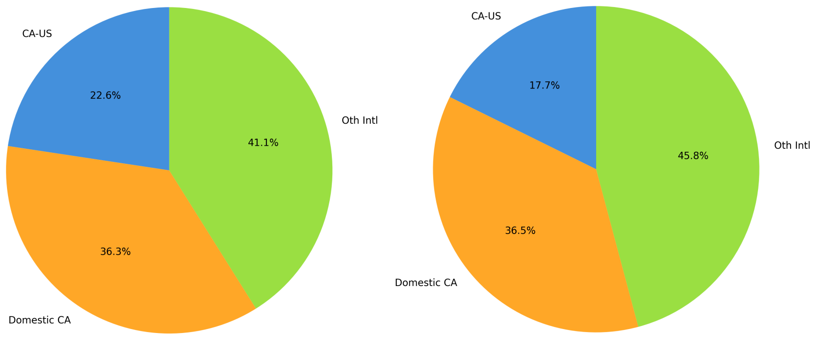

Figure 16: Share by Market Segment (Pre/Post Intervention)

Figure 17 depicts the percentage share of Canadian-origin bookings to the United States over time. To highlight the directional shift in demand, I included average trend lines for the periods before and after January 2025, the onset of the Trump intervention.

Prior to this point, Canada–U.S. bookings accounted for an average of 22.6 percent of all Canadian-origin bookings, with a slight upward trend suggesting stable or modestly increasing demand. Following the intervention, however, the trend line shifts sharply downward, reflecting a pronounced and sustained decline in demand for U.S.-bound travel. In this post-Trump period, the average share drops to 17.7 percent, marking a significant reduction in relative demand for flights to the U.S..

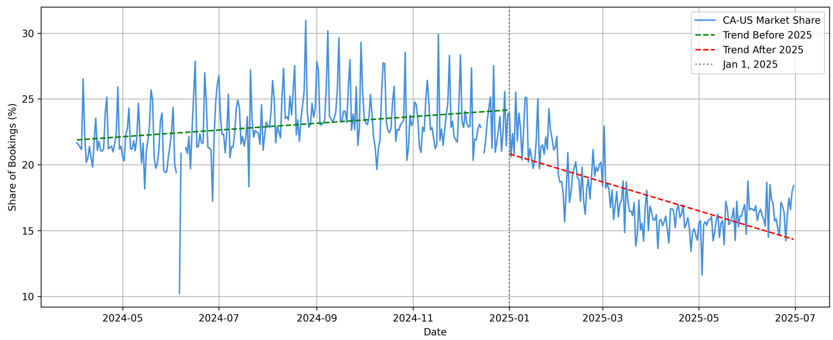

Figure 17: CA-US Share With Pre/Post Trump Trend Lines

6.5.1 Booking SARIMAX Modeling

In this section, I present the results of SARIMAX modeling applied to the trend component of the Canada–U.S. market share time series. Figure 18 depicts the STL decomposition of the daily market share series, which isolates long-term movements from seasonal and irregular fluctuations. Most notably, the trend component shows a clear and sustained decline beginning in early 2025, coinciding with the onset of Trump's second presidential term. This downward shift in the trend provides strong justification for modeling the trajectory of Canada–U.S. demand using a SARIMAX model as a means to estimate the magnitude and direction of the Trump effect.

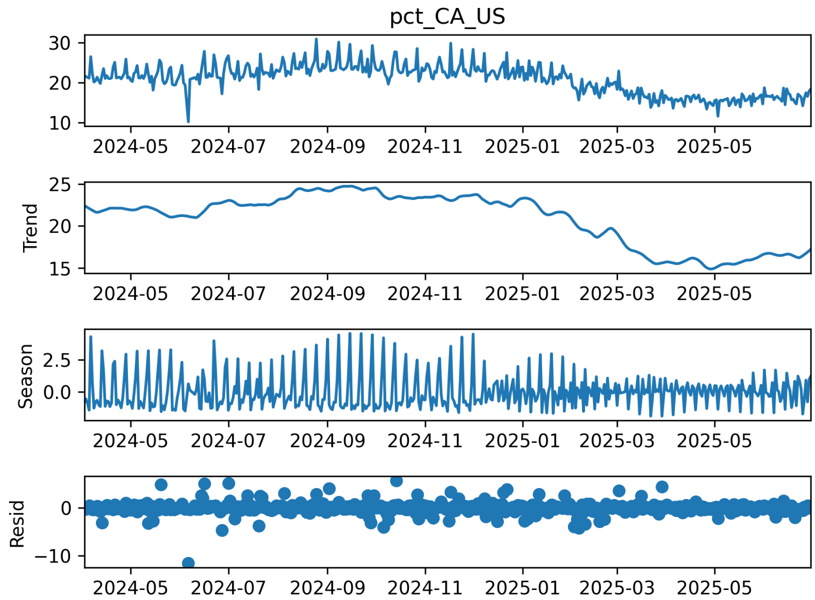

Figure 18: CA-US Market Share STL Decomposition.

The results indicate that the `TrumpEffect` variable is highly statistically significant, with a coefficient of -0.0796 and a standard error of 0.003. This provides strong evidence of a daily decline in the Canada–U.S. booking share beginning in January 2025. The 95 percent confidence interval, ranging from approximately -0.1430 to -0.0160, suggests that the share is declining by roughly 2.39 percentage points per month after the intervention. This coefficient is representative of ramp variable that increases daily from the date of intervention, meaning that the effect is a cumulative marginal increase: after 30 days, the total modeled decline is approximately -2.39 percentage points, after 100 days the expected decline is -7.96 percentage points, and by six months the expected decline grows to -14.33 percent. This approach reflects a steadily worsening structural impact assuming the decline remains persistent over time.

The RMSE of provides a meaningful benchmark for evaluating prediction accuracy. Since the dependent variable is the daily percentage share of Canada–U.S. bookings, the RMSE implies that the model's fitted values deviate from the observed share by about 1.31 percentage points on average per day. While this residual noise is nontrivial, the Trump-Effect's cumulative decline remains clearly distinguishable from typical daily variation especially given its strong statistical significance and steady accumulation over time.

Table 5: STL-Trend SARIMAX on CA-US Share

Variable	Coef	Std Err	95% CI
TrumpEffect	-7.960×10^{-2}	3.200×10^{-2}	$[-1.430 \times 10^{-1}, -1.600 \times 10^{-2}]$
ϕ_1	9.151×10^{-1}	2.200×10^{-2}	$[8.730 \times 10^{-1}, 9.580 \times 10^{-1}]$
σ^2	3.300×10^{-3}	0.000×10^{0}	$[3.000 \times 10^{-3}, 4.000 \times 10^{-3}]$

AIC = -1.262×10^{3}, RMSE = 1.312×10^{0}

7 Conclusion

This method of analysis is particularly useful for natural events– those that are unforseen, and externally caused. The size and nature of such an event would be impossible to recreate experimentally. Here, the observational data inform the understanding of how political sentiment influences human behavior on an international scale. The findings of this study lead to a clear and consistent conclusion that there has been a statistically significant decline in Canadian demand for air travel to the United States since January 2025. By examining this intervention from two independent yet complementary perspectives (historical flights into the U.S. and current and forward-looking bookings from Canada) the findings converge on a well-substantiated outcome.

The magnitude of the decline is notable. A modest 2 percent monthly drop in passenger volume, reflecting the early stages of the Trump effect, and a 2.39 percent monthly loss in market share represent meaningful contractions, especially given Canada's status as the second-largest source of international travelers to the United States. With approximately one million Canadian passengers entering the U.S. each month, this equates to a loss of roughly 20,000 monthly travelers.

This sustained and accelerating reduction in demand has already prompted airlines to restructure their flight networks, including the temporary suspension of select Canada–U.S. routes due to lack of demand. Not only is this meaningful for airlines, but for the U.S. economy as well. Based on estimates from BudgetUSA (2024) [3], the average weekly expenditure by a foreign visitor to the United States was $2,268 in 2024. Assuming a typical duration of stay is one week, a monthly decline of 20,000 passengers corresponds to approximately $45.4 million in lost tourism revenue in the first month, and $90.7 million by the second.

Finally, the analysis of forward bookings reveals a continued downward trend in Canadian travel demand, reinforcing the conclusion that this is not a temporary fluctuation but an accumulating and enduring shift.

A Appendix

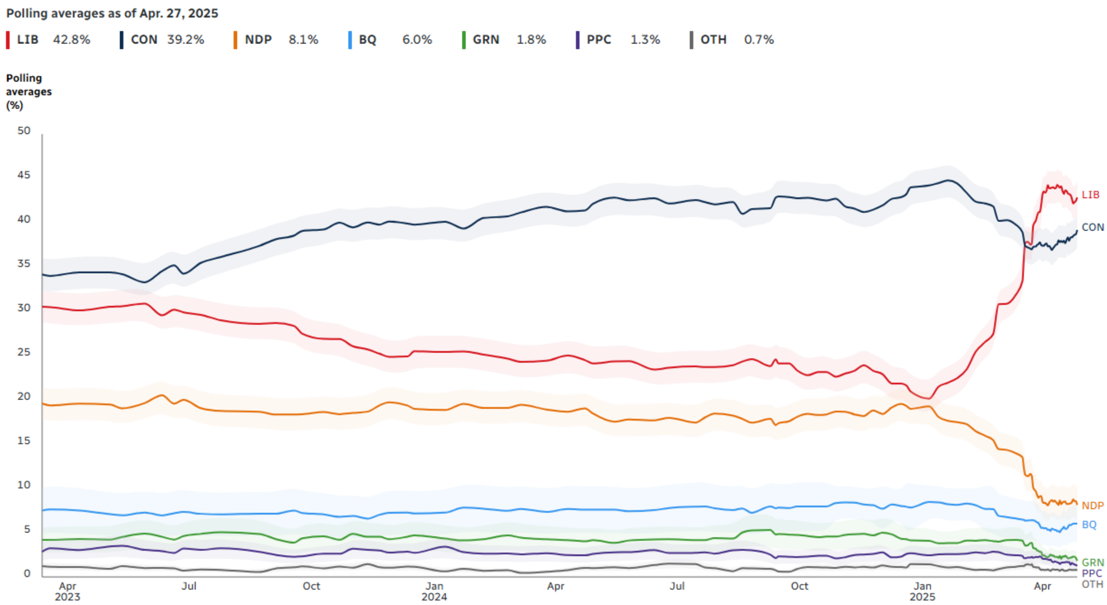

Figure 19: Canada Federal Election Poll Tracker: https://newsinteractives.cbc.ca/elections/poll-tracker/canada/

	January	February	March	April
2012	—	—	—	—
2013	6.9	1.9	5.9	7.7
2014	4.8	5.0	1.9	2.9
2015	7.0	5.4	9.5	3.0
2016	-0.5	1.7	-3.5	-2.6
2017	4.2	0.4	5.3	11.2
2018	5.8	7.7	8.0	3.9
2019	3.5	3.3	2.2	5.3
2020	-1.9	-2.5	-62.8	-99.3
2021	-93.4	-97.8	-94.3	331.4
2022	301.4	1414.6	2164.7	1779.5
2023	221.8	149.9	71.4	53.0
2024	8.9	11.4	9.4	2.6
2025	3.1	-3.3	-4.4	-19.2

Figure 20: Year over Year Percentage Change in CA-US Passenger Volumes (3 Months)

	Actual	Forecast	Residual
2024-02	1160073.0	1120868.3	39204.7
2024-03	1317702.0	1209712.7	107989.3
2024-04	1184688.0	1133417.3	51270.7
2024-05	1199800.0	1102025.7	97774.3
2024-06	1309505.0	1194945.6	114559.4
2024-07	1568996.0	1366446.6	202549.4
2024-08	1496735.0	1355822.6	140912.4
2024-09	1303550.0	1220601.0	82949.0
2024-10	1313883.0	1312623.2	1259.8
2024-11	1174973.0	1259576.1	-84603.1
2024-12	1279532.0	1311916.2	-32384.2
2025-01	1162686.0	1220190.9	-57504.9
2025-02	1121615.0	1230408.3	-108793.3
2025-03	1259871.0	1316975.9	-57104.9
2025-04	957591.0	1239233.5	-281642.5

Figure 21: SARIMA Forecast Trained Until January 2024 Residuals

	Months Before Departure	2024	2025	2026	2023	% Change (2023-2024)	% Change (2024-2025)
12	12	219.0	203.0	127.0	0	—	-7.3
11	11	3909.0	4351.0	2087.0	0	—	11.3
10	10	11060.0	10911.0	5979.0	0	—	-1.3
9	9	17426.0	16546.0	8920.0	0	—	-5.0
8	8	25049.0	22728.0	13207.0	0	—	-9.3
7	7	36096.0	32215.0	17947.0	0	—	-10.8
6	6	51711.0	46137.0	—	0	—	-10.8
5	5	76510.0	70551.0	—	0	—	-7.8
4	4	112969.0	107194.0	—	0	—	-5.1
3	3	175498.0	171280.0	—	0	—	-2.4
2	2	294298.0	279646.0	—	0	—	-5.0
1	1	481460.0	462941.0	—	0	—	-3.8
0	0	649218.0	621556.0	—	0	—	-4.3

Figure 22: January Booking Curves

	Months Before Departure	2023	2024	2025	2026	% Change (2023-2024)	% Change (2024-2025)
12	12	—	99.0	107.0	31.0	—	8.1
11	11	—	6022.0	7187.0	—	—	19.3
10	10	—	17649.0	18543.0	—	—	5.1
9	9	—	27379.0	28332.0	—	—	3.5
8	8	—	38146.0	38360.0	—	—	0.6
7	7	—	56818.0	49775.0	—	—	-12.4
6	6	—	72895.0	65635.0	—	—	-10.0
5	5	103462.0	118488.0	106584.0	—	14.5	-10.0
4	4	162681.0	176850.0	148323.0	—	8.7	-16.1
3	3	266329.0	271449.0	227540.0	—	1.9	-16.2
2	2	420622.0	421061.0	347678.0	—	0.1	-17.4
1	1	734710.0	712490.0	600016.0	—	-3.0	-15.8
0	0	913655.0	875241.0	755247.0	—	-4.2	-13.7

Figure 23: June Booking Curves

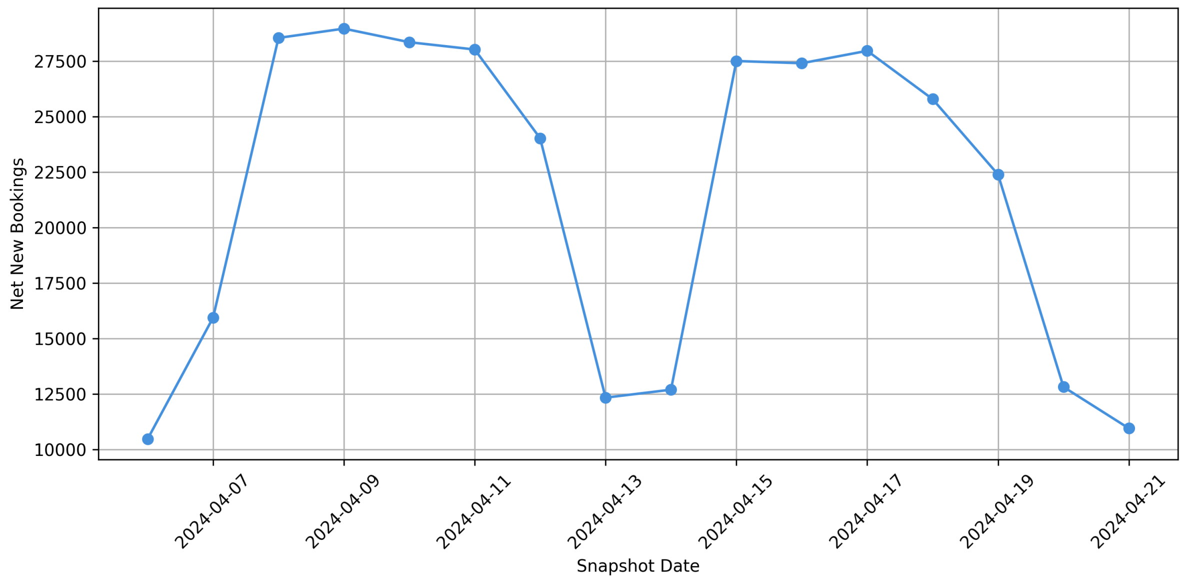

Figure 24: Weekly Booking Pattern

References

[1] George A. Akerlof and Robert J. Shiller. *Animal Spirits: How Human Psychology Drives the Economy, and Why It Matters for Global Capitalism*. Princeton University Press, Princeton, NJ, 2009.

[2] George E. P. Box and George C. Tiao. Intervention analysis with applications to economic and environmental problems. *Journal of the American Statistical Association*, 70(349):70–79, 1975.

[3] Budget Your Trip. How much money will you need for your trip to the united states of america?, 2024.

[4] Christopher D. Carroll, Jeffrey C. Fuhrer, and David W. Wilcox. Does consumer sentiment forecast household spending? if so, why? *American Economic Review*, 84(5):1397–1408, 1994.

[5] Stuart Gilmour, Louisa Degenhardt, Wayne Hall, and Carolyn Day. Using intervention time series analyses to assess the effects of imperfectly identifiable natural events: A general method and example. *BMC Medical Research Methodology*, 6(16), 2006.

[6] CBC News. Canada federal election poll tracker. Online interactive poll tracker, 2025.

[7] H. R. Seddighi and A. L. Theocharous. A model of tourism destination choice: A theoretical and empirical analysis. *Tourism Management*, 23(5):475–487, 2002.