# Leveling Up in Lockdown

A Bayesian Causal Analysis of the Pandemic's Impact on Mobile Gaming

*Statistical Programming with R, Group 12*

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## Abstract

This study investigates the causal impact of the COVID-19 pandemic on the mobile gaming industry, with an emphasis on examining both short-term pandemic effects and longer-term developments in gaming performance. Using a Bayesian Structural Time Series (BSTS) framework, we estimate counterfactual outcomes to assess how key gaming metrics would have evolved in the absence of governmental pandemic-related interventions. The analysis focuses on four countries—the United States, Sweden, the United Kingdom, and Taiwan—chosen to reflect diverse policy responses and behavioral contexts during the pandemic. We examine multiple performance indicators, including revenue, downloads, daily active users (DAU), and average revenue per daily active user (ARPDAU). By constructing counterfactual trajectories based on pre-pandemic data, the BSTS approach disentangles pandemic-related effects from underlying trends and seasonal patterns, allowing for a causal interpretation of observed changes, both in the short-term (immediate pandemic-related shocks) and the long-term (sustained uplift since the pandemic-related shocks).

The results reveal cross-country heterogeneity in both the magnitude and persistence of pandemic effects. The United States and the United Kingdom exhibit more pronounced short-term increases in monetization, while effects observed in Sweden and Taiwan are weaker or more uncertain, indicating that the pandemic affected mobile gaming performance differently across countries. Overall, the findings suggest that the primary impact of more restrictive Governmental policies during the COVID-19 pandemic on the mobile gaming industry lies in short-term changes in spending behavior among existing users. The pandemic did not lead to a sustained expansion of the user base; instead, it temporarily increased average spending among players who were already active in the market.

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# 1 Introduction

The COVID-19 pandemic created an unprecedented external shock that reshaped digital consumption globally, including the mobile gaming industry. As lockdowns, mobility restrictions, and the shift to remote work limited people's ability to go out, individuals relied more heavily on indoor activities for both work and entertainment. This is where mobile gaming emerged as particularly popular pastime. While changes in daily behaviour can be observed during this period of time, these patterns only suggest a relationship with COVID-19, not a proof of causality.

To establish causality, we would have needed to observe a hypothetical world where the pandemic did not occur. Due to the absence of this counterfactual scenario, the observed effects cannot be definitively isolated as effects of the pandemic. In other words, there may be a correlation, but this alone does not inform us whether it was the pandemic or other external influences that caused these changes. In this study, we create this counterfactual scenario by employing the BSTS package. By leveraging Bayesian Structural Time-Series models, this package allows us to predict the "business-as-usual" trajectory of the mobile gaming industry based on pre-pandemic data. This synthetic counterfactual serves as a baseline, allowing us to isolate the specific causal effect of the pandemic from other external influences. The analysis distinguishes between the immediate effects observed during periods of COVID-19 restrictions and the longer-term effects on the subsequent development of the industry.

The analysis is conducted separately for each country—Sweden, the United States, the United Kingdom, and Taiwan—to assess whether a causal relationship between the pandemic and mobile gaming outcomes exists within each national context. Observed differences across countries are discussed descriptively, taking into account their distinct policy environments and cultural backgrounds.

The central questions of this project are as follows:

- Did the pandemic truly cause an increase in the mobile game industry?
- What is the estimated causal impact of the pandemic on the mobile game industry, distinguishing it from existing trends?
- Was the pandemic's impact on the mobile gaming industry transient, or did it cause a permanent structural shift?
- How did heterogeneity in pandemic-related national policies between countries affect the magnitude, timing and duration of the impact?

# 2 Data

To investigate the causal impact of the COVID-19 pandemic on the mobile gaming industry, this study primarily relies on daily time-series data from Sensor Tower, which provide information on downloads, revenue, and player activity. In addition, data from the OECD's Oxford COVID-19 Government Response Tracker (OxCGRT) are used as a reference to define the pandemic period.

## 2.1 Data Collection and Variable Description

The response variables for this study were obtained from Sensor Tower, a leading mobile app intelligence platform. Sensor Tower employs a hybrid data collection methodology, combining direct store scraping (from the Apple App Store and Google Play Store) with a proprietary panel of millions of mobile devices. These raw inputs are processed through statistical models to estimate daily figures for downloads, revenue, and active users. The Sensor Tower data span from January 1, 2017 to November 18, 2025, covering the pre-pandemic, pandemic, and post-pandemic periods.

To answer the research questions regarding market shifts and user behavior, we have chosen metrics across three distinct categories (summarized in Table 1):

- **User Acquisition (Downloads):** Measured as the absolute number of daily unique app installs. This variable is critical for determining if the pandemic drove an influx of *new* players into the ecosystem.
- **Engagement (DAU):** Daily Active Users (DAU) is measured as the number of users recording at least one session in a given day per unique application, meaning users active in multiple games are counted distinctively for each title. This allows us to test the hypothesis that mobility restrictions increased the frequency of play.
- **Monetization (Revenue & ARPDAU):** Revenue is measured in gross USD generated via In-App Purchases (IAP). Average Revenue Per Daily Active User (ARPDAU) serves as a normalized metric to distinguish whether revenue spikes were caused by more users or by existing users spending more.

The intervention timing is defined using the Oxford COVID-19 Government Response Tracker (OxCGRT) Stringency Index, which measures the strictness of pandemic-related government policies for each country. The OxCGRT data cover the period from January 1, 2020 to December 31, 2022. Country-specific intervention points for the Bayesian Structural Time Series models are derived from this index.

Table 1: DESCRIPTION OF VARIABLES USED IN THE ANALYSIS

| Variable | Description | Unit |
|---|---|---|
| *Indices* | | |
| Date | Observation date (daily). | Day |
| Country | Country code (SW, US, GB, TW). | Category |
| *Response Variables* | *(All metrics segmented by iPad, iPhone, Android)* | |
| Downloads | Number of mobile game downloads. | Count |
| Revenue | Total Gross Revenue via In-App Purchases. | USD ($) |
| DAU | Daily Active Users. | Count |
| ARPDAU | Efficiency metric: Revenue divided by DAU. | USD ($) |
| *Intervention Variable* | | |
| Stringency Index | Index representing the strictness of government policies | Index (0-100) |

## 2.2 Data Reliability and Shortcomings

While Sensor Tower data is an industry-standard proxy for mobile performance, it has inherent limitations. First, the data are estimates rather than census-level figures and may be subject to selection bias, as the underlying user panel can over-represent heavy or tech-savvy users. As a result, trends and relative comparisons are likely reliable, while absolute values should be interpreted with caution.

Second, aggregating all mobile game genres may hide heterogeneous responses across game types. Opposing effects across genres could offset each other at the aggregate level and lead to weaker overall estimates.

Finally, the OxCGRT Stringency Index reflects announced government policies rather than actual individual behavior. Differences between policy announcements and real-world compliance may introduce uncertainty in the timing and magnitude of the estimated intervention effects.

## 2.3 Data Transformations and Preprocessing

### 2.3.1 Sensor Tower Data

The outcome variables considered in this study—Downloads, Revenue, DAU, and ARPDAU—are originally reported separately by platform, including iPhone, iPad, and Android. As preliminary analysis revealed a high degree of correlation across platforms (see Appendix A.1), the platform-specific series were aggregated into a single total series for each variable to facilitate a holistic market-level analysis. All data are complete and contain no missing observations. Apart from this aggregation step, no additional preprocessing were applied to the response variables.

While we experimented with log-transformations to address potential heteroscedasticity, diagnostic checks indicated no significant improvement in model fit or residual behavior. Consequently, we retained the original scale to maintain direct interpretability of the absolute cumulative effects and avoid transformation bias.

### 2.3.2 OxCGRT Data

For the OxCGRT dataset, the information is used to define the timing and duration of the pandemic period rather than as a direct input to the outcome models. Specifically, we rely on the Stringency Index, which reflects the overall strictness of government policy responses, as a reference for identifying periods of heightened pandemic intervention.

To account for cross-country differences in policy implementation and baseline stringency levels, a country-specific threshold is adopted. For each country, the median value of the Stringency Index over the study period is computed, and periods in which the index exceeds the country's median are classified as periods of stronger policy intervention, corresponding to the pandemic phase. By defining the binary intervention point based on whether the index exceeds the country-specific median, we ensure that the model captures periods of intensified restriction relative to each nation's unique socio-political responses, thereby preventing false negatives in the causal analysis. This adjustment is necessary to account for the relative nature of policy shocks. The subsequent return below the threshold is used to identify the end of the period with intensified restrictions.

The median Stringency Index values used for this classification are 44.0 for the United Kingdom, 37.6 for Sweden, 25.0 for Taiwan, and 52.2 for the United States.

## 2.4 Exploratory Data Analysis

As a precursor to the primary empirical analysis, we conducted a preliminary Exploratory Data Analysis (EDA) to assess the distributional characteristics and integrity of the dataset. We generated histograms and boxplots to visually inspect the central tendency, dispersion, and potential skewness of key variables. These diagnostic visualizations, which help confirm data consistency and identify potential outliers, are presented in the Appendix A.2.

### 2.4.1 Time Series Plots

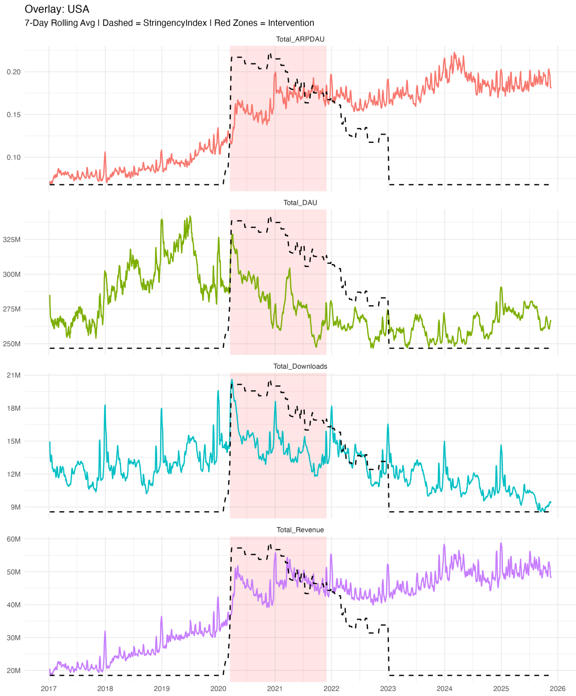
Figure 1 (a)–(d) compare the time series of the outcome variables with the policy stringency index over time. The colored lines represent the outcome variables, while the dashed line indicates the policy stringency index. Shaded areas denote the intervention periods. These plots are used to examine how the outcomes evolve before, during, and after periods of heightened policy restrictions.

**United States (USA).** From Figure 1a, ARPDAU and total revenue rise sharply at the onset of the intervention period and partially revert as policy stringency decreases. In contrast, DAU and downloads decline during the intervention period and show only modest recovery afterward. Compared with the other countries, the changes observed in the U.S. are larger in magnitude and more abrupt around the intervention period.

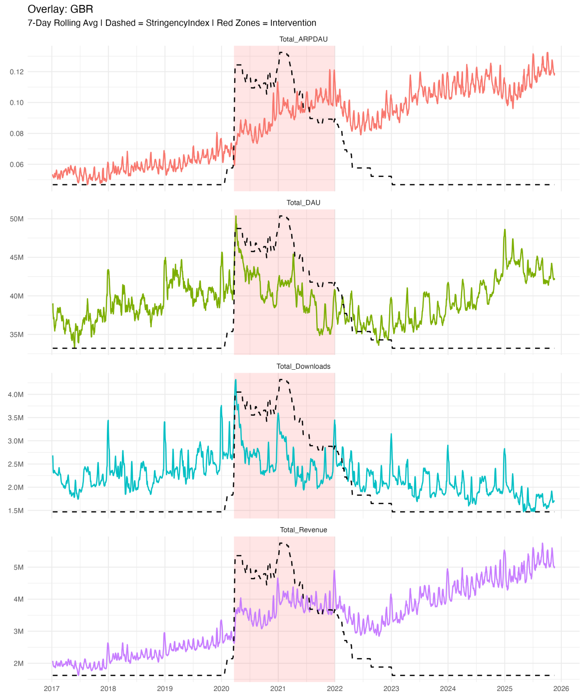
**United Kingdom (GBR).** From Figure 1b, ARPDAU and total revenue increase during the intervention period and remain above pre-intervention levels in the subsequent period. At the same time, DAU and downloads decline during the intervention and stay below their pre-pandemic trajectories afterward. The figure shows consistent directional differences between monetization metrics and user-scale metrics across time.

**Sweden (SWE).** From Figure 1c, ARPDAU and total revenue increase during the intervention period and remain relatively elevated even after policy stringency declines. Though, this remains unclear whether this is specifically a continuation of the trend or a causal link to the policies. In contrast, DAU and downloads show a downward trend starting around the intervention period and do not fully recover afterward. The figure highlights a clear divergence between monetization-related metrics and user-scale metrics over time.

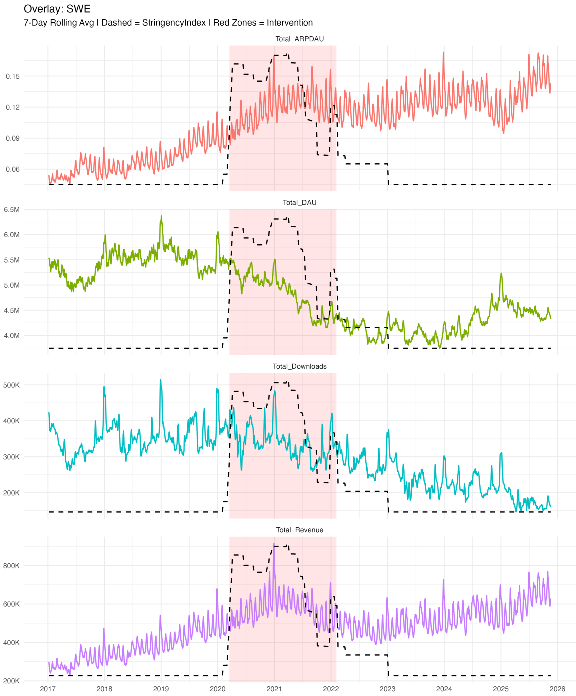
**Taiwan (TWN).** From Figure 1d, changes in gaming metrics appear to show no direct correlation with the stringency. ARPDAU and total revenue appear to continue rising during the intervention period and stabilize afterward, while DAU and downloads decline during the same period and exhibit only limited recovery following the intervention.



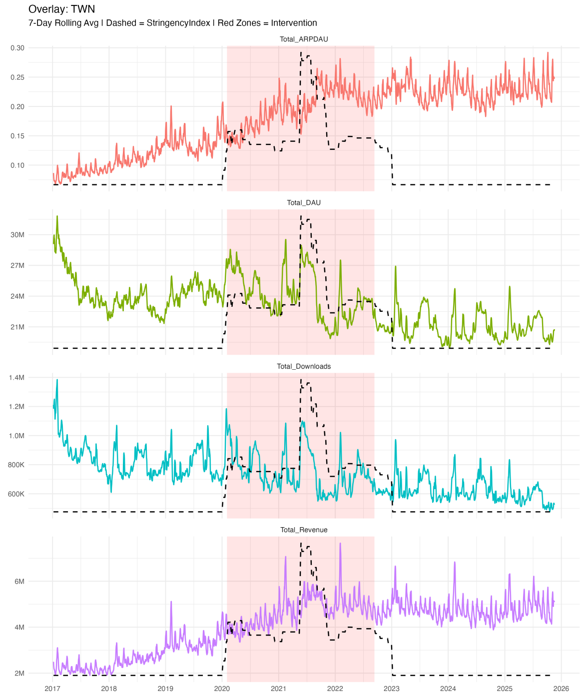

(a) United States




(b) United Kingdom




(c) Sweden




(d) Taiwan

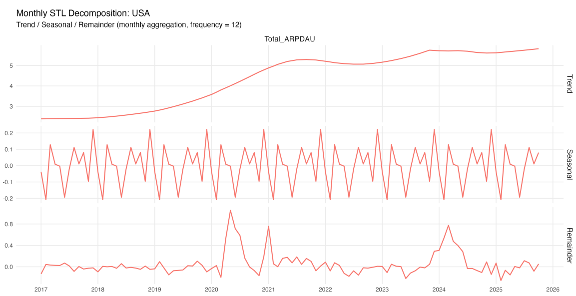
Figure 1: Time-series overlays of gaming outcomes and policy stringency across four countries

### 2.4.2 Seasonal–trend decomposition (STL)

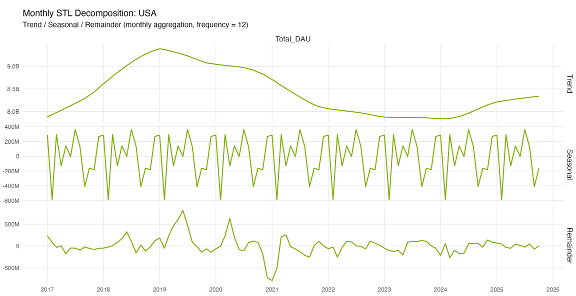
Figure 2 presents the monthly STL decomposition of the four outcome variables in the United States. Each panel decomposes the observed time series into a long-term trend, a seasonal component with annual frequency ($S = 12$), and a remainder capturing irregular fluctuations, allowing persistent structural changes to be separated from recurring seasonal patterns and short-term noise.

Across all outcomes, clear and stable annual seasonal patterns are observed, indicating strong within-year fluctuations in user activity and monetization. The trend components reveal distinct long-term dynamics: ARPDAU and revenue show sustained upward trends following the pandemic onset, whereas DAU and downloads peak around 2019–2020 and decline thereafter. The remainder components fluctuate around zero without persistent structure, suggesting that most systematic variation is captured by the trend and seasonal components. However, distinct structural anomalies align with the COVID-19 timeline, suggesting an exogenous shock consistent with the hypothesized framework.

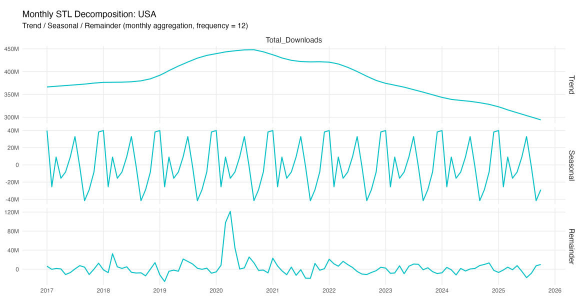
The pronounced seasonality observed across outcomes motivates the inclusion of a seasonal state component with $S = 12$ in the BSTS model specification. Additional STL decompositions for UK, Sweden and Taiwan are provided in the Appendix A.3 and exhibit similar seasonal and trend patterns.



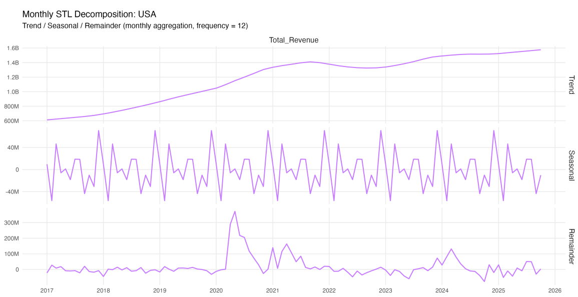

(a) STL decomposition of ARPDAU (USA)




(b) STL decomposition of DAU (USA)




(c) STL decomposition of Downloads (USA)




(d) STL decomposition of Revenue (USA)

Figure 2: Monthly STL decomposition of outcome variables in the United States

# 3 Methods

## 3.1 BSTS Approach and Motivation

We employ a **Bayesian Structural Time Series (BSTS)** [1] framework to estimate the causal impact of COVID-19 policy interventions on mobile gaming activity. While alternative causal inference strategies were considered—specifically Difference-in-Differences (DiD), Interrupted Time Series (ITS), and ARIMA forecasting—the BSTS approach was selected for its unique ability to address the lack of a geographic control group and its flexibility in modeling intervention effects and dynamic components.

1. **Creating a Synthetic Control Group**

   Since the COVID-19 pandemic acted as a global exogenous shock, leaving no "un-treated" market to serve as a baseline, BSTS addresses this by constructing a synthetic counterfactual based purely on the temporal evolution of the treated unit itself. By training the model on pre-pandemic data (2017–2019), BSTS projects this "business-as-usual" trajectory into the post-lockdown period, allowing us to synthetically create a counterfactual group.

2. **Advantages over Rigid Time-Series Models (ITS and ARIMA)**

   Traditional Interrupted Time Series (ITS) regression was rejected due to its reliance on rigid parametric assumptions. ITS typically models trends using linear or polynomial functions, which are ill-suited for the volatile, non-linear growth patterns observed in the mobile gaming sector. Furthermore, while ARIMA is a robust tool for forecasting, it operates as a reduced-form model that aggregates latent components into fixed auto-regressive parameters. Unlike the State-Space framework of BSTS, ARIMA does not explicitly decompose the series into time-varying trend and seasonal states, effectively obscuring the structural drivers of the data. This modularity is essential for distinguishing whether post-pandemic revenue spikes were driven by genuine causal impact or merely by the sector's underlying organic growth.

3. **Bayesian Uncertainty Quantification**

   Finally, the Bayesian framework provides a coherent mechanism for quantifying risk. BSTS yields full posterior distributions for the cumulative causal effect. This probabilistic output allows us to calculate the probability that a causal effect occurred (Posterior Tail Probability) and provides intuitively interpretable Credible Intervals, offering a robust measure of statistical significance that accounts for the uncertainty in both the model parameters and the noise.

## 3.2 Model Specification

The BSTS model decomposes the observed outcome into trend, seasonal, and intervention-related components, allowing us to isolate policy effects from organic growth patterns.

To isolate the causal effect, we employ a state-space model where the relationship between stringency and the outcome variables evolves stochastically.

Let $Y_t$ denote the observed outcome variable at time $t$, where $Y_t$ represents Downloads, Revenue, DAU, or ARPDAU. The BSTS model is applied directly to the raw outcome series $Y_t$ without transformation.

The master observation equation for the counterfactual time series (trained on pre-intervention data) is defined as:

$$y_t = \underbrace{\mu_t}_{\text{Trend}} + \underbrace{\gamma_t}_{\text{Seasonality}} + \underbrace{\epsilon_t}_{\text{Noise}}$$

- $\mu_t$ is the local linear trend (long term level)
- $\gamma_t$ is the seasonal component

- $\epsilon_t \sim \mathcal{N}(0, \sigma_\epsilon^2)$.

Each of the individual components can be broken down as follows.

#### 3.2.1 Local Linear (Baseline) Trend, $\mu_t$

The baseline organic growth of the mobile gaming market is modeled as a local linear trend. This formulation extends a random walk by incorporating a stochastic slope component, allowing the trend direction to drift over time:

$$\begin{aligned} \mu_{t+1} &= \mu_t + \delta_t + \eta_{\mu,t}, \quad && \eta_{\mu,t} \sim \mathcal{N}(0, \sigma_\mu^2) \\ \delta_{t+1} &= \delta_t + \eta_{\delta,t}, && \eta_{\delta,t} \sim \mathcal{N}(0, \sigma_\delta^2). \end{aligned}$$

Here, $\mu_t$ represents the latent trend level and $\delta_t$ the time-varying growth rate. The disturbance terms $\eta_{\mu,t}$ and $\eta_{\delta,t}$ allow both components to evolve gradually over time, with $\sigma_\mu^2$ and $\sigma_\delta^2$ governing the magnitude of these variations.

This component represents the underlying growth trajectory that would have occurred in the absence of the pandemic.

#### 3.2.2 Seasonality, $\gamma_t$.

To account for periodic fluctuations in user activity, we model the seasonal effect such that the sum over $S = 12$ periods approximates zero. For the seasonal component:

$$\sum_{s=0}^{S-1} \gamma_{t+s} = \eta_{\gamma,t}, \quad \eta_{\gamma,t} \sim \mathcal{N}(0, \sigma_\gamma^2).$$

This constraint ensures that seasonal deviations balance out over a full cycle, separating cyclical behavior from the long-term trend.

#### 3.2.3 Observation Error, $\epsilon_t$

The observation error connects the latent state components to the observed data $y_t$. It captures high-frequency noise, measurement errors, and idiosyncratic shocks that are not explained by the structural trend or seasonal components:

$$\epsilon_t \sim \mathcal{N}(0, \sigma_\epsilon^2).$$

This component assumes that deviations from the structural signal are normally distributed with constant variance $\sigma_\epsilon^2$. In the Bayesian framework, the posterior distribution of $\sigma_\epsilon^2$ effectively quantifies the model's uncertainty regarding the "signal-to-noise" ratio of the mobile gaming time series.

### 3.3 Analysis Procedure

For each country and each outcome variable, we estimate a Bayesian Structural Time Series (BSTS) model using Markov Chain Monte Carlo (MCMC) sampling based on the pre-intervention period. The intervention is defined by the onset of the COVID-19 pandemic, with the pandemic period identified using the country-specific Stringency Index to capture the timing of policy restrictions.

The BSTS model captures the underlying trend and seasonal components of each outcome series and is used to generate counterfactual predictions for the post-intervention period. Causal effects are assessed by comparing the observed outcomes with these counterfactual trajectories.

Two complementary causal questions are examined. First, we evaluate whether the onset of the COVID-19 pandemic had a causal impact on the mobile gaming industry by comparing outcomes in the pre-pandemic period with those during the pandemic period as defined by the Stringency Index. Second, we investigate whether the pandemic exerted a persistent, long-term causal effect by extending the post-intervention period from the pandemic onset through November 2025, thereby assessing longer-run deviations from the counterfactual trend.

Posterior inference focuses on the distribution of the estimated causal effects, summarized through average and cumulative effects along with their posterior credible intervals. These intervals are used to evaluate whether the estimated effects are statistically distinguishable from zero.

The analysis is conducted separately for four countries—Sweden, the United States, the United Kingdom, and Taiwan—with results interpreted within each national context.

### 3.4 Interpretation of Posterior Outcomes

The Bayesian Structural Time Series model yields a full posterior distribution of the counterfactual outcome trajectory, which enables a probabilistic assessment of the pandemic's causal impact. Three posterior summaries are used to interpret the results: the counterfactual prediction, the absolute effect, and the relative effect.

**Counterfactual Prediction.** The counterfactual prediction represents the expected level of the outcome that would have been observed in the absence of the COVID-19 pandemic. Formally, it is defined as the posterior mean

$$\hat{Y}_t = \frac{1}{M} \sum_{m=1}^{M} \tilde{Y}_t^{(m)},$$

where $\tilde{Y}_t^{(m)}$ denotes the $m$-th posterior draw from the BSTS model. The associated posterior standard deviation quantifies uncertainty in the counterfactual trajectory induced by model estimation and stochastic variation.

This quantity serves as the baseline against which all causal effects are evaluated and is critical for validating whether observed deviations can be attributed to the pandemic rather than to pre-existing trends or seasonal patterns.

**Absolute Effect.** The absolute causal effect at time $t$ is defined as

$$\Delta_t = Y_t - \hat{Y}_t,$$

and the cumulative effect over the post-intervention period is given by

$$\widehat{\Delta}_{\text{Cumulative}} = \sum_{t=T_0}^{T_{\text{end}}} (Y_t - \hat{Y}_t).$$

This measure captures the total deviation of the observed outcome from its counterfactual path and directly answers the question of whether the pandemic caused a net increase or decrease in the outcome relative to what would have occurred otherwise. A posterior credible interval that excludes zero provides evidence that the estimated effect is statistically distinguishable from random fluctuations.

**Relative Effect.** To facilitate comparison across countries and outcome variables with different scales, we additionally report the relative effect,

$$R_t = \frac{Y_t - \hat{Y}_t}{\hat{Y}_t}.$$

The relative effect expresses the pandemic-induced deviation as a proportion of the counterfactual baseline and is particularly useful for assessing the magnitude of the pandemic's impact in standardized terms, such as percentage changes. This normalization enables meaningful cross-country comparisons even when baseline market sizes differ substantially.

Taken together, these posterior summaries allow us to jointly verify (i) the presence of a causal effect, (ii) its direction and magnitude, and (iii) its economic or behavioral relevance, while fully accounting for uncertainty in the counterfactual estimation.

# 4 Implementation

## 4.1 Package Overview

Our analysis relies on the `bsts` and `CausalImpact` packages. The `bsts` package provides the Bayesian Structural Time Series (BSTS) framework for modeling time-series data, allowing flexible decomposition into components such as trend, seasonality, and noise within a state-space formulation. The `CausalImpact` package builds upon `bsts` and is designed for causal inference in time-series settings by comparing observed outcomes with counterfactual predictions generated from a BSTS model fitted to pre-intervention data. In addition, `CausalImpact` facilitates interpretation by automatically producing posterior summaries and graphical visualizations of the estimated causal effects.

Additional R packages, including `dplyr`, `tidyr`, `lubridate`, `zoo`, and `ggplot2`, are used for data preprocessing, time-series handling, and visualization.

## 4.2 BSTS Model Implementation

For each country and outcome variable, the analysis is conducted on aggregated monthly time-series data. Daily observations are aggregated to the monthly level using summation, and the intervention timing is determined based on date at which the Stringency Index hits the Median for the first time. The pre-intervention period is used to estimate the model, while post-intervention observations are held out for causal evaluation.

The Bayesian Structural Time Series model includes a seasonal component specified with a 12-month period to capture annual seasonality in the aggregated data, along with a local linear trend. Prior distributions for the trend components are calibrated based on the variability observed in the pre-intervention data to ensure stable estimation. When generating the counterfactual data, the model components are estimated using Markov Chain Monte Carlo sampling.

Various other parameters that were chosen are discussed in further detail in Study 2: Auxiliary Setting Investigation to justify our choices. Additionally, we excluded Auto-Regressive and Dynamic Regression components after diagnostic checks revealed they offered no improvement in model fit and introduced significant overfitting. The STL decomposition confirmed that the Local Linear Trend and Seasonal components were sufficient to capture the systematic variation, leaving the remainder residuals as white noise. Therefore, additional complexity would obscure the structural drivers of the data.

### 4.3 Simulation Design

To evaluate the validity and robustness of the BSTS-based `CausalImpact` framework, two complementary simulation exercises are conducted: a controlled simulation using synthetic data and a sensitivity analysis based on real data, using USA ARPDAU.

#### 4.3.1 Method Validation Using Synthetic Data

In the first simulation scenario, synthetic time-series data are generated to mimic key characteristics commonly observed in real-world settings, including a long-term trend, a seasonal component, and random noise. An intervention is introduced at a pre-specified time point, after which a constant effect of known magnitude is added to the outcome variable.

The BSTS-based `CausalImpact` framework is then applied to the synthetic data using the same modeling pipeline as in the empirical analysis. This simulation is designed to assess whether the modeling approach can recover a known intervention structure under controlled conditions.

#### 4.3.2 Sensitivity Analysis

To assess robustness, a series of sensitivity analyses is conducted using real data. Within the BSTS framework, key modeling components are systematically varied while the overall analysis structure is held fixed.

Specifically, sensitivity analyses examine alternative choices for the number of MCMC iterations, prior specifications, and the flexibility of the trend component. These analyses are designed to evaluate whether the empirical findings depend on particular modeling assumptions rather than the underlying data.

#### 4.3.3 Simulation Results

From Table 3, we observe that the estimated causal effects are largely stable across a range of simulation and sensitivity scenarios. Under the baseline specification, the estimated effect serves as a reference point, and alternative model configurations yield comparable effect estimates and credible intervals.

In the synthetic data scenario, where the true intervention effect is known, the estimated effect closely matches the true value and falls well within the corresponding credible interval. This result indicates that the BSTS-based `CausalImpact` framework is capable of recovering a known causal effect under controlled conditions.

Across the sensitivity analyses, varying the number of MCMC iterations, prior specifications, and the flexibility of the trend component does not lead to substantial changes in the estimated effects. While looser prior assumptions increase posterior uncertainty and tighter priors reduce it, the overall direction and magnitude of the effects remain consistent. These findings suggest that the simulation results are robust to reasonable changes in model assumptions.

**Study 1: Method Validation Using Synthetic Data**

**Objective:** To confirm that the package accurately recovers a known intervention effect. We generated a synthetic dataset of length $T = 120$ months, with known Seasonality, Trend and Causal effect from a pre-specified Intervention point.

**Data Generating Process:** The synthetic series was constructed with a deterministic linear trend (slope = 5), a sinusoidal seasonal component (amplitude = 100), and Gaussian noise ($\sigma_\epsilon = 20$). A constant structural break representing the intervention was introduced at month $t = 80$ with a true magnitude of $\beta = 200$.

**Results:** Table 2 summarizes the performance of the estimator over 1000 repetitions.

Table 2: Ideal Model Recovery (SimLand Data)

| Parameter | True Value | Est. Effect | Bias | 95% CI Lower | 95% CI Upper |
|---|---|---|---|---|---|
| Intervention ($\beta$) | 200.0 | 193.67 | -6.33 | 149.84 | 234.77 |

**Commentary & Alignment:** The results strongly align with our expectations. The bias for the intervention coefficient is within reason, and the 95% Credible Interval confirms the statistical significance. These results confirm that the `bsts` package correctly identifies the true causal parameter $\beta = 200$ within the credible intervals, even when the underlying seasonality is sinusoidal.

**Study 2: Auxiliary Setting Investigation**

**Objective:** To assess the sensitivity of the model to hyperparameter choices and ensure the robustness of our results. We tested the impact of varying the MCMC iteration count, the prior standard deviation ($\sigma$), and the trend flexibility.

**Results:** Table 3 presents the estimated effects and credible intervals across six different model specifications using USA ARPDAU data.

**Commentary & Alignment**

The sensitivity analysis demonstrates the robustness of our baseline specification while highlighting the importance of informative priors in this context.

Table 3: Simulation and Sensitivity Analysis Results

| **Scenario** | **Specification** | **Est. Effect** | **CI Lower** | **CI Upper** | **Iter.** |
|---|---|---|---|---|---|
| Baseline (Default) | Prior $\sigma = 0.001$, Prior $N = 10000$ | 0.60 | $-0.28$ | 1.55 | 1000 |
| MCMC (Low) | $N = 500$ | 0.61 | $-0.25$ | 1.48 | 500 |
| MCMC (High) | $N = 50000$ | 0.59 | $-0.36$ | 1.54 | 50000 |
| Tight Prior | $\sigma = 10^{-6}$ | 0.61 | $-0.29$ | 1.54 | 1000 |
| Loose Prior | $\sigma = 1$ | 4.01 | $-89.22$ | 100.31 | 1000 |
| Flexible Trend | Prior $N = 32$ | 0.60 | $-0.28$ | 1.54 | 1000 |

- **MCMC Stability:** The estimated effect remains stable across iteration counts. The point estimates for Low ($N = 500$), Baseline ($N = 1{,}000$), and High ($N = 50{,}000$) iterations are all within the same order of magnitude, and the Credible Intervals overlap almost perfectly. This confirms that our chosen baseline of $N = 10{,}000$ achieves convergence without the computational cost of the High specification.

- **Prior Sensitivity:** The choice of prior variance ($\sigma$) dictates how flexible the model expects the trend to be. As summarized below, our Baseline choice ($\sigma = 0.001$) provides the optimal balance:

| **Prior ($\sigma$)** | **Interpretation** | **Trend Behavior** | **Risk** |
|---|---|---|---|
| $10^{-6}$ | "Growth rate is constant." | Rigid, Straight Line | **Bias:** Fails to capture non-linear organic growth. |
| 0.001 | "Growth rate evolves slowly." | Smooth Curve | **Ideal:** Balances flexibility and stability. |
| 1.0 | "Growth rate changes wildly." | Wobbly, Erratic | **Variance:** Massive uncertainty; absorbs noise. |

  The "Loose Prior" result in Table 3 confirms this risk: specifying $\sigma = 1$ caused the uncertainty interval to expand by two orders of magnitude ($10^2$), rendering the results unusable. This validates our use of the empirically motivated Baseline prior.

- **Model Structure:** The "Flexible Trend" scenario produced results nearly identical to the Baseline, suggesting that our standard local linear trend specification is capturing the underlying dynamics correctly without requiring additional degrees of freedom.

# 5 Results

This section presents the estimated causal effects of COVID-19 policy interventions on mobile gaming outcomes. Results are reported separately for the intervention period ('short-term'), capturing immediate responses during active policy restrictions, and for the overall post-intervention period ('long-term'), reflecting broader and structural shifts to the industry.

The analysis is conducted for four countries—Sweden, the United States, the United Kingdom, and Taiwan—and focuses on four key outcome measures: daily active users (DAU), downloads, average revenue per daily active user (ARPDAU), and total revenue.

### 5.1 Estimated Pandemic Effects Across Countries

Tables 4–7 and Figures 3–6 report the estimated causal effects for the United States, the United Kingdom, Sweden, and Taiwan. Each causal impact figure presents the observed outcome and its counterfactual prediction (top panel), the pointwise causal effect (middle panel), and the cumulative effect over time (bottom panel), with shaded areas indicating posterior credible intervals.

#### 5.1.1 United States (USA)

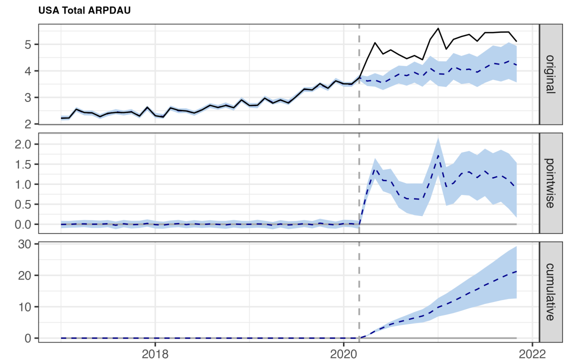
As shown in Table 4, the results for the United States indicate a strong short-term monetization response to the COVID-19 pandemic, followed by weaker and less persistent long-term effects. ARPDAU increases significantly in the short term, suggesting that active users spent more during the intervention period, while the long-term effect remains statistically uncertain. In contrast, DAU declines significantly in the short term, and downloads decrease significantly in both the short and long term, with a larger decline observed over the longer horizon. Revenue reflects this divergence, showing a significant short-term increase driven by higher spending per user, but no statistically significant long-term effect.

Table 4: Causal effects of the COVID-19 pandemic in the United States

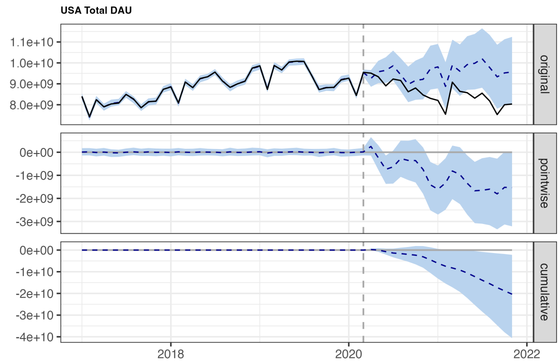
| Outcome | Period | Relative Effect (95% CI) | AvgMonthlyEffect (95% CI) | Sig. |
|---|---|---|---|---|
| ARPDAU | Long-term | +13.8% [-5.0, +40.6] | +0.604M [-0.28, +1.55] | |
| ARPDAU | Short-term | +27.2% [+14.2, +41.2] | +1.062M [+0.63, +1.47] | * |
| DAU | Long-term | -18.9% [-33.7, +2.0] | -2025.05M [-4145.25M, +158.94M] | |
| DAU | Short-term | -10.4% [-19.1, -1.2] | -1017.33M [-2019.25, -101.88] | * |
| Downloads | Long-term | -36.0% [-54.8, -7.5] | -234.71M [-462.53, -30.80] | * |
| Downloads | Short-term | -18.8% [-32.1, -3.1] | -106.64M [-208.32, -13.87] | * |
| Revenue | Long-term | -3.9% [-13.8, +7.8] | -63.45M [-230.09, +103.70] | |
| Revenue | Short-term | +16.5% [+9.4, +24.5] | +198.23M [+120.40, +276.35] | * |

Figure 3 further illustrates these patterns across the four outcome variables. The figure reveals a clear contrast between monetization-related and user-scale outcomes. ARPDAU exhibits a strong positive cumulative effect following the onset of the pandemic, while revenue shows a positive but primarily short-term cumulative effect. In contrast, DAU and downloads display negative cumulative effects, indicating sustained declines in active users and new user acquisition.

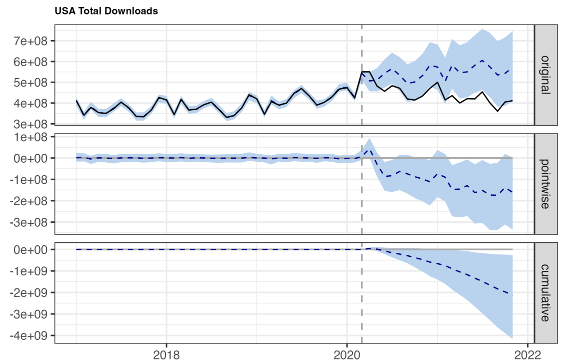
Taken together, these results suggest that short-term revenue gains during the pandemic were driven mainly by higher spending among existing users rather than by market expansion. This pattern is consistent with a temporary reallocation of consumption toward gaming during periods of restricted offline activity. However, the effects weaken over time, with longer-term indicators pointing toward a reversion in consumption behavior as these constraints relaxed.



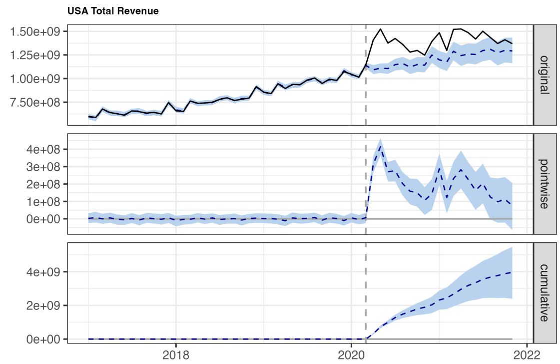

(a) ARPDAU




(b) DAU




(c) Downloads




(d) Revenue

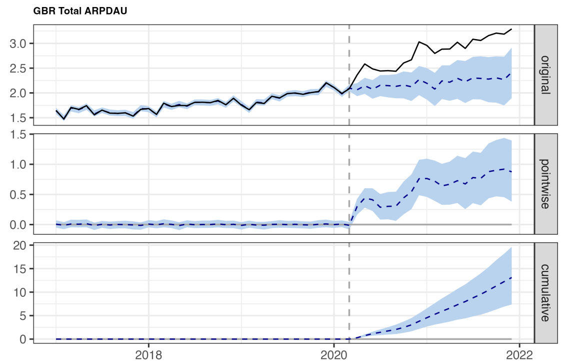
Figure 3: Estimated causal effects of the COVID-19 pandemic on U.S. mobile gaming outcomes.

#### 5.1.2 United Kingdom (GBR)

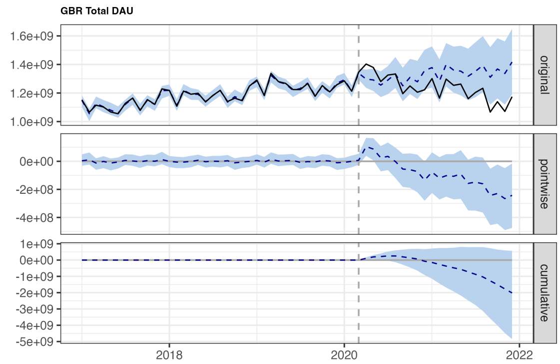
As shown in Table 5 and Figure 4, the results show that the impact of the COVID-19 pandemic on the UK mobile gaming market mainly reflects a contrast between monetization and user scale. The estimated effects point in the same direction in both the short term and the long term, indicating no clear reversal over time. Both ARPDAU and total revenue exhibit positive and statistically significant effects, indicating that active users spent more on average during the pandemic, which supported overall revenue growth. In contrast, DAU and downloads decline, with the reduction in downloads being larger and statistically significant, suggesting that new user acquisition was negatively affected. These patterns imply that revenue growth did not come from an expansion of the user base or higher engagement, but rather from increased spending by existing users. Overall, the pandemic did not expand the market size, but instead shifted the market toward higher monetization among a smaller user base.

Table 5: Causal effects of the COVID-19 pandemic in the United Kingdom

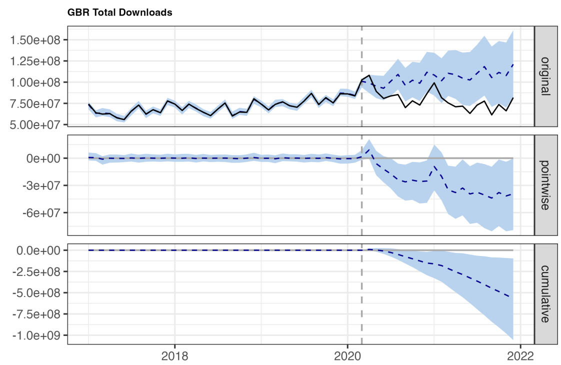
| Outcome | Period | Relative Effect (95% CI) | AvgMonthlyEffect (95% CI) | Sig. |
|---|---|---|---|---|
| ARPDAU | Long-term | +27.2% [-0.1, +70.0] | +0.615M [-0.00, +1.27] | * |
| ARPDAU | Short-term | +28.8% [+14.0, +48.9] | +0.624M [+0.35, +0.93] | * |
| DAU | Long-term | -14.5% [-28.9, +3.2] | -217.05M [-491.61, +37.74] | |
| DAU | Short-term | -7.0% [-15.9, +2.1] | -95.95M [-232.54, +25.74] | |
| Downloads | Long-term | -40.8% [-61.0, -5.8] | -52.05M [-105.00, -4.16] | * |
| Downloads | Short-term | -24.6% [-39.0, -5.7] | -26.98M [-50.18, -4.74] | * |
| Revenue | Long-term | +10.2% [-1.8, +25.3] | +10.84M [-2.23, +24.73] | * |
| Revenue | Short-term | +20.6% [+13.0, +29.4] | +19.39M [+13.12, +25.91] | * |



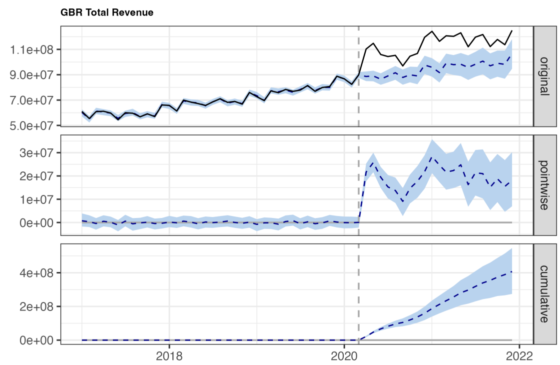

(a) ARPDAU (Short-Term)




(b) DAU




(c) Downloads




(d) Revenue

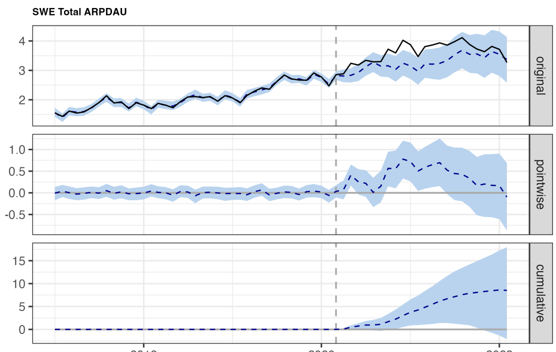
Figure 4: Estimated causal effects of the COVID-19 pandemic on U.K. mobile gaming outcomes.

#### 5.1.3 Sweden (SWE)

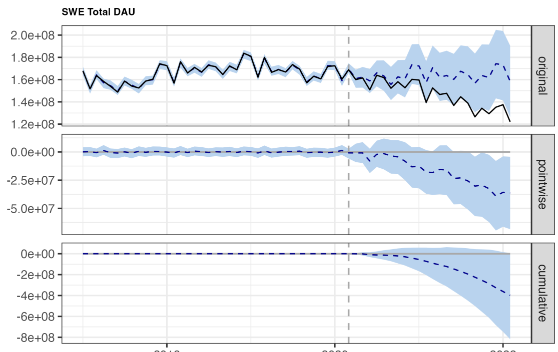
As shown in Table 6 and Figure 5, the results for Sweden show generally weak and mixed effects of the COVID-19 pandemic on the mobile gaming market. ARPDAU increases in the short term, indicating a temporary rise in spending per active user, but this effect does not persist into the long term, where the estimated effect becomes slightly negative and statistically insignificant. DAU declines in both the short term and the long term, suggesting a consistent reduction in the number of active users over time. Downloads also show negative effects in both periods, but these effects are not statistically significant, indicating no clear pandemic-driven change in new user acquisition. Revenue exhibits a clear difference across time horizons: while the short-term effect is close to zero, the long-term effect is significantly negative, pointing to a sustained decline in total revenue. Overall, the Swedish results suggest that any short-term changes in user spending were limited and temporary, and that the dominant impact of the pandemic was a gradual weakening of market performance rather than a short-lived monetization boost.

Table 6: Causal effects of the COVID-19 pandemic in Sweden

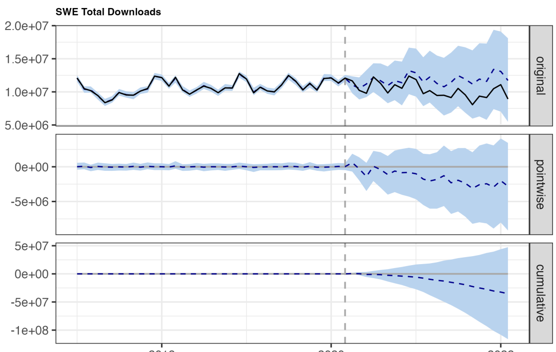
| Outcome | Period | Relative Effect (95% CI) | AvgMonthlyEffect (95% CI) | Sig. |
|---|---|---|---|---|
| ARPDAU | Long-term | -4.4% [-21.8, +19.6] | -0.219M [-1.05, +0.62] | |
| ARPDAU | Short-term | +11.9% [-2.3, +27.3] | +0.370M [-0.09, +0.78] | |
| DAU | Long-term | -17.5% [-32.1, +3.9] | -30.65M [-63.78, +5.07] | |
| DAU | Short-term | -10.3% [-19.5, +0.3] | -17.30M [-35.45, +0.39] | |
| Downloads | Long-term | -16.2% [-56.6, +51.8] | -3.89M [-10.61, +2.78] | |
| Downloads | Short-term | -10.8% [-32.9, +25.3] | -1.53M [-5.03, +2.07] | |
| Revenue | Long-term | -22.8% [-31.3, -11.7] | -5.00M [-7.58, -2.21] | * |
| Revenue | Short-term | -0.3% [-7.8, +8.3] | -0.07M [-1.48, +1.34] | |



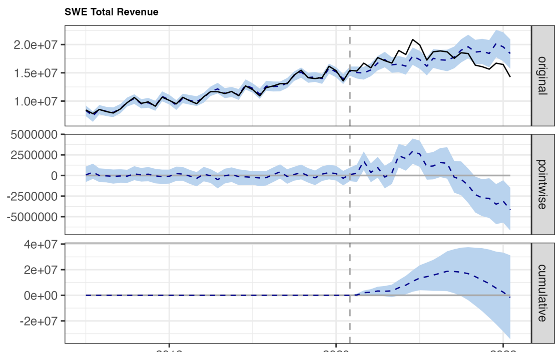

(a) ARPDAU




(b) DAU




(c) Downloads




(d) Revenue

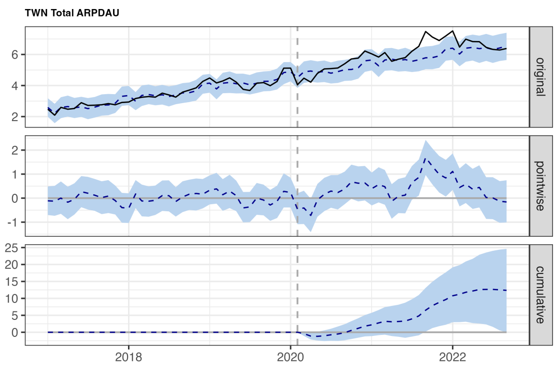
Figure 5: Estimated causal effects of the COVID-19 pandemic on Sweden mobile gaming outcomes.

#### 5.1.4 Taiwan (TWN)

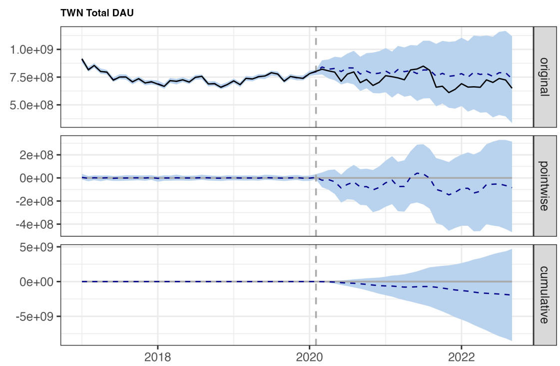
As shown in Table 7 and Figure 6, the results for Taiwan indicate generally weak and uncertain effects of the COVID-19 pandemic on the mobile gaming market. ARPDAU shows a small but statistically significant increase in the short term, suggesting a temporary rise in spending per active user during the intervention period, while the long-term effect becomes slightly negative and statistically insignificant. For DAU, both short-term and long-term effects are negative but highly uncertain, indicating no clear evidence of a systematic change in user engagement. Downloads exhibit large uncertainty in both periods, with wide confidence intervals and no statistically significant effects, suggesting that user acquisition was not strongly affected by the pandemic. Revenue also shows mixed results, with a positive but insignificant short-term effect and a negative but insignificant long-term effect. Overall, the Taiwanese results suggest that any pandemic-related changes were limited and short-lived, with no clear evidence of persistent structural impacts on user behavior or market performance.

Table 7: Causal effects of the COVID-19 pandemic in Taiwan

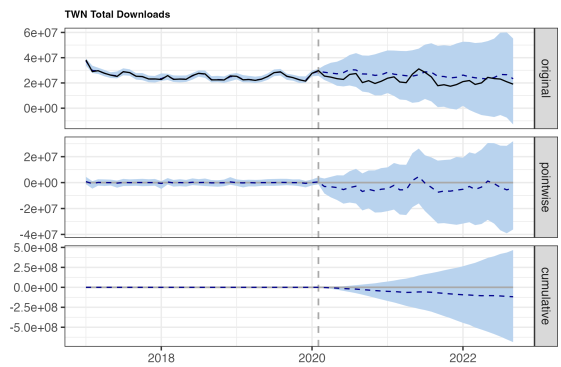
| Outcome | Period | Relative Effect (95% CI) | AvgMonthlyEffect (95% CI) | Sig. |
|---|---|---|---|---|
| ARPDAU | Long-term | -4.5% [-11.9, +3.9] | -0.318M [-0.88, +0.24] | |
| ARPDAU | Short-term | +7.2% [+0.3, +15.2] | +0.399M [+0.02, +0.80] | * |
| DAU | Long-term | -5.0% [-39.3, +87.8] | -57.45M [-422.29, +323.05] | |
| DAU | Short-term | -5.9% [-27.6, +26.2] | -62.68M [-278.10, +151.22] | |
| Downloads | Long-term | +34.9% [-632.3, +876.1] | -0.86M [-33.17, +26.53] | |
| Downloads | Short-term | -6.7% [-52.5, +147.6] | -3.81M [-22.11, +15.02] | |
| Revenue | Long-term | -9.1% [-30.0, +23.6] | -17.48M [-62.03, +27.63] | |
| Revenue | Short-term | +8.2% [-14.3, +48.1] | +8.28M [-23.99, +46.72] | |



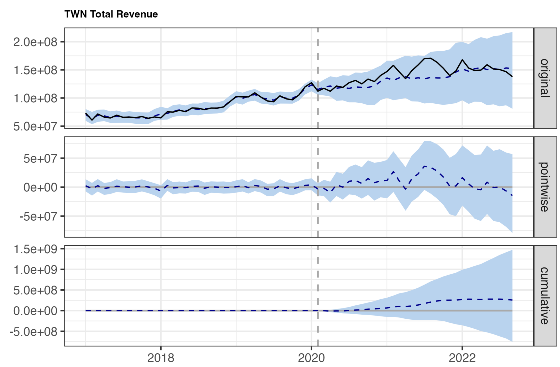

(a) ARPDAU




(b) DAU




(c) Downloads




(d) Revenue

Figure 6: Estimated causal effects of the COVID-19 pandemic on Taiwan mobile gaming outcomes.

## 5.2 Overall Interpretation of Pandemic Effects

The results collectively address the four research questions posed at the outset of this study.

### 5.2.1 Did the pandemic truly cause an increase in mobile game downloads or revenue?

The findings indicate that the pandemic did not lead to a sustained increase in mobile game downloads. In most countries, downloads declined, often significantly, suggesting that the pandemic did not expand the user base. In contrast, revenue-related outcomes, particularly ARPDAU, increased during the pandemic, indicating only temporary higher spending among existing users rather than growth in the number of players.

### 5.2.2 What is the estimated causal impact of the pandemic, distinguishing it from existing trends?

By comparing observed outcomes with counterfactual predictions derived from pre-pandemic data, the estimated effects can be interpreted as causal deviations from existing trends. Relative to the counterfactual trends, ARPDAU increased by approximately 27% in the United States, 29% in the United Kingdom, and 7% in Taiwan during the early pandemic period. For Sweden, the estimated trend is upward, but there is insufficient evidence of a pandemic-induced increase in ARPDAU.

### 5.2.3 Was the pandemic's impact transient, or did it cause a permanent structural shift?

The temporal patterns suggest that the pandemic's impact on monetization was largely transient across countries. Short-term increases in ARPDAU and revenue were observed in several markets during periods of heightened policy stringency, but these effects often weakened or became statistically insignificant over the longer term. In contrast, negative effects on user acquisition tended to persist, indicating that the pandemic did not generate lasting growth and may have contributed to longer-term challenges in expanding the user base.

### 5.2.4 How did heterogeneity in national policies affect the magnitude and timing of the impact?

**United States.** In the USA, these results indicate that short-term revenue gains during the pandemic were driven by higher spending among existing users rather than by market expansion. The observed spending behavior may be best characterized as constraint-induced substitution. The COVID-19 governmental restrictions resulted in a hard, but temporary constraint on the feasible set of consumption choices, forcing existing users to optimize utility by increasing their allocation to gaming in the absence of service-based alternatives. However, the data suggests this equilibrium was transient; while the restriction-driven substitution supported short-term performance, long-term indicators reflect a reversion in consumption behavior as these constraints relaxed.

**United Kingdom.** Similarly, in the United Kingdom, the results indicate that revenue gains during the pandemic were driven by intensified spending among existing users rather than by an expansion of the market. This observed behavior can be characterized as constraint-induced substitution. The strong governmental restrictions created a hard constraint on the feasible consumption choices, forcing existing users to optimize utility by reallocating resources to gaming in the absence of service-based alternatives. However, unlike the transient equilibrium observed in the U.S., the UK data suggests this shift was more durable; while the restriction-driven substitution triggered the initial uplift, the indicators reflect a sustained elevation in spending behavior that persisted even as these constraints relaxed.

**Sweden** Conversely, in Sweden, the results illustrate the limitations of this substitution effect in a less restrictive environment. While the data shows a temporary, short-term increase in ARPDAU, suggesting a momentary rise in spending intensity, though this effect was insufficient to generate a corresponding lift in aggregate revenue, which remained close to zero in the short term.

This divergence supports the causal hypothesis: in the absence of the strict "hard constraints" on service consumption seen in the US, the constraint-induced substitution mechanism in Sweden was significantly dampened. Lacking the exogenous shock of a full lockdown to forcibly displace disposable income into the digital sector, the Swedish market did not experience a monetization-driven windfall. Instead, the dominant causal impact of the pandemic in Sweden was a gradual weakening of market performance rather than a short-lived boost, with long-term trends pointing toward contraction rather than reversion to a higher mean.

**Taiwan** In Taiwan, the observed response appears closer to a short-lived, trend-following behavior rather than a structural change in demand. While some existing users temporarily increased their spending during the early pandemic period, this effect faded quickly and did not translate into sustained growth in either user activity or total revenue.

This pattern reflects Taiwan's relatively mild and adaptive pandemic environment. Most daily activities continued with mask-wearing, including going to gyms, restaurants, and traveling, so offline consumption was never subject to strong "hard constraints." As a result, mobile gaming functioned only as a marginal substitute, and the pandemic's impact manifested primarily as a temporary behavioral adjustment rather than a lasting shift in consumption patterns.

**Overall interpretation.** Overall, the results suggest that the impact of COVID-19 on mobile gaming depended on how much daily life was actually disrupted, rather than on policy strictness alone. In the United States and United Kingdom, strict lockdown caused a significant reduction of consumption choices and distinctly changed daily routines, causing existing users to temporarily redirect their spending towards gaming. In Sweden and Taiwan, where daily activities were less constrained, changes in gaming behavior were weaker and short-lived, with no evidence of lasting structural effects.

# 6 Conclusion

This study applies a Bayesian Structural Time Series (BSTS) framework to examine the causal impact of the COVID-19 pandemic on the mobile gaming industry across four countries: the United States, the United Kingdom, Sweden, and Taiwan. By constructing a counterfactual hypothetical scenario in which the pandemic did not occur, the analysis is able to distinguish pandemic-related effects from underlying long-term trends and seasonal patterns.

Overall, the results indicate that the pandemic did not lead to a sustained increase in the size of the mobile gaming user base. In most countries, long-term changes in downloads and daily active users (DAU) are either negative or statistically insignificant, suggesting that the pandemic did not generate persistent growth in new players, but there may have been an exogenous factor which caused the industry to decline, as observed across all countries. In contrast, monetization-related metrics, particularly ARPDAU, exhibit clear short-term increases, indicating that existing users increased their average spending during periods of mobility restrictions. However, these increases in spending are largely short-lived and tend to weaken or disappear over time.

The findings also reveal substantial cross-country heterogeneity in the magnitude and persistence of pandemic effects. The United States experience more pronounced short-term increases in monetization, while the effects observed in Sweden and Taiwan are weaker or more uncertain. These differences reflect variations in policy stringency, social behavior, and market conditions, which influence both the timing and duration of the pandemic's impact across countries.

From a methodological perspective, this study demonstrates the usefulness of the BSTS framework for causal inference in time-series settings. By relying on counterfactual comparisons rather than explicitly estimating a time-varying intervention coefficient, the analysis captures temporal changes in pandemic effects while maintaining a balance between model stability and interpretability.

In conclusion, the primary impact of the COVID-19 pandemic on the mobile gaming industry lies in short-term changes in the spending behavior of existing users rather than in long-term market growth. The pandemic did not lead to a sustained expansion of the user base; instead, it temporarily increased spending among players who were already active in the market. As pandemic-related effects faded, these changes gradually diminished and may have even contributed to longer-term challenges in user acquisition and sustained growth.

Despite these findings, several limitations should be acknowledged, which point to directions for future research. First, the use of aggregated industry-level data may obscure heterogeneous responses across different game genres or player segments. Second, the Stringency Index serves only as an approximate measure of policy intensity and does not fully capture actual behavioral changes or compliance levels. Future research could incorporate more granular data or adopt alternative intervention specifications to better understand the mechanisms through which the pandemic influenced mobile gaming outcomes.

Furthermore, the consistent negative trends observed across all sampled nations suggest the presence of a latent, globally common exogenous factor driving the industry's contraction. Future research is warranted to isolate and identify the specific determinants of this decline.

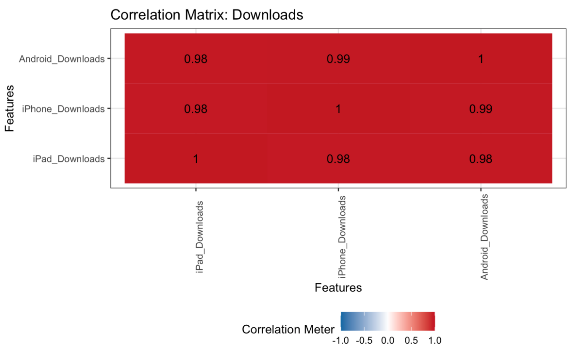
## References

[1] K. H. Brodersen et al. “Inferring causal impact using Bayesian structural time-series models”. In: *The Annals of Applied Statistics* 9.1 (Mar. 2015). ISSN: 1932-6157. URL: http://dx.doi.org/10.1214/14-AOAS788.

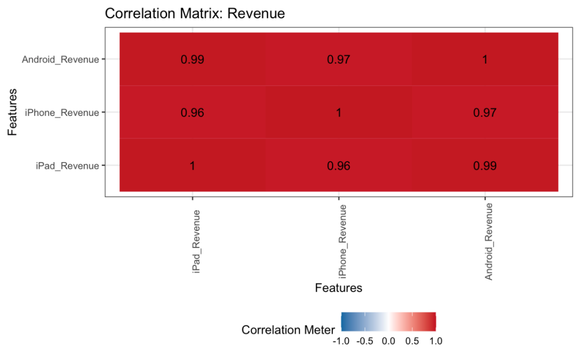
# A Supplementary Exploratory Data Analysis

This appendix provides supplementary plots that are not shown in the main text but assist our data processing steps.

## A.1 Correlation Analysis




(a) Correlation matrix for downloads across platforms




(b) Correlation matrix for revenue across platforms

Figure 7: Correlation structure of acquisition and monetization metrics across platforms

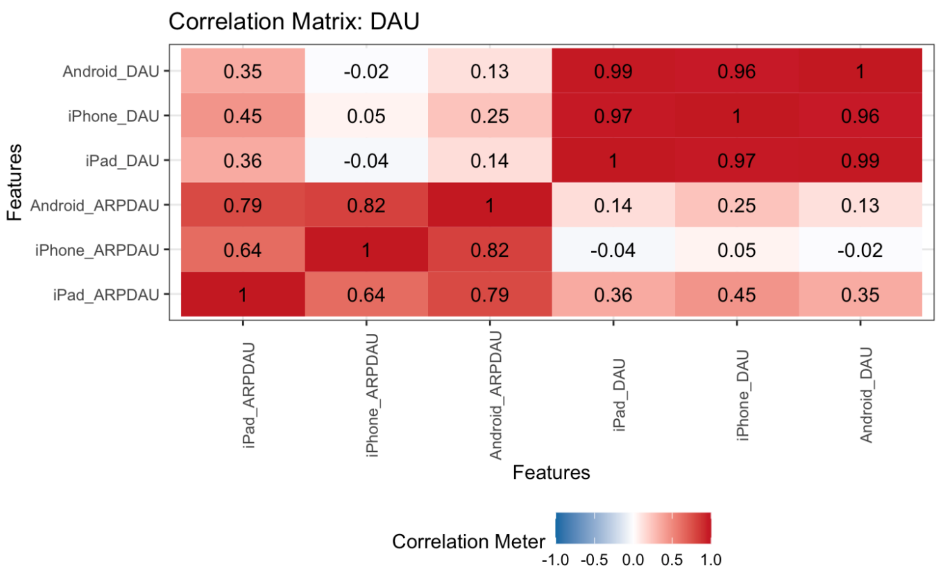



Figure 8: Correlation matrix between DAU and ARPDAU across platforms

## A.2 Descriptive Plots of Key Variables

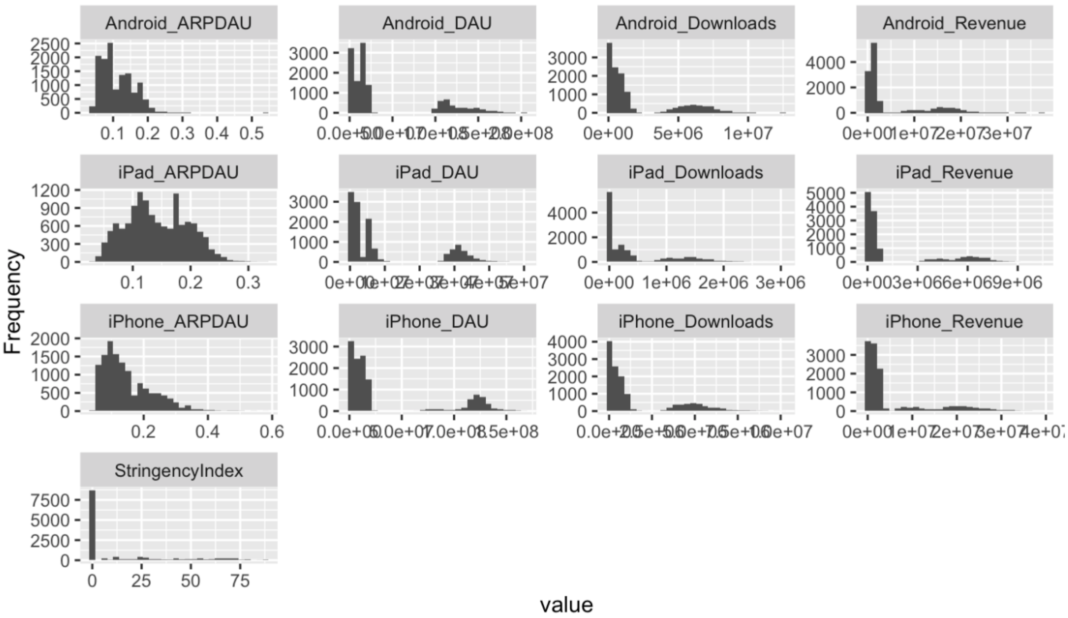



Figure 9: Distribution of key outcome variables and policy stringency

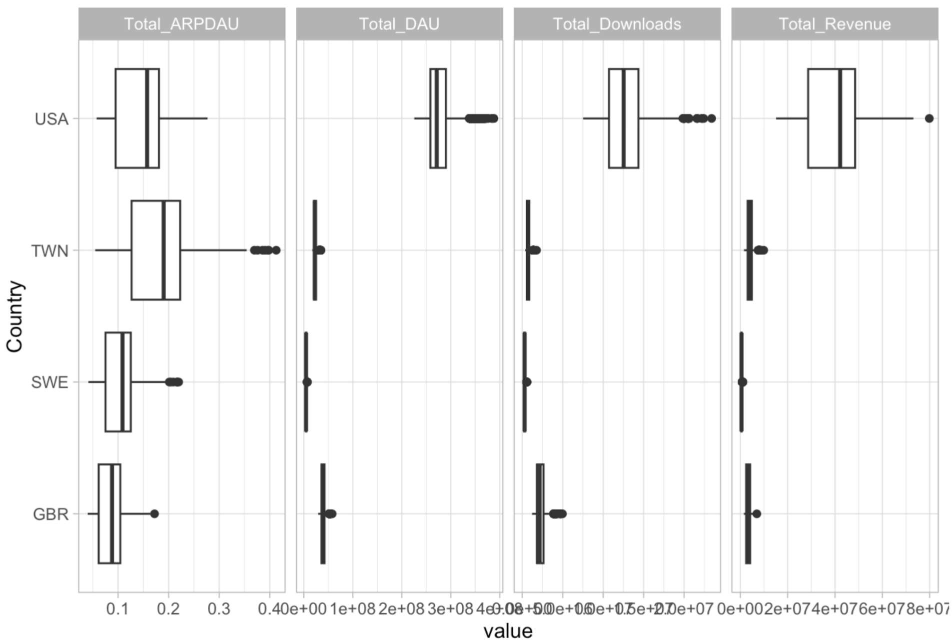
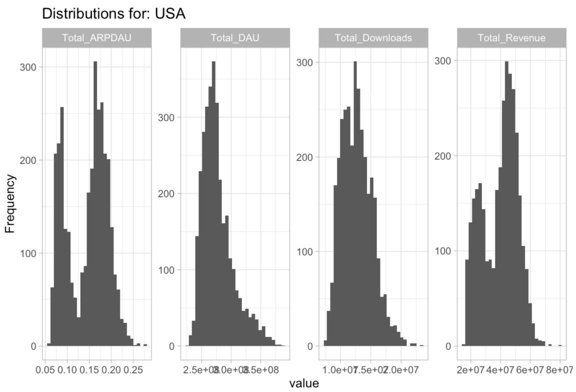
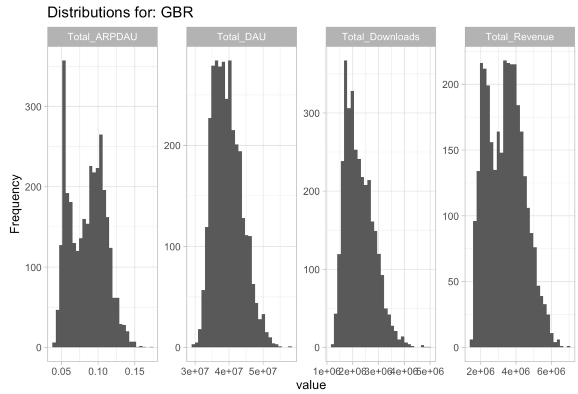


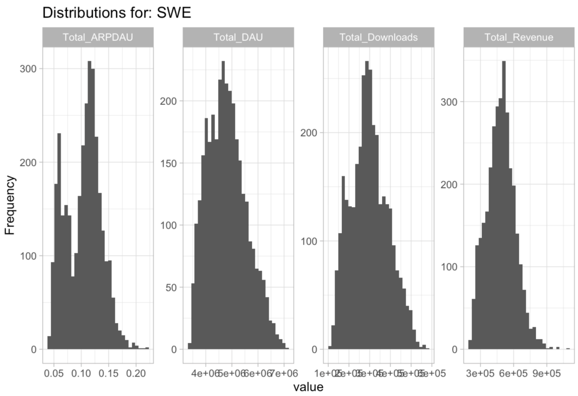

Figure 10: Distribution of key outcome variables and policy stringency



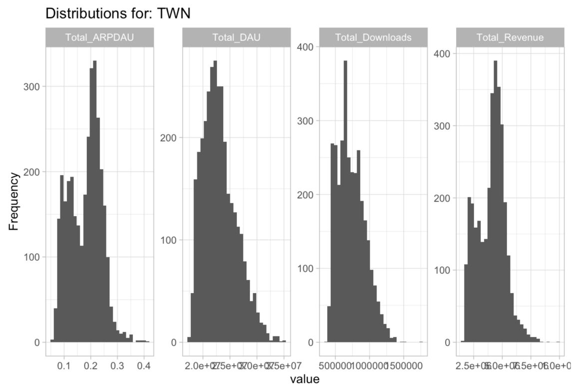

(a) United States (USA)




(b) United Kingdom (GBR)



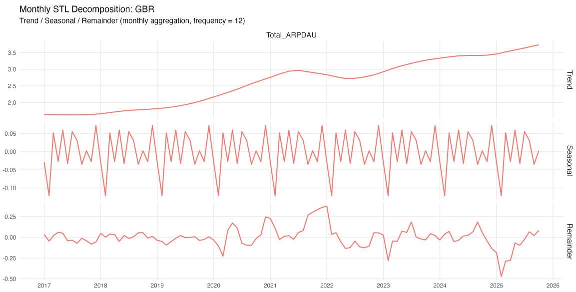

(c) Sweden (SWE)



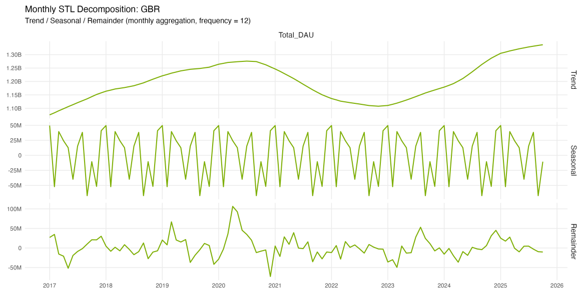

(d) Taiwan (TWN)

Figure 11: Empirical distributions of aggregated outcome variables (ARPDAU, DAU, Downloads, and Revenue) across four countries.

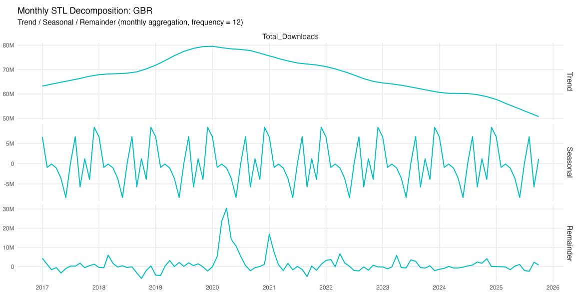
## A.3 Seasonal–trend decomposition for Non-U.S. Markets



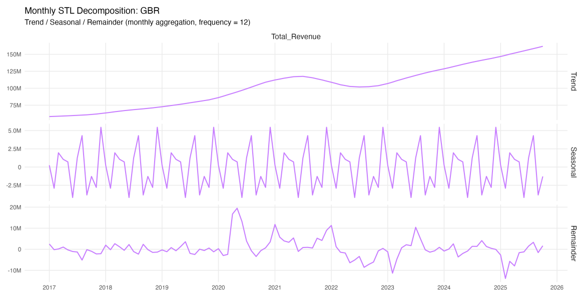

(a) ARPDAU




(b) DAU

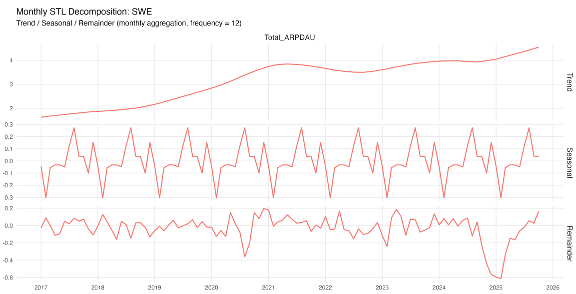



(c) Downloads

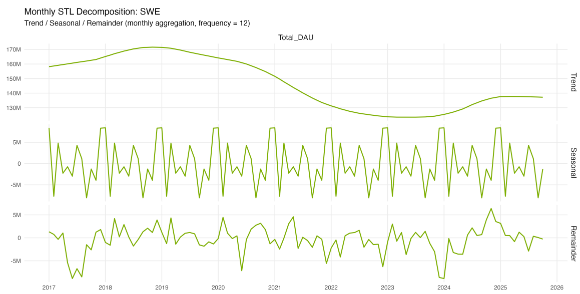



(d) Revenue

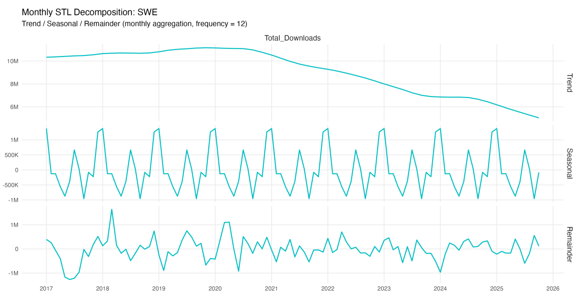
Figure 12: Monthly STL decomposition of outcome variables in the United Kingdom



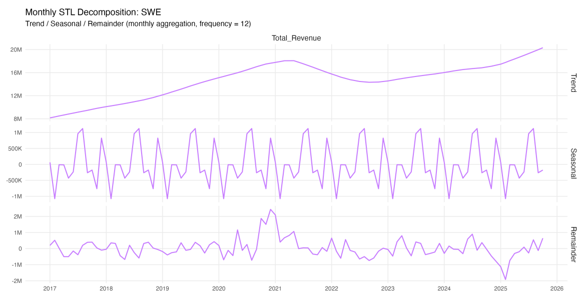

(a) ARPDAU




(b) DAU

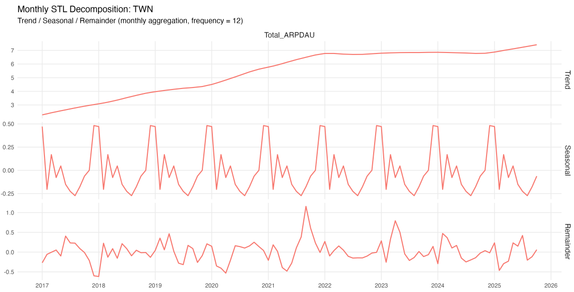



(c) Downloads

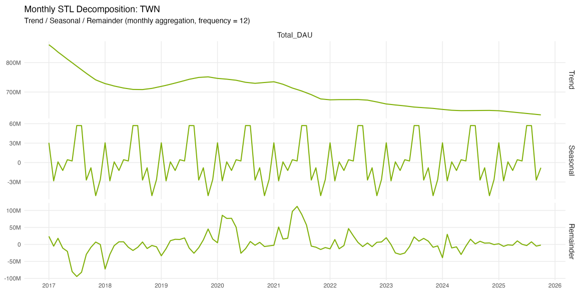



(d) Revenue

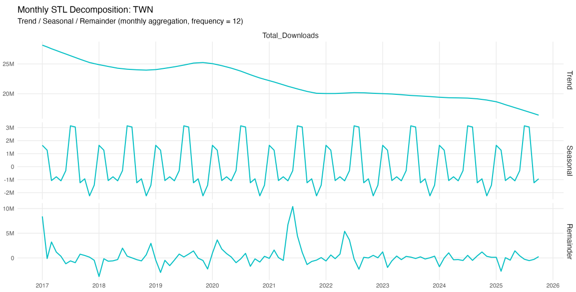
Figure 13: Monthly STL decomposition of outcome variables in Sweden



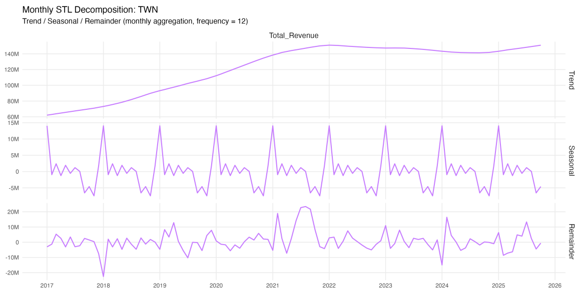

(a) ARPDAU




(b) DAU




(c) Downloads



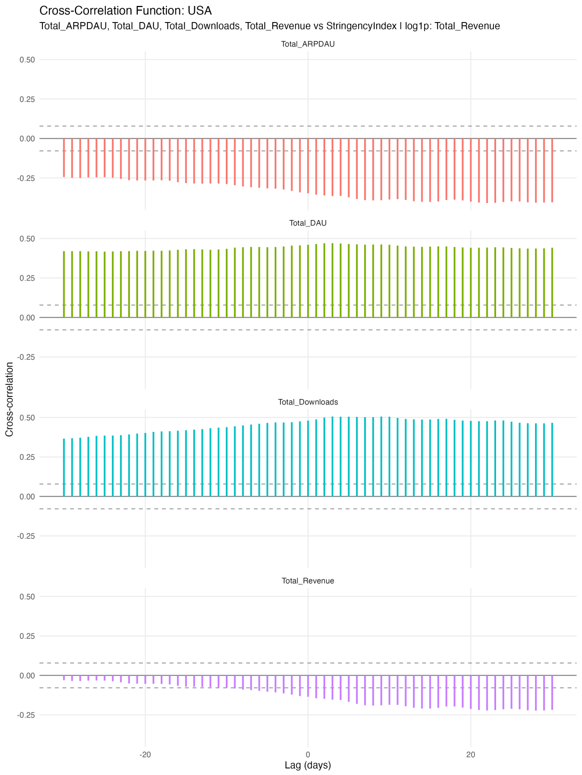

(d) Revenue

Figure 14: Monthly STL decomposition of outcome variables in Taiwan

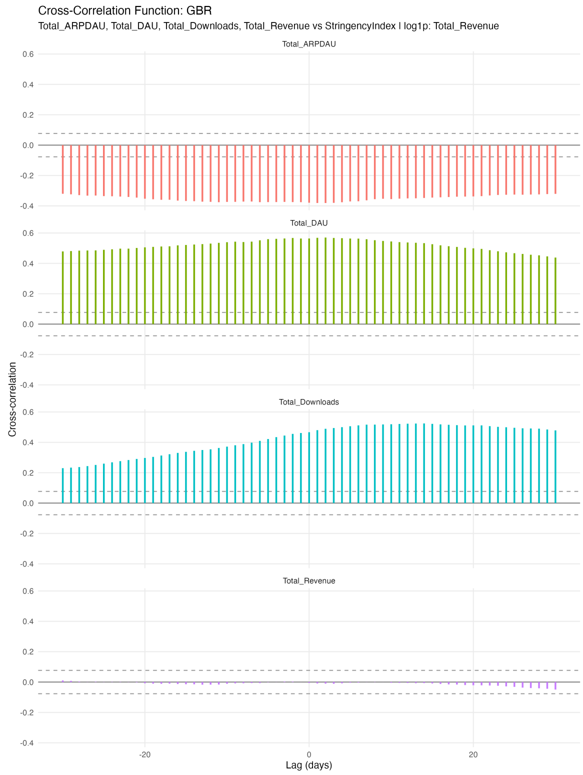
### A.4 Cross-Correlation Function (CCF)

The cross-correlation function (CCF) plot is used to examine the relationship between policy stringency and the outcome variables at different time lags. The horizontal axis shows the time difference between changes in policy and changes in the outcomes, while the vertical axis shows the corresponding correlation. Values outside the dashed lines indicate statistically significant correlations. This plot helps assess whether policy effects occur immediately or with a delay.

Figure 15 shows that correlations are spread over a range of lags and differ across outcome variables, without a clear peak at a specific lag. This suggests that policy effects do not occur at a single fixed delay, but rather evolve gradually over time.

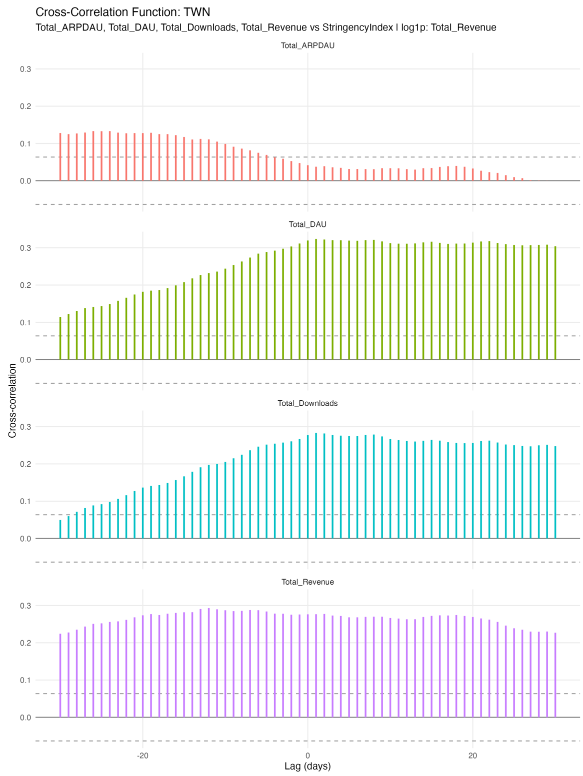



(a) United States




(b) United Kingdom


(c) Sweden




(d) Taiwan

Figure 15: Cross-correlation functions between policy stringency and gaming outcomes across four countries