ECON 599
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Term Paper
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April 27 Spring 2022

Identifying and Quantifying How the Unexpected Terrorism Attack affect Tourism in Bali through Dummy Variable and Ramp Function

I. Abstract

The purpose of this paper is to examine different methods for estimating the impacts of unexpected terrorism attacks on the Bali tourism industry for a better causal understanding. Generally, dummy variables are used the most to identify and capture the impacts of events and interventions. However, although we are given a precise date of the attack, dummy variables might fail to capture the full impact as it is hard to mark when the terrorist attack's impact truly starts and when the impact entirely diminishes. Besides, even if we successfully determine when the attack's impact becomes statistically significant and insignificant through monitoring the significance of the dummy variable in the model. The task remains – can the dummy variable capture the impact well enough? In this paper, I will determine the affected period and then testify dummy variables and ramp function's abilities to identify and quantify the impact. Finally, I will decide which methods can better capture the impact, estimate the loss in the tourism industry, and explore whether there is a structural change in the tourist arrival pattern due to the attack.

II. Introduction

Lying between the Pacific and the Indian Ocean, Bali is a world-famous tourist attraction known for its forested volcanic mountains, coral reefs, cultural heritages, and splendid beaches. As a small island in Indonesia, Bali is Indonesia's largest and most popular tourist destination. The importance of tourism to Indonesia as a country is self-evident - 4.97% of Indonesian GDP is from the tourism industry (Statista, 2022). For Bali Island alone, the tourism industry is of even higher significance to its economy and its people - around 80% of Bali's GDP is attributed to the tourism industry, and about 80% of Bali's residents rely heavily on the tourism industry (Sperling, 2020).

Since the turn of the millennium, the tourism industry has been moving towards globalization and growing at an amazing pace due to a combination of economic, socio-cultural, political, and technological factors (Hollensen, 2020). As estimated by United Nations World Tourism Organization, there were just 25 million international tourist arrivals in 1950, and this number has increased to 1.4 billion 68 years later, reaching a 56-fold increase in 2018 (Roser, 2022). Enjoying the booming of international travel, Bali's economy has grown tremendously since the 90s. In the meantime, dangers are hidden behind the prosperity - Bali's overreliance on tourism and the tertiary sector unavoidably leaves its economy in a fragile and susceptible position.

Over the last few decades, terrorism has become a nonnegligible and recurring topic in the public discourse due to the increasing frequency and magnitude of terrorism attacks witnessed. Since the beginning of the century, both developed and developing countries have witnessed aggravated levels of terrorist events. New York, United States (2001); Bali, Indonesia (2002, 2005); Madrid and Barcelona, Spain (2004, 2017); London and Manchester, United Kingdom (2005, 2017); Paris and Nice, France (2015, 2016, 2017); Istanbul, Turkey (2016, 2017) were some of the places that have experienced terrorist attacks, but the list still goes on (GTD, 2022). Besides the direct casualties and destruction at the attacked location, terrorism represents an extended and event permanent threat to tourism and touristic infrastructures. Even if the attacks against tourists are relatively infrequent, the attacks always cause considerable negative impacts on tourists' travel decisions and thus the local tourism industry. Such impact enlarges to a critical extent when terrorist attacks happen on a small island like Bali. On 12th October 2002, the bombings in Kuta, Bali, caused an enormous loss of life and damage to the local social and economic fabric. Despite the efforts of the Bali government and provincial authorities, direct international tourist arrivals to Bali plumed from 150,747 in September to 31,498 in November 2002 (EuroBali, 2006), and the impact went on.

Two years later, on 1st October 2005, a series of terrorist suicide bombs and a series of car bombs and attacks occurred in Bali, Indonesia (Wikipedia contributors, 2022). These two attacks caused not only direct casualties but also negatively influenced Bali's tourism industry, leaving Bali's economy and the livelihood of its people in a bad situation. To better understand the impact of the terrorist attacks, this study will examine how the two attacks affect the Bali tourism industry using the measure of total monthly foreign tourist arrivals to Bali from the Statistics of Bali Province. The primary focus is to examine the patterns of decline and recovery in tourist arrivals using a dummy variable, ramp function, and difference-in-difference method if a suitable control group is found. Then, I will observe possible structural changes in the tourist arrival pattern after the attack. This analysis focuses on the two terrorist attacks that happened in Bali (2002 and 2005) and Maldives' tourism data as a comparison.

III. Literature Review

1. Dummy Variable in Regression

The dummy variable is a common tool to estimate the impact of an event from the first glance. The use of dummy variables requires the imposition of additional constraints on the parameters of regression equations (Suits, 1957). The dummy variable expresses in the forms of 0s and 1s in the multiple linear regression to represent the two states. Typically, dummy variables are used in the following applications: time series analysis with seasonality or regime switching; analysis of qualitative data, such as survey responses; categorical representation, and representation of value levels (Garavaglia et al., 1998).

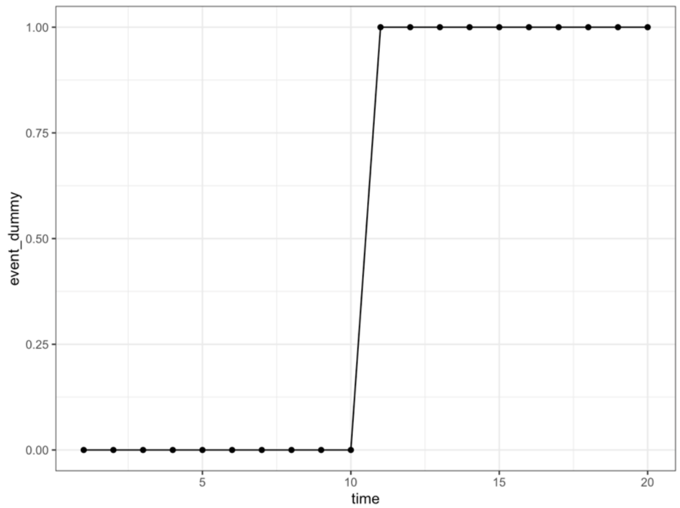

Figure 1 - Representation of Dummy Variable

2. Ramp Function in Regression

Ramp function regression is a tool for quantifying climate transitions over a long period of time and is later also applied to quantifying intervention effects. The physical intuition behind the ramp function is that a system at equilibrium is disturbed by an external factor at once or over a period of time and then returning back to a new equilibrium state. With this intuition, the ramp function is a three-phase model shown in Figure 2 that tries to capture when the impact starts, ends, and the difference between two equilibrium states before and after the impacted period (Mudelsee, 2000).

The mathematical representation of a ramp function is:

$$x_{\mathrm{fit}}(t) = \begin{cases} x1, & \text{for} t \leq t1, \\ x1 + (t - t1)(x2 - x1)/(t2 - t1), & \text{for} t1 \leq t \leq t2, \\ x2, & \text{for} t \geq t2, \end{cases}$$

In this study, I will use 0 as *x1* to represent the unaffected period before the terrorist attack. For the affected period, I would first assume it increases gradually from 1 to n to represent the gradual change. When the impact of the event fully diminishes, the ramp function will become a zero or another constant to capture the difference between new equilibrium and old equilibrium, if there is one.

$$x_{fit}(t) = \begin{cases} x1 = 0 & \text{for } t \leq t1, \\ x2 = 1{:}\ n, & \text{for } t1 \leq t \leq t2, \\ x3 = c, & \text{for } t \geq t2 \end{cases}$$

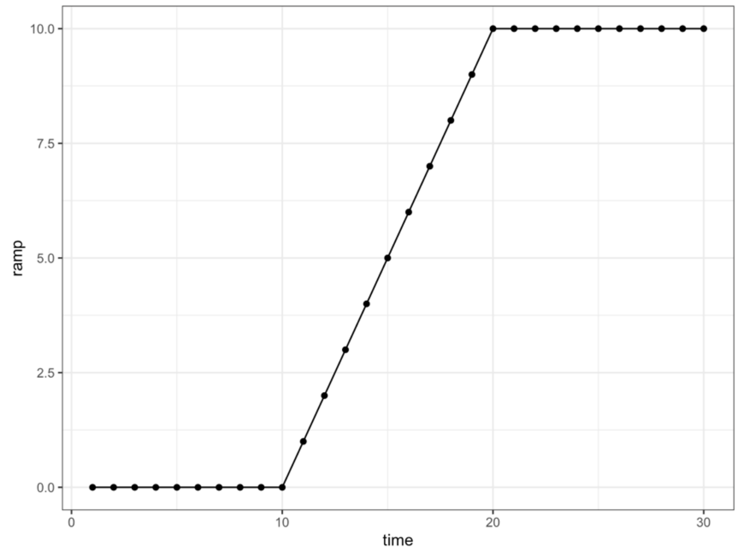

Figure 2- Representation of a Ramp Function Example

3. Difference-in-Difference

The difference-in-Difference method is an econometric method that's used to estimate the effect of a treatment by comparing the changes in outcomes over time between the treatment/intervention group and the control group. DID relies on a strict exchangeability assumption that in the absence of the treatment, the unobserved differences between treatment and control groups are the same over time (Columbia Public Health, 2022). In order to conduct a difference-in-difference analysis, a location of high similarity with Bali is needed.

IV. Event Study Data

1. Bali

I primarily examined how the two terrorist attacks have affected Bali tourism regarding the number of direct tourist arrivals. The first attack was on 12th October 2002. This terrorist attack involved the detonation of three bombs on the Indonesian island of Bali that killed 202 people

(Britannica, 2021). The second attack was on 1st October 2005, which claimed the lives of 20 people and injured more than 100 others (Wikipedia contributors, 2022).

2. Island of Comparison – Maldives

I select the Maldives as the island of comparison for Bali for the following reasons. Above all, there was no terrorist attack in the Maldives during the period time of the study. Besides, Maldives is at a similar geographical location as Bali Island, both situated in the Indian Ocean. Moreover, Bali and Maldives serve tourists of similar nationalities, both serving large groups of tourists from China, Japan, Britain, and India (Ministry of Tourism, 2016) (Bali Tourism Directory, 2020). Last but not least, Maldives is an island country whose economy is also highly dependent on the tourism industry – tourism is the largest sector of Maldives' economy, accounting for more than 28% of Maldives' GDP (World Bank, 2020).

However, Maldives might not be a perfect control group for Bali as it is of a smaller size and mainly provides a high-end vacation experience, while Bali is larger and provides a broader range of options for its tourists. The Maldives also serves fewer Australian tourists, which account for 23.35% of Bali visitors (Bali Tourism Directory, 2020). I will compare the Maldives and Bali tourist arrival data to determine if Maldives can be used as the control group for Bali.

V. Economic Model

1. Data

This study's response variable is the monthly Bali tourist arrival (Bali). It is the chosen parameter to measure the tourism industry performance in Bali. For the ARIMA model, the response variable is just the monthly Bali tourist arrival. For the Hedonic regression, I did a log transformation of the monthly Bali tourist arrival to measure the effects in percentage change from predicted demand and eliminate the impact of possible interactions between explanatory variables.

2. Proposing Range for Affected Period

a) First, I use the Bali data before the two terrorism attacks (the 58 data points before October 2002) to train a suited ARIMA model and then use this model to predict what the arrival would be like if there was no attack. Assuming this prediction can well represent the data in the world with no attack, it will be utilized as the but-for-attack data for comparison and calculating losses.

Assumptions in step a):

i. The span of the training data is enough to demonstrate the cyclical pattern for the ARIMA model to capture.

ii. The Arima model is able to capture the systematic characteristics, including seasonal and cyclical trends, well enough.

b) The tourist arrival data after the bombing attack is the affected data. By comparing the difference between the affected data and ARIMA model predictions in a time series, I determine approximate t1 and t2 values (when the impact of terrorist attacks starts and fully diminishes).

Assumptions in step b):

i. Throughout the time period, there were no other factors that significantly influenced the data other than the two terrorist attacks (i.e., the ARIMA model predictions still reflect the systematic characteristics of the data well enough).

3. Hedonic Regressions for Bali Tourist Arrival

c) I run three multiple linear regression models with monthly Bali tourist arrival in the log form as the response variable. The first model regresses the response variable against Global GDP, global tourism demand trend, Bali's trade balance, and the real broad exchange rate for Bali, Australia, and Japan. The second model regresses the response variable against all the explanatory variables in model 1 and the dummy variable for the terrorism attack affected period. The last model regresses the response variable against all the explanatory variables in model 1 and the ramp function for the terrorist attack affected period.

4. Quantification

d) I assess and quantify the losses in direct tourist arrival using both ARIMA and Hedonic prediction.

VI. Results

1. ARIMA Model

ARIMA model trains a model using Bali's monthly tourist arrival data before the two terrorism attacks (58 data points). According to auto.arima function in r, the most suited ARMA model is (0, 0, 0)(1, 1, 0) [12] with drift.

Table 1 - ARIMA Model Results

```
Series: train1
ARIMA(0,0,0)(1,1,0)[12] with drift
Box Cox transformation: lambda= 1.999927

Coefficients:
         sar1     drift
      -0.7131  38336655
s.e.   0.1181  11805523

sigma^2 = 2.175e+18:  log likelihood = -1017.12
AIC=2040.23   AICc=2040.82   BIC=2045.65

Training set error measures:
                   ME     RMSE      MAE        MPE     MAPE     MASE      ACF1
Training set 396.4705 11743.11 8379.385 -0.6371526 7.797125 0.606726 0.7325706
```

The training set's MAPE value for this ARIMA model is 7.797125, which means that the average difference between the forecasted and the actual values is 7.797125%. A MAPE value below 10 indicates an excellent model (Allwright, 2021). This MAPE means that the ARIMA model has captured the systematic characteristics well, meeting the second assumption for step (a).

Mathematical formula for MAPE:

$$\mathrm{M} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|$$

However, the ARIMA model's prediction cannot provide an accurate prediction for the long run as it only takes in 58 observations (4.8 years). According to Hyndman, it usually takes from a minimum of two years to nine years for the data to demonstrate the cyclical pattern (2011), meaning that the training set is not meeting the second assumption in step (b) about the cyclical pattern. So, the complete cyclical pattern for tourist arrival trend might not be shown in the 58 observations. Consequently, predictions using this model for the far future might cause extrapolation problems. Also shown in Figure 3, this ARIMA model prediction fails to capture the tourist arrival pattern in the very long run (after 2009). So, the second assumption in step (a) is not guaranteed.

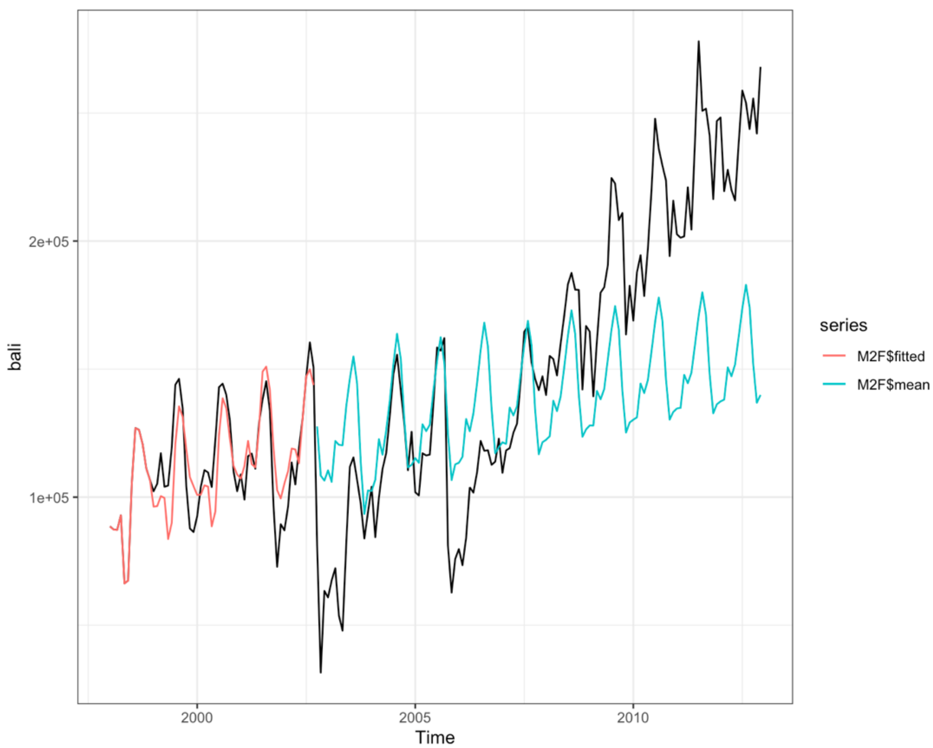

Figure 3 - Arima Model Fitted and Predicted Value vs. Response Variable Values [1]

Assuming the ARIMA predictions are accurate in the short run (before 2009), we can observe from Figure 3 that the impact of the 2002 terrorist attack started immediately in October 2002 and disappeared around January 2004. The impact of the 2005 attack started immediately in October 2005 and disappeared around June 2007. These two ranges of time will be used as the affected period to build the dummy variable and ramp function.

[1] Black line represents the Response Variable (Bali tourist arrival). Red line represents ARIMA model's fitted value for the training set. Turquoise line represents ARIMA model's prediction for the testing period.

2. Dummy Variable and Ramp Function

For the dummy variable, I used 0 to represent the time unaffected by the terrorist attacks (time before the terrorist attack in October 2002 and January 2004 to October 2005, and after June 2007) and 1 for the affected time period derived (October 2002 to January 2004, and October 2005 to June 2007).

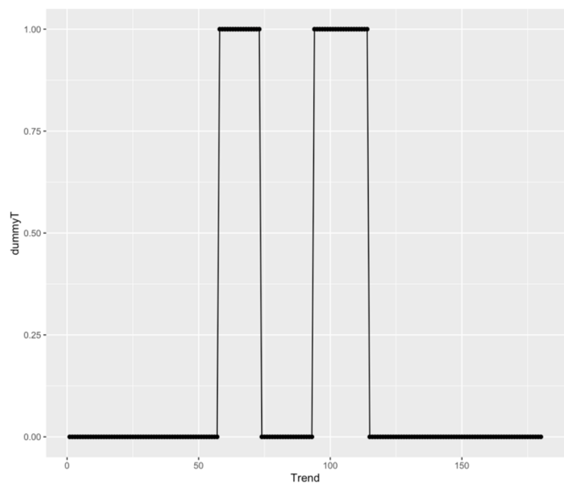

Figure 4 – Representation of Dummy Variable for Affected and Unaffected Period

For the Ramp function, I used 0 to represent the time unaffected by the terrorist attacks (before the terrorist attack in October 2002 and January 2004 to October 2005, and after June 2007). For the two affected periods (October 2002 to January 2004 and October 2005 to June 2007), the ramp function increases from 1 and increases by one for each affected month (1 to 16 for the 2002 attack affected period, 1 to 21 for the 2005 attack affected period).

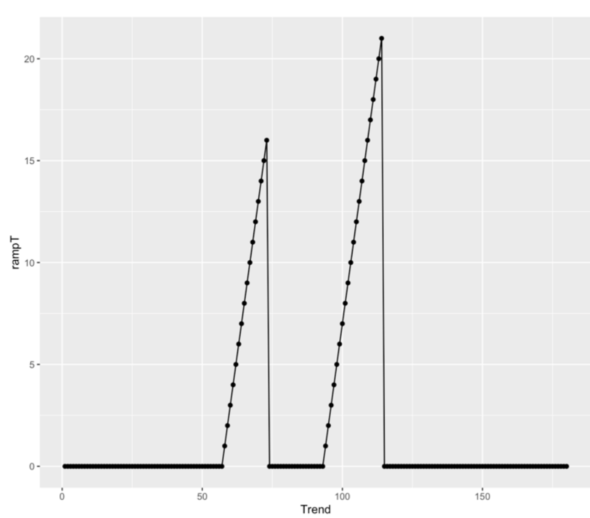

Figure 5 - Representation of Ramp Function

For the Inversed Ramp function, I used 0 to represent the time unaffected by the terrorist attacks (before the terrorist attack in October 2002 and January 2004 to October 2005, and after June 2007). For the two affected periods (October 2002 to January 2004 and October 2005 to June 2007), the inverse ramp function decreases by 1 for each affected month (16 to 1 for the 2002 attack affected period, 21 to 1 for the 2005 attack affected period).

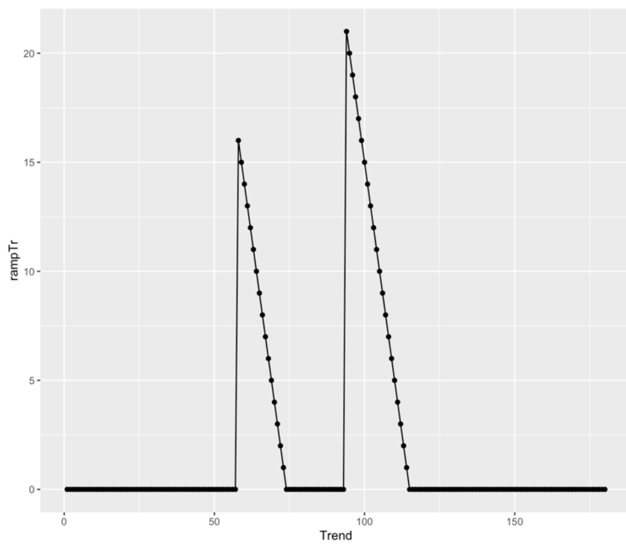

Figure 6 - Representation of Inversed Ramp Function

3. First Hedonic Regression Model without Dummy Variable or Ramp Function

The first hedonic model regresses the response variable against Global GDP, global tourism demand trend, Bali's trade balance, and the real broad exchange rate for Bali, Australia, and Japan. This hedonic model without any dummy variable or ramp function serves as a baseline model for comparison and a better understanding of how well the dummy variable and the ramp function can capture the decline pattern.

The adjusted R-squared value of the first hedonic regression model is 0.7789, and this value will be the baseline R-squared value of comparison.

Table 2 - First Hedonic Regression Model Results

```
lm(formula = logBali ~ monthd + wGDP + IntTourismR + IndoER +
    AusER + JanER, data = dataset)

Residuals:
     Min       1Q   Median       3Q      Max
-0.86703 -0.06877  0.01387  0.10996  0.35541

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  9.667e+00  2.460e-01  39.299  < 2e-16 ***
monthdAug    2.932e-01  6.658e-02   4.404 1.92e-05 ***
monthdDec    3.232e-03  6.678e-02   0.048 0.961459
monthdFeb   -1.049e-01  6.653e-02  -1.577 0.116794
monthdJan   -1.194e-01  6.669e-02  -1.791 0.075170 .
monthdJul    2.820e-01  6.662e-02   4.234 3.83e-05 ***
monthdJun    1.154e-01  6.651e-02   1.735 0.084544 .
monthdMar   -1.809e-02  6.652e-02  -0.272 0.786023
monthdMay   -2.128e-02  6.647e-02  -0.320 0.749325
monthdNov   -1.357e-01  6.679e-02  -2.032 0.043776 *
monthdOct    6.750e-02  6.678e-02   1.011 0.313590
monthdSep    2.249e-01  6.661e-02   3.377 0.000918 ***
wGDP         3.399e-14  9.905e-15   3.432 0.000761 ***
IntTourismR -3.932e-14  9.673e-14  -0.407 0.684891
IndoER      -5.313e-03  1.880e-03  -2.826 0.005307 **
AusER       -1.661e-03  2.674e-03  -0.621 0.535293
JanER        1.127e-02  1.540e-03   7.315 1.10e-11 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.182 on 163 degrees of freedom
Multiple R-squared:  0.7986,    Adjusted R-squared:  0.7789
F-statistic:  40.4 on 16 and 163 DF,  p-value: < 2.2e-16
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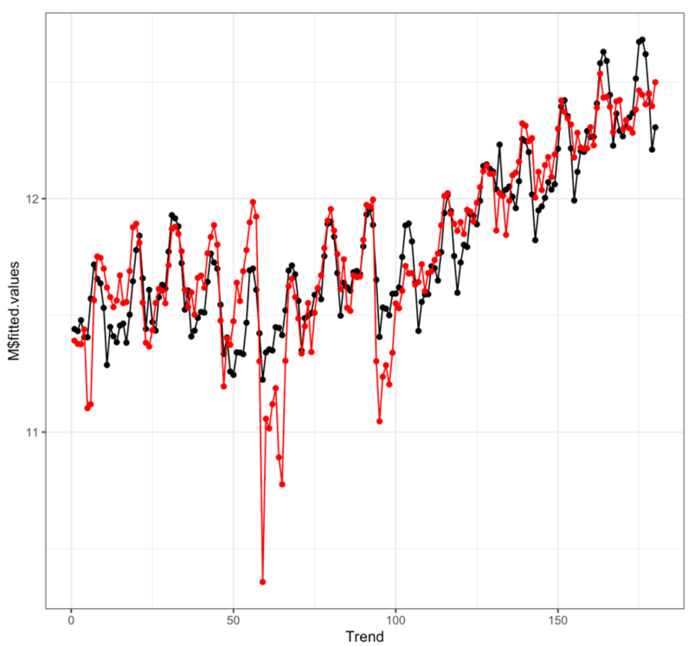

Figure 7 - Hedonic Model (without Dummy Variable) Fitted and Predicted Value vs. Response Variable Values [2]

[2] Red line represents the Response Variable (Bali tourist arrival) and the black line represents the fitted value of Hedonic regression without dummy variable.

4. Hedonic Regression Model with Dummy Variable

The second hedonic regression model regresses the response variable against Global GDP, global tourism demand trend, Bali's trade balance, the dummy variable for the terrorist attack affected period, and the real broad exchange rate for Bali, Australia, and Japan.

The second model returns an adjusted R-squared value of 0.865. Compared to the baseline adjusted R-squared value of 0.7789, the dummy variable helps to capture better 8.61% more of the variations in the response variable. Also shown in the results, the t-value of the dummy variable is -10.249, meaning that there is a significant negative impact of terrorist attacks on the response variable.

Table 3 - Second Hedonic Regression Model Results

```
lm(formula = logBali ~ monthd + wGDP + IntTourismR + IndoER +
    dummyT + AusER + JanER, data = dataset)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.73735 -0.07505  0.01379  0.08393  0.30379 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)  1.020e+01  1.992e-01  51.227  < 2e-16 ***
monthdAug    2.580e-01  5.213e-02   4.949 1.86e-06 ***
monthdDec    2.592e-02  5.222e-02   0.496   0.6204    
monthdFeb   -8.562e-02  5.201e-02  -1.646   0.1017    
monthdJan   -6.060e-02  5.242e-02  -1.156   0.2493    
monthdJul    2.496e-01  5.214e-02   4.787 3.78e-06 ***
monthdJun    1.171e-01  5.196e-02   2.254   0.0256 *  
monthdMar   -4.528e-04  5.200e-02  -0.009   0.9931    
monthdMay   -2.025e-02  5.193e-02  -0.390   0.6972    
monthdNov   -1.031e-01  5.227e-02  -1.972   0.0503 .  
monthdOct    9.726e-02  5.225e-02   1.861   0.0645 .  
monthdSep    2.091e-01  5.206e-02   4.017 9.01e-05 ***
wGDP         3.146e-14  7.742e-15   4.063 7.53e-05 ***
IntTourismR -1.283e-13  7.607e-14  -1.687   0.0936 .  
IndoER       4.071e-03  1.731e-03   2.352   0.0199 *  
dummyT      -3.732e-01  3.641e-02 -10.249  < 2e-16 ***
AusER       -1.212e-03  2.090e-03  -0.580   0.5627    
JanER        4.169e-03  1.388e-03   3.003   0.0031 ** 
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1422 on 162 degrees of freedom
Multiple R-squared:  0.8778,	Adjusted R-squared:  0.865 
F-statistic: 68.48 on 17 and 162 DF,  p-value: < 2.2e-16
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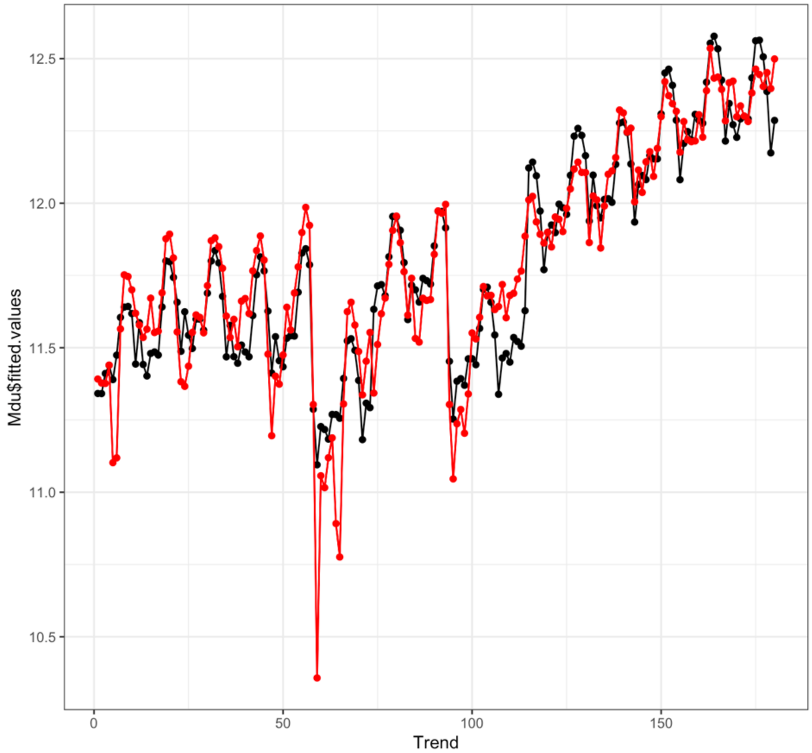

Figure 8 - Hedonic Model (with Dummy Variable) Fitted and Predicted Value vs. Response Variable Values [3]

5. Hedonic Model with Ramp Function

The third hedonic regression model regresses the response variable against Global GDP, global tourism demand trend, Bali's trade balance, the ramp function for terrorism attack affected period, and the real broad exchange rate for Bali, Australia, and Japan.

The third model returns an adjusted R-squared value of 0.7858. Although the ramp function is a statistically significant factor when explaining the variations in the response variable, it is not as good as using the dummy variable to explain the decline pattern. Compared to the baseline adjusted R-squared value of 0.7789 and 0.865 of the second model with a dummy variable, this ramp function generates a value of 0.7858, which means it fails to capture the decline pattern in the response variable and even deteriorates the original regression model. It is reasonable to conclude that the response variable's decline pattern does not increase every month after the attack, with the slightest effect in the beginning.

[3] Red line represents the Response Variable (Bali tourist arrival) and the black line represents the fitted value of Hedonic regression with dummy variable.

Table 4 - Third Hedonic Regression Model Results

```
lm(formula = logBali ~ monthd + wGDP + IntTourismR + IndoER +
    rampT + AusER + JanER, data = dataset)

Residuals:
     Min       1Q   Median       3Q      Max
-0.89702 -0.05799  0.01520  0.11023  0.31038

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  9.806e+00  2.483e-01  39.491  < 2e-16 ***
monthdAug    2.846e-01  6.561e-02   4.338 2.52e-05 ***
monthdDec    5.267e-03  6.573e-02   0.080 0.936226
monthdFeb   -1.037e-01  6.548e-02  -1.584 0.115117
monthdJan   -1.070e-01  6.582e-02  -1.626 0.105839
monthdJul    2.723e-01  6.567e-02   4.146 5.43e-05 ***
monthdJun    1.191e-01  6.547e-02   1.819 0.070737 .
monthdMar   -1.556e-02  6.547e-02  -0.238 0.812448
monthdMay   -1.927e-02  6.542e-02  -0.294 0.768758
monthdNov   -1.337e-01  6.573e-02  -2.035 0.043509 *
monthdOct    6.671e-02  6.572e-02   1.015 0.311611
monthdSep    2.224e-01  6.556e-02   3.392 0.000873 ***
wGDP         3.168e-14  9.791e-15   3.235 0.001473 **
IntTourismR -4.306e-14  9.520e-14  -0.452 0.651674
IndoER      -3.371e-03  2.005e-03  -1.681 0.094645 .
rampT       -8.808e-03  3.505e-03  -2.513 0.012944 *
AusER       -1.233e-03  2.637e-03  -0.468 0.640666
JanER        9.462e-03  1.677e-03   5.642 7.32e-08 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1791 on 162 degrees of freedom
Multiple R-squared:  0.8062,	Adjusted R-squared:  0.7858
F-statistic: 39.64 on 17 and 162 DF,  p-value: < 2.2e-16
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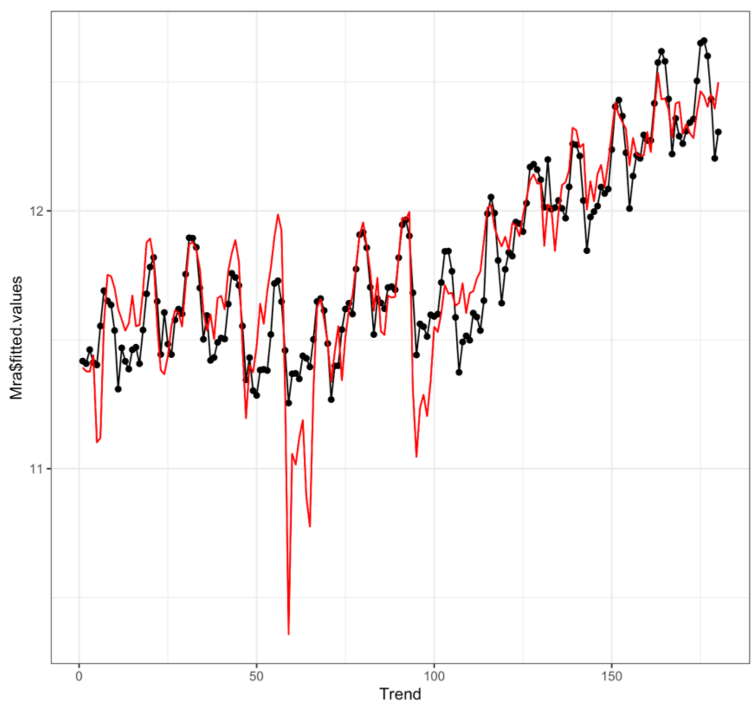

Figure 9 - Hedonic Model (with Ramp Function) Fitted and Predicted Value vs. Response Variable Values [4]

[4] Red line represents the Response Variable (Bali tourist arrival) and the black line represents the fitted value of Hedonic regression with ramp function.

6. Hedonic Model with Reverse Ramp Function

The fourth hedonic regression model regresses the response variable against Global GDP, global tourism demand trend, Bali's trade balance, the inversed ramp function for terrorism attack affected period, and the real broad exchange rate for Bali, Australia, and Japan.

The fourth model returns an adjusted R-squared value of 0.8878. Compared to the baseline adjusted R-squared value of 0.7789 and the second model's 0.865, the inversed ramp function captures the downwards trend in the response variable better than the dummy variable. Also, as shown in the results, the t-value of the dummy variable is -12.621, meaning that there is a significant negative impact of terrorist attacks on the response variable. As a result, the inverse ramp function is a good tool to capture the impact of terrorist attacks on the response variable, which has the most significant impact right after the attack and diminishes as time goes by.

Table 5 - Fourth Hedonic Regression Model Results

```
lm(formula = logBali ~ monthd + wGDP + IntTourismR + IndoER +
    rampTr + AusER + JanER, data = dataset)

Residuals:
     Min       1Q   Median       3Q      Max
-0.61409 -0.06536  0.01376  0.07274  0.23386

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.024e+01  1.809e-01  56.579  < 2e-16 ***
monthdAug    2.623e-01  4.748e-02   5.523 1.30e-07 ***
monthdDec    3.354e-02  4.763e-02   0.704 0.482276
monthdFeb   -7.513e-02  4.745e-02  -1.583 0.115286
monthdJan   -6.810e-02  4.768e-02  -1.428 0.155078
monthdJul    2.589e-01  4.749e-02   5.452 1.83e-07 ***
monthdJun    1.055e-01  4.738e-02   2.227 0.027306 *
monthdMar    3.120e-03  4.741e-02   0.066 0.947606
monthdMay   -2.615e-02  4.735e-02  -0.552 0.581516
monthdNov   -8.823e-02  4.772e-02  -1.849 0.066292 .
monthdOct    1.202e-01  4.775e-02   2.517 0.012810 *
monthdSep    2.059e-01  4.747e-02   4.337 2.53e-05 ***
wGDP         3.490e-14  7.056e-15   4.947 1.87e-06 ***
IntTourismR -1.371e-13  6.933e-14  -1.977 0.049693 *
IndoER       2.785e-03  1.485e-03   1.876 0.062512 .
rampTr      -3.218e-02  2.549e-03 -12.621  < 2e-16 ***
AusER       -2.778e-03  1.907e-03  -1.457 0.147135
JanER        4.796e-03  1.211e-03   3.961 0.000112 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1296 on 162 degrees of freedom
Multiple R-squared:  0.8985,    Adjusted R-squared:  0.8878
F-statistic: 84.32 on 17 and 162 DF,  p-value: < 2.2e-16
```

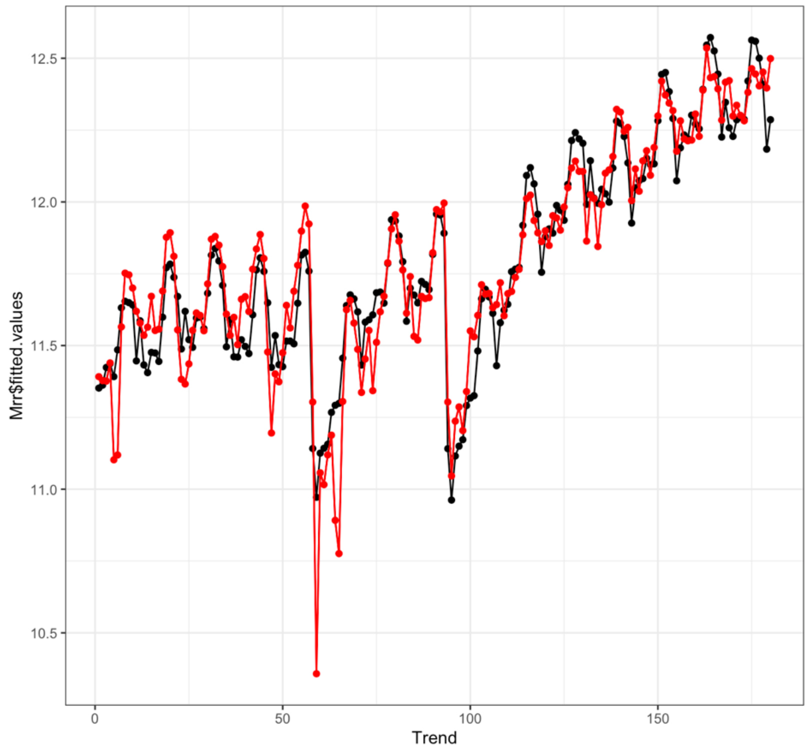

Figure 10 - Hedonic Model (with Inversed Ramp Function) Fitted and Predicted Value vs. Response Variable Values [5]

7. Estimation of the Loss in Bali Tourist Arrivals

a. Using Arima Predictions

The estimated losses of Bali tourist arrivals due to the two terrorist attacks is 1,170,624 for October 2002 to January 2004 and October 2005 to June 2007.

b. Using Hedonic Regression Predictions

Using the first hedonic regression model, the estimated losses of Bali tourist arrivals due to the two terrorist attacks is 537356.3 for October 2002 to December 2003 and October 2005 to October 2006.

The MAPE value for the first hedonic regression model is 13.27695, while the MAPE value for the ARIMA model is 7.797125. So, the ARIMA model is more accurate given its training set. As a result, I will use 1,170,624 as the loss of tourist arrivals in Bali due to the terrorist attacks.

---

[5] Red line represents the Response Variable (Bali tourist arrival) and the black line represents the fitted value of Hedonic regression with inversed ramp function.

8. Bali and Maldives

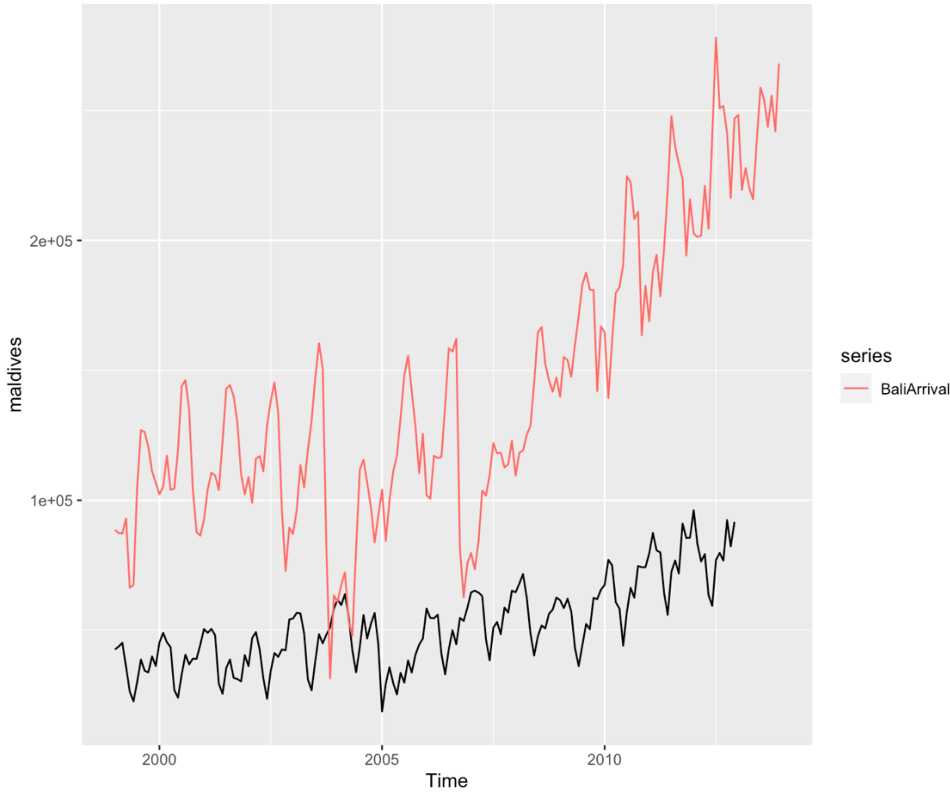

Figure 11 - Maldives and Bali Monthly Direct Tourist Arrival

As shown in Figure 11 above, the volume of Maldives' direct tourist arrival is not comparable to Bali's. Besides, during the focus period (1998-2012), Maldives experienced a tsunami in December 2004, which led to an immediate drop in tourist arrival entering 2005 (World Bank, 2005). Moreover, other factors, including but not limited to the exchange rate and maximum resort capacity, limit the growth for Maldives. Thus, it might not be a suitable control group or not even a good comparison group for Bali.

Although the Maldives failed to be a good control group for Bali, it still gives an idea of how the general trend of tourist arrival would be on a similar island without a terrorist attack. Compared with the pattern in Maldives, there might be a panted demand due to the terrorist attacks that lead to a higher arrival after the impact of attacks fully diminished. However, this panted demand needs further testing and is not within the scope of this research.

VII. Conclusions and Implications

In this paper, I use an adjusted r-squared value as the parameter to assess how well each model captures the variations, setting up a baseline adjusted r-squared value of 0.7789 using a model without a dummy variable or ramp function. The adjusted r-squared value results suggest that the inverse ramp function is the best tool out of the four models examined to capture the downwards trend in the response variable well, as the decline pattern is most significant right after the attack, and the impact diminishes over time. On the other hand, the ramp function, which means the impact of the event increases over time, failed to capture the downwards trend in tourist arrival. Although the dummy variable is proved to be a statistically significant way to capture the effect in the hedonic analysis, it simply assumes that the impact of the event happens right away and the pattern of the impact lasts in a fixed pattern through time. By comparing the data with dummy variables, it is similar to simply comparing the averages for the affected and unaffected periods. So, the dummy variable is not a good tool for capturing the decline pattern.

Using the ARIMA model, the estimated losses caused by two terrorist attacks are 1,170,624 direct tourist arrivals to Bali. The average expenditure per international visitor to Indonesia was 1120 dollars in 2011 (Statista, 2020). So, the two terrorist attacks caused a combined loss of 1,311,098,880 USD (1.31 billion) to Bali. The Bali GDP in 2011 was 74,030 billion IDR (8.16 billion USD using the 2011 exchange rate). The loss of tourism revenue during the affected period of time is about 16% of Bali's GDP in the whole of 2011. Apparently, this is a very significant loss to a small island, indicating the need for Bali to seek opportunities to develop industries other than tourism for a more stable and sustainable economic condition. Moreover, in reality, the loss might be more significant. As a vacation destination providing services for tourists with a wide range of budgets, Bali might lose more high spending tourists as such tourists have more options when planning for trips. So, the negative association of dangerous attacks with Bali might potentially drive this group of tourists further.

When identifying possible structural change before and after the attacks, although the ARIMA model predictions seem like there are two different states, the model itself does not have enough observations and thus fails to capture the cyclical cycles in Bali tourist arrivals for the long run. So, the ARIMA model is not sufficient to observe a possible structural break. With more observations available in the hedonic models, I observe for a possible structural break based on the fourth model. Referring to the r squared value of the fourth model and the visualization in Figure 10, the model can well capture the variations in the response variable before and after the terrorist attacks. So, there is no need to test for structural change.

VIII. Further Discussion

1. Model Improvements

To test whether the fourth hedonic regression is sufficient, I ran the ACF (autocorrelation function) and PACF (partial autocorrelation function) for the residuals of the fourth model. The blue line represents the ACP and PACF values statistically different from zero. Compared with the blue line and PACF values, there is one very significant lag (lag1). So, the regression is insufficient, and adding the first lag of the response variable would be helpful to improve the model.

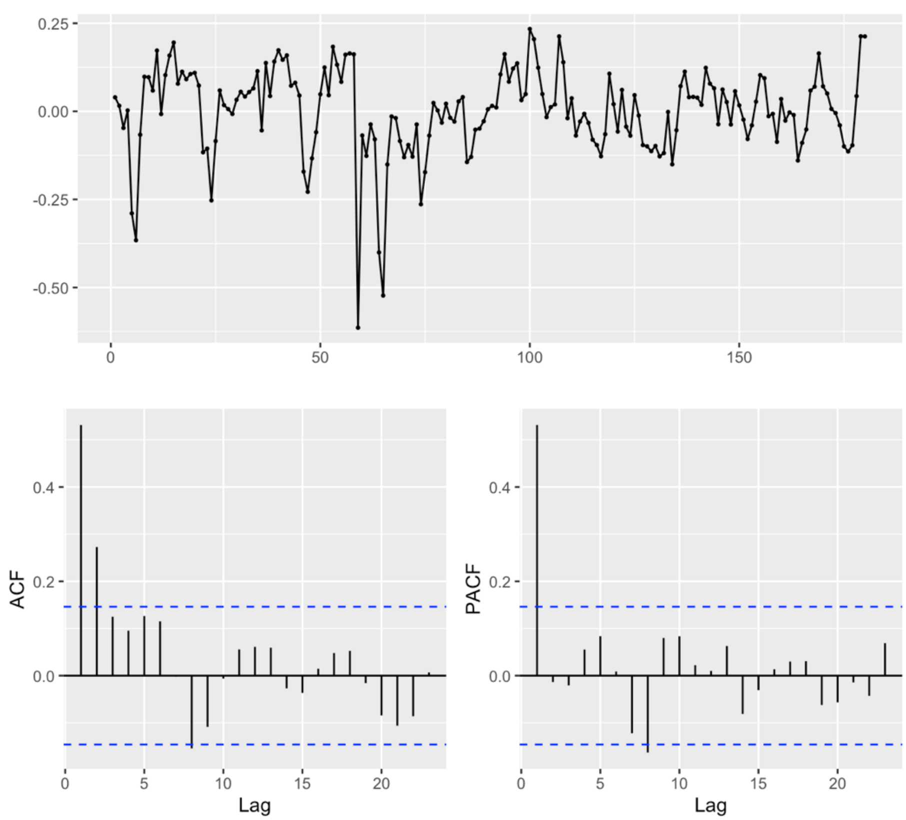

Figure 12 - ACP and PACF for 4th model residuals

After including the first lag of the response variable in the fourth model, the adjusted r-squared value improved to 0.9212 from 0.8878. The lag of the response variable is also statistically significant, with a t-value of 8.397. So the tourist arrival from last month has an impact on the arrivals in this month.

Table 6 - Improved Fourth Hedonic Regression Model Results

```
lm(formula = logBali ~ monthd + wGDP + IntTourismR + IndoER +
    rampTr + AusER + JanER + laglogBali, data = dataset)

Residuals:
     Min       1Q   Median       3Q      Max
-0.65296 -0.04595  0.00468  0.06162  0.26228

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  5.321e+00  6.043e-01   8.806 2.03e-15 ***
monthdAug    1.402e-01  4.236e-02   3.309 0.001157 **
monthdDec    8.432e-02  4.038e-02   2.088 0.038350 *
monthdFeb   -3.588e-02  4.004e-02  -0.896 0.371558
monthdJan   -4.178e-02  4.086e-02  -1.022 0.308101
monthdJul    2.085e-01  4.025e-02   5.181 6.57e-07 ***
monthdJun    1.202e-01  3.975e-02   3.025 0.002895 **
monthdMar    4.571e-02  4.005e-02   1.141 0.255448
monthdMay   -2.148e-02  3.968e-02  -0.541 0.589024
monthdNov   -1.369e-01  4.041e-02  -3.388 0.000888 ***
monthdOct   -6.144e-03  4.274e-02  -0.144 0.885879
monthdSep    8.385e-02  4.234e-02   1.980 0.049387 *
wGDP         1.963e-14  6.196e-15   3.169 0.001833 **
IntTourismR -9.860e-14  5.845e-14  -1.687 0.093546 .
IndoER       2.657e-03  1.280e-03   2.076 0.039532 *
rampTr      -1.993e-02  2.594e-03  -7.684 1.46e-12 ***
AusER       -1.559e-03  1.623e-03  -0.960 0.338274
JanER        1.464e-03  1.091e-03   1.342 0.181414
laglogBali   4.867e-01  5.796e-02   8.397 2.32e-14 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1086 on 160 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.9291,    Adjusted R-squared:  0.9212
F-statistic: 116.5 on 18 and 160 DF,  p-value: < 2.2e-16
```

2. Improvements for the Loss Estimation

When estimating the loss in revenue for the Bali tourism industry, I used the average expenditure for an international tourist in Indonesia in 2011. To reach a more precise loss estimation, the average expenditure for an international tourist in Bali for 2002, 2003, 2004, 2005, 2006, and 2007 should be utilized. However, there is no valid database proving these statistics online. A more accurate loss estimation can be determined if these statistics are found. In this study, the number of direct tourist arrival is the chosen parameter to assess the impact of the terrorist attack on the Bali tourism industry. However, there are other parameters that can also be used to capture the loss caused by terrorist attacks. For instance, we should also take a look at how the average hotel occupancy rate and the average stay in Bali changed before and after the terrorist attacks, as these two factors are also closely related to the revenue of the tourism industry. In fact, although the tourist arrival quickly recovered around the beginning of 2004, the monthly room occupancy of star-rated hotels in Bali returned to the pre-attack rates around 2008. While the monthly average length of stay in Bali has experienced a persistent downwards trend since 2002 (Woods, 2020). Although further analysis is needed to prove the causal relationship between the terrorist attacks and these two observations, these two trends are worth attention for a more comprehensive assessment of the terrorist attack' impact on Bali tourism performance.

3. Comparison with Models from other Studies

Professor Dubin had previously worked on a project with his former student, Natalie Ryan, around the same topic, but they approached it by identifying the habituation effects of the two attacks. Although their research task slightly differs from this research, both studies tried to capture the variations in the log of Bali tourist arrivals during the affected period of time. The model they suggested to capture the variations in the Bali tourist arrivals has an adjusted r squared value of 0.826, while the fourth model in this research has a value of 0.8878.

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X. Appendix: Data Sources

1. Period of Observations

For the Bali event study, I examined the period January 1998 through December 2012. For the Maldives event study, I examined the period January 1999 through December 2012.

2. Response Variables

For the Bali event study, we source a measure of total monthly foreign tourist arrivals to Bali from the Statistics of Bali Province[67]. For the Maldives event study, we source a measure of total monthly foreign tourist arrivals to Maldives from Ministry of Tourism, Republic of Maldives[8].

3. Control Variables for Hedonic Regression

a. Monthly Dummy Variables

I set up a dummy variable for each month to capture the seasonality in the model.

b. Terrorism Attack Impact Dummy Variable

I set up the dummy variable for a period of time affected by the two terrorist attacks with 1 and unaffected period with 0.

c. Terrorism Attack Impact Ramp and reverse Ramp Variable

I set up the ramp function for a period of time affected by the two terrorist attacks in a gradual change order and unaffected period with 0.

---

6 Statistics of Bali Province. (1998-2008). Number of Monthly Foreign Visitor to Bali, 1982-2008. Retrieved April 22, 2022, from: https://bali.bps.go.id/statictable/2018/02/09/21/banyaknya-wisatawan-mancanegara-bulanan-ke-bali-1982-2008.html

7 Bali Hotels Association. (2008-2012). The Monthly Arrival Statistic Based on Nationality to Bali. Retrieved April 22, 2022, from: https://www.balihotelsassociation.com/media-centre/stats/

8 Republic of Maldives, Ministry of Tourism. (2004-2012). Statistics. Retrieved April 22, 2022, from: https://www.tourism.gov.mv/en/statistics/annual/

d. World Domestic Product in current U.S. Dollars

I employed an annual, not seasonally adjusted measure of Gross Domestic Product for the World in current U.S. Dollars to account for the wealth of international tourists. This data is sourced from the Federal Reserve[9].

e. Global Tourism Demand Trend

I employed a measure of annual worldwide tourism demand trends by sourcing Annual World Tourism Receipts from the World Bank[10].

f. Trade Balance - Net Trade: Value Goods for Indonesia

I employed a measure of trade balance to account for potential fluctuations in business travel for the Bali by sourcing Net trade of Value Goods for Indonesia from the Federal Reserve[11].

g. Real Broad Effective Exchange Rate for Indonesia [12]

I employed a measure of the real broad effective exchange rate to account for fluctuations in the cost of living as well as exchange rates for the destination country by sourcing from the Federal Reserve [13].

h. Real Broad Effective Exchange Rate for Australia

I employed a measure of the real broad effective exchange rate of Australia, where majority of tourists in Bali are from, as an important economic variable of its Economy by sourcing the statistics from the Federal Reserve [14].

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[9] FRED Economic Data. (2022). Gross Domestic Product for World. Retrieved April 24, 2022, from: https://fred.stlouisfed.org/series/NYGDPMKTPCDWLD

[10] World Band. (2020). International Tourism, Receipts (current US$). Retrieved April 24, 2022, from: https://data.worldbank.org/indicator/ST.INT.RCPT.CD?end=2013&start=2000

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[12] FRED Economic Data. (2022). Real Broad Effective Exchange Rate for Indonesia. Retrieved April 24, 2022, from: https://fred.stlouisfed.org/series/RBIDBIS

[13] FRED Economic Data. (2022). Real Broad Effective Exchange Rate for Indonesia. Retrieved April 24, 2022, from: https://fred.stlouisfed.org/series/RBIDBIS

[14] FRED Economic Data. (2022). Real Broad Effective Exchange Rate for Australia. Retrieved April 24, 2022, from: https://fred.stlouisfed.org/series/RBAUBIS

i. Real Broad Effective Exchange Rate for Japan

I employed a measure of the real broad effective exchange rate of Japan, where majority of tourists in Bali are from, as an important economic variable of its Economy by sourcing the statistics from the Federal Reserve [15].

Table 7 - Data Glossary for attached Excel Sheet

date	The date from Jan 1998 to Dec 2012 in Month-Year format
monthd	month (factor)
Trend	Trend variable from 1 to 180
bali	The direct tourist arrival to Bali
wGDP	World Domestic Product in current U.S. Dollars
IntTourismR	Annual World Tourism Receipts
IndoER	Real Broad Effective Exchange Rate for Indonesia
IndoTB	Trade Balance - Net Trade: Value Goods for Indonesia
dummyT	Dummy variable for the attack-affected period of time
rampT	Ramp function for the attack-affected period of time
rampTr	Inversed ramp function for the attack-affected period of time
AusER	Real Broad Effective Exchange Rate for Australia
JanER	Real Broad Effective Exchange Rate for Japan
logBali	log of Bali
lagBali	first lag of Bali
laglogBali	first lag of log Bali

[15] FRED Economic Data. (2022). Real Broad Effective Exchange Rate for Japan. Retrieved April 24, 2022, from: https://fred.stlouisfed.org/series/RBJPBIS