The Effects of Changes in the National Terror Alert Level on Consumer Behavior

A thesis submitted to the Miami University Honors Program in partial fulfillment of the requirements for University Honors with Distinction

by

Joshua K. Montes

May 2006
Oxford, Ohio
ABSTRACT

The Effects of Changes in the National Terror Alert Level on Consumer Behavior

by Joshua K. Montes

Using daily observations of ridership on the New York City subway system from March 12, 2002 through October 31, 2005, this paper studies the effects that changes in the national terror alert level as set by the U.S. Department of Homeland Security has on consumer behavior in the subway system. Applied time-series intervention analysis shows that increasing the national terror alert level to high (color coded as orange) leads to a 4% decrease, both statistically and economically, in daily subway ridership in New York City. Furthermore, an increased national terror alert level decreases consumer surplus by as much as $1.80 million per day, approximately 3.3% of which is due to a decrease in subway ridership.
The Effects of Changes in the National Terror Alert Level on Consumer Behavior

by Joshua K. Montes

Approved by:

_________________________, Advisor
(George K. Davis, Professor, Economics)

_________________________, Reader
(Dennis H. Sullivan, Professor, Economics)

_________________________, Reader
(Michael A. Curme, Professor, Economics)

Accepted by:

_________________________, Director,
University Honors Program
Table of Contents

1. Introduction ........................................................................................................... 1
2. Terrorism and the National Terror Alert Level System ......................................... 2
3. Previous Literature ............................................................................................... 4
4. Data ....................................................................................................................... 6
5. Estimation Techniques .......................................................................................... 9
6. Estimation Results ............................................................................................... 12
7. Discussion ............................................................................................................ 15
    7.1 Case 1. Elastic Demand Function \( \varepsilon^d = -1.25 \) and a Price per Day of $2.53 ................................................................. 17
    7.2 Case 2. Elastic Demand Function \( \varepsilon^d = -1.25 \) and a Price per Day of $7.00 ................................................................. 18
    7.3 Case 3. Inelastic Demand Function \( \varepsilon^d = -0.25 \) and a Price per Day of $2.53 ................................................................. 19
    7.4 Case 4. Inelastic Demand Function \( \varepsilon^d = -0.25 \) and a Price per Day of $7.00 ................................................................. 19
    7.5 Analyzing the Lost Consumer Surplus .......................................................... 20
8. Conclusion .............................................................................................................. 23
Figure 1. New York City Subway Ridership, March 2002-October 2005

Ridership in Millions

Note: Ridership numbers are monthly averages.

Figure 2. Relationship Between New York City Subway Riders’ Willingness to Pay and Changes in the National Terror Alert Level

Note: The shaded region represents the change in consumer surplus when the national terror alert level, T, is elevated to orange (denoted by T=1).
Table 1. Annual Subway Ridership by City, 2004\(^a\)

<table>
<thead>
<tr>
<th>City</th>
<th>Ridership</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Moscow</td>
<td>3.2 billion</td>
</tr>
<tr>
<td>2. Tokyo</td>
<td>2.8 billion</td>
</tr>
<tr>
<td>3. Seoul</td>
<td>2.3 billion</td>
</tr>
<tr>
<td>4. Mexico City</td>
<td>1.4 billion</td>
</tr>
<tr>
<td>5. New York City</td>
<td>1.4 billion</td>
</tr>
<tr>
<td>6. Paris</td>
<td>1.2 billion</td>
</tr>
<tr>
<td>7. London</td>
<td>976 million</td>
</tr>
<tr>
<td>8. Osaka</td>
<td>912 million</td>
</tr>
<tr>
<td>9. Hong Kong</td>
<td>834 million</td>
</tr>
<tr>
<td>10. St. Petersburg</td>
<td>821 million</td>
</tr>
</tbody>
</table>

Note: Mexico City Ridership: 1.442 billion; New York City Ridership: 1.426 billion

a. This table is reproduced from the one originally created by the MTA. For the original table, please see the following website: http://www.mta.nyc.ny.us/nyct/facts/ffsubway.htm

Table 2. New York City Subway System Ridership Descriptive Statistics

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>3,889,431</td>
</tr>
<tr>
<td>Median</td>
<td>4,509,563</td>
</tr>
<tr>
<td>Maximum</td>
<td>5,155,501</td>
</tr>
<tr>
<td>Minimum</td>
<td>25</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>1,144,657</td>
</tr>
</tbody>
</table>

Note: The descriptive statistics are calculated using 1,330 daily observations from March 12, 2002 through October 31, 2005.

Table 3. Augmented Dickey-Fuller Test for a Unit Root

<table>
<thead>
<tr>
<th>Variable</th>
<th>ADF τ-stat(^a)</th>
<th>Number of Lags(^b)</th>
</tr>
</thead>
<tbody>
<tr>
<td>New York City Subway Ridership</td>
<td>-5.89*</td>
<td>21</td>
</tr>
</tbody>
</table>

a. The Augmented Dickey-Fuller τ-stat is tested against the Augmented Dickey-Fuller τ\(_μ\) critical value with a constant but no time trend term for 1,330 observations.

b. The number of lagged differences is the same for both the AIC and SBC.

* The time series is stationary at the 1%, 5%, and 10% Augmented Dickey-Fuller significance levels.
Table 4. Relationship Between New York City Subway System Ridership and Changes in the National Terror Alert Level

<table>
<thead>
<tr>
<th>Variable(x)</th>
<th>Estimated Coefficient</th>
<th>Prob-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>2482547.0 (224583.0)</td>
<td>0.000</td>
</tr>
<tr>
<td>Ridership(_{t-1})</td>
<td>0.343 (0.028)</td>
<td>0.000</td>
</tr>
<tr>
<td>Ridership(_{t-2})</td>
<td>0.004 (0.029)</td>
<td>0.904</td>
</tr>
<tr>
<td>Ridership(_{t-3})</td>
<td>0.021 (0.029)</td>
<td>0.479</td>
</tr>
<tr>
<td>Ridership(_{t-4})</td>
<td>-0.006 (0.029)</td>
<td>0.830</td>
</tr>
<tr>
<td>Ridership(_{t-5})</td>
<td>0.037 (0.029)</td>
<td>0.205</td>
</tr>
<tr>
<td>Ridership(_{t-6})</td>
<td>0.040 (0.029)</td>
<td>0.174</td>
</tr>
<tr>
<td>Ridership(_{t-7})</td>
<td>0.040 (0.029)</td>
<td>0.178</td>
</tr>
<tr>
<td>Ridership(_{t-8})</td>
<td>-0.016 (0.029)</td>
<td>0.581</td>
</tr>
<tr>
<td>Ridership(_{t-9})</td>
<td>0.011 (0.029)</td>
<td>0.710</td>
</tr>
<tr>
<td>Ridership(_{t-10})</td>
<td>-0.043 (0.028)</td>
<td>0.126</td>
</tr>
<tr>
<td>National</td>
<td>-122123.2 (45686.5)</td>
<td>0.008</td>
</tr>
<tr>
<td>Monday</td>
<td>636933.0 (168816.8)</td>
<td>0.000</td>
</tr>
<tr>
<td>Tuesday</td>
<td>151730.7 (122444.2)</td>
<td>0.216</td>
</tr>
<tr>
<td>Thursday</td>
<td>63076.5 (117555.1)</td>
<td>0.592</td>
</tr>
<tr>
<td>Friday</td>
<td>153365.8 (145773.4)</td>
<td>0.293</td>
</tr>
<tr>
<td>Saturday</td>
<td>-1790339.0 (140411.4)</td>
<td>0.000</td>
</tr>
<tr>
<td>Sunday</td>
<td>-1819712.0 (150414.9)</td>
<td>0.000</td>
</tr>
<tr>
<td>Month</td>
<td>Ridership</td>
<td>National</td>
</tr>
<tr>
<td>------------</td>
<td>------------</td>
<td>----------</td>
</tr>
<tr>
<td>February</td>
<td>128137.7</td>
<td>(65063.0)</td>
</tr>
<tr>
<td>March</td>
<td>187505.7</td>
<td>(63985.9)</td>
</tr>
<tr>
<td>April</td>
<td>169474.6</td>
<td>(62428.6)</td>
</tr>
<tr>
<td>May</td>
<td>144794.0</td>
<td>(63262.9)</td>
</tr>
<tr>
<td>June</td>
<td>196486.5</td>
<td>(61803.5)</td>
</tr>
<tr>
<td>July</td>
<td>23610.40</td>
<td>(58445.80)</td>
</tr>
<tr>
<td>August</td>
<td>-45348.2</td>
<td>(57380.4)</td>
</tr>
<tr>
<td>September</td>
<td>162987.3</td>
<td>(59683.8)</td>
</tr>
<tr>
<td>October</td>
<td>208350.4</td>
<td>(63912.64)</td>
</tr>
<tr>
<td>November</td>
<td>108467.2</td>
<td>(68166.1)</td>
</tr>
<tr>
<td>December</td>
<td>95520.84</td>
<td>(64653.0)</td>
</tr>
</tbody>
</table>

Adjusted R²: 0.871  
AIC: 28.71  
SBC: 28.83

Note: Standard errors are in parentheses.

a. Variable List:  
Ridership<sub>t-n</sub> = daily ridership on the New York City subway system at period t-n; National = 1 if national terror alert level is the color orange, 0 otherwise;  
Monday, Tuesday, Thursday, Friday, Saturday, Sunday = 1 for the particular day of the week, 0 otherwise (Wednesday is omitted); February, March, April, May, June, July, August, September, October, November, December = 1 for the particular month of the year, 0 otherwise (January omitted)
Table 5. Model Selection Statistics for Terror Alert Level Intervention Analysis on New York City Subway Ridership

<table>
<thead>
<tr>
<th>Number of Ridership Lags Included as Predictors</th>
<th>Significant Lags</th>
<th>AIC</th>
<th>SBC</th>
<th>Lagrange Multiplier prob-value</th>
<th>Ljung-Box Q-Statistic prob-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>Ridership&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>28.71019</td>
<td>28.80780</td>
<td>0.671</td>
<td>0.959</td>
</tr>
<tr>
<td>9</td>
<td>Ridership&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>28.71006</td>
<td>28.80376</td>
<td>0.421</td>
<td>0.952</td>
</tr>
<tr>
<td>8</td>
<td>Ridership&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>28.70856</td>
<td>28.79837</td>
<td>0.451</td>
<td>0.954</td>
</tr>
<tr>
<td>7</td>
<td>Ridership&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>28.70734</td>
<td>28.79324</td>
<td>0.720</td>
<td>0.974</td>
</tr>
<tr>
<td>6</td>
<td>Ridership&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>28.70726</td>
<td>28.78926</td>
<td>0.283</td>
<td>0.919</td>
</tr>
<tr>
<td>5</td>
<td>Ridership&lt;sub&gt;t-1&lt;/sub&gt;, Ridership&lt;sub&gt;t-5&lt;/sub&gt;</td>
<td>28.70766</td>
<td>28.7875</td>
<td>0.163</td>
<td>0.883</td>
</tr>
<tr>
<td>4&lt;sup&gt;a&lt;/sup&gt;</td>
<td>Ridership&lt;sub&gt;t-1&lt;/sub&gt;, Ridership&lt;sub&gt;t-5&lt;/sub&gt;</td>
<td>28.70622</td>
<td>28.78040</td>
<td>0.149</td>
<td>0.881</td>
</tr>
<tr>
<td>4</td>
<td>Ridership&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>28.71203</td>
<td>28.78621</td>
<td>0.052</td>
<td>0.872</td>
</tr>
<tr>
<td>3&lt;sup&gt;b&lt;/sup&gt;</td>
<td>Ridership&lt;sub&gt;t-1&lt;/sub&gt;, Ridership&lt;sub&gt;t-5&lt;/sub&gt;</td>
<td>28.70535</td>
<td>28.77563</td>
<td>0.151</td>
<td>0.903</td>
</tr>
<tr>
<td>3</td>
<td>Ridership&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>28.71055</td>
<td>28.78083</td>
<td>0.048</td>
<td>0.864</td>
</tr>
<tr>
<td>2&lt;sup&gt;c&lt;/sup&gt;</td>
<td>Ridership&lt;sub&gt;t-1&lt;/sub&gt;, Ridership&lt;sub&gt;t-5&lt;/sub&gt;</td>
<td>28.70405*</td>
<td>28.77043**</td>
<td>0.129</td>
<td>0.766</td>
</tr>
<tr>
<td>2</td>
<td>Ridership&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>28.71066</td>
<td>28.77704</td>
<td>0.032</td>
<td>0.769</td>
</tr>
<tr>
<td>1</td>
<td>Ridership&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>28.70916</td>
<td>28.77163</td>
<td>0.116</td>
<td>0.771</td>
</tr>
</tbody>
</table>

Note: The indicator variables representing the change in the terror alert level; days Monday, Tuesday, Saturday, and Sunday; and months January, February, March, April, May, June, September, October, November, and December are included in each model.

Note: Each model includes lags Ridership<sub>t-1</sub> through Ridership<sub>t-n</sub>, where n is the number of ridership lags included as predictors, unless otherwise noted.

- a. The model includes the variables Ridership<sub>t-1</sub> through Ridership<sub>t-3</sub> and Ridership<sub>t-5</sub>.
- b. The model includes the variables Ridership<sub>t-1</sub>, Ridership<sub>t-2</sub>, and Ridership<sub>t-5</sub>.
- c. The model includes the variables Ridership<sub>t-1</sub> and Ridership<sub>t-5</sub>.

* Denotes the minimum AIC value.
** Denotes the minimum SBC value.
Table 6. Relationship Between New York City Subway System Ridership and Changes in the National Terror Alert Level

<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimated Coefficient</th>
<th>Prob-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>2714918.0</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(121237.5)</td>
<td></td>
</tr>
<tr>
<td>Ridership_{t-1}</td>
<td>0.353</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(0.026)</td>
<td></td>
</tr>
<tr>
<td>Ridership_{t-5}</td>
<td>0.040</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td></td>
</tr>
<tr>
<td>National</td>
<td>-128181.4</td>
<td>0.005</td>
</tr>
<tr>
<td></td>
<td>(45094.4)</td>
<td></td>
</tr>
<tr>
<td>Monday</td>
<td>589504.6</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(80469.1)</td>
<td></td>
</tr>
<tr>
<td>Tuesday</td>
<td>91981.6</td>
<td>0.026</td>
</tr>
<tr>
<td></td>
<td>(41341.6)</td>
<td></td>
</tr>
<tr>
<td>Saturday</td>
<td>-2053141.0</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(38617.3)</td>
<td></td>
</tr>
<tr>
<td>Sunday</td>
<td>-1961543.0</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(67692.1)</td>
<td></td>
</tr>
<tr>
<td>February</td>
<td>143256.0</td>
<td>0.005</td>
</tr>
<tr>
<td></td>
<td>(51239.1)</td>
<td></td>
</tr>
<tr>
<td>March</td>
<td>209895.1</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(46060.72)</td>
<td></td>
</tr>
<tr>
<td>April</td>
<td>188357.2</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(44822.5)</td>
<td></td>
</tr>
<tr>
<td>May</td>
<td>166779.5</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(44213.39)</td>
<td></td>
</tr>
<tr>
<td>June</td>
<td>213847.8</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(44612.2)</td>
<td></td>
</tr>
<tr>
<td>September</td>
<td>180227.5</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(44474.8)</td>
<td></td>
</tr>
<tr>
<td>October</td>
<td>229868.8</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(44508.3)</td>
<td></td>
</tr>
<tr>
<td>November</td>
<td>131277.2</td>
<td>0.008</td>
</tr>
<tr>
<td></td>
<td>(49402.7)</td>
<td></td>
</tr>
<tr>
<td>December</td>
<td>106274.9</td>
<td>0.029</td>
</tr>
<tr>
<td></td>
<td>(48700.3)</td>
<td></td>
</tr>
</tbody>
</table>

Adjusted R^2: 0.871
AIC: 28.70405
SBC: 29.77043
Lagrange Multiplier Prob-Value: 0.129
Ljung Box Q(1)-Statistic Prob Value: 0.766

Note: Standard errors are in parentheses.

a. Variable List: Ridership_{t-n} = daily ridership on the New York City subway system at period t-n; National = 1 if national terror alert level is the color orange, 0 otherwise; Monday, Tuesday, Saturday, Sunday = 1 for the particular day of the week, 0 otherwise; February, March, April, May, June, September, October, November, December = 1 for the particular month of the year, 0 otherwise
Table 7. The Inverse Demand Relationship Between the Price of a One Day Unlimited Ride Subway Ticket and New York City Subway Ridership Based on the National Terror Alert Level With an Elasticity of Demand Equal to –1.25 at Price $2.53

<table>
<thead>
<tr>
<th>National Terror Alert Level</th>
<th>Constant</th>
<th>Slope</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yellow</td>
<td>$4.554</td>
<td>$-5.20385\times10^{-7}$</td>
</tr>
<tr>
<td>Orange</td>
<td>$4.554</td>
<td>$-5.38119\times10^{-7}$</td>
</tr>
</tbody>
</table>

Note: The inverse demand functions were derived using the known information price of a one day subway ticket at $2.53, the elasticity of demand, and the mean subway ridership under both levels of the national terror alert.

Table 8. The Inverse Demand Relationship Between the Price of a One Day Unlimited Ride Subway Ticket and New York City Subway Ridership Based on the National Terror Alert Level With an Elasticity of Demand Equal to –1.25 at Price $7.00

<table>
<thead>
<tr>
<th>National Terror Alert Level</th>
<th>Constant</th>
<th>Slope</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yellow</td>
<td>$12.60</td>
<td>$-1.43980\times10^{-6}$</td>
</tr>
<tr>
<td>Orange</td>
<td>$12.60</td>
<td>$-1.48887\times10^{-6}$</td>
</tr>
</tbody>
</table>

Note: The inverse demand functions were derived using the known information price of a one day subway ticket at $7.00, the elasticity of demand, and the mean subway ridership under both levels of the national terror alert.

Table 9. The Inverse Demand Relationship Between the Price of a One Day Unlimited Ride Subway Ticket and New York City Subway Ridership Based on the National Terror Alert Level With an Elasticity of Demand Equal to –.25 at Price $2.53

<table>
<thead>
<tr>
<th>National Terror Alert Level</th>
<th>Constant</th>
<th>Slope</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yellow</td>
<td>$12.65</td>
<td>$-2.60192\times10^{-6}$</td>
</tr>
<tr>
<td>Orange</td>
<td>$12.65</td>
<td>$-2.69060\times10^{-6}$</td>
</tr>
</tbody>
</table>

Note: The inverse demand functions were derived using the known information price of a one day subway ticket at $2.53, the elasticity of demand, and the mean subway ridership under both levels of the national terror alert.
Table 10. The Inverse Demand Relationship Between the Price of a One Day Unlimited Ride Subway Ticket and New York City Subway Ridership Based on the National Terror Alert Level With an Elasticity of Demand Equal to –.25 at Price $7.00

<table>
<thead>
<tr>
<th>National Terror Alert Level</th>
<th>Constant</th>
<th>Slope</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yellow</td>
<td>$35.00</td>
<td>$-7.19900 \times 10^{-6}$</td>
</tr>
<tr>
<td>Orange</td>
<td>$35.00</td>
<td>$-7.44433 \times 10^{-6}$</td>
</tr>
</tbody>
</table>

Note: The inverse demand functions were derived using the known information price of a one day subway ticket at $7.00, the elasticity of demand, and the mean subway ridership under both levels of the national terror alert.

Table 11. The Daily Loss in Subway Rider Consumer Surplus Due to Changes in the National Terror Alert Level

<table>
<thead>
<tr>
<th>Case</th>
<th>Total Daily Loss in Consumer Surplus</th>
<th>Daily Loss in Consumer Surplus Due to the Decrease in Ridership</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. $\varepsilon_d = -1.25; P = $2.53$</td>
<td>$129,719.58$</td>
<td>$4,063.35$ (3.13%)</td>
</tr>
<tr>
<td>2. $\varepsilon_d = -1.25; P = $7.00$</td>
<td>$358,907.92$</td>
<td>$11,831.14$ (3.30%)</td>
</tr>
<tr>
<td>3. $\varepsilon_d = -0.25; P = $2.53$</td>
<td>$648,597.88$</td>
<td>$21,181.98$ (3.27%)</td>
</tr>
<tr>
<td>4. $\varepsilon_d = -0.25; P = $7.00$</td>
<td>$1,794,539.60$</td>
<td>$59,142.90$ (3.30%)</td>
</tr>
</tbody>
</table>

Note: The percentage of the total loss in consumer surplus due to a decrease in subway ridership is in parentheses.
1. Introduction

Since the September 11, 2001 terrorist attacks on New York City’s twin towers, governments worldwide have emphasized combating terrorism. Led by the United States and its war on terror, the many of the world’s leaders have developed policy to fight current terror threats and to protect its nation from future attacks. These policies not only have a clear impact on the world’s political landscape, they also have an economic impact on society. Specific policies for fighting terror levy an economic cost on the society by changing the behavior of people.

This paper sets out to show that people take notice of changes in the national terror alert level, view increases in the alert level as evidence of a significant increase in the risk of a terrorist attack, alter their behavior as consumers, and lose welfare as a result. I use the New York City subway ridership as a proxy to measure consumers’ reactions to changes in the national terror alert level. This data presents an attractive opportunity since New York City subway ridership provides a large sample of consumers in a large city that has been the target of terrorist attacks. Finally, I investigate the size of the consumer surplus loss when the national terror alert level increases. I break this loss into two components: the loss from fewer rides and the loss from the reduced surplus of those who continue to ride.
2. Terrorism and the National Terror Alert Level System

Terrorism is the planned use or threatened use of force or violence by individuals or organized groups to obtain ideological or political goals through the intimidation or coercion of a mass audience beyond that of the immediate victims.\(^1\) Terrorism becomes transnational when the aggressors, victims, or targets are of an international mix. Thus, the September 11, 2001, terrorist attacks on New York City’s twin towers are transnational since the aggressors originated from the Middle East and attacked a target in the United States.

Terrorist events often appear to be random occurrences, and this randomness often forces governments and societies to use its resources to protect a wide range of possible targets. From the terrorists’ point of view, they have forced a society to alter its behavior and divert its resources to terrorist defense, thereby succeeding in exacting a cost on its targeted society. Therefore, one of the more successful ploys of terrorists is inducing society-wide anxiety from the threat of a terrorist attack instead of an actual attack itself. (Sandler and Enders 2004)

A role of government in protecting a society against possible terrorist attacks is to implement cost efficient policies that both quickly react to terrorist attacks in order to minimize their damage and to put into place measures that may prevent terrorist attacks from occurring. Clearly, the latter measure is a rational society’s most desirable, ceteris paribus. Since the September 11 terrorist attacks, the United States has instituted such preventive policies through its war on terror. Among these policies is the national terror

\(^1\) This definition or terrorism is a standard definition with influence from Sandler and Enders 2005.

The national terror alert level system consists of five increasing stages of alert, each represented by a color: low (green), guarded (blue), elevated (yellow), high (orange), and severe (red). The goal of the national terror alert system is sometimes misunderstood. Often it is believed that the national terror alert level is a notification device to society indicating the likelihood of a terrorist attack. However, the actual purpose of the national terror alert level system is to notify federal law enforcement agencies to prepare for anti-terror activities so that there shall be prompt “implementation of an appropriate set of Protective Measures.”

\[^2\] Taken from: http://www.whitehouse.gov/news/releases/2002/03/20020312-5.html
3. Published Literature

Previous research on economics and terrorism examines strategies for terrorist organizations fighting for their cause, governments’ response by to terrorist effects, the economic effects of anti-terror policies, and the dynamics of terrorist activities and organizations. Much focus has been placed on using time series techniques to examine the economic costs and benefits from government responses to terrorist activities and policies implemented to protect the public, particularly in the form of break points and intervention analysis. Other techniques for terror analysis include game theory and utility-maximizing models.

Todd Sandler and Walter Enders use time-series analysis to explore the current threat of transnational terrorist events. They find that although terrorist activity has declined since the end of the Cold War, each terrorist event is almost 17% more likely to result in death or injuries. Furthermore, their analysis shows that threats and hoaxes show no significant drops since the end of the Cold War (Sandler and Enders 2000). Sandler and Enders also explore how antiterrorist activities may result in unintended consequences and identify the problem of measuring the benefit of anti-terrorist policies (Sandler and Enders 2004) and how terrorism has changed little since September 11, 2001, in face of the U.S.-led “war on terror” (Sandler and Enders 2005).

Jonathan Klick and Alexander Tabarrok examine the role that the national terror alert levels can play in identifying the effect of police presence on crime in Washington D.C. They find that crime statistically decreases on days when the national terror alert level is orange and suggest the decrease in crime is due to an increase in police presence throughout the city on those days (Klick and Tabarrok 2005).
Enders, Sandler, Klick, and Tabarrok provide insight into how terrorism affects government policy decisions and its resulting costs on the government and terrorist organizations. Previous research, however, fails to explore the cost that terror levies on consumers, and examining the national terror alert levels further may provide insight into consumer reaction towards terrorism. Time-series intervention analysis on the national terror alert level and the behavior of New York City subway riders helps measure some of this cost.
4. Data

New York City’s Metropolitan Transportation Authority (MTA) provided daily ridership data for all of the New York City subway systems serving to Manhattan, Queens, Brooklyn, the Bronx, and Staten Island through 26 subway routes and 468 subway stations. The MTA measures daily ridership by the number of riders who pass through the subway station turn-styles on a given calendar day. Table 1 shows 2004 Annual Subway Ridership for world cities. The New York City subway system experienced the fifth largest traffic flow through in the world.

Table 2 shows the New York City subway system ridership descriptive statistics for 1,330 observations from March 12, 2002 through October 31, 2005. The mean ridership is 3,889,431 per day with a standard deviation of 1,144,657. The median value for the ridership variable is 4,509,563 per day. The maximum value is 5,155,501, which occurred on October 27, 2005, and the minimum value is 25 riders, which occurred on August 15, 2003.

Figure 1 shows a time series graph of the averaged monthly ridership values from March 2002 through October 2005 for the New York City subway system. To test for a unit root, I perform an augmented Dickey-Fuller test with an intercept and no time trend on the data, checking both the augmented Dickey-Fuller model in which the Akaike

---

3 The MTA provides service to Staten Island through the Staten Island Railway. The MTA’s website is http://www.mta.nyc.ny.us/
4 2004 Annual Ridership is the most recent annual total available.
5 On August 14, 2003, a widespread power outage affected most of the northeastern United States. Power had yet to be restored to many northeastern cities on August 15, 2003, including New York City, accounting for the low ridership value on this date. The terror alert level during the power outage remained at yellow.
6 The time series shows averaged monthly values as opposed to the observed daily values in order to investigate patterns among the times series more clearly. Otherwise, a time series plot of 1,330 observations from March 2002 through October 2005 renders the graph unreadable.
Information Criteria (AIC) determines the appropriate lag lengths and the model in which
the Schwartz Bayesian Criteria (SBC) determines the appropriate lag lengths for the test.\textsuperscript{7}

The AIC and SBC are model selection criteria that measure fit of the model,
particularly when lags of the predictor variable are added to the explanatory side of the
equation.\textsuperscript{8} Adding explanatory variables to the model reduces the degrees of freedom,
and the AIC and SBC help to determine whether adding the extra explanatory variables
produces a better fitting model. The number of explanatory variables that are included in
the model minimizes the AIC or SBC. If an explanatory variable that tells nothing about
the predictor variable is added to the model, then the AIC and SBC values will increase.
A model is said to be a better fit than other models if the AIC or SBC is the smallest
when compared to the AIC or SBC of the alternative models. Although the SBC is
superior when estimating large sample sizes such as the subway ridership data, I check
both the AIC and SBC for completeness throughout the analysis.\textsuperscript{9}

Table 3 shows the results of the augmented Dickey-Fuller test using the AIC. The
AIC is minimized when twenty-one lagged differences of the ridership variable are
included as explanatory variables. The augmented Dickey-Fuller test statistic (-5.89) is
significant at the 1\%, 5\%, and 10\% levels (\(\tau_{\mu}\) critical values of -3.44, -2.86, and -2.57,
respectively), so I reject the null hypothesis that ridership has a unit root. The augmented

\textsuperscript{7} I check both the AIC and SBC augmented Dickey-Fuller models since conflicting results would cast
doctor on the model’s appropriateness. If both models yield the same result, then I can proceed with
confidence in the model.

\textsuperscript{8} AIC = T*ln(sum of squared residuals) +2p; SBC = T*ln(sum of squared residuals) + p*ln(T) where p is
the number of parameters estimated and T is the number of observations used in estimation

\textsuperscript{9} The justification for this assertion comes from Walter Enders’ \textit{Applied Econometric Time Series} (2004)
textbook, page 70.
Dickey-Fuller test yields the same results when using the SBC statistic to determined the appropriate number of lagged differences of the ridership variable.

Data for changes in the national terror alert level as set by the United States Department of Homeland Security can be gathered on the Department of Homeland Security’s website through the department’s press releases.\textsuperscript{10} The data set is constructed by using an indicator variable to represent an increase in the national terror alert level from yellow to orange. Since the national terror alert level has only been two out of the five possible colors (yellow and orange) since its inception, only one indicator variable is required to capture the change in the terror alerts. The national terror alert level has been raised from yellow to orange a total of five times for a total of 98 days. The alert level was orange from September 10, 2002 through September 24, 2002, February 7, 2003 through February 27, 2003, March 17, 2003 through April 16, 2003, May 20, 2003 through May 30, 2003, and December 21, 2003 through January 9, 2004.

\textsuperscript{10} The Department of Homeland Security’s press releases document each date when the national terror alert level was raised from yellow to orange and lowered from orange to yellow. The Department of Homeland Security’s website is http://www.dhs.gov
5. Estimation Techniques

Intervention analysis and least squares are used for estimation. The model consists of an autoregressive process with indicator variables representing an increase in the national terror alert level from yellow to orange as set by the Department of Homeland Security, days of the week, and months of the year.\textsuperscript{11} To avoid the indicator variable trap with days of the week and months of the year, I omit the indicator variables representing Wednesday and January.

The rationale for including indicator variables for days of the week follows the apparent fluctuation in subway ridership based on the day of the week that is made obvious by the drastic fall in ridership on Saturdays and Sundays. The drop off in ridership on the weekend days suggests that subway ridership is driven by the typical United States work week (Monday through Friday,) as ridership tends to be higher during the work week and lower on the weekends. Furthermore, adding indicators for Monday through Friday may capture fluctuations due to those workers who may be on a four day work week or other random fluctuations not easily identified.

Observing the time series of the New York City subway system ridership monthly averaged data in figure 1 suggests that there is a monthly seasonal component to the ridership data. The seasonal fluctuations may coincide with changes in weather (such as a shift from warm weather to cold weather, or vice versa) that provide more (or less) incentive to ride the subway as opposed to other means of transportation such as walking.

\textsuperscript{11} Although I experimented with models excluding the indicators for days of the week and months of the year, the robustness of the results when including the day and month indicator variables confirmed that their inclusion in the model was necessary. I also experimented with an indicator variable representing holidays, but the inclusion of the holiday indicator in the model creates a significant serial correlation problem that autoregressive processes and moving averages of high orders could not correct.
Increases in monthly ridership averages may also coincide with the major tourism seasons in New York City. Therefore, I place monthly indicator variables into the model to capture seasonal fluctuations driven by weather, tourism, or other random occurrences.

I begin by estimating an autoregressive process of order 10 including the indicator variables for the national terror alert level changes, days of the week, and months of the year with the goal of targeting insignificant day and month indicator variables in order to shift focus to the AR portion of the model. Table 4 shows the results of the least squares estimation. Ridership lags 2 through 10 and the indicator variables representing Tuesday, Thursday, Friday, July, August, November, and December initially show to be statistically insignificant at the 5% significance level. The low prob-values for the indicator variables Tuesday, November, and December (using a threshold of 0.25 for the indicator variable prob-values) suggest that their inclusion in the model may prove to be important; therefore, I leave Tuesday and December in the model and remove the other insignificant indicator variables.

Table 5 shows the model selection results for the intervention analysis estimation. After removing the insignificant day and month indicator variables, I once again estimate an autoregressive process of order 10 with the national terror alert indicator variable and appropriate day and month seasonal variables. OLS estimation yields statistically insignificant lags of the ridership variable from 2 periods in the past through 10 periods in the past at the 5% significance level; the AIC and SBC statistics are 28.710 and 28.808, respectively, and Ljung-Box Q-statistic prob-value of 0.959 and Lagrange Multiplier prob-value of 0.671 shows there is no serial correlation. Therefore, I remove
lag 10 and continue. I repeat this process, removing insignificant lags one at a time, until the AIC and SBC are minimized and the errors are serially uncorrelated.

The most appropriate intervention analysis model contains significant lags of the ridership variable at 1 and 5 periods in the past, and significant indicator variables representing the change in the national terror alert level; days of the week for Monday, Tuesday, Saturday, and Sunday; and months of the year for February, March, April, May, June, September, October, November, and December at the 5% significance level. Diagnostic checks suggest that the model is appropriate, as the AIC and SBC are both minimized at 28.70405 and 28.77004, respectively. Furthermore, inspection of the errors indicate that there is no evidence of serial correlation, as Lagrange multiplier prob-value is 0.129 and the Ljung-Box Q-statistic is 0.089 with a prob-value of 0.766.

To check that the model accounts for all appropriate seasonal variables, I once again place the day and month indicator variables for Thursday, Friday, July, and August in the model. Estimating the equation shows that the day and month indicator variables are not statistically different from zero and should not be included in the model. Therefore, the model discussed above is the appropriate model to represent the relationship between New York City subway ridership and the changes in the national terror alert level.

12 All discussed variables actually show to be statistically significant at the 3% significance level.
6. Estimation Results

Table 6 shows the estimation results of the national terror alert level intervention analysis including the appropriate lags of the predictor variable (New York City subway ridership) and seasonal indicator variables as discussed in the above section. Diagnostic tests show the errors to be serially uncorrelated, as the Lagrange multiplier prob-value is 0.129 and the Ljung-Box Q(1) statistic prob-value is 0.766. Model selection statistics suggest the model is fitted well, as the AIC and SBC are both minimized compared to the alternative models, and the adjusted $R^2$ statistic is 0.871.

The indicator variable representing a change in the national terror alert level from yellow to orange as set by the U.S. Department of Homeland Security is statistically different from zero at the 1% significance level. On the days that the national terror alert level is increased from yellow to orange, an average of 128,121.4 fewer people choose to ride the New York subway. Therefore, the change in subway ridership on the days in which the national terror alert level is orange represents an approximate 3.3% decrease in subway ridership from the mean value of riders. The remainder of this section discusses the estimation results of the other variables included in the model.

Ridership at lags one and five is positively correlated with ridership in the current period and statistically different from zero at the 1% significance level. On average, 35.3% of the subway ridership total from one period in the past is used to forecast ridership in the current period, and 4.0% of the subway ridership total from five periods in the past is used to forecast ridership in the current period. Although the statistical significance of the lag 5 variable is a bit surprising, the model selection statistics in table 5 suggest that its inclusion in the model is desirable.
The constant term is statistically different from zero at the 1% significance level, and its estimated value is 2,714,918.0, approximately 69.8% of the mean of the ridership variable. The constant term includes the omitted day and month indicator variables Wednesday, Thursday, Friday, January, July, and August.\textsuperscript{13}

Day indicator variables for Monday, Saturday, and Sunday are statistically different from zero at the 1% significance level, and the day indicator variable for Tuesday is statistically different from zero at the 3% level. Subway ridership increases on both Mondays and Tuesdays by 589,504.6 (or approximately 15.2% of the mean) and 91,981.6 (approximately 2.4% of the mean) riders on average, respectively. Saturdays and Sundays, however, show an average decrease in subway ridership by 2,053,141.0 (approximately 52.8% of the mean) and 1,961,543.0 (approximately 50.4% of the mean) riders, respectively.

Month indicator variables for February, March, April, May, June, September, October, and November are statistically different from zero at the 1% significance level, and the month indicator variable for December is statistically different from zero at the 3% significance level. The average estimated increase in subway ridership for February is 143,256.0, approximately 3.7% of the mean. March shows a large average seasonal increase in ridership, as subway ridership increases 209,895.1 riders, approximately 5.4% of the mean. During April, an estimated 188,357.2 extra people on average ride the New York City subways, approximately 4.8% of the mean value. May yields an average increase of 166,779.5 subway riders, approximately 4.3% of the mean. The second

\textsuperscript{13} As described in the section above, Wednesday and January are omitted to avoid the indicator variable trap, and Thursday, Friday, July, and August are statistically insignificant from zero and are thus omitted from the model.
The largest monthly increase in ridership takes place in June, as, on average, an extra 213,847.8 riders use the New York City subway system, which is approximately 5.5% of the ridership mean. In September, subway ridership increases, on average, by 180,227.5 riders, approximately 4.6% of the mean. The largest monthly increase in subway ridership occurs in October, as, an average of 229,868.8 more people ride the subway, approximately 5.9% of the mean. The average estimated increase in subway ridership for November is 131,227.1, approximately 3.4% of the variable’s mean. The smallest monthly increase in subway ridership occurs in December, as an average of 106,274.9 more people ride the New York City subway system, approximately 4.1% of the mean.
7. Consumer Surplus Analysis

New York City was attacked on September 11, 2001, and has emerged as the focal point of the U.S.-led war on terror. The New York City subway system provides a forum to analyze the economic impact of terror threats since subway systems worldwide have increasingly been major targets of terrorist plots, as evidenced by the attacks on the Madrid, Spain (March 2004) and London, United Kingdom (July 2005) subway systems. Additionally, New York City has the largest population in the country, a large sample of its population chooses to use the subway each day and it has the largest volume of riders of any subway system in the United States.

A change in the national terror alert level levies an economic cost on subway riders, and I have found that subway ridership decreases on days in which the national terror alert level is increases to orange. The economic cost can be measured by the subway riders’ willingness to pay in order to have the national terror alert level returned to yellow. The cost can be measured by the loss in consumer surplus due to the high alert level.

I use linear demand functions to represent the consumers’ willingness to pay schedules when the national terror alert level is at either the yellow or orange levels in both elastic and inelastic cases. I estimate the loss in consumer surplus for four cases: 1.) an elastic demand function with elasticity of demand, $\varepsilon^d$, equal to -.25 and the daily subway ticket price, $P$, equal to $2.53; 2.$ an elastic demand function with $\varepsilon^d = -.25$ and $P = $7.00; 3.) an inelastic demand function with $\varepsilon^d = -1.25$ and $P = $2.53; 4.) an inelastic demand function with $\varepsilon^d = -1.25$ and $P = $7.00. I chose the two prices, $P = $2.53 and $P = $7.00.
$7.00, since they were the least and most expensive average cost, respectively, for a one-day unlimited ride pass on the New York City subway system. Choosing elasticities and prices in this way should provide a boundary that contains the loss of consumer surplus due to an increase in the national terror alert level from yellow to orange.

Figure 2 shows the relationship between the price of a one-day unlimited ride subway pass, $P$, and the level of ridership on the New York City subway system, $R$, for the situations when the national terror alert level, $T$, is yellow or orange. To illustrate the loss in consumer surplus, I use the inverse demand schedule, which is a function of the number of riders on the New York City Subway system and the indicator variable for the national terror alert level, $T$, where $T = 1$ when the national terror alert level is raised to orange and 0 otherwise:

$$D(R, T) = P = -\frac{A}{B} + \frac{1}{B}R + CT*R$$  \hspace{1cm} (1)

where $A$, $B$, and $C$ are constants. To find the loss in consumer surplus when the terror alert level is increased to orange, I integrate the inverse demand curve with respect to $R$ under both possible cases for the national terror alert level, find the difference in the two values, and subtract the total revenue lost due to the decrease in $R$ from $R_1$ to $R_0$ when the national terror alert level increases from yellow to orange:

$$\int_0^{R_1} D(R, T=0)dR - \int_0^{R_0} D(R, T=1)dR - P(R_1 - R_0)$$  \hspace{1cm} (2)

---

14 $P = $7.00 represents the cost of a one-day unlimited ride pass on the New York City subway system; $P = $2.53 is the average one day cost of a 30-day unlimited ride pass on the New York City subway system. The total cost of a 30-day unlimited ride pass is $76.00.

15 The inverse demand function is derived from the demand function $R = \frac{B}{(1+BCT)}*P + \frac{A}{(1+BCT)}$, where $T=1$ when the national terror alert level is raised to orange and 0 otherwise.
where $R_1$ is the mean ridership for the New York City subway system (3,889,431), and $R_0$ is the adjusted mean ridership for the New York City subway system when the national terror alert level is orange (3,761,249.6).\footnote{R_0 is determined by subtracting the value of the national terror alert indicator variable (128,181.4) as shown in table 6 from $R_1$, the mean ridership (3,889,431) as shown in table 2. Thus, $R_1 - 128,181.4 = 3,761,249.6$.}  

7.1 Case 1. Elastic Demand Function ($\varepsilon_d = -1.25$) and a Price per Day of $2.53$.  

With $P = 2.53$ and an elastic demand function when the national terror alert level is yellow or orange, I use $R_0$, $R_1$, and the elasticity of demand formula to determine the slope of each inverse demand function. Once the slope is derived, I use the known values of $R_0$, $R_1$, and $P$ to find the intercept for each inverse demand function. I then proceed to construct the inverse demand functions when the national terror alert level is either yellow or orange.  

Table 7 shows the derivation of the inverse demand functions with elasticity of demand equal to $-1.25$ for the yellow and orange national terror alert levels. The slope of the inverse demand function $D(R, T=0)$ is $-5.20385 \times 10^{-7}$, and the slope of the inverse demand function $D(R, T=1)$ is $-5.38119 \times 10^{-7}$. The vertical intercept is the same for both inverse demand functions with a value of $4.554$.  

Integrating the inverse demand functions and calculating the lost total revenue due to a decrease in ridership when the national terror alert level is elevated provides the necessary information to determine the loss in consumer surplus for riders on the New York City subway system when the national terror alert level is elevated to orange. I integrate the inverse demand function $D(R, T=0)$ from 0 to 3,889,431 (which yields a value of $13,776,364.60$) and subtract from it the result of integrating the inverse demand
function $D(R, T=1)$ from 0 to 3,761,249.6 (which yields a value of $13,322,346.08$.) Lastly, I subtract the loss in total revenue ($324,298.94$) to arrive at the change in consumer surplus. Therefore, when the price is $2.53$ and the elasticity of the inverse demand functions is equal to $-1.25$, the loss in consumer surplus due to an increase in the national terror alert level from yellow to orange is approximately $129,719.58$.

7.2 Case 2. Elastic Demand Function ($\varepsilon_d = -1.25$) and a Price per Day of $7.00$.

For the case when $P = 7.00$ and the elasticity of demand is equal to $-1.25$, I use the known values of $R_0$ and $R_1$ to derive the intercept of the inverse demand curves and their subsequent slopes by the same means used in case 1. Table 8 shows the results of the derivations of the inverse demand functions at the yellow and orange national terror alert levels. The slope for the inverse demand function $D(R, T=0)$ is $-1.43980 \times 10^{-6}$, and the slope of the inverse demand function $D(R, T=1)$ is $-1.48887 \times 10^{-6}$. The vertical intercept is once again the same the inverse demand functions $D(R, T=0)$ and $D(R, T=1)$ with a value of $12.60$.

I calculate the loss in consumer surplus by integrating each inverse demand function and calculating the loss in total revenue from the decrease in ridership due to an increase in the national terror alert level as described in equation 2. Integrating the inverse demand curve $D(R, T=0)$ from 0 to 3,889,431 yields a value of approximately $38,116,423.80$, and integrating the inverse demand curve $D(R, T=1)$ from 0 to 3,761,249.6 yields a value of approximately $36,860,246.08$. Additionally, the loss in total revenue due to a decrease in subway ridership as a result of an increase in the national terror alert level is $897,269.80$. Solving for equation 2, the loss in consumer
surplus when the inverse demand functions’ elasticity is $-1.25$ and the price is $7.00$ is $358,907.92$.

7.3 Case 3. Inelastic Demand Function ($e_d = -.25$) and a Price per Day of $2.53$.

The inverse demand functions in case 3 have an elasticity of $-0.25$, and the price of a one day unlimited ride subway pass is $2.53$. I again utilize the methods described in cases 1 and 2 in order to find the slopes of the inverse demand functions and the vertical intercept, and table 9 shows the results of the derivations. The slope for the inverse demand function $D(R, T=0)$ is $-2.60192\times10^{-6}$, and the slope for the inverse demand function $D(R, T=1)$ is $-2.69060\times10^{-6}$. The intercept for both inverse demand functions $D(R, T=0)$ and $D(R, T=1)$ is $12.65$.

Integrating the inverse demand functions as described in equation 2 and calculating the loss in total revenue due to a decrease in ridership from $R_1$ to $R_0$ again allows me to find the loss in ridership consumer surplus as a result of an increase in the national terror alert level from yellow to orange. Under the case 3 scenario, integrating $D(R, T=0)$ from 0 to 3,889,431 yields a value of approximately $29,520,781.29$, and integrating $D(R, T=1)$ from 0 to 3,761,249.6 yields a value of approximately $28,547,884.46$. Furthermore, the loss in total revenue due to a change in ridership from $R_1$ to $R_0$ is approximately $324,298.94$. Thus solving for equation 2, the loss of consumer surplus in case 3 is $648,597.88$.

7.4 Case 4. Inelastic Demand Function ($e_d = -.25$) and a Price per Day of $7.00$.

For case 4, I choose inverse demand functions $D(R, T=0)$ and $D(R, T=1)$ both with an elasticity of $-0.25$ and set the price of a one day unlimited ride subway pass at
$7.00. By the methods employed in cases 1 through 3, I derive the slopes of both inverse demand functions and the vertical intercept, and table 10 shows the results of the derivations. The slope for the inverse demand function \( D(R, T=0) \) is \(-7.19900 \times 10^{-6}\), and the slope for \( D(R, T=1) \) is \(-7.44433 \times 10^{-6}\). The vertical intercept for the inverse demand functions \( D(R, T=0) \) and \( D(R, T=1) \) is $35.00.

To find the loss in subway rider consumer surplus accompanied with a change in the national terror alert level, I use the formula as described in equation 2 with the inverse demand functions and total revenue loss specific to case 4. Integrating \( D(R, T=0) \) from 0 to 3,889,431 yields an approximate value of $81,678,051.00, and integrating \( D(R, T=1) \) from 0 to 3,761,249.6 yields an approximate value of $78,986,241.6. The loss in total revenue due to a decrease in ridership from \( R_1 \) to \( R_0 \) at the price of $7.00 is approximately $897,269.80. Therefore, by equation 2, the loss in consumer surplus in case 4 when the national terror alert level is increased to orange is approximately $1,794,539.60.

7.5 Analyzing the Loss in Consumer Surplus

Through using elasticities of demand equal to –0.25 and –1.25 for the demand functions and prices of $2.53 (the least expensive one day unlimited ride subway pass, as averaged from the cost of a 30-day pass) and $7.00 (the most expensive one-day unlimited ride subway pass) to analyze four different cases of the subway riders’ willingness to pay, I can plausibly bound the actual inverse demand function for the New York City subway system, so the total loss in consumer surplus associated with an
increase in the national terror alert level from yellow to orange.\textsuperscript{17} The total loss in consumer surplus should fall between the minimum and maximum values calculated in the above four case analysis. Therefore, the total loss in consumer surplus is bounded by the values $129,719.58 \text{ (case 1, } \epsilon^d = -1.25; P = $2.53) \text{ and }$1,794,539.60 \text{ (case 4, } \epsilon^d = -.25; P = $7.00).}

Examining the total loss in consumer surplus further, I inspect its two main components: the loss in consumer surplus due to those riders not using subway transportation when the national terror alert level is orange and the loss in consumer surplus due to a decrease in the willingness to pay of those still riding the subway when the national terror alert level is orange. The triangle marked by points X, Y, and Z in figure 2 shows a graphical representation of the loss in consumer surplus due to a decrease in ridership when the national terror alert level is orange. Riders on the portion of the inverse demand schedule marked by triangle XYZ recognize the risk of riding the subway during a time when the national terror alert level is elevated to be too great to continue riding the subway. These riders will no longer be willing to pay the price of a subway ticket during the times of an elevated national terror alert level, therefore causing a decrease of consumer welfare in the magnitude of the triangle XYZ.

The triangle marked by points X, Z, and the vertical intercept $-(A/ B)$ in figure 2 shows a graphical depiction of the loss in consumer surplus by those who continue to ride the New York City subway system when the national terror alert level is orange. The riders along this portion of the inverse demand schedule recognize the increase in the risk

\textsuperscript{17} Although the actual demand function can not be determined with the given information, the nature of the New York City subway system allows me to assume that the elasticity of the actual demand function lies between $- .25 \text{ and } -1.25.$
of riding the subway system when the national terror alert level is elevated, but the risk is not great enough to warrant finding a new mode of transportation. The added risk, though, does cause the riders’ willingness to pay to decrease, thus decreasing their welfare by the area of the triangle marked by points X, Z, and the vertical intercept. However, the riders’ willingness to pay does not decrease past the price of a subway ticket.

Table 11 shows the total loss in consumer surplus and the loss in consumer surplus due to a decrease in ridership when the national terror alert level is orange in each of the above four cases. In case 1 ($\epsilon^d = -1.25; P = $2.53,$) the total loss in consumer surplus due to the decrease in ridership is approximately $4,063.35, or 3.13% of the total loss in consumer surplus. Case 2 ($\epsilon^d = -1.25; P = $7.00$) shows a loss in consumer surplus due to the decrease in ridership to have an approximate value of $11,831.14$, or 3.30% of the total loss in consumer surplus. Case 3 ($\epsilon^d = -.25; P = $2.53$) shows a loss in consumer surplus due to the decrease in ridership to be approximately $21,181.98$, or 3.27% of the total loss in consumer surplus. For case 4 ($\epsilon^d = -.25; P = $7.00,$) the loss in consumer surplus as a result of a decrease in ridership is approximately $59,142.90$, or 3.30% of the total loss in consumer surplus. The percentage of the total loss in consumer surplus due to a decrease in subway ridership as calculated in the four cases serve as bounding values. Thus, the actual percentage of the total loss in consumer surplus due to a decrease in ridership lies between 3.13% and 3.30% of the total loss in consumer surplus.
8. Conclusion

Consumers observe changes in the national terror alert level and use this information when determining their behavior. In particular, this paper uses intervention analysis to show that riders of the New York City subway system are sensitive to increases in the national terror alert level, so much so that the welfare derived from riding the subway system drops considerably in some cases (approximately as much as $1.80 million per day.) Of this total lost welfare, approximately 3.3% comes from riders choosing to no longer ride the New York City subway system when the national terror alert level is high (orange.) Therefore, significant consumer welfare is lost on the New York City subway system due to consumer reaction to increases in the national terror alert level.

Possible future extensions of this work could analyze the effects that the national terror alert level system has on other industries, such as the financial sector, and on output as a whole. Perhaps the financial market trades differ on days when the national terror alert is at a high level out of fear that an imminent attack may send the market into a downward spiral. More research is needed to determine what effect the national terror alert system has on economic output. The results of this paper show that fewer people ride the subway system in New York City on days of high alert, but exactly to what degree this heightened alert alters their behavior is unclear. Of the people choosing to no longer ride the subway system, how many of them are choosing other modes of transportation and how many of them are choosing to avoid New York City on those days? If there is a significant portion in the latter of the two scenarios, then it is quite
possible that the economic impact of a high national terror alert may extend beyond the New York City subway system.
References


