August 2015

The Economics of Crime

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THE ECONOMICS OF CRIME

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A Dissertation Submitted in

Partial Fulfillment of the

Requirements for the Degree of

Doctor of Philosophy

in Economics

The University of Wisconsin- Milwaukee

August 2015

ABSTRACT

THE ECONOMICS OF CRIME

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The University of Wisconsin-Milwaukee, 2015

Under the Supervision of Professor John S. Heywood and Professor Hamid Mohtadi

Essay 1: “Can Safe Ride Program Reduce Urban Crime?” This paper evaluates the influence of a safe ride program at a public university on neighborhood crime in a major urban area. Using an hours of the week panel, the program's operation is associated with an approximate 14 percent reduction in crime. The program being open appears to have roughly similar influence in reducing violent and non-violent crime. Moreover, increases in rides (the intensity of the program) are also associated with reductions in crime. Such increases in program intensity are also associated with notably greater reductions in crime occurring on weekends. The cost of the safe ride program suggests it is a relatively efficient means of reducing crime.

Essay 2: “University Provided Transit and Urban Crime.” This paper uniquely examines the influence of a new university bus service on urban crime. It concentrates on the interaction between the new bus service and a long-standing safe ride program. The new bus service reduces the number of students using the safe ride program and such substitution raises the well-known concern that a fixed transit route may concentrate victims and criminals increasing crime along the new bus routes. Despite this concern, a

series of difference-in-difference estimates demonstrate that the bus service reduces crime in the entire university neighborhood and that this reduction is actually largest along the new bus routes.

Essay 3: “Modeling Adversary Decisions and Strategic Response.” This work uses a sequential game of conflict between a government and a terrorist organization to analyze the strategic choices between large extreme and large conventional threats. Some of these extreme options: chemical, biological, radiological, and nuclear attacks (CBRN), are both terrifying and highly improbable. Conversely, conventional attacks using firearms or explosives, are comparatively more likely but less destructive. Rather than leaving the game as a theoretical exercise, we calibrate the model to real data from global terror attacks, and forecast anticipated casualties when an informed adversary prepares a large attack against an uninformed government.

ACKNOWLEGEMENTS

Thanks are expressed to Professor Heywood and Professor Hamid Mohtadi for their advice and guidance on these works. Detailed descriptions of the transit programs and critical information on their use were provided by Sargent Kolosovsky at Marquette University, as well as Anthony Gomez and Dr. Longwell-Grice at University of Wisconsin-Milwaukee. Invaluable experience and information was provided by the Department of Student Services at University of Wisconsin, Milwaukee. Richard Roy Martin III deserves thanks for comments on this work, as well as throughout graduate school. Lisa Sutton helped greatly by assisting with GIS software. John Sawyer, Gary Ackerman, and other researchers at National Consortium for the Study of Terrorism and Responses to Terrorism (START) at the University of Maryland, College Park. Finally, my friends and family have been incredibly supportive while I focused on this task.

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Chapter 1: Can Safe Rides Reduce Urban Crime?

1. Introduction

This paper examines a longitudinal case study designed to determine if safe ride programs, common at many universities, reduce urban crime. The study design matches local crime data to the area and service hours of the safe ride program. The estimates control for the hourly fixed effects and sensible covariates. They suggest the safe ride program reduces crime counts by 14%. This influence persists among different categories of crime. Moreover, increased program intensity, as measured by the number of rides delivered, also decreases crime counts. This influence is greater on weekends, as one might anticipate. The cost of the safe ride program suggests it is a relatively efficient way to reduce crime.

This investigation is important as private expenditures on crime deterrence and prevention are enormous. As but one illustration, Americans spend more on private security forces ($41B) than on police ($13B) (U.S. Census Bureau, 2012). Colleges and universities are particularly concerned about safety. Their expenditures on safety not only include safe ride programs, but also foot patrols , night-time escort services, emergency phone systems, increased lighting, and safety and crime prevention presentations. Indeed, 14% of all US higher education institutions claim that the primary responsibility for their campus security lies with private security forces and initiatives (Lewis et al., 1997).

As one such initiative, safe ride programs pick up and deliver students and staff for transportation near the university. The programs vary substantially, but most are designed to prevent victimization, or to reduce drunk driving by students (Lewis et al., 1997). Additionally, the programs are often touted for their convenience to students (Binghamton University, 2013). As of the latest examination by the National Center for Education Statistics, 34% of public four-year universities, and 24% of their private four-year counterparts had safe ride programs set up for students and staff (Lewis et al., 1997). Since the Jeanne Clery Act of 1991, universities must make crime data public for their campus area. These data are often pivotal in the enrollment decisions of potential students and their families. This creates an additional private incentive for safe ride programs.[1]

The research on safe rides remains largely anecdotal, and to the best of my knowledge there has been no prior economic evaluation of their efficiency in reducing crime.[2] This reflects, in part, the remarkable diversity in these programs as there is no federal or state design or regulation of the many individual safe ride programs implemented by US universities. Survey data suggest that the majority of students (60%) believe that safe ride programs are effective, while an equal percentage claim safe ride programs also promote drinking (Elam et al., 2006). Moving beyond such surveys is warranted, as safe ride programs represent a substantial and commonplace investment, and there exists a growing academic interest in the broad relationship between transportation and crime.

Jackson and Owens (2011) study the relationship between the operating hours of the Washington DC subway, DUI's and drinking-related crimes. They create an hour of the week panel to show that a 1999 expansion of the subway service by 3 hours per week reduced DUI arrests by 14%. At the same time, the expansion increased other alcohol related crimes by 5.4%. They suggest that the subway simultaneously provides an alternative to drunk driving, while increasing access to alcohol. Other research explores whether or not transit station s are associated with greater crime in surrounding neighborhoods (Poister, 1996; Liggett et al., 2003). The existing economic theory suggests that safe ride programs influence crime by changing the profits of illegal activity (Becker, 1968). Safe ride program s lower the number of potential victims around the university, creating a less target rich environment for criminals. Moreover, universities may use the transit vehicles as additional eyes on the street, so pedestrians and frequently passed households will be safer. As a consequence, the ride program increases the costs of committing crime near the university, lowering the profit of crime, and motivating potential criminals to instead pursue legal activities, or choose another time or place for their criminal activities. Finally, and with some irony, safe ride programs may transport, and thereby contain, students who otherwise might choose criminal behavior while walking on the streets.

The possibility remains that the program need not decrease crime. The safe ride program examined here makes trips to and from entertainment districts with bars, which increase student access to alcohol. Alcohol causes impaired judgment, resulting in victimization, or leading to students committing crime (Liggett et al., 2003). Since the net effect and the magnitude of the impact is not inherently clear, empirical analysis is needed.

The remainder of the paper is organized as follows. The next section describes the safe ride program in detail, and examines the source of identifying variation in its provision. The matching of crime data and controls are then described. The third section describes the methodology, which addresses the possibility for reverse causality. It also presents basic results, and alternative specifications. The fourth section checks for heterogeneity in the impact of the program. The fifth section makes a comparison of the cost-effectiveness of this program versus that of the police. The sixth and final section concludes and suggests further research.

2. Safe Rides and Crime: The Case Study

2.1 Description of the Safe Ride Program

The data follows Be On the Safe Side (BOSS), a safe ride program operate d by the Student Services Department of University of Wisconsin-Milwaukee (UWM). UWM has about 30,000 students, and is located on the upper east side of Milwaukee. About 1/3 of all students are residential and live on campus or in the immediate area. A new initiative beginning fall of 2013 requires first-year students to live in student housing for one year, suggesting that this proportion will increase (University Housing Department, 2012).

At UWM, all students and staff have access to BOSS, which provides taxi-like services in a region surrounding UW-Milwaukee (See Figure 1). These services are free at the point of service, but each student pays a segregated fee, which includes $10.30 a semester to support BOSS (University of Wisconsin-Milwaukee, 2012). Students call for a ride, wait indoors until a van arrives, and then the van takes them to their destination, which must be an address rather than a street corner. Vans are marked by combinations of unique lights and paint, and are connected by radio with a central station in the student union.

Typically, the program operates at night, being open about 25% of all hours. The safe ride program takes students to any destination within an operating radius of approximately 1.5 miles around campus, including bars, supermarkets, and residence halls. The program operates in all seasons, including summer, permitting students to anticipate it being available for reasons varying from grocery runs to replacing designated drivers. Over the study period from 2005 to 2008, BOSS provided an average of 133,733 rides a year at an average cost of $3.18 each.[3] Such trips add up to a great distance, with BOSS vans traveling 255,000 miles per year (University of Wisconsin-Milwaukee, 2012). The program began operating on September 5th, 2001, and school officials anticipate it continuing well into the future.

2.2. Data on the Safe Ride Program

Data on operating hours and the number of rides has been collected hourly from January 1st, 2005 to June 30th, 2008. This data window reflects the employment of a data entry worker, and as such there are no comparable records outside this period. Our initial independent variable is whether or not the safe ride program is open during any particular hour of the week. The program is typically open during the evening and early morning hours, both when school is in session and otherwise, but does close for inclement weather and holidays. In addition, policy changes have occasionally altered the operating hours of the service. The result is a large amount of variation, as shown in Table 1. The hours of 2am through 4pm show no variation, because the program was always closed. The remaining hours of the week, the early morning and late evening hours, average 24 separate instances of transitioning between open and closed each, out of the potential

181. This variation allows for testing the impact of the changing hours of the program, and suggests that the provision, or absence, of the safe ride program is not clearly associated with any singular event. Ultimately, the data is arranged into an hour of the week panel. This arrangement follows Jackson and Owens (2011), and yields 168 (7x24) hourly observations for each of 182 weeks. Thus, a unit of observation would be the first hour of Monday, observed for 182 weeks. In the fixed effect model, I examine the variation generated by changes within each hour of the week. Thus, for the 182 weeks, there are a maximum of 181 changes that could occur within the first hour of Monday.[4]

2.3. Matching Crime Data to the Safe Ride Program

Crime data is gathered from the Milwaukee Police Department (MPD), and is available through the online system Community Mapping and Analysis for Safety Strategies (COMPASS) (City of Milwaukee, 2014). This system identifies the hour and date of each separate crime, the exact address where the crime occurred, and the type of crime.[5] The system tracks 35 different crime types, tabulated in Table 23, placed in Appendix A. COMPASS has an entry for every report issued within city boundaries, but only after January 1st, 2005. Using geographic information systems (GIS) software, only those crimes with addresses inside the strict boundaries of the safe ride program service region are selected. The crime types are aggregated into a single total crime count variable. Within that region, there is an average of one crime an hour.[6] After the crime data were limited to the geographic area of the program and aggregated into hourly totals, the data is then restricted to the 2005-2008 window where both crime and safe ride data are available. The crime data were matched to the safe ride data in hour of the week panels for all 182 weeks. Thus, for every hour, I know the number of crimes in the service region, and whether or not the program was in service. The data in Figure 2 indicate that crime is trending up over the data window, while the program hours show no trend.[7] Empirical estimates will disaggregate the crime count data into more narrow types of crime to check for variation in the impact of the safe ride program and will account for the apparent trend.

2.4. Matching Data on Controls

While the ultimate objective is to obtain an estimate of the impact of the safe ride program on crime counts, there is a recognized need to control for other short-term determinants of crime. Obvious controls, such as the month of the year, day, and hour, are extracted from the time on the crime report. Beyond that, UWM's official records provide full information on the dates class was in session. This includes finals week, and keeps track of various mid-semester breaks and vacations. Any calendar day with school in session is marked as a school day. Both school days and month of the year are strong determinants of the number of students around campus.

A complementary selection of weather controls from the National Oceanic and Atmospheric Administration (NOAA) (NOAA, 2012) was obtained. These controls are daily measures of precipitation, snowfall, snow on the ground, and minimum temperature.[8] Such controls have been shown to be deterrents of crime (Falk, 1952; Anderson, 1989; Cohn, 1990; Jacob et al., 2004), and are also strong determinants of the number of rides provided by the safe ride program. The daily weather is matched to each hour of that calendar day.

While a number of other demographic controls could be added, such as income, age, or racial demographics, they would not vary substantially over the data window. The final data set then consists of 30,648 consecutive hourly observations. For each hour, the data set provides the day of week and the month, the number of crimes in the service region, an indicator if the safe ride program operated or not, the number of rides provide if operating, an indicator that school was in session or not, and indicators of weather. The summary statistics for all data are shown in Table 2.

3. Estimation Strategy and Initial Results

In thinking about the influence of safe ride programs on crime, there is concern with reverse causality. One might anticipate that university policy makers would target a safe ride program to be open during high crime hours and leave it closed in low crime hours. If this influence dominates, one could find a positive correlation between the hours the program is open and the count of crime. Indeed, data gathered across US cities confirms that more crimes occur during the hours the safe ride program is in operation, 5pm to 2am (Falk, 1952). Generally, national data confirm that relatively little crime occurs between 2am and noon, and the night hours before 2am have more crime than daylight hours (Dudzinski, 2011). Again, a rational policy maker would target high crime night hours, potentially generating a misleading correlation with crime counts.

The above concern emphasizes the importance of selecting an estimation strategy that controls for this reverse causality. In order to measure the impact of the safe ride program, a variety of specifications were explored, but ultimately I select a specification that controls for fixed effects in an hour of the week panel. Each hour of the week is presumed to have a unique propensity for crime over the data window. This propensity can be controlled for because of the frequent openings and closings of the safe ride program within any hour over the time series. The estimates show that failure to control for these fixed effects generates an estimate for the safe ride program that conflates the program's crime reducing influence with the tendency of the program to operate during high-crime hours. By comparing pooled and fixed effect estimates, the size of this confounding effect is isolated.

3.1. Primary Specification and Results

As suggested, the variation in the provision of the safe ride program permits identification of the programs' impact on crime. The following regression is estimated, adding controls to build a more complete specification:

$$crime_{it} = open_{it} * \delta_1 + x_{it} * \beta + \varepsilon_{it}$$

The unit of observation is the hour of week, *i*, from week *t* in the 182 weeks of the time frame. The variable of interest is $open_{it}$, where $open_{it}$ is 1 if the safe ride service is available that particular hour, and 0 otherwise. The coefficient δ_1 indicates the relationship between the safe ride program being open and crime. The contents of the control vector, x_{it}, vary with the specific estimate. Noting that the crime data is count data, Poisson estimates are typically presented, but I will show that OLS produces very similar estimates.

3.2. Primary Results

In Table 3, the basic Poisson estimates are shown with four different specification s of the control vector, x_{it}. Conveniently, the coefficients can be interpreted as the approximate response in the percentage of hourly crimes from a unit increase in the independent variable.[9]

Poisson data may suffer from overdispersion, which occurs when the standard errors are greater than the mean (Cameron and Trivedi, 1998; Atkins and Gallop, 2007). This can create incorrectly small estimates of the standard errors. In order to prevent overdispersion from creating false positives, the coefficients are bootstrapped 200 times following the recommendation from Efron and Tibshirani (1993).[10]

Concern about correlation within the hours of the week leads to clustering standard errors by each hour of the week. After bootstrapping and clustering, the estimated standard errors are about twice as large as the unadjusted errors. As a consequence, false positives are less likely.

Column 1 of Table 3 shows the initial simple regression when pooling the data (not controlling for fixed effects), and indicates that the safe ride program is correlated with a weakly significant 9% decline in crime. In Column 2, I include dummies for whether school is in session, and to compensate for the cyclical components of yearly crime, dummies were added for the month of the year. When school is in session, crime is 15% greater than when school is closed. I found that the months of August through November emerge as higher crime months, perhaps because of the large number of new first year students arriving in those months. The pooled estimate of the effect of the safe ride program remains about the same at 8%, suggesting that these variables are not correcting for a large omitted variable bias. Column 3 adds weather to the controls, since weather clearly impacts both demand for transportation as well as crime. These weather controls are precipitation, snowfall, snow on the ground, and minimum temperature. The weather effects suggest a general theme: crimes are more likely in hospitable weather and less likely in inclement weather, such as snow, rain, or cold. The impact of weather on crime is attributed to criminals facing limited access and availability of victims on the street. Such a result also fits with the suggestion that hot weather itself may induce criminal behavior (Falk, 1952; Anderson, 1989; Cohn, 1990; Jacob et al., 2004). In any event, the estimated impact of the safe ride program remains at roughly 8%, again suggesting that weather, while clearly an important determinate of crime counts, appears to be uncorrelated with the impact of the safe ride program being open. While the signs on the controls seem reasonable, the regressions have not yet accounted for the fixed hour of the week effect.

The next regression accounts for the fact that each hour of the week tends to have different amounts of total crime. Thus, the estimate is generated by variation over time within the hour of week. The fixed effect Poisson estimation (Wooldridge, 2001) is one of the few nonlinear fixed effect estimates which avoids the incidental parameter problems (Cameron and Trivedi, 1998). The estimated effect of the safe ride program, shown in Column 4, jumps dramatically to 14%, suggesting that almost half the true impact (6%) was hidden by the placement of the program in high crime hours. Thus, while adding the other controls had no noticeable impact on the program's coefficient, the fixed effects appear to be critical omitted variables.

For comparison, the regressions in Table 3 have been repeated using naive OLS estimates in Table 4. In the estimates, the coefficient on the program represents the reduction in crime counts associated with the program being open. The influence of the program is a reduction of 0.07 crimes an hour in early estimates, but grows to 0.12 when using fixed effects. The OLS estimates, therefore, also exemplify the strong impact of the fixed effects. Again suggesting much of the impact is hidden behind the tendency for the program to be placed in high crime hours. Overall, the similarity of the OLS estimates suggests that the results do not appear to be dependent on the functional form.[11]

It is emphasized that there are two reasons why the hour of the week fixed effects could be critical. First, as has been suggested, it may be that the hours in which the safe ride program is typically open are those with high crime. Second, it could simply be that within the hours the program is typically open, but may be closed, there are important hour of the week fixed effects. In this second possibility, there could be peripheral hours (very late at night or early in the morning) that tend to have lower crime and these are the hours that the safe ride program is less likely to be open. To distinguish between these two cases, the sample of hours is limited to the hours of the week in which the safe ride program has been open at least once, a restricted sample of \typically open hours". Table 5 reproduces the four Poisson estimates from Table 3 on this restricted sample of typically open hours.

The estimated coefficients on the open dummy, indicating the program is open, are essentially the same across all specifications. Moreover, the coefficient on the open dummy is virtually identical (14%) to the fixed effects Poisson estimates in Table 3. For example, a simple comparison between open and closed hours in the smaller sample shows the safe ride program is associated with a 14% reduction in crime, and the further addition of fixed effects only changes the estimate by 1%. Therefore, it is concluded that within the typically open hours, the fixed effect component in the variation of crime is not critical. The important distinction for estimation is, in fact, that the program is typically provided in high crime hours.

3.3 Challenges to Identification

There exist several potential reasons why one might question the results presented so far. First, the estimates have not tested for a time trend in crime. The results could reflect the program growing or contracting while crime simply has a trend in the opposite direction. To test for this possibility, I include a weekly linear time trend for the entire data window for Tables 3, 4, and 5, and find no meaningful change. For example, in Table 3, column 4, when including the time trend, the coefficient on the trend, while significant, is estimated as a very small 0.00198, suggesting a very small an increase in crime rates. The coefficient of interest measuring the association of rides with crime counts remains in the same neighborhood at a negative and significant -13.3%. As an alternative, I added dummies for each calendar year. While several were significant, the coefficient on the program remained 13% and highly significant.

Second, it remains possible that general patterns in the city's crime count are somehow driving the results. We provide a falsification test to emphasize that the results are, indeed, unique to the treatment area. The model was re-estimated using the crime counts for a city neighborhood that was eight miles away from the program boundary, Bay View. This neighborhood has the most similar demographics of the remaining city areas, which leads to its informal nickname as “The Other East Side". The hope is that such a neighborhood will have similar crime dynamics as the treatment area. Reestimating the hour fixed effects model, the influence of the program being open on crime in Bay View returns an insignificant coefficient of -0.028 with a standard error of 0.059. Had this falsification test generated a significant coefficient, the estimated influence of the program on the university neighborhood might be doubted. The coefficient in the treated region was estimated at -0.152, more than two of these standard errors smaller than the value of the Bay View coefficient.

A third concern is that the estimates can only control for time-invariant fixed effects. Thus, if policy makers have placed the program in consistently high-crime hours, we can hold that constant. What is not accounted for is the potential for a stochastic change in crime influencing policy. A classic example would be if crime is unusually high and policy makers expand the program. This is then followed by a natural mean reversion generating a misleading picture of the program's influence. While we cannot completely rule this out, we follow Priks (2009), by arguing that our falsification test provides some reassurance. If the spike in crime that generated the policy change was evident around the city, our Bay View results should have also returned negative and significant results. These results suggest that the pattern is not driven by sudden and temporary spikes in crime, at least, at the city wide level.[12]

3.4 The Role of Zero Inflation

The earlier results in Table 5 show that the fixed effects estimates from the all hours sample are broadly similar to any estimate from the smaller sample of typically open hours. Yet, even within the typically open sample used for Table 5, 53% of the hourly observations have a crime count of zero, suggesting zero-inflation.[13]

Despite the indication that ZIP may be a better fit for the data, the computational advantages of using the simple Poisson approach in this context are enormous. Several efforts are made to estimate the ZIP. In this case, the computing time of the ZIP model in the full sample proved infeasible. Even when restricting attention to the typically open hours, the estimate needed to be moved onto a 96 core processor as parallel tasks (University of Wisconsin-Milwaukee, 2013) in order to resample and estimate coefficients. The output of these re-estimations were then aggregated and used to calculate the standard errors of the ZIP model.[14]

To obtain an estimate of the impact of the safe ride program, the average marginal effects (AME) must be calculated (Bartus, 2005). The standard errors of the AME were bootstrapped 200 times and accounted for clustering among hours of the week.

Two separate estimates were undertaken. In the first estimate, the outcome relies upon the broad similarity found in the earlier estimates between the sample of typically open hours and the fixed effect estimates in the all hours sample. Thus, the estimates use the typically open hours sample, without hour fixed effects. The results are presented in Column 1 of Table 6, and the controls play a broadly similar role to that isolated earlier. The results also suggest a significant 14% decrease in crime when accounting for zero inflation in the model. The estimate is virtually identical to those without the ZIP. In the second estimate, the typically open sample is again used, but includes dummies for each hour of the week, recognizing the possible bias associated with doing so (Greene, 2001, 2004).[15] The large number of dummies makes both bootstrapping and clustering more difficult, but the point estimate remains nearly identical and significant, as shown in Column 2.

While not the same functional form as estimated in the previous tables, the critical point estimates remain quite firmly around 14%. Thus, there is no indication that failure to account for zero-inflation results in misleading estimates in the earlier tables. As a consequence, in order to save substantial time and present a full range of estimates, focus remains on Poisson estimates when examining treatment heterogeneity and robustness.

4. Extensions

In this section, the simple Poisson estimates are re-examined, with the intention to examine heterogeneity in the measured treatment effect. First, the influence of the program is examined for variation across types of crime. Second, differences in the impact of the program during the weekend as compared to during the weekdays are examined. In the second subsection, an investigation is conducted of a measure of program intensity, the number of rides delivered in an hour. At issue is whether this measure is associated with reduced crime, and whether the heterogeneity identified with the dichotomous measure remains important.

4.1 Heterogeneity in Treatment

One might expect differentiation in impacts across types of crime, as have been found in other papers (Levitt, 2002; Jackson and Owens, 2011). Typically, violent crimes are thought of as crimes of impulse, and therefore less responsive to economic incentives, as compared to nonviolent crimes. We use the Uniform Crime Report's (UCR) definition of crime against persons as a measure of violent crimes, and compare it with the remaining categories, crimes against property and against society (US Department of Justice, 2000).[16] Thus, each hour includes a number of violent and a number of nonviolent crimes. This allows two separate estimates of the influence of the program. The sample is that of all hours, and the controls remain the same. The estimates continue to be bootstrapped and account for clustering.

Table 7 shows that the estimated impact of the program is roughly similar in preventing each type of crime. The magnitudes of the impact (17% for crimes against property and against society, and 13% for personal crimes) are both significant, and roughly comparable to the overall estimate of 14%. Both estimate s are within a standard deviation of the other, also suggesting a relatively homogeneous impact. If anything, there is a slightly greater impact on violent crimes than nonviolent ones. Again, the pattern of coefficients on the controls remain broadly similar to all previous regressions. Weekends on and around campus involve frequent trips associated with social events, parties, and entertainment districts. These trips appear different in kind from the typical weekday trips between home and campus. Criminals may target those traveling to and from these locations differently. Those traveling for entertainment purposes likely carry more cash, increasing the potential revenues earned by criminals. Moreover, providing rides to events with alcohol may actually increase student victimization, since they are generally less aware of their surroundings. Alcohol may even encourage criminal behavior by students themselves, such as disorderly conduct or destruction of property as they walk between locations. This suggests there could be a different impact from program operation in the weekends than on the weekdays.

To test for heterogeneous impacts, the aggregate total crime counts are once again examined. An interaction term between open and the weekend is added, taking the value 1 when the program is open on Friday and Saturday, and 0 otherwise, to the all hours specifications from Table 3.[17] The new set of estimates are shown in Table 8. The results show no significant impact of either open or its interaction with weekends until fixed effects are added in Column 4. Again, this demonstrates the importance of controlling for the policy makers tendency to offer the program in high crime hours. After adding fixed effects, the coefficient on open again doubles from a negative but insignificant 7% to a negative and significant 16%. The coefficient on the interaction term is positive, but remains far from significant. Nonetheless, the positive coefficient on the interaction between open and weekend hints the program may be less effective when open on the weekends. Again, the controls behave similarly to previous results. The next section compares these estimates with those obtained from examining the program intensity, where a far stronger difference is discovered.

4.2. Program Intensity

Beyond simply being open and closed, the number of hourly rides given while the program is open dramatically varies between zero to one hundred seventy-five. This variation largely reflects not the policy-makers supply, but rather the potential victims' demand for rides.[18] It seems reasonable that demand is highest at times or during circumstances of the greatest anticipated crime. This might imply a positive association between the number of rides and crime. Yet, the provision of additional rides indicates the extent to which potential victims are moved off the street and so may be associated with a genuine reduction in crime, a reduction that could hopefully be isolated.

To isolate this influence, the sample is limited to include only the hours in which the program is open. Within that sample, the total number of rides given in the hour is the measure of treatment intensity. The estimates, shown in Table 9, use the same bootstrapping and clustering as previously discussed. The first column uses the intensity measure in a simple Poisson regression. It indicates a statistically significant decline in crime of about a fourth of a percent per ride. The second two columns display the additional influence of school in session, weather, and month controls. These controls appear associated with both crime and the demand for rides, as shown by the now small and insignificant coefficient on the number of rides delivered. While weather was not an important omitted variable when examining the coefficient indicating when the program is open, it does emerge as influential on the rides coefficient. This seems reasonable as weather likely influences the number of rides during hours the safe ride program is open, but does not affect whether or not the safe ride program is open.

The final estimate in Table 9 adds hour of the week fixed effects, and more than doubles the magnitude of the coefficient on rides. It is now highly significant, and the magnitude implies that an increase in the number of rides by one standard deviation (17 rides in an hour) is associated with a crime count that is 8.4% lower in that hour. Once again, controlling for hour of the week fixed effects is critical in estimating the influence of the program on crime. Failure to do so results in estimates that suggest the program is ineffective. Yet, this suggestion largely reflects the tendency of the program to give more rides in hours of high crime. The pattern of controls remain roughly unchanged as a result of the fixed effects.[19]

Next, the rides measure is examined for heterogeneity in treatment. Crimes are again divided into two types, crimes against persons, which represents violent crimes, and the remaining categories, crimes against property and crimes against society. The sample continues to include only those hours in which the program is open. The results, shown in Table 10, indicate that more rides are correlated with a lower crime count for both types of crime. It is noted that the weather controls are weaker in this regression, likely due to a strong correlation with requests for rides. This does not detract, however from the main point of this table. An increase in the number of rides by one standard deviation (17 rides in an hour) is associated with a decline in nonviolent crime of 7%, and a decline in violent crimes of 11%. Both estimates are significant. This suggests the delivering of rides may be more effective at preventing violent crimes in the targeted neighborhood. While a formal test of differences is unavailable, it should be noted that each estimate is more than 2.5 standard deviations from the other.

The next investigation aims to isolate the variation in the influence of program intensity between weekends and weekdays. Continuing to use the sample of only open hours, I use the weekend dummy and interact it with the number of rides given by the program in each hour, and repeat the estimations from Table 9. The same clustering and bootstrapping techniques continue to be used. Column 1 of Table 11 shows that the estimate without other controls indicates that rides given on weekends are associated with a significantly larger decrease in crime than rides given on weekdays. Columns 2 and 3 introduce controls and this results in the coefficients on rides becoming statistically insignificant. Yet, column 4 adds the fixed effects, and again causes the coefficient on rides to become large and highly significant, a pattern seen earlier. The result of the fixed effect estimate is a doubling of the coefficient on hourly rides back to a similar value as seen in Column 1. The point estimate suggests that an additional ride lowers the number of crimes by 0.3 percent. At the same time, the addition of fixed effects has an even larger impact on the interaction term, quadrupling the point estimate to a negative 0.5 percent. Thus, each ride on the weekend is associated with a total reduction of crime of 0.8 percent. Again, this suggests the fixed effects account for a large conflating effect, namely the higher demand for rides in hours of the week prone to high crime. It is noted that the coefficients for the controls are otherwise similar to previous estimates.

The relative magnitudes suggest that an increase in rides by one standard deviation lowers the crime in that weekday hour by 5%, but if the same number of rides are delivered on a weekend, the crime during that hour declines by 13%. This suggests that the rides the program delivers on the weekend are noticeably and significantly more effective. On the weekend, a marked increase in students who are relatively easy and lucrative targets for criminals is anticipated. On the weekend, students may be carrying cash for entertainment costs, and alcohol may impair their judgment. The rides program removes high probability targets from the streets and so appears to have a larger influence on the weekend than on weekdays. This suggests a particularly strong effect of increasing program intensity on the weekends.

When comparing the two measures of the program's impact, there was no significant difference between weekends and weekdays when looking at the open status of the program, but now, a significant difference when examining rides delivered. The simple indication of whether or not the program is open pools high ride hours with low ride hours together into simply open hours. It emerges that this variation within the open hours masked a critical difference how the program influences crime on weekends and weekdays.

5. Cost-effectiveness Comparison

A rough comparison shows that the safe ride program may be at least as cost-effective as police. Calculations support that this program was associated with an estimated reduction of 220 crimes a year.[20] This is about 0.6% of the city's total yearly crime reported to the UCR (Federal Bureau of Investigation, 2011). Comparing this to the effectiveness of officers as measured by (Levitt, 2002), it is found that to eliminate the same number of crimes, an increase of 1.2% in the police force would be needed.[21] This would cost over $1,300,000.[22] The safe ride program itself costs about $425,000, suggesting that the program may be very cost-effective.

It is recognized that this estimate is only a very rough approximation of the relative cost-effectiveness. It is possible that the safe ride program does not eliminate crime, but simply displaces it. See Bowers and Johnson (2003) on the general issue of measuring crime displacement. If displacement occurs, criminals respond by relocating crime to another time or place where net returns are higher. As a consequence, the actual reduction of crime from the program will be lower than estimated here. Thus, the program may cause crime to move out of the university area and into the surrounding neighborhoods not serviced by the program. This may not influence the efficiency of the program from the universities' perspective, but is relevant from a social welfare perspective.

I have undertaken two separate regressions to test for the presence of the displacement. Checking for spatial displacement, I examine the relationship between the hours the program is open and the crime rate in a postal code adjacent to the safe ride program's operating boundaries. Estimating the hours fixed effect model, I now use crime counts from the outside postal code, but all else remains the same. I find that the open hours of the program are correlated with an insignificant reduction in crime of -1.8% in the adjacent postal code.[23] This does not support the idea that the program is causing substantial displacement in the neighboring postal code. I next return to crime counts in the program service region but add two indicator dummies, one for the hour before the program opens, and one for the hour after the program closes. These coefficients are insignificant with t-stats less than one, and are both negative. Overall, none of these estimates find evidence to support the claim that displacement is occurring, but it is possible that the displacement is more complex than these tests could uncover.

Another concern is that the safe ride program operates in a middle class college neighborhood, while police operate across the entire city. It seems intuitive that other neighborhoods, such as very low income or industrial areas, will vary in responsiveness to measures to reduce crime. Consequently, placing a safe ride program in a dramatically different area is unlikely to have an equivalent effect. Therefore, one should be cautious in generalizing the effectiveness of the program to areas that lacks similar demographic characteristics.

In addition, there is likely complementarity between police and the safe ride program. Police are present at all times in the analysis. As a result, no evidence has been generated that the program reduces crime independent of police, but rather, the program does so in conjunction with police presence.[24] To assume the program will reduce crime with a reduction of police presence would be unwarranted.

Finally, it also seems sensible that the university provides implicit subsidies to the program. It is also unclear whether I have sufficiently itemized the full cost of the program. Use of school infrastructure, such as rooms and email services for advertising to students, may not be included in the costs of the BOSS program.

Despite these concerns, the evidence suggests that the safe ride program has been an effective method of obtaining time and location specific reductions in crime for this particular university neighborhood. As this rough estimate seems to suggest, it appears to be a cost-effective alternative in comparison to adding officers to an existing police force.

6. Conclusion

In this paper I examine a safe ride program operating in a major metropolitan area. Using fixed effect estimates in a Poisson regression, I find that an open safe ride program is associated with a reduction in the overall crime count of 14%. About half this impact becomes apparent only when recognizing the tendency of the policy makers to put the safe ride program into high crime hours and either using fixed effects, or dropping the hours in which the program never operates. A ZIP model confirms that 14% reduction in crime. The impacts of the program being open remains relatively homogeneous among days of the week and between different types crime.

It is further found that the crime count responds to the intensity of the safe ride program. As the program increases the rides delivered by one standard deviation, crime declines by more than 8%. Increasing the program's intensity is at least as effective at reducing violent crime as it is at reducing nonviolent crime. An increase in intensity appears to be more effective in reducing weekend crime than weekday crime.

Using the estimate of 14% to generate a rough guess of the cost-effectiveness of the program, I find that the program accomplishes crime reduction in a cost-effective manner relative to expanding the police force. I recognize the limitation of this comparison but suggest that for the particular neighborhood examined that the program has been a relative success.

Chapter 2: University Provided Transit and Urban Crime

1. Introduction

Recent research demonstrates that “safe ride” programs, common to urban universities and hospitals, can reduce crime by providing taxi-like transport to students and staff (Weber 2014). Yet, safe rides are only one of a variety of transportation programs often provided by urban universities, and broader comparisons should be undertaken that take account of this mix. This paper examines reported neighborhood crime as a major private urban university supplements a large safe ride program with a dedicated and scheduled bus service along prime commuting routes.[25] We find that the advent of the bus service reduces use of the safe-ride program. This raises the concern that the bus service may concentrate potential victims and crime along its fixed routes. Our difference-in-difference estimates show that the new bus service reduced crime in the campus neighborhood overall, and that the largest reductions were actually along the bus route.

While the details vary substantially, urban universities, major medical facilities and, to a lesser extent, private secondary schools frequently offer dedicated transport services. These services can be provided directly by the institution or they can be provided by private firms through contract. The private firm University Shuttle is representative when they argue in their promotional material that their services “improve campus safety and security” (University Shuttle 2014). The services can be designed to reduce drunk driving by providing trips to and from bars (Sacramento State University 2014), or can consciously exclude such trips to focus on “preventing robbery and assaults” during trips between home and campus (Oregon State University 2014).

Critically, the services can be either safe rides with radio dispatched point-to-point service (essentially a taxi), or they can be scheduled shuttle services that stop at prime locations or along major commuting thoroughfares (essentially a bus). Often combinations of the two types of services are provided. Their interaction has not previously been examined.

Our subject university had a large and well-used safe ride program that provided point-to-point service within an area that included an urban campus and the surrounding neighborhood dominated by student housing. After fifteen years of offering this service, the university augmented it with two regularly scheduled bus lines that cross the safe ride area on major thoroughfares. This new option to transport students may reduce crime by lowering the number of students walking the neighborhood. The bus service also creates additional eyes and ears that may increase the probability of crime detection, and reduce the expected profitability of crime. Moreover, like all student transportation systems, the bus service may reduce crime committed by students themselves, who may be contained on the bus rather than disrupting others in the neighborhood (Weber 2014).

Alternatively, as the safe ride program remained in operation, one might anticipate that the bus service substituted for this earlier program. Those taking the bus service do so instead of calling the safe ride service. Individuals that might otherwise wait inside for a safe ride and be taken to a destination, now walk to the bus route, wait for transport, and potentially walk again at the other end. To the extent that this substitution happens, those who use the service may be more vulnerable to crime. Moreover, the bus service brings together groups of students at known times to wait for, or be dispersed from, the bus. This could improve the ability of criminals to target students. Thus, the advent of the bus service could increase crime, especially when substituting for the existing safe ride program. This increase in crime would be especially evident along the bus routes.

Our exploration of this issue fits with a long line of economic research on the relationship between public transit and crime. Becker (1968) presents the general argument that the amount of crime reflects its profitability. Subsequent researchers argue that transit availability and cost influence this profitability, although the influence is often ambiguous and depends on the particular circumstance. Lower cost transit can get potential victims off the street, but criminals may also use lower-priced transit to target victims or to expand their own search for victims. Critically, some forms of transit require waiting periods that may make riders vulnerable. For example, evidence from Chicago makes clear that commuter rail stations have particularly high rates of robberies (Bernasco and Block, 2011; Bernasco, et. al. 2013) and more sophisticated examination of crime counts shows a modest increase in neighborhood crime associated with the opening a new commuter rail station (Poister, 1996; Liggett, et. al. 2003). Yet, there remains evidence to the contrary (Billings, et al. 2011) and one reason for these mixed results may be that criminals themselves use transit. Phillips and Sandler (2015) show that temporary closings of a commuter rail station reduces crime at neighboring stations as criminals have reduced access to the transit network. Moreover, Ihlanfeldt (2003) presents earlier evidence that commuter rail is associated with increased crime in low income areas, but slightly decreased crime in high income areas. In addition to the quantity of crime, the type of crime may also be influenced by transit. Jackson and

Owens (2011) show that an expansion of hours for the DC subway decreased drunk driving crimes, but increased other types of alcohol-related crimes (such as assault).[26]

The evidence directly on public bus transport is not as extensive. Qin (2013) provides descriptive evidence from Cincinnati showing elevated crime at bus stops. Loukaitou-Sideris (1996) provides earlier descriptive evidence that crime tends to cluster around popular but relatively isolated bus stops. It may not be the bus stop *per se* but rather that they are an example of infrastructure that causes congregations of people in public spaces (Loukaitou-Sideris, et. al. 2002). Evidence shows that police officers whose patrol routes were moved onto bus routes during a police initiative dramatically increased their number of arrests (Newton, et.al. 2004). As is clear, these studies do not attempt to provide rigorous causal evidence.

Survey evidence shows that riders on a dedicated university bus service report mixed sentiments regarding its influence on crime (Elam, et. al. 2006). While some survey respondents felt it provided safer transport, others felt it encouraged drinking by students making them more susceptible to crime, or more likely to commit crime. This survey evidence reflects a bus service for a university without a safe ride program. Weber (2014) uses arguably exogenous changes in the hours of a public university safe ride service to show that when the program is open, crime is lowered. Thus, policy makers might worry about the advent of transportation alternatives that reduce the use of safe rides. We are the first to estimate the influence of adding a dedicated university bus service on reported crime, and we do so in a context in which an existing safe ride program serves the same population.

In what follows, Section 2 details the case study describing the university, its neighborhood, and its transit programs. This section also describes the data that were collected. Section 3 presents the methodology used to investigate the influence of the new student bus service on university neighborhood crime. The results are presented in Section 4. The results show that the advent of bus service reduced the use of the safe ride program. Nonetheless, crime in the university neighborhood falls relative to the control. Despite the substitution between programs, the reduction in crime is actually concentrated along the bus routes. Section 5 provides a series of robustness checks and Section 6 concludes and suggests further research.

2. Description of the Intervention and Data

The subject neighborhood surrounds Marquette University, an urban Catholic university on the west side of downtown Milwaukee Wisconsin that enrolls approximately 12,000 students. The campus blends into governmental and business buildings on its east side but on other sides is surrounded by residential neighborhoods that house students. These neighborhoods have relatively high crime rates. Historically, the university has undertaken a variety of initiatives to protect students including moving academic buildings and fraternities closer to the core of the campus, increasing housing immediately on campus and developing student transit programs.[27] The safe ride program began in 1990 as the Local Intercampus Mobile Operation (LIMO). The LIMO safe ride program continues to transport Marquette students, faculty and staff with valid ID within an area around campus, spanning a total area of about 60 blocks. A rider calls LIMO, a shuttle is sent the address and takes the rider to his or her destination. Both the pickup and destination must be within the 60 block boundary. The area of safe ride program is identified by darkened area in Figure 3.

Note that these boundaries have remained constant with one modest exception. In September of 2008 the boundary was expanded to include two additional blocks identified by dark blue in Figure 3. This change reflected an increase in private student housing in those two blocks. We will be careful to try a variety of robustness checks to account for this modest change, but find that our results are largely insensitive to how we deal with this expansion. We emphasize that our primary interest is how the advent of the bus service influences crime and the bus service does not go through or near the two blocks. Nonetheless, we explore the role of the expansion to make sure that it does not confound our findings.

The LIMO program runs daily around the year from 5pm-3am (5pm - 4am on academic weekends). The program uses vans for transport and keeps one or more vans in reserve in case of break-downs or unusual demand. The safe ride program averages around 5,000 rides a week across the entire year, both when school is in and out of session. It has shown substantial growth since its inception. Indeed, the growing demand for safe ride services convinced the university it should augment it with a cheaper fixed-route bus service.

The fixed route bus service began in March of 2008 and can again be used by students, faculty and staff with valid identification. It consists of two routes which cross the width of the safe ride program area. Each route is a loop of about 1.5 to 2 miles in length. The routes do not trace the perimeter of the safe ride area but more nearly run through the heart of the area along arterial roads. The hours of the bus service exactly match those of the safe ride program and it has seen substantial use. Approximately 1000 rides a week are provided by the dedicated bus service.

As crime can exhibit both secular and cyclical patterns, we sought a control that most nearly matched our treatment jurisdiction. While we show results using alternative controls, our primary control uses the only other university in the downtown area, the Milwaukee School of Engineering (MSOE). The control neighborhood around MSOE is somewhat smaller in area but includes the Water Street entertainment district known for elevated crime. Like the area around Marquette the neighborhood includes residential areas with student housing and blends into the office and government buildings of downtown. MSOE enrolls around 3000 students and maintains a long-standing safe ride program that has serviced our control neighborhood throughout the study period.

2.1 Data Sources and Descriptive Statistics:

Weekly crime data comes from the Milwaukee Police Department (MPD) through an online tool called COMPASS.[28] The data includes the address of the crime, date and time of the crime and the broad type of crime. This service complements written records and has been available since January 2005. Critically, this predates the initiation of the bus service we examine. It does, however, come well after the long-standing safe ride program. Thus, this data allows studying the influence of the bus service on crime given the existence of the safe ride program. The records provide no personal information about victims or perpetrators.[29]

Using GIS software, the crime records are matched to geographical areas. The treatment area mimics the Marquette University safe ride service boundaries and the control area mimics the MSOE safe ride service boundaries. The areas include all legal parcels that are completely within or along the service boundaries. The crime counts are the total weekly crime measured separately within the two respective areas. We face no issue of zero inflation as only a single observation has a crime count of zero across the entire time interval and both areas.

As part of the objective is to examine the potential for crime relocating within the treatment safe ride area, we also make use of a geographic division within that area. The area along the bus route is contrasted with the remainder of the safe ride area (again see Figure 3). To focus on the possibility of substitution we develop a bus route area that includes only those properties along the actual routes. We later add the areas interior to the routes as a robustness check. The primary data window is roughly centered on the advent of the bus lines and runs from January 2005 to the January 2012. Again, we alter this to test for robustness.

Weather data are collected as controls. Weather may influence both the weekly demand for campus transit services and crime. Certainly, it is well known that snow and cold temperatures are associated with lower rates of urban crime and, especially, robbery and other street crime (Falk, 1952; Anderson, 1989; Cohn, 1990; Jacob et al., 2004; Tompson and Bowers 2015). The weather indicators we collect are the minimum temperature for the week and the average daily snow on the ground for each week. These are taken from the nearest National Oceanic and Atmospheric Administration (NOAA) weather station. We experiment with a variety of alternative weather measures but with no real change in the pattern of results. Additional controls identify the three terms of the academic calendar for each university as classes being in session may also influence both rides and crime (Jacob and Lefgren, 2003).[30] Again, we note the transit services runs year round.

Finally, for some specifications we will be interested in the actual ride data from Marquette University. We know the number of rides given each week in both the safe ride program and on the bus route. These, and the remainder of descriptive statistics, are shown in Table 12 and we note that there are about 45 crimes per week averaged across the Marquette university neighborhood.

3. Methodology

The primary research objective is to determine the influence of the bus service on crime in the urban neighborhood around Marquette University. The secondary objective is to examine the possible relocation of crime within the treated university neighborhood. In examining this secondary objective, we initially show that the new bus service corresponds with a decrease in the number of safe rides given. This fuels our inquiry of the impact of the bus service on crime and the distribution of that crime.

To examine the policy influence we estimate a series of difference-in-difference estimates that compare the weekly crime counts before and after the bus service. These first compare crime in the treated university neighborhood to crime in the control neighborhood, as the new bus service is added to the existing safe ride program in the treated neighborhood. This gives rise to a traditional difference-in-difference specification:

$$Crime_{it} = \alpha_i + \beta_1 * Policy_t + \beta_2 * Policy_t * TreatedNeighborhood_i + \beta_3 * TreatedNeighborhood_i + \beta_4 * Controls_{it} + \varepsilon_{it} \tag{1}$$

in which the dependent variable is the crime count in neighborhood *i* at time *t*. In our initial specification, the treated neighborhood is the entire Marquette University safe ride area, and for inference *robust standard errors are used (*Bertrand, et al. *2002)*.

The specification includes three types of controls. First, crime varies with weather and so the weekly average snow on the ground (mm) and weekly minimum temperature (°C) are included. Second, crime can vary in the neighborhoods with the class schedule of the relevant university (Weber 2014). To account for this the weeks in which each of the three academic terms meet for each university are included as dummies and interacted with the neighborhood.[31] Third, we directly address the likely cycles and trends by including 51 weekly time dummies and a time trend. The focus in the initial specification is the magnitude and significance of β_2, which measures the impact of the policy on the treated Marquette University neighborhood relative to the control.

We next break down the difference-in-difference estimate to contrast crime along the new bus lines directly with crime in the control. This is augmented by contrasting the crime in the safe ride area, but not along the bus lines, directly with crime in the control. Finally, we examine crime exclusively within the treated neighborhood to determine if the new bus service shifted the location of crime toward the bus line routes. A series of robustness exercises are then presented.

Figure 4 compares a simple moving average of the crime counts for the treated Marquette University neighborhood with crime in the MSOE control neighborhood. The vertical line indicates the introduction of the new bus service. The figure shows the cycles over the year that we control for in our estimates, as crime routinely increases during fall and spring weeks. The Marquette university area has routinely higher crime counts than the control, but is also a larger geographic area. The spline functions show crime counts fall substantially in the treated neighborhood after the introduction of the bus service and become more nearly similar to the counts in the control. Other than this decline, there appears to be no secular pattern in the crime counts in the treated neighborhood. There does appear to be a slight downward trend in counts for the control neighborhood, causing us to explore differential trends in our estimation.

While the visual evidence in Figure 4 suggests that crime declines with the advent of the bus line in the treated neighborhood relative to the control, it presents no evidence on the statistical significance of that decline or on the possible concentration of crime along the bus routes. We now turn to the statistical evidence on these issues.

4. Estimation Results

To set the stage for our investigation we examine whether the new bus service may have reduced the number of students using the safe ride program. We note that the growing use of the safe ride program and the associated growth in expenses was a stated factor in introducing the bus service. In Table 13 the number of rides provided weekly is regressed against a simple time trend and the advent of the bus service. In this basic specification the advent of the bus service is associated with a decline in ridership for the safe ride program of about 1700 rides per week, about 35 percent of the average weekly rides. The results in column 2 control for our explanatory variables and those in column 3 also add weekly dummies. These additions do not meaningfully change the estimated magnitude. The 1700 fewer weekly rides provided by the safe ride program may well have saved money but it also raises concerns over an association between the advent of the bus service, reduced safe rides and crime.

Issues of crime relocation can be tricky. On the one hand, the bus may concentrate victims along the route as discussed. Yet, the reduction in demand for the safe-rides may actually improve its influence on crime in those regions far away from the bus route. With many students taking the bus, the waiting time for such more distant safe rides could be shortened actually increasing the number of such more distant rides. Thus, at the same time that one might anticipate more waiting outside and walking near the bus routes, there could simultaneously be less walking in the more remote areas. To the extent that either of these are true, the distribution of crime could move away from distant areas toward the bus line. This shift could remain true even as overall crime declines.

The first column of Table 14 presents the simple difference-in-difference estimate of the influence of the new bus line on crime in the treated neighborhood, relative to the control neighborhood. The coefficient on the interaction indicates that crimes decline by about 6 a week in the treatment neighborhood. Using the robust standard error, this is highly significant. As the mean crime level before the bus service was about 45 crimes per week, this represents a large reduction of about 13 percent. The other estimates in that column show that the treatment area tends to have higher crime counts (Figure 4) and that the period after the policy has slightly lower crime counts.

Column 2 adds controls for weather and for school sessions. There are three terms for each university interacted with neighborhood as the term dates are not identical. The coefficients on the controls indicate that crime is lowest in the summer when there are fewer students and highest in the fall and winter terms, when students are plentiful. The arrival of new students, who are not yet accustomed to the neighborhood and campus life, may be responsible for the comparatively higher crime in fall (Weber 2014). Reflecting the typical pattern, crime declines in inclement weather as indicated by the significant positive on temperature. The inclusion of these relevant controls does not change the estimated influence of the bus service in reducing crime. Column 3 adds 51 weekly dummies to capture the evident cyclicality, and to recognize that crime may vary with holidays or events in the school calendar. A variety of the individual week coefficients take significance and the entire vector of weekly controls is jointly significant at a 10 percent level. Critically, their inclusion leaves the difference-in-difference coefficient largely unchanged. Moreover, replacing weekly controls with broader monthly controls also results in no meaningful change in the policy estimate.

There appeared to be a modest secular decline in the crime count for the control that was not evident in the treatment. We show in column 4 that a single time trend takes a negative but insignificant coefficient and leaves the influence of the bus service unchanged. Allowing a differential time trend in column 5 shows that the negative trend for the control neighborhood is statistically significant and offset by a positive (but insignificant) coefficient for the treatment neighborhood. The differential trend model not only fits the data better but it generates a substantial movement in the estimated policy influence. The advent of the new bus line now emerges as much more important. The estimate now indicates that following the new bus service crimes in the treatment neighborhood fell by over 11 crimes per week.[32] This is a 24 percentage point decline in crime counts in the treatment neighborhood.

We recognize the count nature of the dependent variable and in Table 24, Appendix B, show a variety of alternative specifications. We estimate the log of the count, the Poisson estimate and the negative binomial. These are each compared to the linear specification shown in the first column. The 24 percent reduction shown in that first column is matched by a significant 27 percent reduction in the log estimate and very similar magnitudes in the Poisson and negative binomial. While the latter suggests there is significant underdispersion, the estimated difference-in-difference coefficient is virtually identical in the Poisson and in the negative binomial. We again note there is only one week with zero crimes and that inflation is not an issue. For ease of interpretation we continue to present the linear results but note that none of the critical findings are altered when using these alternatives.

Table 15 examines the influence of the new bus service on crime along the bus route area and within the remainder of safe ride area. It contrasts each of these areas with the control neighborhood. The first column reproduces the final column of Table 14 showing the significant decline within the entire treatment neighborhood. The second column focuses on the crime in the treatment neighborhood that is along the bus routes and reveals a significant decline of 7 crimes per week relative to the control. Thus, there appears to be no evidence that the bus route has concentrated crime. Instead, it seems that the additional eyes and ears of the bus lines have outweighed the potential hazards of additional waiting and the concentration of potential victims. There is no evidence from this estimate that safety concerns are warranted at least for this small scale neighborhood transit program.

The final column in Table 15 examines the remainder of the safe ride neighborhood away from the bus route. As we have suggested, the new bus route has a potentially ambiguous influence on crime in this area. The estimate in the final column suggests an insignificant decline of between 4 and 5 crimes per week relative to the control. At minimum, there is no evidence that crime has increased and the suggestion that the safe-ride program can concentrate on more remote services and lower crime remains a possibility. Viewed this way, the more than 11 crime reduction in the treatment neighborhood could be seen as divided with approximately 7 of those happening along the bus route and the remainder in the safe-ride only area.

Table 16 directly compares crime along the bus routes to that in the safe ride only area. We do not suggest that the safe ride only area is a control. Indeed, we have explicitly recognized that crime in both areas are likely to be influenced by the policy. Instead, these estimates are simply designed as another examination of whether or not crime in the treatment area has been concentrated along the bus routes. The first column indicates that post policy period has lower crime across the entire Marquette University neighborhood as the previous estimates (relative to the control) have suggested. Critically, the estimate indicates there is no statistical difference in the influence of the policy on the two regions within the neighborhood. In short, there is no evidence that relative location of crime has changed with the advent of the bus service. Adding additional controls for weather, school sessions, and weeks of the year does not change this uniformity in the policy's impact. Similarly, accounting for expansion and time trends makes very little difference.[33] The estimates in Table 16 show that the new bus routes have not concentrated crime.

5. Robustness and Heterogeneity

We now conduct a series of robustness checks and examine for heterogeneous treatment influences. The first column of Table 17 simply reproduces the key results from the previous section showing a decline of more than 11 weekly crimes in the treatment neighborhood relative to the control. It also shows the absence of any evidence that crime becomes concentrated along the bus route.

The second column reproduces the same series of estimates but imagines a false treatment date one year prior to the policy. If long term factors other than the bus service cause crime to be failing in the treatment neighborhood, one might anticipate that the false treatment date will perform similarly to the actual treatment date. The coefficient on the false policy date for the treatment neighborhood is insignificantly different from that in the control. Moreover, there is no evidence with the false treatment date that crime fell along the bus route. Indeed, the critical coefficients are insignificant in all specifications. This result suggests that the significance of the true policy is not coincidental. As a further check, the third column uses a false treatment date of one year after the actual policy date. Again, there is no evidence of any influence providing further reassurance.

The fourth column of Table 17 examines the impact of adding two lead periods, one for six-months before the policy and a second for a year to six months before the policy. These lead periods are also interacted with the treatment area, and capture any variation in crime that occurs prior to the introduction of the bus service. The interactions are typically insignificant but more importantly including the new variables never materially changes the estimated policy influence. Despite the leads, the bus service still significantly reduces crime by about 11 counts per week. There remains no evidence of crime concentrating along the bus routes. The decrease in crime along the routes remains significant and of roughly similar size. The inclusion of the leads highlights the possibility raised earlier that the bus service could also reduce crime in the safe ride only area by freeing up this service for more distant users. The reduction in crime counts for the safe ride only area looks similar to that along the bus route.

The fifth column of Table 17 adopts an entirely different control neighborhood. While the area around another university near downtown (our preferred control) is in many ways more comparable, we complement it with a control that has no university avoiding issues of academic calendars and the possibility that MSOE undertook actions we are not aware of that kept crime constant. The Bay View neighborhood on Milwaukee's south side consists disproportionately of younger residents, many just out of college. At the same time it is not a typical neighborhood for college students to live in (it is more than four miles away) suggesting that it is independent of the transit decisions of Marquette. Again, we use the start of the bus service as the policy period and compare crime within the treated neighborhood to that in Bay View. The estimates indicate that the policy generates a large and significant decline of 15 crimes per week in the treatment neighborhood.[34] There is a significant decline in crime along the bus route and, again, no evidence of crime concentrating along the bus route. As we have seen in some earlier specifications, there is a modestly significant reduction in crime in the safe ride only area. In short, the change of control neighborhoods reinforces our earlier evidence that the bus service is effective in reducing crime both in the overall neighborhood and along its route.

Table 18 provides additional robustness checks. Again, the first column shows the primary results from Tables 14, 15 and 17. Column 2 recognizes that some reported crimes are unlikely to be influenced by the bus service. These potentially irrelevant crimes include such things as counterfeiting, embezzlement and wire fraud.[35] While there are relatively few reports of such crimes in the university neighborhood, it seems that they should not vary with the advent of the bus service. When dropping potentially irrelevant offences, the estimated influence of the bus service remains virtually identical. The new service remains associated with a significant reduction of 11 crimes per week in the entire neighborhood and 7 crimes a week along the bus route. There continues to be no evidence of crime concentrating along the routes.

Column 3 considers the potential relevance of the modest expansion to the safe ride program. While the previous estimates simply omit crimes in the expansion (two blocks at the northern boundary of the treatment neighborhood), here we include the crime occurring in the expansion area. The expansion occurred in September of 2010, sixteen months after the start of the bus service. If we leave the specification unchanged but simply count all crimes in the expansion area over the study period, the result remains a significant decline of 13.5 crimes per week in the expanded university neighborhood relative to the control. This larger reduction occurs on modestly larger base of 49 crimes per week. The slightly larger decline reflects a decline of the original magnitude along the bus route and a larger decline in safe ride only area which included the expansion. As a second test, we include a separate control for the post-expansion period. This returns an unchanged reduction of 13.5 crimes per week. Finally, we augment this second specification with an interaction of the expansion period dummy and the treatment neighborhood. The coefficient on the new interaction is negative and that on the expansion dummy is essentially zero. The resulting decline in crimes associated with the bus service grows to approximately 17 per week but there remains no evidence of crime concentrating along the bus route.[36]

Column 4 presents estimates that enlarge the definition of the bus routes to include all area interior to the routes. This highlights the possibility that the area encircled by the bus service receives important treatment. It divides the university neighborhood into two contiguous regions. This redefinition provides only modest changes. Obviously the overall influence on the entire treatment neighborhood is unchanged. The newly enlarged bus area shows a negative and significant reduction of 9 crimes a week. The reduced safe ride area again shows an insignificant reduction of about 4 crimes a week. The policy reduces crime and seems to especially do so near the bus service.

Several efforts were made to examine heterogeneous treatment impacts. We explored whether there existed different influences during hot and cold weather but could not identify such a difference. Similarly, we found no distinct differences based on snow cover or by academic term. We recognize that additional treatment heterogeneity mays exist by type of rider (women vs. men for example). Unfortunately, the crime data does not record personal information such as gender or age. Moreover, the bus service does not track the characteristics of its users.

We did, however, find substantial differences in the policy influence by day of the week. Table 19 provides a separate estimate for Friday night, Saturday and Sunday and compares that to an estimate for the remainder of the week. This comparison suggests that the policy impact is concentrated on the weekend. Indeed, the vast majority of the overall reduction in crimes (approximately 76 percent) happens in the weekend despite being a smaller share of the week. This could make sense if students use the service for weekend leisure activities (including drinking) and this is when they are most vulnerable. In fact, Playboy magazine awarded Marquette University the dubious honor of the "Best Catholic Party University" (Playboy 2010) suggesting that this particular leisure activity may be common. The results in Table 19 also suggest that crime decreases both along the bus route and in the safe ride area during the weekend but provide no evidence of significant declines during the weekdays. In sum, this argues that the new bus service does not help provide safer transit to and from classes but could be critical for transport associated with social activities.

6. Conclusions

We uniquely examine the influence of a dedicated university bus route on neighborhood crime. The advent of the bus route led to a significant drop in weekly crime relative to the control. This suggests that the bus kept students off the streets at times when they were vulnerable and acts as additional eyes and ears. Critically, the bus substituted for the long-standing safe ride program as fewer safe rides were given with the advent of the bus service. Recognizing the advantage of the door-to-door safe ride, we worried that a more dangerous transport mode replaced a safer one. Yet, we found no evidence of this despite previous suggestions in the literature. Instead, the reduction in crime is actually centered along the bus routes. This may reflect the fact that while some students use the bus instead of the safe ride, others use the bus instead of walking. Indeed, despite the substitution, the total number of students transported by both programs increases after the advent of the bus service. Moreover, the bus may come sufficiently frequently that wait times are minimal and walking distances are short so that vulnerability does not increase.

The evidence on the influence of the bus service on the safe-ride only area is mixed. The estimated policy influence was routinely negative but significantly so only in some specifications. It remains clear that the substitution toward bus rides did not cause crime to increase in the safe ride area only. The suggestions that the bus service might have actually decreased crime in the safe ride only area (say on the weekends) could follow if the bus service freed additional safe ride capacity for those farthest away and perhaps most vulnerable. Nonetheless, the critical point is that there was no evidence of crime concentrating geographically as a result of new policy.

This pattern proved robust to a long series of robustness checks. The estimates correctly lost significance when we considered false treatment dates either before or after the true start date of the bus service. In contrast, the addition of lead periods, as well as an alternative choice of control, did not substantially alter the results. Continued checks revealed that the results remain robust to a narrower definition of crime and to broader definitions of both the university area (which includes expansions) and the treatment area within the bus route. Despite these many changes, the pattern of results consistently shows a reduction in crime in the Marquette University neighborhood after the addition of the bus service. There also continued to be no evidence that crime became more concentrated along the bus routes. The influence of the bus service on crime does appear to be concentrated on weekends when students are more likely to use transit for social activities.

Chapter 3: Modeling Adversary Preference and Strategic Response

1. Introduction

The notion that terrorism may well be a rational act has found strong support in the rational choice literature (Landes 1978, Pape 2003, Sandler 2013). In this research, we share the view that adversaries are rational actors, and therefore at least some parts of their attack strategy can be predicted. Moving towards that goal, we create a parametrized model describing the behavior of two rational agents in conflict. We then fit that model to data by a simple calibration technique. This gives us a broad picture of the otherwise invisible effort by both sides, and a measure of the otherwise unknown ex ante difficulty of conventional and unconventional attacks. While previous work has estimated the *de facto* status of terrorists as either in a "high attack regime" or "low attack regime" (Enders and Sandler 2002), or changes in intensity of attacks (Faria 2003, Faria and Arce 2012), this model provides an explanation of how a group may actually switch from one type of attack to another. Using this model, the importance of military intelligence (Arce and Sandler 2007) can be measured. This calibrated model estimates casualties when a well-informed adversary has unusually high rates of success, or succeeds in carrying out particularly lethal attack against a less informed defending nation.

The key to our modeling and calibration is that uncertainty is central to conflict. For example, it is uncertain if an attack will succeed or fail.[37] Even if an attack was guaranteed success, the number of casualties is uncertain until after the fact. It is clear from historical evidence that some attacks have been devastating, and casualties from adversary attacks follow heavy tail distributions (Mohtadi and Murshid 2006, 2009a, 2009b; Bohorquez, et. al. 2009, Newman, 2005, Clauset et. al. 2007). Others may not. We carefully take into account both of these types of uncertainty.

We begin by describing the conflict model, and discussing its components and solutions. We examine the parameters of the model: effort by both sides, and the complexity (i.e., intrinsic difficulty) of each type of attack. We show that when initial parameters are changed, participants respond in manner consistent with *a priori* expectations. Taking this as a sign of plausibility, we then examine two sources of data about adversary attack damages created by the University of Maryland's START Center. The first dataset, *Profiles of Incidents Involving CBRN by Non-State Actors Database* (POICN), stresses a key category of attacks that have the potential to be extreme and catastrophic. The complementing second dataset, the *Global Terrorism Database* (GTD), stresses attacks that are more conventional in nature, but nevertheless have the potential to be large. This categorical distinction between different types of attack motivates using two different distributions in our modeling and calibration exercise. Since both datasets are used to jointly calibrate a single model, a key issue is the compatibility of the two dataset. After greater discussion of both types of attacks, and the key features of each of the datasets, we find a subset of the data to be comparable, calibrate the model to fit the data.

In what follows, Section 2 develops the model, discusses each of the critical unknowns that need to be evaluated, and presents comparative statics. Section 3 discusses the data set, and walks readers through critical features of each data set. Section 4 uses the data to identify the distribution for each type of large attack, and estimates the defining parameters. Section 5 then calibrates the entire conflict model to these distributions, and shows the resulting set of anticipated behaviors, attack obstacles, and quality of fit. Section 6 presents predicted casualties when attacks parameters are poorly anticipated and prepared for by the defender. Two parameters of focus are attacks with greater lethality than expected, or those with greater ease for the adversary than anticipated by the government. We model these through shocks unanticipated by the defending government. Section 7 presents concluding remarks.

2. Model

2.1 General Model Overview

The model characterizes a strategic interaction between an adversary and the government. The two principal forms of substantial attacks that we are interested in, unconventional attacks (CBRN), and conventional attacks (non-CBRN), capture the nature of strategic trade-off that may be confront an adversary. An adversary who carries out a substantial conventional attack faces a certain risk of failure and a distribution of casualties in the event of success. The adversary's alternate strategy is a substantial unconventional attack (CBRN), with its own distinct profile of failure risk and casualty.

Two factors influence the probability of failure in either attack type. First, the government establishes defensive efforts to protect against attacks. In keeping with the conclusions of the 9/11 report (Roth et al., 2004), it seems likely that the adversary observes the government's protective effort level, perhaps by observing the extent of protection of targets. Second, there are potential inherent complexities that represent logistical, terrain, informational, and coordination obstacles associated with any attack. This complexity is independent of the government and the adversary effort. Both government defensive efforts, and the complexity factors, compound to lower the chance of a successful attack. We assume that the complexity of the operation is common knowledge to participants (though we as researchers had to estimate it via calibration to actual data). We later allow for adversary to have superior knowledge of the complexity of an operation relative to the government, indicating the value of intelligence to the government.

Observing government counterinsurgency effort, the adversary chooses its optimal effort as a best response and the level of attack associated with a specific inherent complexity. The government chooses optimal levels of protective effort against each type of attack, given budgetary constraints, and keeping the reactions of the adversary in mind.[38] Previous literature has examined budget choice as a part of the conflict (Zhuang and Bier, 2007), but here we consider budgets as a fixed and important limiting factor, such as by Congressional decision at the start of a fiscal year. At the end of the game, payoffs are given, and the game ends. Figure 5 shows a flowchart outlining the basic pattern of the game:

This flowchart shows how CBRN and conventional attacks fit into the model. Government allocates its resources to defend against the two types of attack. Adversaries see the government's choice, and then allocate their own resources. The attack then has a possibility of being successful, contingent on the compounding factors of each parties' effort, and the natural complexity of the attack type. Successful attacks lead to benefits for the adversary, and losses for the government, in the form of casualties.

2.2 Critical Unknowns

To account for the uncertain nature of conflict, we have included two critical factors into our model: number of casualties from each type of attack, and probabilities of success in each type of attack. Each unknown will be estimated by our empirical approach. We discuss each in turn.

As a first unknown, the true importance of an attack is only clear once an attack has been realized. Participants begin conflict with an expectation about the value of an attack. This valuation will be found in the respective utility functions of each party. We admit such valuations or payoff may be argued to include casualties, property damage, or other intangible assets. In our case, we will focus on casualties, the sum of fatalities and injuries, since we anticipate human life and health to be a dominant feature of such evaluations, and do not wish to engage in the comparability of human life to other assets. We again point out that these damages are likely to have heavy tails (Mohtadi and Murshid, 2009). The expected number of casualties given that an attack is successful is represented by the weight w_{conv}, w_{CBRN} for the two types of attack. Put explicitly,

$$w = E(Casualties|SuccessfulAttack) \tag{1}$$

Until section 6, we will assume shared expectations about fatalities,

$$E(w|\ Adversary) = E(w|\ Government) \tag{2}$$

As a second set of unknowns, different effort levels correspond to different probabilities of success. A priori, the effort of each party interacts with the effort of their opponent, and further interacts with natural complexities inherent to performing an attack. All else equal, the probability of success will increase with adversary effort (a_{conv}, a_{CBRN}), and decline with the preventive efforts of the government (g_{conv}, g_{CBRN}).

Some attacks may be notably challenging, such as coordinating multiple shooters. More challenging attacks require greater logistical precision, or greater luck. As a consequence, they are less likely to succeed than a simpler attack at a comparative level of effort. Such attacks are marked as having a higher "complexity" ($\delta_{conv}, \delta_{CBRN}$). We assume that the government's assessment of δ is accurate until section 6, where we consider the case that it is wrongly assessed.

We note that estimation of the parameters determining probability of success ($a_{conv}, a_{CBRN}, g_{conv}, g_{CBRN}, \delta_{conv}, \delta_{CBRN}$) is particularly challenging. The desired information is often either unknown or deliberately obscured. Adversary effort is deliberately hidden from the government and consequently to any researcher. Conversely, the government effort may also be unknown to the adversary (and researcher). For example, even the US Coast guard randomizes its surveillance and counter-insurgency efforts (Ordónez, et. al., 2013). In principle such mixed strategies are not without merit, as they keep the opponent uncertain. However, since one important contribution of this work is to shed light on the value of better intelligence about the adversary's potential actions, to the government, it is more relevant to focus on uncertainty about the adversary actions to the government than vice-versa. In the following section, we develop a model in which we can infer the underlying effort levels of the participants, especially the adversary, by matching theoretical variables with counterparts in actual data.

Our model, therefore, must address the eight critical unknowns of government effort (g_{conv}, g_{CBRN}), adversary effort (a_{conv}, a_{CBRN}), target complexity ($\delta_{conv}, \delta_{CBRN}$), and finally the damages of successful substantial attacks (w_{conv}, w_{CBRN}).

2.3 Probability of Successful Attack

We now combine the above components of an attack into a single probabilistic form. In our model, the probability of success at type of attack $n = \{CBRN, Conventional\}$, is modeled by:

$$P(a_n, g_n, \delta_n) = \left(1 - e^{\frac{-a_n}{\delta_n}}\right)\left(e^{-\delta_n g_n}\right) \quad (3)$$

This value can also be interpreted as the probability of damage from attack type *n*. In keeping with previous literature, we will use the probability of success terminology throughout this paper (Bier and Hausken, 2011), and the exponential functional form matches the example of Biers, et al (2007). For an attack to succeed, the adversary must trigger a successful attack, as shown by the first part of the product, and the government must fail to defend, as shown in the second part of the product. The common parameter δ is both attack-augmenting and defense-augmenting, since it is clear that logistical challenges affect both parties, assisting the government and obstructing the adversary.[39]

Granting the assumptions that effort and complexity are positive, $a_n, g_n, \delta_n \geq 0$, this probability has the basic properties we would expect. To begin with, at no point does this probability rise above one or fall below zero. Next, all else being held fixed, the typical comparative statics are clear and intuitive. First, attacks are more likely to succeed with greater adversary effort $\left(\frac{dP(a,g,\delta)}{da} \geq 0\right)$. Appropriately, in the boundary case where adversary effort is zero, the probability of a successful attack is also zero. Second, attacks are less likely to succeed with greater government effort $\left(\frac{dP(a,g,\delta)}{dg} \leq 0\right)$, but no finite amount of government effort can force the probability of successful attack to zero. Last of all, attacks are less likely to succeed as target complexity increases $\left(\frac{dP(a,g,\delta)}{d\delta} \leq 0\right)$. As

$\delta \to \infty$, the probability of successful attack approaches zero. Again, we note that none of these values a_n, g_n, δ_n are available to us as raw data. Instead, we only know $P(.)$, the probability of success in the real world.

We expect that rational actors would perform some mental estimate of the probabilities of success in their decision-making process. Our model hinges on the belief that adversaries will attempt to maximize the expected casualties from both conventional and CBRN attacks. Conversely, the government will attempt to minimize these casualties. We use the structure of our model, and our information about $P(.)$ to provide an estimate of the many unknowns.

2.4 Adversary Behavior

We assume that a hostile adversary will have the goal of maximizing casualties, given some resource constraints. Rational adversaries will keep in mind their probability of success, $P(.)$, for each type of attack, and have conditional expectations, about the mean number of casualties from a successful attack. We assume that these expectations coming from equation 1 enter into the utility function of the adversary and later, the government. As such, their expected utility function is the expected number of casualties from their efforts:[40]

$$E(U_a) = w_{conv}P(a_{conv}, g_{conv}, \delta_{conv}) + w_{CBRN}P(a_{CBRN}, g_{CBRN}, \delta_{CBRN}) \qquad (4)$$

This is subject to the simple expenditure restriction:

$$r_a = a_{conv} + a_{CBRN} \qquad (5)$$

We assume that the government acts as a Stackelberg leader. We justify this assumption by noting many strategic decisions made by the government, are visible to the adversary. Such examples may be airport scanners, additional patrol boats, or improving firearms for security guards (Ordónez, et al. 2013). We first solve for the best response function of the adversary. This is derived in Appendix C, and is found to be:

$$a_{conv}^{*}(g_{conv}, g_{CBRN}) = \frac{ln\left(\frac{w_{conv}\delta_{CBRN}}{w_{CBRN}\delta_{conv}}\right) - g_{conv}\delta_{conv} + g_{CBRN}\delta_{CBRN} + \frac{r_a}{\delta_{CBRN}}}{\frac{1}{\delta_{conv}} + \frac{1}{\delta_{CBRN}}} \tag{6}$$

We assume that the resource constraint is binding, since additional resources serve no other purpose in our model other than investing in attacks. Thus, the remainder of the resources are spent on CBRN type attacks: $a_{CBRN}^{*}(g_{conv}, g_{CBRN}) = r_a - a_{conv}^{*}(g_{conv}, g_{CBRN})$. For simplicity and no loss of generality adversary resources are normalized to unity. This allows us to focus on using variations in δ to generate the observed probability of success.

2.5 Interpreting the Adversary's Best Response Function

The best response function for an attack implies the following effects, all else being held constant (see Appendix C equations C9-C14):

$$\frac{da^{*}{}_{conv}}{dw_{conv}} \geq 0, \frac{da^{*}{}_{conv}}{dg_{conv}} \leq 0, \frac{da^{*}{}_{conv}}{d\delta_{conv}} \gtreqless 0 \tag{7}$$

$$\frac{da^{*}{}_{CBRN}}{dw_{CBRN}} \geq 0, \frac{da^{*}{}_{CBRN}}{dg_{CBRN}} \leq 0, \frac{da^{*}{}_{CBRN}}{d\delta_{CBRN}} \gtreqless 0 \tag{8}$$

The first two derivatives, for w and g are as one would expect for a simple game.[41] To illustrate each of the three cases, consider the reactions of adversary effort in the case of conventional weapon attacks. First, the adversary would increase effort if the expected casualties from a successful attack increased, say from improved explosive technology or access to superior firearms training. Second, if the government counterinsurgency effort increased exogenously, it would decrease the adversary effort to attack the overly defended site.

The third result, for δ, shows that a reduction in complexity can direct the adversary in either direction. If the attack experienced lower executional complexity, say by the development of a new explosive or concealed firearm, it could increase adversary effort by promise of success, or decrease effort by allowing effort to be diverted to other sites. Recall that both types of attack are linked through the resource constraints. As a consequence, substitution can occur between the two types of attack.

Noting that $r_a - a^*_{conv} = a^*_{CBRN}$, the complementary results hold for the "cross effects" of attacks:

$$\frac{da*_{conv}}{dw_{CBRN}} \leq 0, \frac{da*_{conv}}{dg_{CBRN}} \geq 0, \frac{da*_{conv}}{d\delta_{CBRN}} \gtreqless 0 \tag{9}$$

$$\frac{da*_{conv}}{dw_{conv}} \leq 0, \frac{da*_{conv}}{dg_{conv}} \geq 0, \frac{da*_{conv}}{d\delta_{conv}} \gtreqless 0 \tag{10}$$

The key subtlety remains the impact of complexity, δ. The direction of this impact is ambiguous. The intuition is as follows: if the first type of attack becomes complex or simple enough, the marginal benefit of adversary effort becomes small, as the outcome for that type of attack is almost certain. This leaves a relative excess of resources to expend on the alternative (second) attack. As a result, the direction of impact for delta is not monotonic and depends on parameter values $\left(\frac{da_{conv}}{d\delta_{CBRN}} \gtreqless 0\right)$. A critical implication of this finding is that an increase in the complexity of one type of attack offers little comfort to the government, as it may encourage adversary to pursue alternative attack strategies that may be even more deadly (Bier, et al. 2007).

Finally, the Appendix C confirms the adversary's second order condition is always satisfied for positive values of parameters $w, g, \delta, a, r > 0$, assuring the optimality of the solutions.

2.6 Government Defensive Behavior

The government is interested in impeding the progress of the adversary. It moves first in the context of the game, acting as a Stackelberg leader, establishing defenses prior to the attack. We will assume that the actions of the government, and therefore, the probability of success or failure is public knowledge. This probability enters both directly as shown below in the government objective function as well as indirectly through the adversary response function. The government would like to maximize its expected utility as follows:[42]

$$E(U_g) = w_{conv}(1 - P(a_{conv}, g_{conv}, \delta_{conv})) + w_{CBRN}(1 - P(a_{CBRN}, g_{CBRN}, \delta_{CBRN})) \tag{11}$$

Note that the government is assumed to share the same weight on the importance of an attack with the adversary, w, i.e., the conditional expectation of an attack, given it that it is successful. Naturally, the greater this weight is the larger in both party's interest in the attack, one is producing it, the other in deterring it.

The government action is naturally also subject to constraints on its expenditures:

$$r_g = g_{conv} + g_{CBRN} \tag{12}$$

We find that the fit is best with assuming government expenditures, $r_g = 1$.[43] As might be expected, the solution to government maximization problem is more complex, owing to the inclusion of a^*, the adversary's best response. As a consequence of including a^* in the governments' behavior, the governments' behavior does not reduce to a simple behavior in δ or w. Due to the intractability of the equation, we simply solve for g* numerically in each instance.

For the relevant cases, we find that the second order condition is satisfied and we have a maximum. Thus, the players do not have incentive to deviate from their behavior and the resulting equilibrium is Nash. The equation for the first order condition is shown in Appendix C (equation C20), as is the second order condition (equation C21).

In Figure 6, a graph of the numerical estimates of their behavior is shown below for a neighborhood of values near the suspected equilibrium. We begin by first displaying the equilibrium efforts by both parties in the conventional types of attacks, in a region of $\hat{\delta}_{conv}$varying from 1 to 10, and holding $\hat{\delta}_{CBRN}$ constant at 2. The value of w_{conv}=66.7 and w_{CBRN}=168.5 are determined later from actual data, and we assume both sides have unitary resources. In the neighborhood of our best estimate, we find that increasing the complexity of conventional attacks results in a reduction of effort for the adversary. The reduction in effort by the adversary is matched by a similar reduction in effort by the government. We note that any attack with a complexity greater than 8 is left essentially undefended by the government. To provide a grounding for a complexity measure of 8 for the adversary, one could imagine an adversary devoting its entire effort to the attack since the government does nothing and the site is undefended. Yet, evaluating P(.), equation 3, with these aformentiond assumptions, $a = 1, g = 0, \delta = 8$, would provide only about a 12% chance of success. Thus the optimal level of adversary effort at conventional attacks will be indeed far less than unity, and the adversary's chance of successful conventional attacks for the equilibrium level of effort will be only near 3%.

We next consider how changes in CBRN attack complexity changes the effort at conventional sites in Figure 7, the cross-attack complexity. We use similar regions, this time varying $\hat{\delta}_{CBRN}$ from 1 to 10, and holding $\hat{\delta}_{conv}$ constant at 2. The value of w_{conv}=66.7 and w_{CBRN}=168.5 remain as before. To gain a better understanding of this result, we note that the basic principle at work here is one of strategy substitution: the government exerts no effort defending conventional attacks when the more lethal CBRN alternative has a a very low level difficulty of 1 (not shown here). To put such an attack into perspective, this attack would be so easy that a government could devote all its resources to protecting a site and still fail to protect against the attack 37% of the time.[44] As CBRN attacks become more difficult at the equilibrium, the government takes advantage of the fact that it is relatively easy to defend against CBRN, and shifts effort towards protecting against conventional attacks. The adversary also substitutes away from increasingly difficult CBRN attacks and into the conventional attacks. We note the government shifts effort at a faster rate as it capitalizes on increasingly efficient defense against CBRN. The fraction of effort relative to their total resources are approximately equal for both parties at the difficulty index of $\hat{\delta}_{CBRN}$ = 5.5.

While the theoretical model provides a modest contribution by highlighting the multifaceted effects of target complexity on terrorist behavior, a vital contribution of this research arises from the model's calibration to the data. We acknowledge that target complexity and adversary effort are inherently unobservable to laypersons, but still provide an estimate of these values. In next section, we will present the data we do have, and note that their distributions match those we would expect from previous literature.

3. Data

We begin with access to a very large, well known, and publicly available dataset on conventional attacks, known as Global Terrorism Database (GTD). We also have access to a unique dataset on unconventional CBRN types of attacks, the Profiles of Incidents Involving CBRN by Non-state Actors Database (POICN). This newly developed database is a detailed collection of exclusively CBRN attacks. While GTD has initially evolved from different sources, in the more recent past it has been maintained and greatly expanded by the START Center at the University Maryland. The POICN data has been exclusively developed within the START Center. This has afforded us the unique opportunity to discuss with those who maintain both databases to ensure maximum compatibility.

To avoid double-counting we use the GTD to examine only conventional attacks, and POCIN to examine only CBRN attacks.[45] While POICN dataset includes a valuable component associated with "thwarted" attacks or planned attacked, the GTD dataset only captures attacks that are actually attempted. To render the two datasets comparable for our purposes, we exclude all aborted attack plans from our POICN dataset and focus exclusively attacks that were actually attempted, so called "out-the-door" attempts. As an additional precaution, we only include attacks noted as being reliably documented by the database administrators.

We focus on casualties, which includes both injuries and fatalities. We believe this serves as a proxy for intended size of the attack, because if an adversary is willing to injure a victim, it is likely they would be willing to see them as a fatality. Appropriately, we do not include adversaries' own injuries and fatalities in our count. Since we focus on modeling adversaries that prioritize inflicting substantial casualties, in order to avoid biasing our estimates we exclude attacks such as kidnappings, assassinations, or hostage-taking. This leaves us with two complementary databases of potentially substantial attacks, one for conventional, the other for CBRN. Summary statistics for the data are presented in Table 20.

We note that in both types of attack, the mean far outpaces the median, suggesting the distribution of attack casualties is highly right-skewed. There appears to be a much thicker tail for CBRN attacks than conventional attacks, but on the whole, CBRN attacks tend to be much less frequent. We recognize that this data is best characterized by a distribution with thick tails and a strong right skew, and take it expressly into account in the next step.

4. Determining Mean of Successful Attacks

As we calibrate the model to the data, we first focus on the values of the weights, w_{conv} and w_{conv}, entering the adversary and defender expected utility functions. Since we are interested in rare but extremely high-casualty events, rather than on low-casualty events with nonlethal motives, we restrict the relevant weights by this additional condition as well. Thus, equation 1 is modified as follows:

$$w = E(Casualties|attack\ is\ substantial\ in\ size|attack\ is\ succesful) \quad (1`)$$

There are several probability distributions available that represent large or extreme events. Among them, the family of extreme value (EV) distributions as well as the associated generalized Pareto distributions stand out (see Cole 2001). Mohtadi and Murshid (2009) were among the first to apply EV methodology to predict the likelihood of terrorism events.[46] About the same time as the conception of the Mohtadi-Murshid paper, Bohorquez et. al. (2009) used Pareto distribution to examine the incidence of terrorist attacks during Iraq war. The origin of these methodologies is the Fisher-Tippett (1928) theory of extremal distributions in which an asymptotic pattern emerges from the set of extremes of a sequence (e.g. the distribution of the hottest months of each year in the past century).

The use of the EV family, however, is not appropriate for our purposes here because it leads to a great loss of observations, and we have a small sample size of our POICN dataset. Further, we are interested in modeling all substantial attacks, rather than simply the largest attack per week, month, or year. Instead, we will opt for using Generalized Pareto (GP) as the distribution of choice to fit to our dataset. Fortunately under certain conditions the equivalence of the two distributions can be in fact established. In particular, it can be shown (Coles, et al. 2001) that if a random variable X is any arbitrary member of the sequence of independent random variables, $X_1, X_2, \ldots Xn$ subject to block maxima, $M_n = Max\{X_1, X_2, \ldots X_n\}$ so that by the Fisher-Tippett (1928) Theory above, $\Pr\{M_n \leq z\} \approx G(z)$ where *G(z)* is the Generalized Extreme Value distribution, then for a large enough value of a threshold, u, the probability that the exceedance, X-u, is larger than some value, y, is given by the Generalized Pareto distribution,

$$\Pr\{(X-u) \geq y \mid X > u\} = H(y) = 1 - \left(1 + \frac{\xi y}{\sigma + \xi(u-\mu)}\right) \qquad (13)$$

In this distribution, ξ is the shape parameter which represents the thickness of the tail (probability of catastrophic events), σ represents a scale parameter, and a location parameter μ.[47] While the shape, scale and location parameters can be determined by maximum likelihood estimation, we are required to parametrically select a threshold value over which substantial events occur. The choice of threshold is determined by fitting each choice in threshold to the data and then examining the QQ plots. In Appendix D, we examine the common choices of 10, 25, and 50 casualties. Using QQ plots and seeking a threshold value to best fit the data, we find that the threshold value of 25 casualties fits best for both GP distributions. The mean of these GP distributions, therefore, when they exist should serve as a better estimate of the intended damage for ambitious and successful attackers. To highlight the difference between the two types of attack sets, we compare the means of the raw data, representing all attempted attacks, and the means of the GP distribution, representing an estimate of the potential damage from a substantial attack. We then show the parameters derived from fitting each of the two types of attack to GP distributions in Table 21.

It is worth noting from this table that the mean number of casualties from historical data is lower than the mean of the GP distribution. In part, the difference is because the historical data includes attacks with no casualties, and those with relatively few casualties (<25). By contrast, the GP distribution has the heavy tail which, while it is inferred from the data, admits the possibility of attacks far more deadly than the historical data allows. In the case of CBRN attacks, the tail is so heavy that it does not have a finite standard deviation. Still, we are able to obtain a finite mean and this allows us to perform our estimation and analysis moving forward. One implication of using the mean from GP distribution, rather than directly using the historical mean, is that the point estimates of w_{conv} and w_{CBRN} more accurately reflect the idea of *substantial*, successful attacks.

Ignoring small attacks and focusing on the likelihood of large attacks has one additional advantage for our modeling: If an attack has relatively few casualties, it seems plausible that attackers and the government consider the attack to have failed or been prevented in some important capacity. For example, a low-casualty biological attack may only inflict a few casualties because they failed to properly aerosol the biological agent, or the intended release location may have been blocked by security patrols. On the other hand, the attackers may still consider their low-casualty attack a success. If the attackers had the goal of delivering few casualties with a biological weapon, then the attackers had specific goals other than inflicting mass casualties, such as spreading fear (Abrahms 2008). Avoiding low intensity attacks bypasses this ambiguous definition of what constitutes a successful attack.[48]

5. Estimating δ at Equilibrium

Granting the model, data, and the threshold of 25 established above, we would like to estimate key variables of the model. As previously mentioned, critical parameters are unobserved due to the secretive preferences of the actors. The only critical pieces of information we have are our estimated mean casualties from each type of attack, w, and the threshold of 25 grants us a probability of a successful substantial attack *ex post*, $P(.) = \frac{\#\ of\ Attacks\ with\ over\ 25\ Casualties}{\#\ of\ Attacks}$. Using this as a baseline, we are able to establish an estimate of the values of the unobservable parameters a, g and δ.

To do this, we first note that the game only requires two pieces of information to start: δ and w. Having used the data to determine w, we evaluate the outcome of the game at many various values of the exogenously determined parameter δ. We then solve the model for values of a and g, given δ. From there, the equilibrium probability of successful substantial attack $P(a^*(g,w,\delta), g(w,\delta), \delta)$, is calculated. This theoretical probability has an empirical counterpart from the actual value which we know from the data for both types of attack: the percentage of attacks of each type above the threshold μ=25.[49] We would like to choose δ as best as possible to fit this probability for both types of attack. Consequently, we chose a simple minimization of squared errors as our criteria for best fit, selected for its resemblance to the classic ordinary least squares regression and because it leads to a fit in both dimensions.[50] We therefore seek the values of $\hat{\delta}_n$ that will minimize the error function below:

$$\min\{\left(P_{conv}(\hat{\delta}_{conv}) - P_{conv,given}\right)^2 + \left(P_{CBRN}(\hat{\delta}_{CBRN}) - P_{CBRN,given}\right)^2\} \quad (14)$$

Here, P_{given}, is the probability found from our data, $\hat{\delta}_n$is our exogenously chosen estimate of δ, which results in $P_n(\hat{\delta}_n)$ being found from our model. Performing a simple search of the values $\delta[1 \dots 10]$ by steps of 1 allows us to find a value of $\hat{\delta}_n$ that minimizes our squared error function. These search boundaries should be more than sufficient because e^{-10} is much smaller than P_{given}, and our functional form of $P(.)$, is the product of two exponential functions.

Having found our estimated value of $\hat{\delta}_n$, we also can obtain estimated current adversary expenditures, $\hat{a}_n$ and the estimated optimum counter-terrorism investments, $\hat{g}_n$. Table 22 shows all relevant values for the equilibrium solution. We evaluate them for $r_g = \{1,10,20,30\}$ to consider a range of adversary/government expenditure ratios, and find the fit clearly matches the correct probabilities and smallest error function best when $r_g = 1$.

We find that the initial estimate of delta suggests different levels of complexity parameter for different types of attack, $\delta_{conv} = 4$, while $\delta_{CBRN} = 2$. One possible explanation for this result is that a CBRN attack that has reached the "near-execution stage (so called "out of the door"), is perhaps slightly simpler- deploying a bomb or pressing a button. The difficulty of these attacks lies within the assembly of such a device. For example, during the US anthrax scare of 2001, the creation of anthrax was difficult, but the execution (simply mailing them) was not. On the other hand, there seems to be many complexities and pre-existing barriers against executing large conventional attacks. Such things like already existing local police forces, and rapidly responding police and other emergency forces well trained for conventional attacks, may make organized conventional attacks struggle to break the barrier of 25 casualties.

Effort at security for the government is tilted towards suppressing CBRN attacks: $g_{conv} = 0$, $g_{CBRN} = 1$. While this is probably not to be taken as a literal 100% it is likely that national security system heavily focuses on detection and prevention of any CBRN attacks, rather than focusing on preparing for conventional armed skirmishes. This seems rational given the higher number of expected casualties in large CBRN attacks, and their comparative simplicity in execution: once they are "out the door" they are simply taken to a crowded location and deployed.

Conversely, the adversary also invests in committing and deploying CBRN weapons once an attack is prepared. We find that the adversary interested in substantial attacks focuses their effort in deploying CBRN weapons. $a_{conv} = 0.2279$, $a_{CBRN} = 0.7721$. The emphasis in CBRN can be attributed towards their relatively large anticipated casualties, and their relative ease of deployment once out-the-door. Even though the government has heavily invested in protecting against CBRN, the adversary might still inflict casualties. They can do this by emphasizing conventional weapons, even though they are more logistically complex to use in a large attack, and have lower anticipated casualties when successful.

While it cannot be asserted that our proposed solution perfectly matches real investment by either party, the close fit suggests that they are at least plausible. In fact, we correctly identify each of the probabilities of attack within an average of 2%.[51]

6. Consequences of Unexpectedly Large Attacks

At this point, we have estimated values for the complexity and effort levels, $\hat{\delta}_n, \hat{a}_n$, and $\hat{g}_n$ obtained from fitting of the current observed data on actual "out-the-door" attacks to the theory. These are the Nash equilibrium values. But in real world new unforeseen shocks imply that the government's guess about the behavior, the plans and the strategies of the adversary will be inaccurate, due perhaps to imperfect intelligence about the adversary's capabilities. As an example, unbeknownst to the defender government, adversary may have developed a way of delivering a successful attack with much greater casualties than the defender government expects from past history. Alternatively, again unbeknownst to the defender government, the adversary may have the capability of using a new technology that would allow it to execute a relatively complex attack with greater simplicity. We examine each of these two scenarios below.

In the first scenario, based on their own private information, adversary groups anticipate their CBRN attack is of different severity than the mean, while the uninformed government merely prepares for attacks at the mean level of severity. For illustration we consider a case of underestimation here, where $E(w_{CBRN}|\ Adversary) \neq E(w_{CBRN}|\ Government)$. Again we use the equilibrium values of: $\delta_{conv} = 2$, $\delta_{CBRN} = 1$, $r_a = 1$, $r_g = 1$, $w_{conv} = 66.7$, and $w_{CBRN} = 168.5$ from Table 22 as the base conditions, due to their superior fit quality. We then consider that the adversary is better informed than the government as to the true realization of w_{CBRN}. To model this, we assume that w_{CBRN} is revealed to the adversary prior to the attack, but after the government has already established defenses, and the government does not know such a revelation is occurring. For the sake of simplicity, the government is considered to be entirely unaware of such a potentiality. To capture the variation in potentially realizable outcomes, we imagine w_{CBRN} could range from -60% to +60% of the expected value of w_{CBRN}. It is shown in Figure 8 how this information gap affects the outcome, or the casualty count. Obviously, as the realization of w_{CBRN} shown to the adversary increases, so does the expected number of CBRN casualties. However, the CBRN casualties increase at a rate *faster* than the simple increase in w_{CBRN}. Conversely, the total number of casualties from conventional attacks declines, and eventually reaches zero. The net number of casualties, from both types of attack together, gradually climbs at an accelerating rate until it because linear and remains such indefinitely.

As shown by the subsequent Figure 9, this decline in conventional casualties, and faster-than-linear increase in CBRN casualties, can be explained by the adversary recognizing the unique opportunity for CBRN attacks against the misinformed government, and thus focusing more effort on CBRN attacks. As such, the growth in CBRN casualties is due to both the higher lethality and the increased adversary investment in CBRN. The increase in total casualties is softened by the reduction in conventional casualties, but with very large increases in CBRN casualties, the adversary will entirely divest from conventional attacks. Again, the government is relatively unprepared for such attacks, having not been informed about any potential changes in casualty counts.

Next consider the case where the lethality (w) of potential attacks are again well understood and fixed, but complexity of a potential attack (δ) by the adversary is not well understood by the defender government. In this scenario, the adversary has access to a technique or technology unforeseen by the defending government that simplifies the process of attack. An example may be bringing a firearm into a secure building becoming far simpler through improved plastic technology. Such improvements, if not anticipated by the defender government, would falsely lead the government to believe that a type of attack is too complex for the adversary to invest heavily in. The overconfidence leads to an inferior defense of the target, allowing the adversary to opportunistically take advantage of superior information, and inflict additional casualties. Compared to the correctly informed setting, the target society will experience larger casualties.

Figure 10 and 11 depict this scenario of unusually simple or complex attacks, again using the same equilibrium parameters identified in Table 22 as a base. Again, we then vary the value of our parameter of interest, this time δ_{CBRN}, for the adversary, but only make this change after the government has established defenses, and without foresight of this change on the part of the government. Figure 10 plots the total number of casualties that will occur if the government plans its defense based on a faulty estimation of what the government estimates the adversary capabilities for carrying out a complex

CBRN attack. Notice the range of casualties after mis-estimation are potentially much larger than the casualties in Figure 8 . This suggests that estimating the complexity of the attack correctly is of much greater importance than correctly assessing the impending casualties. If both are inaccurate by a large proportion, the casualties from inaccuracies in complexity far outweigh those of a proportionally equivilant error in lethality. The complexity parameter entering exponentially into the probability of success (see equation 3) plays a much larger role in the value of that probability, and thus of the expected number of causalities. We note that there appears to be an eventual spike in conventional casualties when the complexity of CBRN attacks is very low, and turn to the behavior of the adversary in Figure 11 to identify why.

In Figure 11, we note that the adversary's efforts are not shifting purely in one direction. As a CBRN attack becomes less complex from our equilibrium values, the adversary initially invests more into the attack. This is because they see greater marginal returns for their effort within a CBRN attack as it becomes simpler to perform. However, as the attack complexity reaches very low levels, the success of the CBRN attack is nearly assured. Additional effort towards CBRN at this point does not substantially increase the probability of a successful CBRN attack. Adversaries then take some of their resources and divert them away from the nearly assured CBRN event and towards the potentially contentious conventional efforts. The result is that net casualties continue to increase, as that there is not only extremely likely a large number of CBRN casualties, but it will be further supplemented by the adversary's ability to assign surfit effort from CBRN into conventional attacks.

In sum, we have identified that a goverment error in anticipating the complexity of an attack can result in substantially more casualties. An immediate policy implication is that intelligence efforts should focus on establishing (and increasing) the obstacles opponents face in performing an attack, rather than assessing how catastrophic the consequences of a large attack might be.

7. Conclusion

We have developed a sequential game of conflict between a government and an adversary organization. This model is used to analyze the strategic choices of effort allocation between large CBRN and large conventional threats. Using this model, we match theory and data by estimating a key parameter of the model that describes the relative complexity of each type of attack. We do so by minimizing sum squared error between the observed and the theoretical probability of success in an attack in a model where all other starting parameters can be identified beforehand. With this parameter estimate, we are then able to back out the Nash equilibrium values of effort by both sides.

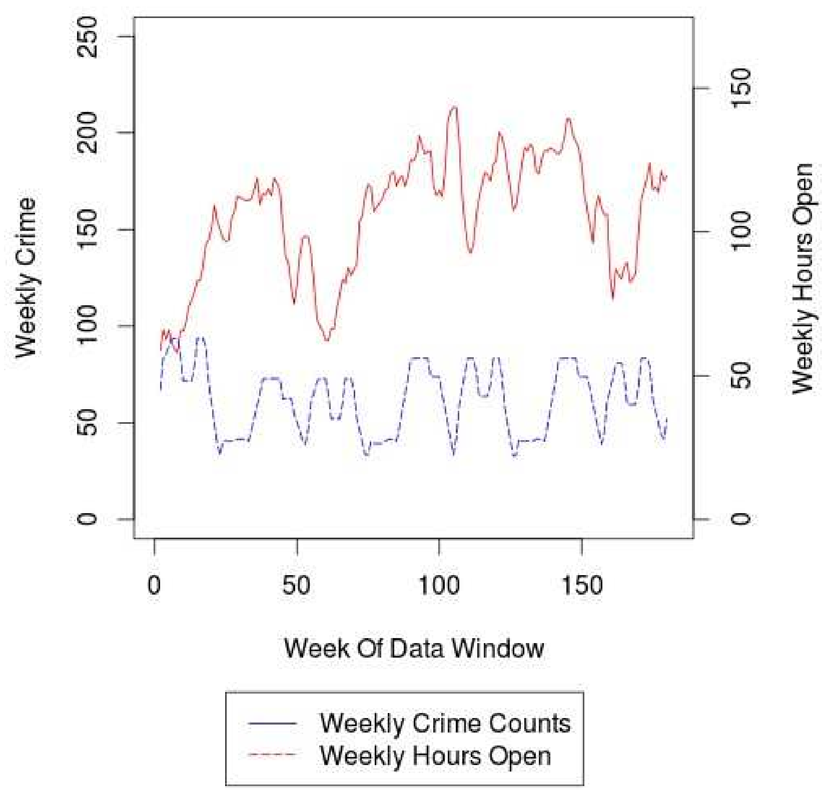
Finally, anticipating that the government will eventually be caught unaware by some shock, we model the consequences of such unfortunate surprises in attack complexity and lethality. This forecast of casualties identifies the scale of potential future disasters when the attack size or its complexity are grossly misestimated *ex anti*. We identify that while it may be important to measure changes in the size of incoming attacks, the most critical challenge for the defending government is to accurately estimate the complexity of in the execution of the attack.

Figures

Figure 1: BOSS Operating Range

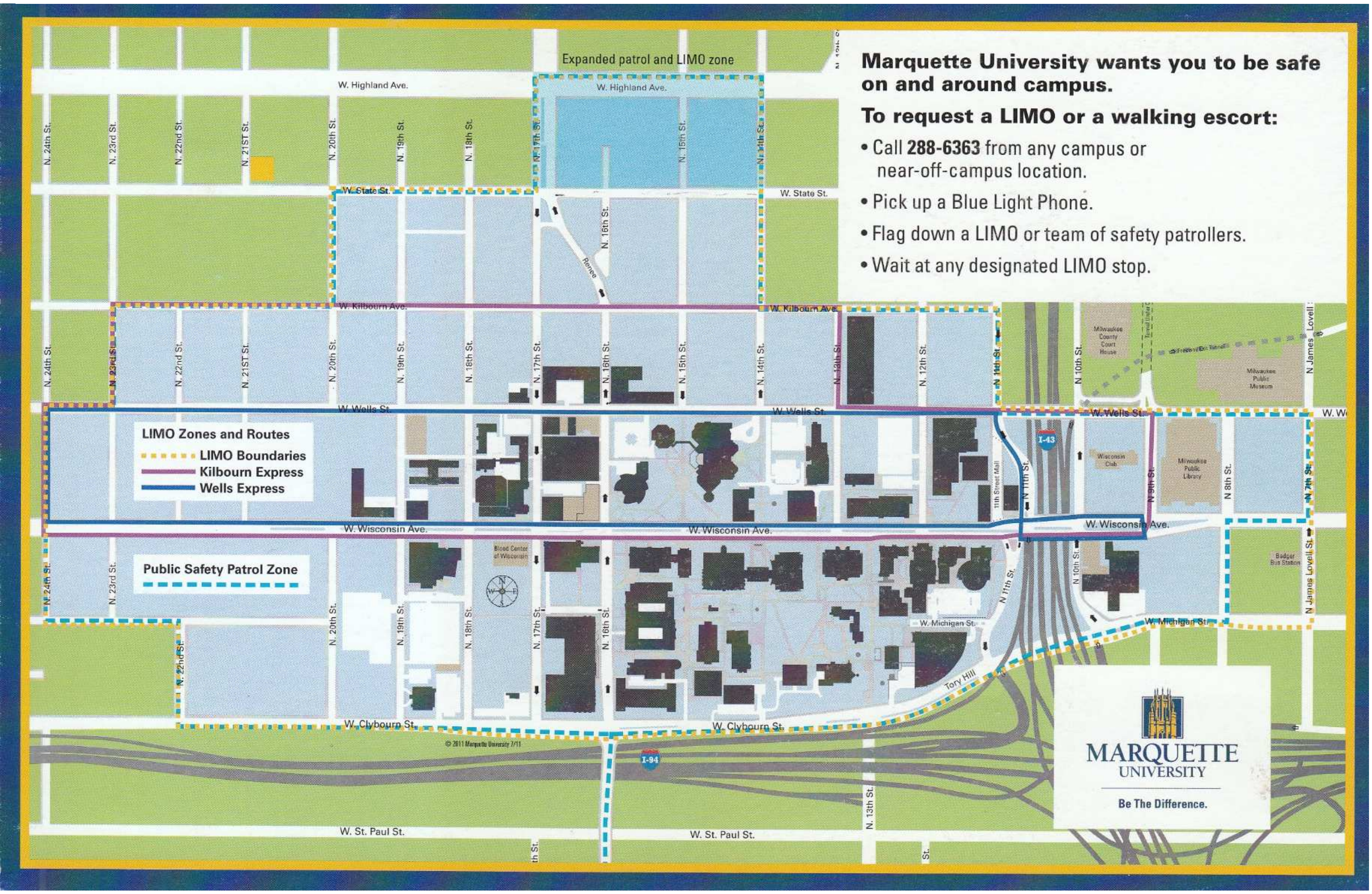
Notes: Marked Points Represent UWM Facilities, and the dark boarder represents the boundary of BOSS operations.

Figure 2: Plot of Weekly Crime and Hours Open



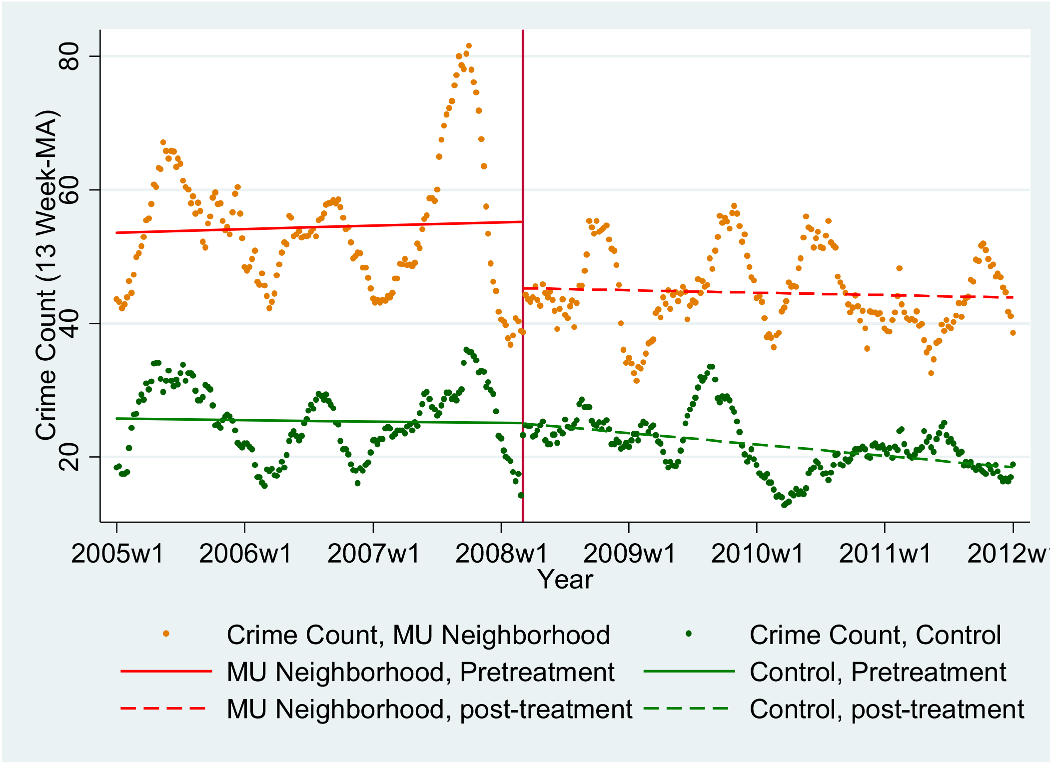
Notes: Displays 5-week moving averages

Figure 3: Boundaries of the Safe Ride Program and the Bus Routes



Notes: The entire blue area outline in dashed blue line is service by the safe-ride program. The purple and dark blue lines through the center are the dedicated bus routes.

Figure 4: Weekly Crime Counts across the Data Window



Notes: Weekly crime counts are shown as a 13 week moving average. The 13 week moving average is not evaluated across the treatment start date, represented by the vertical line.

Figure 5: The Model of Government Defense Against Adversary Attacks

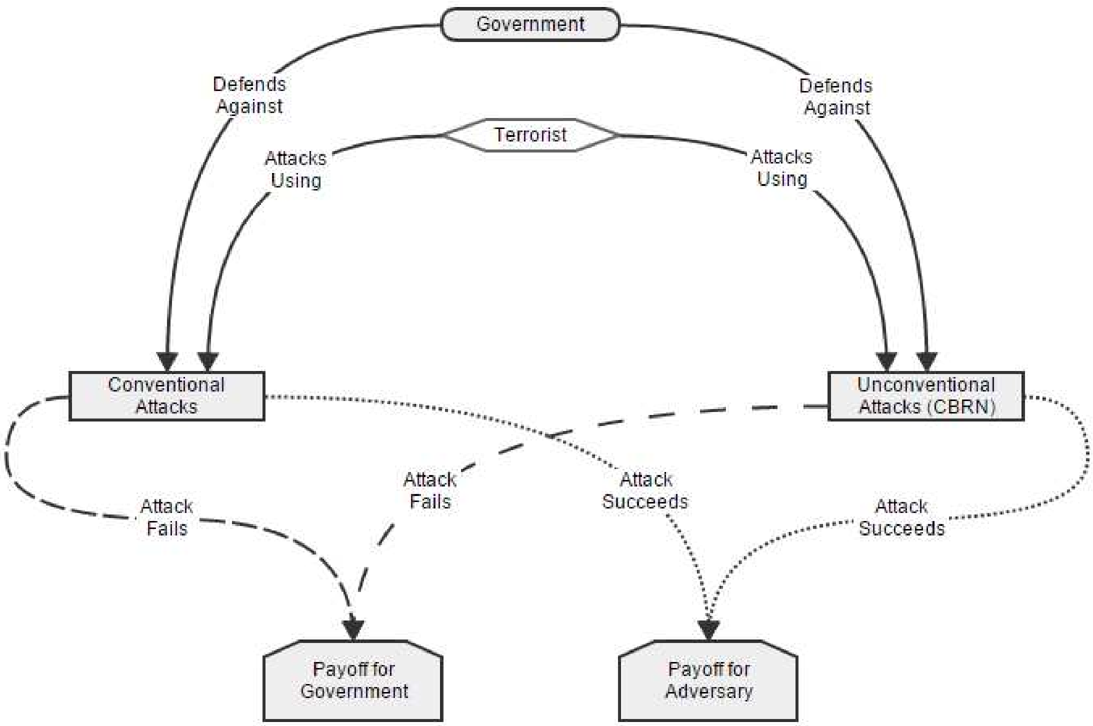


Figure 6: Equilibrium Effort in Response to Attack Complexity

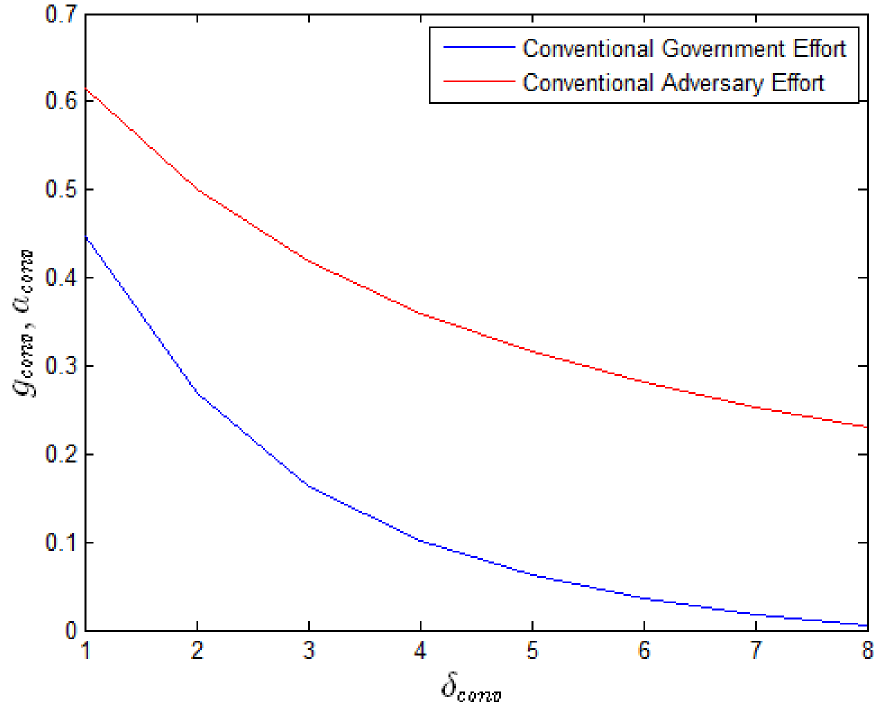


Figure 7: Equilibrium Effort in Response to Cross Attack Complexity

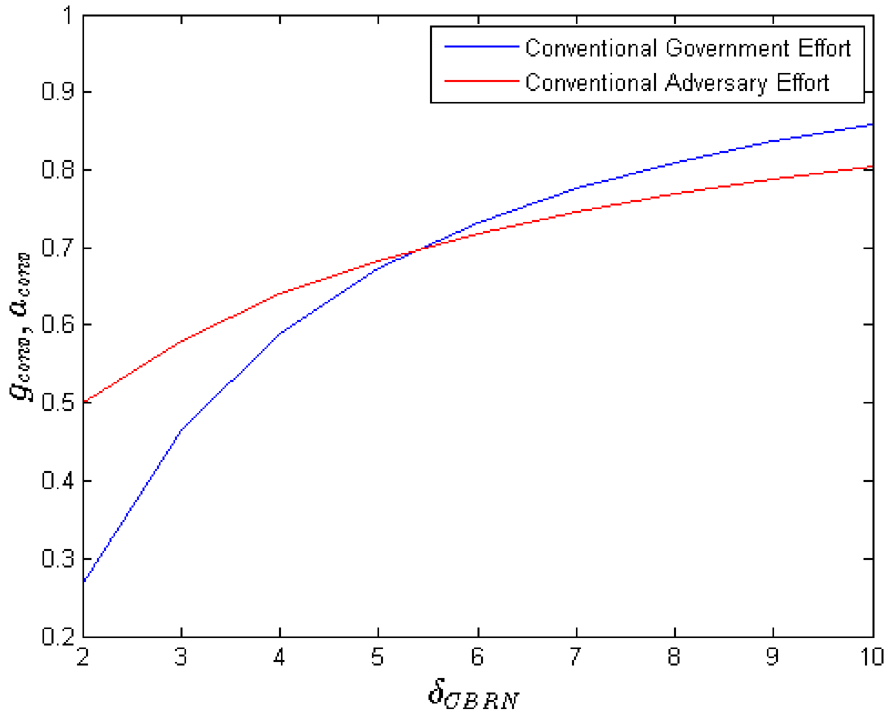


Figure 8: Number of expected casualties with respect to size of shock to CBRN Casualties

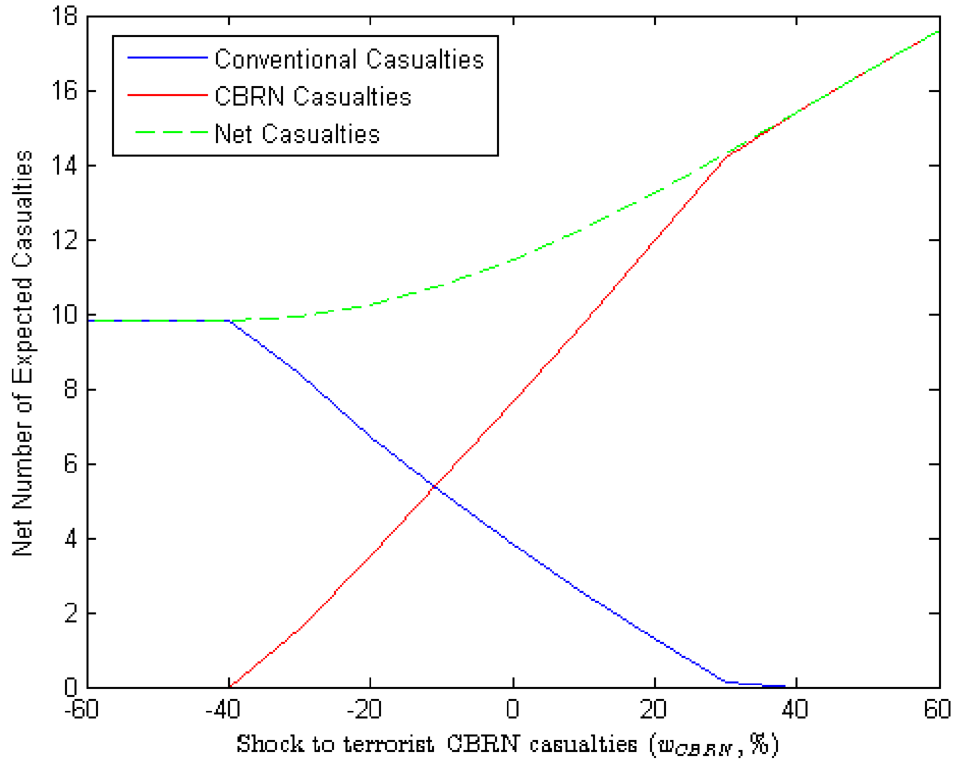


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Figure 9: Effort with respect to size of shock to CBRN casualties

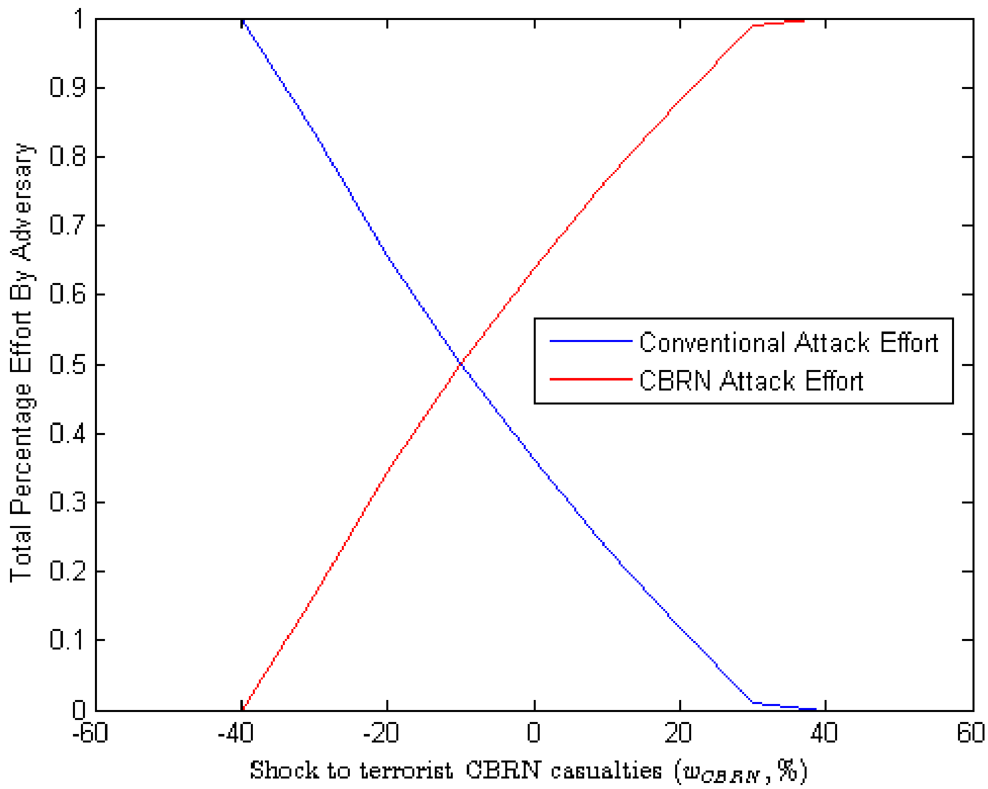


Figure 10: Casualties occurring in response to a shock in CBRN complexity

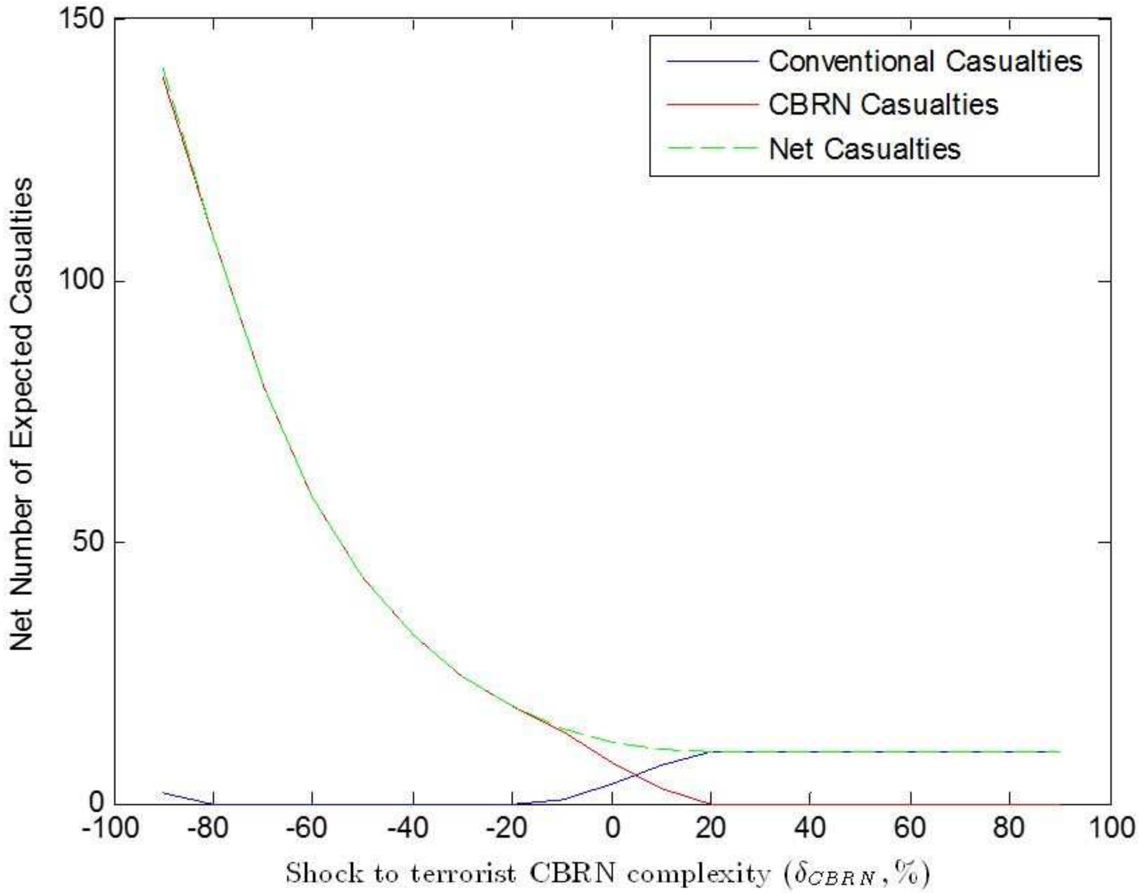


Figure 11: Adversary effort in response to a shock in CBRN complexity

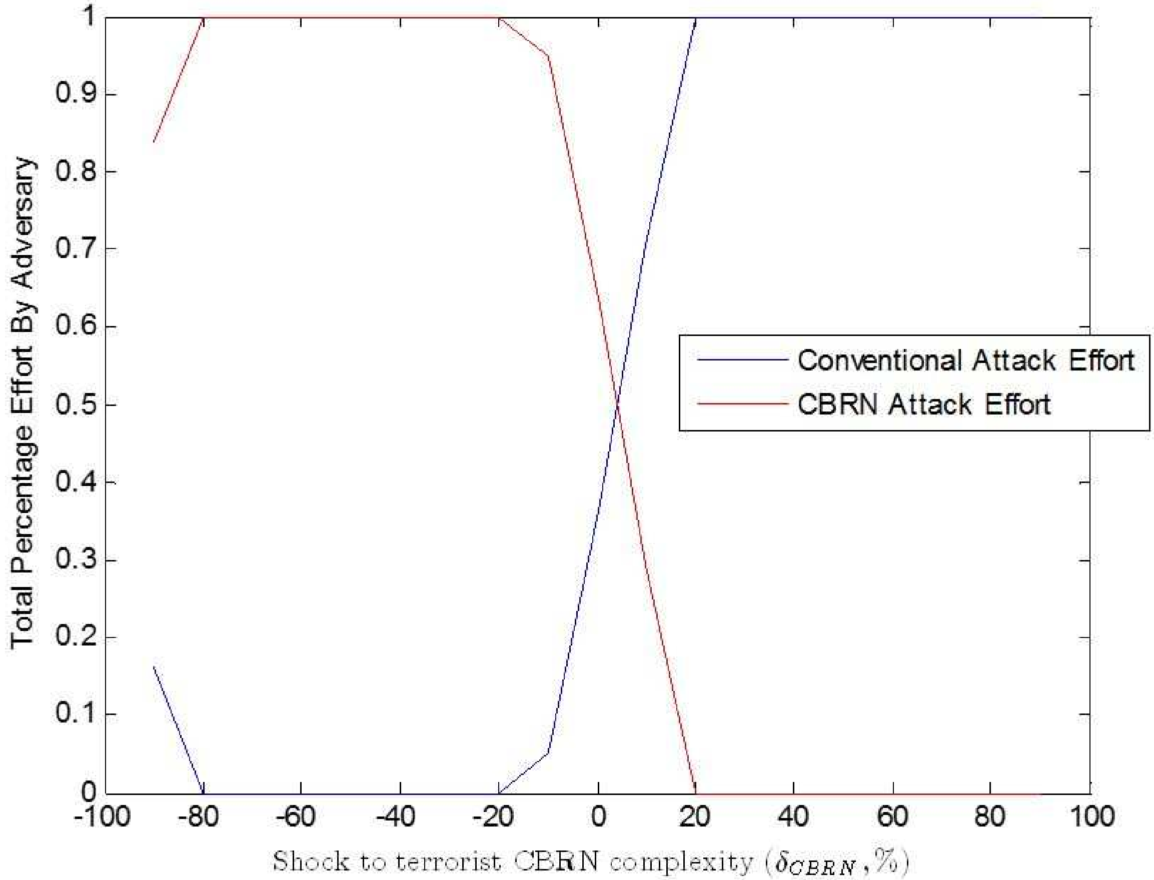


Figure 12, Appendix D: Quantile-Quantile Plots of Conventional Attack Casualties at Thresholds of 10, 25, and 50

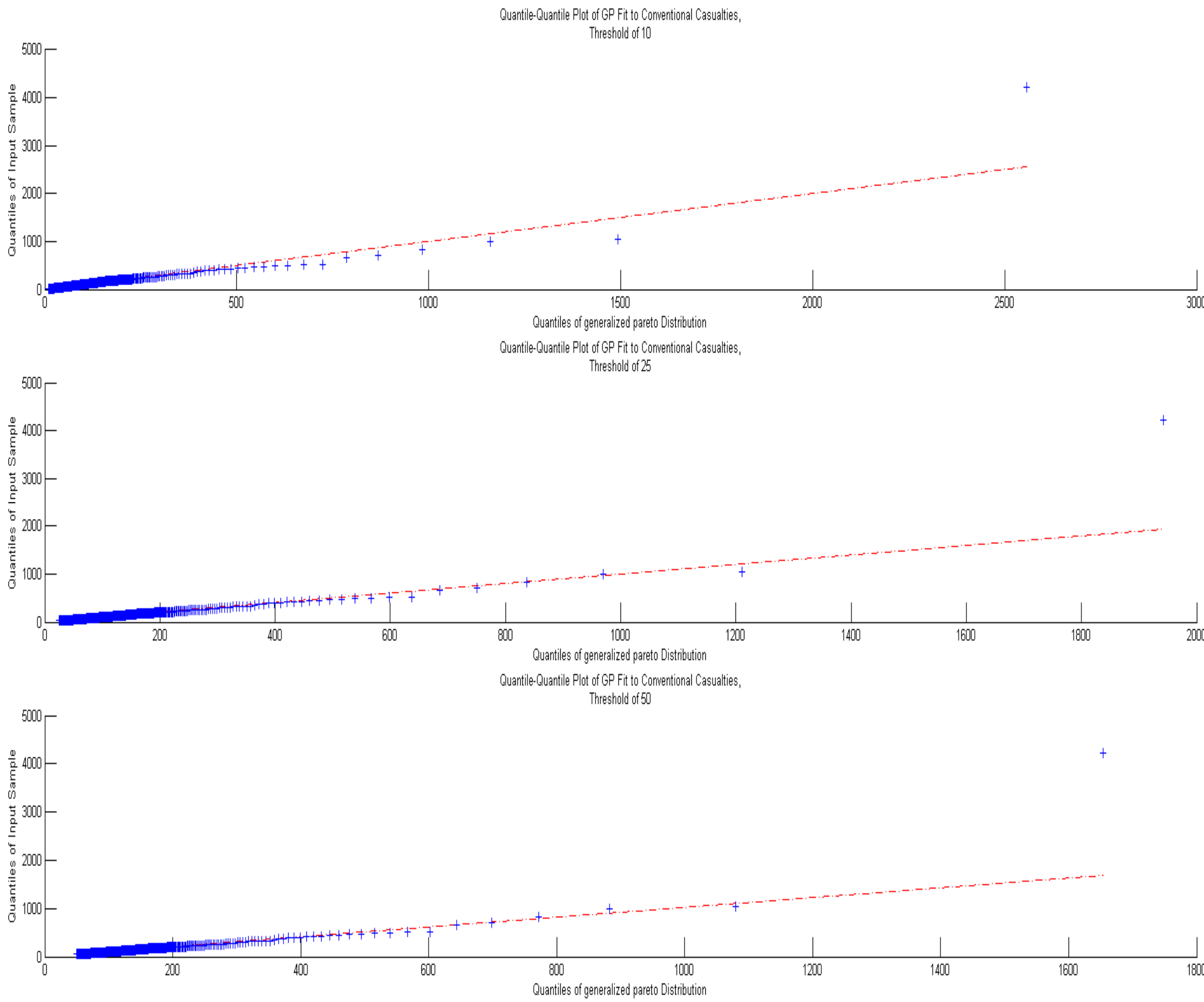
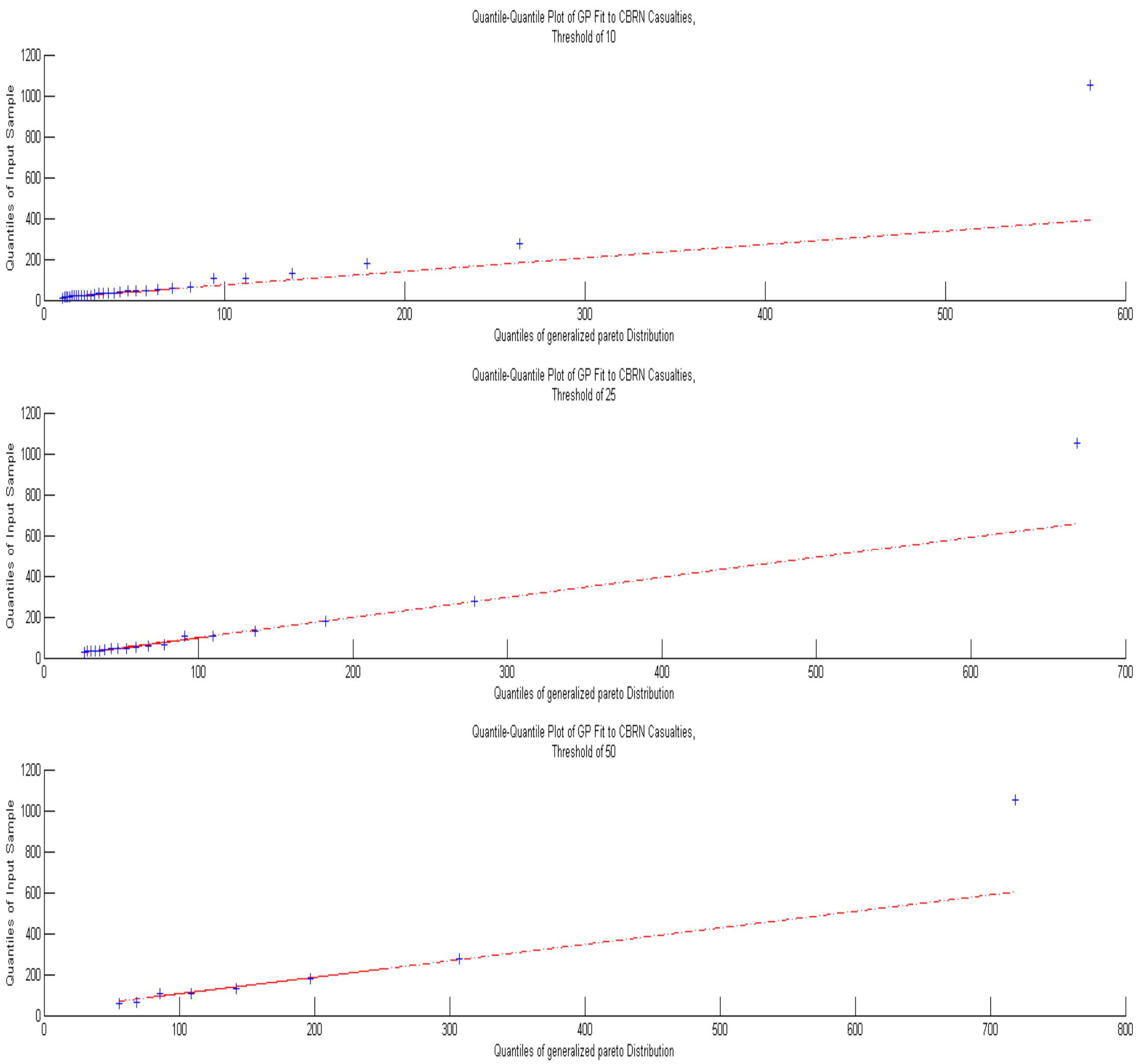


Figure 13, Appendix D: Quantile-Quantile Plots of CBRN Attack Casualties at Thresholds of 10, 25, and 50



Tables

Table 1: Number of Changes between Open and Closed by Hour of Week

	Hour	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
Morning	0	28	26	23	21	27	27	30
	1	20	18	16	16	20	20	20
Evening	17	4	5	3	3	3	3	4
	18	26	27	23	29	27	27	28
	19	27	38	24	30	28	28	29
	20	27	38	24	30	28	28	29
	21	27	38	24	30	28	28	29
	22	27	38	24	30	28	30	29
	23	27	24	22	28	28	30	29

Note: The hours from the 2nd to 16th hour of the day were suppressed because the program was always closed during those hours

Table 2: Summary Statistics of the Data

Variable	Mean	Std. Dev.
Rides Given	15.266	29.661
Program is Open (1 if Open, 0 otherwise)	0.248	0.432
Daily Precipitation (cm)	0.249	0.728
Daily Snowfall (cm)	0.048	0.233
Daily Snow on Ground (cm)	0.267	0.637
Daily Minimum Temperature (degrees C)	4.779	10.38
Total Crime	0.934	1.647
School in Session (1 if Open, 0 otherwise)	0.914	0.281
Total Probability of Crime	47.30%	-

Note: Averages are taken over the entire data set.

Table 3: Poisson Regression of Crime Counts in the Safe Ride Region

	(1)	(2)	(3)	(4)
Open	-0.09102	-0.08757	-0.0848	-0.15179
	*(1.84)**	*(1.74)**	*(1.68)**	*(3.56)****
School in Session		0.16624	0.17256	0.18292
		*(4.49)****	*(4.63)****	*(5.35)****
Daily Precipitation (cm)			-0.01742	-0.0186
			(1.42)	*(1.47)*
Daily Snowfall (cm)			-0.10731	-0.09934
			*(2.64)****	*(2.46)***
Daily Snow on Ground (cm)			-0.02491	-0.02535
			(1.21)	*(1.21)*
Daily Minimum Temperature (C^o)			0.00505	0.00437
			*(2.29)***	*(1.96)**
Constant	-0.04617	-0.20954	-0.15056	
	(1.15)	*(3.55)****	*(2.56)***	
N	30,648	30,648	30,648	30,648
Clustering by Hour of Week	Yes	Yes	Yes	Yes
Month Controls		Yes	Yes	Yes
Hour of Week Fixed Effects (168)				Yes

Note: T-statistics are in parentheses, and reflect bootstrapping with a clustering option 200 times to avoid overdispersion. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 4: OLS Regression of Crime Counts in the Safe Ride Region

	(1)	(2)	(3)	(4)
Open	-0.08307	-0.08012	-0.07765	-0.12474
	*(1.82)**	*(1.72)**	*(1.67)**	*(3.25)****
School in Session		0.14422	0.15119	0.15954
		*(4.56)****	*(4.74)****	*(5.54)****
Daily Precipitation (cm)			-1.65092	-1.73386
			(1.47)	*(1.51)*
Daily Snowfall (cm)			-7.50984	-6.78262
			*(2.79)****	*(2.51)***
Daily Snow on Ground (cm)			-1.86833	-1.92437
			(1.20)	*(1.19)*
Daily Minimum Temperature (C^{o})			0.04694	0.04085
			*(2.35)***	*(2.04)***
Constant	0.95488	0.95488	0.81339	0.86347
	*(24.74)****	*(16.11)****	*(16.81)****	*(18.40)****
N	30,648	30,648	30,648	30,648
Clustering by Hour of Week	Yes	Yes	Yes	Yes
Month Controls		Yes	Yes	Yes
Hour of Week Fixed Effects (168)				Yes

Note: T-statistics are in parentheses, and reflect bootstrapping with a clustering option 200 times to avoid overdispersion. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 5: Poisson Regression of Crime Counts in the Safe Ride Region Among Typically Open Hours

	(1)	(2)	(3)	(4)
Open	-0.14664	-0.14923	-0.14165	-0.1605
	*(2.48)***	*(2.38)***	*(2.21)***	*(3.45)****
School in Session		0.32689	0.33163	0.33355
		*(4.36)****	*(4.40)****	*(4.54)****
Daily Precipitation (cm)			-0.02248	-0.02545
			(1.07)	*(1.15)*
Daily Snowfall (cm)			-0.25187	-0.24199
			*(3.27)****	*(2.98)****
Daily Snow on Ground (cm)			-0.01018	-0.01183
			(0.38)	*(0.43)*
Daily Minimum Temperature (C°)			0.00777	0.00712
			*(2.28)***	*(2.17)***
Constant	0.00945	-0.327	-0.24743	
	(0.15)	*(3.04)****	*(2.28)***	
N	30,648	30,648	30,648	30,648
Clustering by Hour of Week	Yes	Yes	Yes	Yes
Month Controls		Yes	Yes	Yes
Hour of Week Fixed Effects (168)				Yes
Dropped Hours 2am-4pm (inclusive)	Yes	Yes	Yes	Yes

Note: T-statistics are in parentheses, and reflect bootstrapping with a clustering option 200 times to avoid overdispersion. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 6: ZIP Regression of Crime Counts in the Safe Ride Region Among Typically Open Hours

	Marginal Effects	Marginal Effects with Dummies
Open	-0.13720	-0.13443
	*(2.15)***	*(3.04)****
School in Session	0.32779	0.26084
	*(4.36)****	*(6.00)****
Daily Precipitation (cm)	-0.024	-0.02163
	(1.17)	*(0.93)*
Daily Snowfall (cm)	-0.2097	-0.1777
	*(2.30)***	*(2.29)***
Daily Snow on Ground (cm)	0.00015	-0.00344
	(0.01)	*(0.11)*
Daily Minimum Temperature (C^o)	0.00822	0.00699
	*(2.41)***	*(2.16)***
N	11,493	11,493
Clustering by Hour of Week	Yes	Yes
Month Controls	Yes	Yes
Hour of Week Dummies Included (168)		Yes
Dropped Hours 2am-4pm (inclusive)	Yes	Yes

Note: T-statistics are in parentheses, and reflect bootstrapping with a clustering option 200 times to avoid overdispersion. In both regressions, the sample was restricted to hours in which the program was typically open. The second column represents the results from distributing the tasks onto the larger computer in order to support the addition of dummies to the estimation. * p < 0.1; ** p < 0.05; *** p < 0.01

Table 7: Poisson Regressions of the Two Types of Crime Counts in the Safe Ride Region

	Social and Property Crimes	Personal Crimes
Open	-0.14011	-0.1818
	*(3.11)******	*(2.35)****
School in Session	0.16874	0.2405
	*(4.46)******	*(3.65)******
Daily Precipitation (cm)	-0.0088	-0.0589
	(0.69)	*(1.91)**
Daily Snowfall (cm)	-0.09855	-0.10304
	*(2.28)****	*(0.90)*
Daily Snow on Ground (cm)	-0.03488	0.01334
	(1.49)	*(0.40)*
Daily Minimum Temperature (C^o)	0.00348	0.00791
	(1.37)	*(2.00)****
N	30,648	30,648
Clustering by Hour of Week	Yes	Yes
Month Controls	Yes	Yes
Hour of Week Dummies Included (168)	Yes	Yes

Note: T-statistics are in parentheses, and reflect bootstrapping with a clustering option 200 times to avoid overdispersion. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 8: Poisson Regressions of the Crime Counts in the Safe Ride Region with a Weekend Interaction Term

	(1)	(2)	(3)	(4)
Open	-0.07129	-0.06925	-0.06773	-0.16965
	(1.32)	*(1.28)*	*(1.25)*	*(3.32)****
Open * Weekend	*-0.07190*	*-0.06675*	*-0.06243*	*0.06278*
	(0.95)	*(0.92)*	*(0.86)*	*(0.75)*
School in Session		0.16516	0.17153	0.18315
		*(4.49)****	*(4.64)****	*(5.35)****
Daily Precipitation (cm)			-0.01772	-0.01856
			(1.44)	*(1.47)*
Daily Snowfall (cm)			-0.10638	-0.09913
			*(2.60)****	*(2.46)***
Daily Snow on Ground (cm)			-0.02496	-0.02527
			(1.22)	*(1.20)*
Daily Minimum Temperature (C^{o})			0.00496	0.00439
			*(2.25)***	*(1.97)***
Constant	-0.04617	-0.20870	-0.15035	
	(1.15)	*(3.54)****	*(2.55)***	
N	30,648	30,648	30,648	30,648
Clustering by Hour of Week	Yes	Yes	Yes	Yes
Month Controls		Yes	Yes	Yes
Hour of Week Fixed Effects (168)				Yes

Note: T-statistics are in parentheses, and reflect bootstrapping with a clustering option 200 times to avoid overdispersion. The weekend is defined as any time during Friday, Saturday, or Sunday. Alternative definitions show minimal change. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 9: Poisson Regression of the Crime Counts in the Safe Ride Region on Program Intensity

	(1)	(2)	(3)	(4)
Rides Given	-0.00375	-0.00179	-0.00171	-0.00484
	*(3.94)******	*(1.38)*	*(1.32)*	*(4.81)******
School in Session		0.23457	0.22194	0.22519
		*(2.73)******	*(2.58)******	*(2.71)******
Daily Precipitation (cm)			-0.01921	-0.01245
			(0.69)	*(0.42)*
Daily Snowfall (cm)			-0.30602	-0.31332
			*(3.49)******	*(3.53)******
Daily Snow on Ground (cm)			0.00423	0.01205
			(0.13)	*(0.36)*
Daily Minimum Temperature (C^{o})			0.00648	0.00384
			(1.34)	*(0.83)*
Constant	0.08904	-0.33866	-0.24794	
	(1.29)	*(2.70)******	*(1.82)**	
N	7,598	7,598	7,598	7,598
Clustering by Hour of Week	Yes	Yes	Yes	Yes
Month Controls		Yes	Yes	Yes
Hour of Week Fixed Effects (168)				Yes

Note: T-statistics are in parentheses, and reflect bootstrapping with a clustering option 200 times to avoid overdispersion. The sample was restricted to contain only the hours in which the program was open. Alternative definitions show minimal change. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 10: Poisson Regression of the Two Types of Crime Counts in the Safe Ride Region on Program Intensity

	Social and Property Crimes	Social and Property Crimes
Rides Given	-0.00401	-0.00688
	*(3.29)******	*(3.76)******
School in Session	0.00254	-0.05397
	(0.08)	*(1.01)*
Daily Precipitation (cm)	-0.29023	-0.37316
	*(2.76)******	*(1.94)**
Daily Snowfall (cm)	0.02503	-0.02397
	(0.75)	*(0.40)*
Daily Snow on Ground (cm)	0.00355	0.00472
	(0.69)	*(0.62)*
Daily Minimum Temperature (C^{o})	0.21977	0.23922
	*(2.25)****	*(1.57)*
Constant		
N	7,598	7,598
Clustering by Hour of Week	Yes	Yes
Month Controls	Yes	Yes
Hour of Week Fixed Effects (168)	Yes	Yes

Note: T-statistics are in parentheses, and reflect bootstrapping with a clustering option 200 times to avoid overdispersion. The sample was restricted to contain only the hours in which the program was open. The weekend is defined as any time during Friday, Saturday, or Sunday. Alternative definitions show minimal change. * p < 0.1; ** p < 0.05; *** p < 0.01

Table 11: Poisson Regression of Crime Counts in the Safe Ride Region on Program Intensity with a Weekend Interaction Term

	(1)	(2)	(3)	(4)
Rides Given	-0.00295	-0.00081	-0.00078	-0.00306
	*(3.00)****	*(0.62)*	*(0.58)*	*(2.81)****
Rides Given * Weekend	-0.00185	-0.00193	-0.00187	-0.00513
	*(1.91)**	*(2.00)***	*(1.94)**	*(3.36)****
School in Session		0.22222	0.21065	0.22103
		*(2.53)***	*(2.40)***	*(2.65)****
Daily Precipitation (cm)			-0.02148	-0.01318
			(0.76)	*(0.45)*
Daily Snowfall (cm)			-0.30165	-0.31940
			*(3.38)****	*(3.57)****
Daily Snow on Ground (cm)			0.00462	0.01195
			(0.14)	*(0.36)*
Daily Minimum Temperature (C^o)			0.00590	0.00372
			(1.23)	*(0.80)*
Constant	0.07288	-0.34875	-0.26222	
	(1.05)	*(2.71)****	*(1.87)**	
N	7598	7598	7598	7598
Clustering by Hour of Week	Yes	Yes	Yes	Yes
Month Controls		Yes	Yes	Yes
Hour of Week Fixed Effects (168)				Yes

Note: T-statistics are in parentheses, and reflect bootstrapping with a clustering option 200 times to avoid overdispersion. The sample was restricted to contain only the hours in which the program was open. The weekend is defined as any time during Friday, Saturday, or Sunday. Alternative definitions show minimal change. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 12: Summary Statistics

	Mean	Standard Deviation
Marquette Weekly Crime Count	45.59	18.75
MSOE Weekly Crime Count	23.65	11.27
Snow on Ground (mm)	24.45	57.72
Minimum Temperature (˚C)	5.24	109.99
Spring Semester	0.34	0.47
Fall Semester	0.28	0.45
Summer School	0.25	0.43
Safe Rides Delivered	4794.34	2797.38
Bus Rides Delivered	623.10	752.84
Total Rides Delivered	5417.44	3289.56

Notes: Bus rides delivered are averaged over the weeks of bus service

Table 13: Evidence of Substitution between Transit Services

VARIABLES	(1)	(2)	(3)
Policy	-1736*	-1771***	-1680***
	(899.1)	*(589.8)*	*(452.2)*
Policy *Time Trend	5.841	7.901**	7.693***
	(5.412)	*(3.478)*	*(2.654)*
Time Trend	-0.666	-2.751	-2.666
	(4.516)	*(2.897)*	*(2.180)*
Spring Semester		4,174***	4,847***
		(365.6)	*(1,178)*
Fall Semester		3,989***	2,212***
		(389.2)	*(741.8)*
Summer Semester		66.75	-46.17
		(471.0)	*(910.1)*
Snow on Ground (mm)		5.466**	-4.107***
		(2.201)	*(1.391)*
Minimum Temperature (C)		-1.538	-9.204***
		(1.622)	*(2.091)*
Constant	4,798***	2,257***	711.2***
	(433.1)	*(401.6)*	*(272.5)*
Week of Year Dummies			YES
Observations	365	365	365
R-squared	0.011	0.627	0.815

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: Dependent variable is the number of rides delivered by the safe ride program.

Table 14: Crime in the Marquette University Neighborhood vs Control

VARIABLES	(1)	(2)	(3)	(4)	(5)
Policy	-3.693***	-3.934***	-3.936***	-1.198	0.879
	(1.192)	*(1.174)*	*(1.182)*	*(2.231)*	*(2.350)*
Policy*MU Neighborhood	-6.328***	-6.783***	-6.929***	-6.926***	-11.08**
	(2.250)	*(2.137)*	*(2.147)*	*(2.148)*	*(4.378)*
MU Neighborhood	29.65***	32.05***	37.17***	37.10***	35.34***
	(1.760)	*(3.491)*	*(4.369)*	*(4.388)*	*(4.663)*
Snow on Ground (mm)		-0.0176	-0.00505	-0.00401	-0.00405
		(0.0109)	*(0.0125)*	*(0.0125)*	*(0.0125)*
Minimum Temperature (C)		0.0360***	0.0274*	0.0295*	0.0295*
		(0.00802)	*(0.0151)*	*(0.0152)*	*(0.0153)*
Time Trend				-0.0150	-0.0263**
				(0.0105)	*(0.0114)*
MU Neighborhood*Time Trend					0.0227
					(0.0208)
School Calendar Interactions		YES	YES	YES	YES
Week of Year Dummies			YES	YES	YES
Constant	25.67***	22.63***	19.08***	20.64***	21.39***
	(0.953)	*(1.631)*	*(5.944)*	*(6.007)*	*(6.010)*
Observations	730	730	730	730	730
R-squared	0.455	0.512	0.545	0.547	0.548

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 15: Decomposition of MU

VARIABLES	MU vs MSOE (Original Estimate)	MU Bus vs MSOE	MU Safe Rides vs MSOE
Policy	0.879	0.890	0.655
	(2.350)	*(2.306)*	*(2.273)*
Policy*MU Neighborhood	-11.08**		
	(4.378)		
Policy*MU Bus Neighborhood		-7.235**	
		(3.361)	
Policy*MU Safe Ride Neighborhood			-4.912
			(3.216)
MU Neighborhood	35.34***		
	(4.663)		
MU Bus Neighborhood		6.256	
		(3.802)	
MU Safe Ride Neighborhood			4.338
			(3.373)
Snow on Ground (mm)	-0.00405	0.00140	-0.0149
	(0.0125)	*(0.0101)*	*(0.0105)*
Minimum Temperature (C)	0.0295*	0.0176	0.00639
	(0.0153)	*(0.0122)*	*(0.0117)*
Time Trend	-0.0263**	-0.0268**	-0.0255**
	(0.0114)	*(0.0112)*	*(0.0109)*
MU Neighborhood*Time Trend	0.0227		
	(0.0208)		
MU Bus Neighborhood*Time Trend		0.0346**	
		(0.0164)	
MU Safe Ride Neighborhood*Time Trend			0.0162
			(0.0151)
School Calendar Interactions	YES	YES	YES
Week of Year Dummies	YES	YES	YES
Constant	21.39***	24.89***	19.14***
	(6.010)	*(5.533)*	*(3.763)*
Observations	730	730	730
R-squared	0.548	0.191	0.186

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 16: MU Safe Ride vs MU Bus Areas

VARIABLES	(1)	(2)	(3)
Policy	-4.479***	-4.821***	-5.889**
	(1.292)	*(1.248)*	*(2.429)*
Policy*MU Safe Ride Neighborhood	-1.064	-1.054	2.239
	(1.719)	*(1.659)*	*(3.282)*
MU Safe Ride Neighborhood	-5.236***	-3.840	-2.285
	(1.313)	*(2.583)*	*(2.793)*
Snow on Ground (mm)		0.00444	0.00467
		(0.0108)	*(0.0107)*
Minimum Temperature (C)		0.0334***	0.0338***
		(0.0126)	*(0.0126)*
Time Trend			0.00589
			(0.0120)
MU Safe Ride Neighborhood*Time Trend			-0.0181
			(0.0156)
School Calendar Interactions		YES	YES
Week of Year Dummies		YES	YES
Constant	30.28***	35.14***	34.68***
	(0.999)	*(5.420)*	*(5.292)*
Observations	730	730	730
R-squared	0.101	0.229	0.231

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 17: Initial Robustness Checks

Regions Included in Regression	Original Estimates	False Treatment (One Yr. Prior)	False Treatment (One Yr. After)	Two Leads (6 month)	Alternative Control (Bay View)
University vs Control	-11.08**	-0.991	3.660	-10.82**	-14.98**
	(4.378)	*(3.882)*	*(4.278)*	*(5.271)*	*(6.398)*
Bus Area vs Control	-7.235**	-2.292	0.0733	-8.438**	-11.95**
	(3.361)	*(3.067)*	*(3.226)*	*(4.085)*	*(5.813)*
Safe Ride Only Area vs Control	-4.912	-4.511	4.517	-8.474**	-9.734*
	(3.216)	*(2.821)*	*(3.160)*	*(3.973)*	*(5.744)*
Bus Area vs Safe Ride Only	2.239	-2.250	4.332	-0.324	2.239
	(3.282)	*(3.012)*	*(3.163)*	*(4.023)*	*(3.282)*

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: Each entry is from a different regression. The leads are the two six month periods prior to the bus service and these are also interacted with the treatment areas. The alternative control is a comparable neighborhood in the same city. The comparison between the bus area and safe ride only area is independent of the choice of control.

Table 18: Additional Robustness Checks

Regions Included in Regression	Original Estimates	Dropping Irrelevant Offenses	Including Expansion	MU Interior (Including Bus Line Interior as Treated)
University vs MSOE	-11.08**	-10.97**	-13.54***	-11.08**
	(4.38)	*(4.332)*	*(4.450)*	*(4.38)*
Bus Area vs MSOE	-7.235**	-7.006**	-7.235**	-9.238**
	(3.361)	*(3.326)*	*(3.361)*	*(3.742)*
Safe Ride Only Area vs MSOE	-4.912	-4.838	-6.027*	-3.590
	(3.216)	*(3.188)*	*(3.147)*	*(2.953)*
Bus Area vs Safe Ride Only	2.239	2.091	0.0622	-4.311
	(3.282)	*(3.249)*	*(3.432)*	*(3.412)*

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Each entry is from a different regression. MU interior (including bus line interior as treated), line 1 is the same as original estimates by necessity, nothing changes in either of the comparison groups.

Table 19: Bus Program Is More Effective On Weekends

VARIABLES	Full Sample	Weekends Only	Weekdays Only
University vs MSOE	-11.08**	-8.371***	-2.707
	(4.378)	*(2.983)*	*(2.635)*
Bus Area vs MSOE	-7.235**	-5.301**	-1.934
	(3.361)	*(2.409)*	*(2.021)*
Safe Ride Only Area vs MSOE	-4.912	-4.455*	-0.459
	(3.216)	*(2.360)*	*(1.892)*
Bus Area vs Safe Ride Only	2.239	0.910	1.329
	(3.282)	*(2.357)*	*(2.056)*

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: Each entry is from a different regression

Table 20: Summary Statistics of Terrorism Data

VARIABLES	Conventional	CBRN
Mean Casualties	6.1	14.7
Median Casualties	1	0
$P(Casualties > 0)$	0.65	0.441
$P(Casualties > 5)$	0.216	0.188
$P(Casualties > 10)$	0.124	0.167
$P(Casualties > 25)$	0.047	0.097
$P(Casualties > 50)$	0.018	0.043
$P(Casualties > 100)$	0.006	0.032
N	47476	186
Types of Attacks Included	Firearms Explosives/Bombs/Dynamite Fake Weapons Incendiary Melee Vehicle Sabotage Equipment	Chemical Biological Radiological Nuclear

Table 21: Comparison of Means

VARIABLES	Conventional	CBRN
Historical Mean Casualties of All Attacks	6.1	14.7
Estimated Mean Casualties of Substantial Attacks (Generalized Pareto)	66.7	168.5
Standard Deviation	105	Infinite
Xi (Shape)	0.4213	0.7610
	*(0.0293)****	*(0.3767)***
Sigma (Skew)	24.1192	34.288
	*(0.8399)****	*(15.4721)***
Threshold (Chosen Parametrically)	25	25

Note: The standard errors for the estimated parameters are listed in parentheses below the estimate. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 22: Results of Calibration Process

r_a	r_g	$\hat{\delta}_{conv}$	$\hat{\delta}_{CBRN}$	Sum of Squared Errors	$\hat{g}_{conv}$	$\hat{g}_{CBRN}$	$\hat{a}_{conv}$	$\hat{a}_{CBRN}$	$\hat{P}_{conv}$	$\hat{P}_{CBRN}$
1	1	4	2	0.0027	0.1016	0.8984	0.3602	0.6398	0.0574	0.0454
1	10	2	1	0.0114	2.9341	7.0659	0.3851	0.6149	4.9534e-4	3.9211e-4
1	20	2	1	0.0115	6.2674	13.733	0.3851	0.6149	6.3043e-07	4.9879e-07
1	30	2	1	0.0115	9.6007	20.399	0.3851	0.6149	8.0236e-10	6.352e-10

Tables, Appendix A: Can Safe Rides Reduce Urban Crime?

Table 23, Appendix A: Summary of Crime Count Data

	Offense Type	Count of Offenses
1	AGGRAVATED ASSAULT†‡	1488
2	ALL OTHER LARCENY‡	3815
3	ALL OTHER OFFENSES	97
4	ARSON‡	82
5	BURGLARY‡	2730
6	COUNTERFEITING/FORGERY	4
7	CREDIT CARD/ATM FRAUD	9
8	DESTRUCTION OF PROPERTY	5081
9	DISORDERLY CONDUCT	262
10	EXTORTION/BLACKMAIL	0
11	FALSE PRETENSES/SWINDLE/CONFIDENCE GAME	1
12	FORCIBLE FONDLING†‡	97
13	FORCIBLE RAPE†‡	75
14	FORCIBLE SODOMY†‡	53
15	HOMICIDE†‡	28
16	IMPERSONATION	4
17	INCEST†	1
18	INTIMIDATION†	29
19	KIDNAPPING†	100
20	LIQUOR LAW VIOLATIONS	20
21	MOTOR VEHICLE THEFT‡	2493
22	POCKET PICKING	51
23	PURSE SNATCHING	110
24	ROBBERY†‡∗	1788
25	SEXUAL ASSAULT WITH AN OBJECT†‡	15
26	SHOPLIFTING‡	333
27	SIMPLE ASSAULT†	1912
28	STATUTORY RAPE†	45
29	STOLEN PROPERTY OFFENSES	8
30	THEFT FROM BUILDING‡	198
31	THEFT FROM COIN-OPERATED MACHINES‡	33
32	THEFT FROM MOTOR VEHICLE‡	5655
33	THEFT OF MOTOR VEHICLE PARTS‡	1951
34	TRESPASSING	66
35	WEAPON LAW VIOLATIONS	0

Note: Crimes were categorized as a crime against persons (†) or otherwise according to the Uniform Crime Reporting classification system. ∗ = This crime always is accompanied by an assault, so it has an element of crimes against persons which is not recorded separately. Crimes reported to the UCR are marked with a ‡.

Tables, Appendix B: University Provided Transit and Urban Crime

Table 24, Appendix B: Crime in the Marquette University Neighborhood vs Control: Alternative Specifications

VARIABLES	(1) Linear Model	(2) Log Crime Model	(3) Poisson Model	(4) Negative Binomial Model
Policy	0.879	0.0777	0.0475	0.0468
	(2.350)	(0.110)	(0.0953)	(0.0916)
Policy*MU Neighborhood	-11.08**	-0.311**	-0.251**	-0.241**
	(4.378)	(0.137)	(0.119)	(0.116)
MU Neighborhood	35.34***	0.996***	0.921***	0.959***
	(4.663)	(0.150)	(0.127)	(0.134)
Snow on Ground (mm)	-0.00405	-0.000521	-0.000201	-0.000306
	(0.0125)	(0.000484)	(0.000402)	(0.000391)
Minimum Temperature (C)	0.0295*	0.000471	0.000833**	0.000520
	(0.0153)	(0.000491)	(0.000420)	(0.000417)
Time Trend	-0.0263**	-0.00115**	-0.00117**	-0.00115**
	(0.0114)	(0.000537)	(0.000466)	(0.000458)
MU Neighborhood*Time Trend	0.0227	0.00120*	0.00111*	0.00104*
	(0.0208)	(0.000667)	(0.000576)	(0.000574)
Constant	21.39***	2.894***	3.167***	3.078***
	(6.010)	(0.194)	(0.169)	(0.174)
School Calendar Interactions	YES	YES	YES	YES
Week of Year Dummies	YES	YES	YES	YES
Alpha (Dispersion Parameter)				-2.111***
				(0.0815)
Observations	730	728	730	730
R-squared	0.548	0.511		
Pseudo-R-Squared			0.3725	
Log Pseudolikelihood			-3729.86	-2901.37

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Tables, Appendix C: Modeling Adversary Preference and Strategic Response

Table 25, Appendix C: Derivative of Model at Estimated Nash Values

r_a	r_g	$\hat{\delta}_{conv}$	$\hat{\delta}_{CBRN}$	$\hat{g}_{conv}$	$\hat{g}_{CBRN}$	$\hat{a}_{conv}$	$\hat{a}_{CBRN}$	w_{conv}	w_{CBRN}	$\frac{da_{conv}}{d\delta_{conv}}$	$\frac{da_{conv}}{d\delta_{CBRN}}$
1	1	4	2	0.1016	0.8984	0.3602	0.6398	66.7	168.5	-0.4388	1.6514
1	10	2	1	2.9341	7.0659	0.3851	0.6149	66.7	168.5	-2.2252	4.9674
1	20	2	1	6.2674	13.733	0.3851	0.6149	66.7	168.5	-4.4473	9.4124
1	30	2	1	9.6007	20.399	0.3851	0.6149	66.7	168.5	-6.6696	13.8561

Table 26, Appendix C: Government Second Order Conditions for Conventional δ

r_a	r_g	$\hat{\delta}_{conv}$	$\hat{\delta}_{CBRN}$	w_{conv}	w_{CBRN}	$\hat{g}_{conv}$	$\hat{g}_{CBRN}$	$\hat{a}_{conv}$	$\hat{a}_{CBRN}$	SOC (C21)
1	1	1	2	66.7	168.5	0.4480	0.5520	0.6149	0.3851	-149.6119
1	1	2	2	66.7	168.5	0.2683	0.7317	0.5000	0.5000	-312.0027
1	1	3	2	66.7	168.5	0.1637	0.8363	0.4189	0.5811	-279.3436
1	1	4	2	66.7	168.5	0.1017	0.8983	0.3602	0.6398	-224.4579
1	1	5	2	66.7	168.5	0.0623	0.9377	0.3160	0.684	-212.1286
1	1	6	2	66.7	168.5	0.0359	0.9641	0.2815	0.7185	-224.5097
1	1	7	2	66.7	168.5	0.0175	0.9825	0.2538	0.7462	-241.5723
1	1	8	2	66.7	168.5	0.0043	0.9957	0.2311	0.7689	-255.4606

Table 27, Appendix C: Government Second Order Conditions for CBRN δ

r_a	r_g	$\hat{\delta}_{conv}$	$\hat{\delta}_{CBRN}$	w_{conv}	w_{CBRN}	$\hat{g}_{conv}$	$\hat{g}_{CBRN}$	$\hat{a}_{conv}$	$\hat{a}_{CBRN}$	SOC (C21)
1	1	2	2	66.7	168.5	0.2683	0.7317	0.5000	0.5000	-312.0027
1	1	2	3	66.7	168.5	0.4656	0.5344	0.5811	0.4189	-361.1654
1	1	2	4	66.7	168.5	0.5894	0.4106	0.6398	0.3602	-425.0426
1	1	2	5	66.7	168.5	0.6730	0.3270	0.6840	0.3160	-502.0573
1	1	2	6	66.7	168.5	0.7324	0.2676	0.7185	0.2815	-591.0325
1	1	2	7	66.7	168.5	0.7766	0.2234	0.7462	0.2538	-691.3171
1	1	2	8	66.7	168.5	0.8104	0.1896	0.7689	0.2311	-802.5532
1	1	2	9	66.7	168.5	0.8370	0.1630	0.7879	0.2121	-924.5398
1	1	2	10	66.7	168.5	0.8584	0.1416	0.8040	0.1960	-1.0572e03

Appendix C: Modeling Adversary Preference and Strategic Response

Model Solutions

Adversary:

We begin by maximizing the adversary utility function, who is the second mover, subject to its resource constraint:

$$U_a = w_{conv}\left(1 - e^{\frac{-a_{conv}}{\delta_{conv}}}\right)\left(e^{-\delta_{conv}g_{conv}}\right) + w_{CBRN}\left(1 - e^{\frac{-a_{CBRN}}{\delta_{CBRN}}}\right)\left(e^{-\delta_{CBRN}g_{CBRN}}\right) \quad \text{(C1)}$$

$$st.\ r_a = a_{conv} + a_{CBRN} \quad \text{(C2)}$$

This leads us to:

$$L_a = w_{conv}\left(1 - e^{\frac{-a_{conv}}{\delta_{conv}}}\right)\left(e^{-\delta_{conv}g_{conv}}\right) + w_{CBRN}\left(1 - e^{\frac{-a_{CBRN}}{\delta_{CBRN}}}\right)\left(e^{-\delta_{CBRN}g_{CBRN}}\right) +$$
$$\lambda_a(r_a - a_{conv} - a_{CBRN}) \quad \text{(C3)}$$

The first order condition for this problem is algebraically symmetric. Thus, for either attack type, n ($n = 1{,}2$) the derivatives are:

$$\frac{\partial L}{\partial a_n} = \frac{w_n e^{\frac{-a_n}{\delta_n}} e^{-g_n\delta_n}}{\delta_n} - \lambda_a = 0 \quad \text{(C4)}$$

$$\frac{\partial L}{\partial \lambda_a} = r_a - a_{conv} - a_{CBRN} = 0 \quad \text{(C5)}$$

It is clear from the above equations that only a constrained condition can hold (i.e., $\lambda_a \neq 0$), otherwise $\partial L/\partial a_n$ will be positive for all finite a_n values, only approaching 0 as $a_n \to \infty$. Thus, eliminating λ_a the FOC, implies $\partial L/\partial a_{conv} = \partial L/\partial a_{CBRN}$ or,

$$\frac{w_{conv} e^{\frac{-a_{conv}}{\delta_{conv}}} e^{-g_{conv}\delta_{conv}}}{\delta_{conv}} - \frac{w_{CBRN} e^{\frac{a_{conv}-r_a}{\delta_{CBRN}}} e^{-g_{CBRN}\delta_{CBRN}}}{\delta_{CBRN}} = 0 \quad \text{(C6)}$$

Substituting for $a_{CBRN} = r_a - a_{conv}$, the best response function of the adversary, in the case of conventional weapon's strategy is:

$$a^*_{conv}(g_{conv}, g_{CBRN}, \delta_{conv}, \delta_{CBRN}, w_{conv}, w_{CBRN}) = \frac{ln\left(\frac{w_{conv}e^{-g_{conv}\delta_{conv}}\delta_{CBRN}}{w_{CBRN}\delta_{conv}}\right)+g_{CBRN}\delta_{CBRN}+\frac{r_a}{\delta_{CBRN}}}{\frac{1}{\delta_{conv}}+\frac{1}{\delta_{CBRN}}} \tag{C7}$$

The second order conditions is:

$$\frac{-w_{CBRN}e^{\frac{-g_{CBRN}\delta_{CBRN}{}^2-a_{conv}+r_a}{\delta_{CBRN}}}}{\delta_{CBRN}{}^2} - \frac{w_{conv}e^{\frac{-g_{conv}\delta_{conv}{}^2+a_{conv}}{\delta_{conv}}}}{\delta_{conv}{}^2} < 0 \tag{C8}$$

This is always negative under a simple expected condition. The adversary has positive interest in destroying the area: $w_n > 0$.

Comparative Statics

Since the remainder of the resources are fully spent, best response for CBRN strategy become: $a^*_{CBRN}(g_{conv}, g_{CBRN}) = r_a - a^*_{conv}(g_{conv}, g_{CBRN})$. Thus all comparative statics below hold with a reverse sign for the latter.

To examine the comparative statics, first we examine the effect of higher government counterinsurgency effort. We find that,

$$\frac{da_{conv}}{dg_{conv}} = -\frac{\delta_{conv}{}^2\delta_{CBRN}}{\delta_{conv}+\delta_{CBRN}} < 0 \tag{C9}$$

$$\frac{da_{conv}}{dg_{CBRN}} = \frac{\delta_{conv}\delta_{CBRN}{}^2}{\delta_{conv}+\delta_{CBRN}} > 0 \tag{C10}$$

Notice the presence of a substitution in best response: A rise in government counterinsurgency effort in CBRN category causes adversary to shift resources towards great effort in the conventional category.

Next we examine the weight in the adversary utility function of each class of attack and find the results as expected:

$$\frac{da_{conv}}{dw_{conv}} = \frac{\delta_{conv}\delta_{CBRN}}{w_{conv}(\delta_{conv}+\delta_{CBRN})} > 0 \tag{C11}$$

$$\frac{da_{conv}}{dw_{CBRN}} = -\frac{\delta_{conv}\delta_{CBRN}}{w_{CBRN}(\delta_{conv}+\delta_{CBRN})} < 0 \tag{C12}$$

Finally, we focus on the best response functions of the logistical complexity parameter, δ :

$$\frac{da_{conv}}{d\delta_{conv}} = -\frac{\delta_{CBRN}(\delta_{conv}+\delta_{CBRN}-r_a-\delta_{CBRN}\log(\frac{\delta_{CBRN}w_{conv}}{\delta_{conv}w_{CBRN}})+\delta_{conv}{}^2 g_{conv}-\delta_{CBRN}{}^2 g_{CBRN}+2\delta_{conv}\delta_{CBRN}g_{conv})}{(\delta_{conv}+\delta_{CBRN})^2} \tag{C13}$$

$$\frac{da_{conv}}{d\delta_{CBRN}} = \frac{\delta_{conv}(\delta_{conv}+\delta_{CBRN}-r_a+\delta_{conv}\log(\frac{\delta_{CBRN}w_{conv}}{\delta_{conv}w_{CBRN}})-\delta_{conv}{}^2 g_{conv}+\delta_{CBRN}{}^2 g_{CBRN}+2\delta_{conv}\delta_{CBRN}g_{CBRN})}{(\delta_{conv}+\delta_{CBRN})^2} \tag{C14}$$

Here, we find the results to be ambiguous. One reason for this is the complex manner by which this parameter enters in to the optimal decision. To see this examine, for example equation C6). Here one can see that a rise delta has several conflicting effects. We have numerically estimated these values at the Nash equilibrium in Table 25, Appendix C.

In this section, it has been shown that best response function for the adversary. This best response function is indeed a maximum by the second order condition, equation C8. Now the best response function is given to the first mover, the government.

Government:

The government, as a Stackelberg leader, maximizes the utility function:

$$E(U_g) = w_{conv}\left(1-\left(1-e^{\frac{-a^*_{conv}}{\delta_{conv}}}\right)e^{-\delta_{conv}g_{conv}}\right) + w_{CBRN}\left(1-\left(1-e^{\frac{-a^*_{CBRN}}{\delta_{CBRN}}}\right)e^{-\delta_{CBRN}g_{CBRN}}\right) \tag{C15}$$

where $a^*_{conv}(g_{conv}, g_{CBRN}, \delta_{conv}, \delta_{CBRN}, w_{conv}, w_{CBRN})$is from the adversaries best response (equation C7) and $a^*_{CBRN}(g_{conv}, g_{CBRN}, \delta_{conv}, \delta_{CBRN}, w_{conv}, w_{CBRN})$ is from the counterpart of that equation. It is subject to the resource constraint:

$$st. \;\; r_g = g_{conv} + g_{CBRN} \tag{C16}$$

The Lagrangian for this problem is:

$$L_g = w_{conv}\left(1 - \left(1 - e^{\frac{-a^*_{conv}}{\delta_{conv}}}\right)e^{-g_{conv}\delta_{conv}}\right) + w_{CBRN}\left(1 - \left(1 - e^{\frac{-a^*_{CBRN}}{\delta_{CBRN}}}\right)e^{-g_{CBRN}\delta_{CBRN}}\right) \\ +\lambda_g\left(r_g - g_{conv} - g_{CBRN}\right) \tag{C17}$$

Using similar reasoning as for the adversary, we note that the constraint must bind. For, if it does not, there is a trivial solution as $g_n \to \infty$, and U_g takes its highest possible value of $w_{conv}+w_{CBRN}$.

Substituting for the best response functions for a^*_{conv}, a^*_{CBRN}.

$$L_g = w_{conv}\left(e^{-\delta_{conv}g_{conv}}\left(e^{\frac{-log\left(\frac{\delta_{CBRN}w_{conv}e^{-\delta_{conv}g_{conv}}}{\delta_{conv}w_{CBRN}}\right)+\delta_{CBRN}g_{CBRN}+\frac{r_a}{\delta_{CBRN}}}{\delta_{conv}\left(\frac{1}{\delta_{conv}}+\frac{1}{\delta_{CBRN}}\right)}} - 1\right) + 1\right) \\ +w_{CBRN}\left(e^{-\delta_{CBRN}g_{CBRN}}\left(e^{\frac{-r_a-\frac{log\left(\frac{\delta_{CBRN}w_{conv}e^{-\delta_{conv}g_{conv}}}{\delta_{conv}w_{CBRN}}\right)+\delta_{CBRN}g_{CBRN}+\frac{r_a}{\delta_{CBRN}}}{\frac{1}{\delta_{conv}}+\frac{1}{\delta_{CBRN}}}}{\delta_{CBRN}}} - 1\right) + 1\right) \\ -\lambda_g\left(g_{conv} + g_{CBRN} - r_g\right) \tag{C18}$$

We note the constraint must bind, so after substituting in $r_g - g_{CBRN} = g_{conv}$, we can solve this as a function of a single variable, g_{conv}.

$$L_g = w_{conv}\left(e^{-\delta_{conv}g_{conv}}\left(e^{\frac{-log\left(\frac{\delta_{CBRN}w_{conv}e^{-\delta_{conv}g_{conv}}}{\delta_{conv}w_{CBRN}}\right)+\delta_{CBRN}(r_g-g_{conv})+\frac{r_a}{\delta_{CBRN}}}{\delta_{conv}\left(\frac{1}{\delta_{conv}}+\frac{1}{\delta_{CBRN}}\right)}}-1\right)+1\right)+$$

$$w_{CBRN}\left(e^{-\delta_{CBRN}(r_g-g_{conv})}\left(e^{\frac{-r_a-\frac{log\left(\frac{\delta_{CBRN}w_{conv}e^{-\delta_{conv}g_{conv}}}{\delta_{conv}w_{CBRN}}\right)+\delta_{CBRN}(r_g-g_{conv})+\frac{r_a}{\delta_{CBRN}}}{\frac{1}{\delta_{conv}}+\frac{1}{\delta_{CBRN}}}}{\delta_{CBRN}}}-1\right)+1\right)$$

(C19)

Then taking derivatives with respect to g_{conv}, we get the FOC:

$$w_{conv}\mathrm{e}^{-\frac{r_a+\log(\frac{w_{conv}\delta_{CBRN}}{w_{CBRN}\delta_{conv}})\delta_{CBRN}+\delta_{conv}{}^2g_{conv}-\delta_{CBRN}{}^2g_{conv}+\delta_{CBRN}{}^2r_g}{\delta_{conv}+\delta_{CBRN}}}\delta_{CBRN} -$$

$$w_{conv}\mathrm{e}^{-\frac{r_a+\log\left(\frac{w_{conv}\delta_{CBRN}}{w_{CBRN}\delta_{conv}}\right)\delta_{CBRN}+\delta_{conv}{}^2g_{conv}-\delta_{CBRN}{}^2g_{conv}+\delta_{CBRN}{}^2r_g}{\delta_{conv}+\delta_{CBRN}}}\delta_{conv} -$$

$$w_{CBRN}\mathrm{e}^{-\frac{r_a-\log\left(\frac{w_{conv}\delta_{CBRN}}{w_{CBRN}\delta_{conv}}\right)\delta_{conv}+\delta_{conv}{}^2g_{conv}-\delta_{CBRN}{}^2g_{conv}+\delta_{CBRN}{}^2r_g}{\delta_{conv}+\delta_{CBRN}}}\delta_{conv} +$$

$$w_{CBRN}\mathrm{e}^{-\frac{r_a-\log\left(\frac{w_{conv}\delta_{CBRN}}{w_{CBRN}\delta_{conv}}\right)\delta_{conv}+\delta_{conv}{}^2g_{conv}-\delta_{CBRN}{}^2g_{conv}+\delta_{CBRN}{}^2r_g}{\delta_{conv}+\delta_{CBRN}}}\delta_{CBRN} +$$

$$w_{conv}\mathrm{e}^{-g_{conv}\delta_{conv}}\delta_{conv} - w_{CBRN}\mathrm{e}^{\delta_{CBRN}(g_{conv}-r_g)}\delta_{CBRN} = 0 \qquad \text{(C20)}$$

While the first order condition does not allow us to isolate for g_{conv}*, we can solve for it numerically, allowing us to solve the model.

Then taking derivatives with respect to g_{conv}, we get the SOC:

$$\frac{w_1 \mathrm{e}^{-\frac{r_a+\log\left(\frac{w_{conv}\delta_{CBRN}}{w_{CBRN}\delta_{conv}}\right)\delta_{CBRN}+\delta_{conv}{}^2 g_{conv}-\delta_{CBRN}{}^2 g_{conv}+\delta_{CBRN}{}^2 r_g}{\delta_{conv}+\delta_{CBRN}}}\delta_{conv}\left(\delta_{conv}{}^2-\delta_{CBRN}{}^2\right)}{\delta_{conv}+\delta_{CBRN}} -$$

$$\delta_{CBRN}{}^2 w_{CBRN}\mathrm{e}^{\delta_{CBRN}(g_{conv}-r_g)} - \delta_{conv}{}^2 w_{conv}\mathrm{e}^{-g_{conv}\delta_{conv}} -$$

$$\frac{w_{conv} \mathrm{e}^{-\frac{r_a+\log\left(\frac{w_{conv}\delta_{CBRN}}{w_{CBRN}\delta_{conv}}\right)\delta_{CBRN}+\delta_{conv}{}^2 g_{conv}-\delta_{CBRN}{}^2 g_{conv}+\delta_{CBRN}{}^2 r_g}{\delta_{conv}+\delta_{CBRN}}}\delta_{CBRN}\left(\delta_{conv}{}^2-\delta_{CBRN}{}^2\right)}{\delta_{conv}+\delta_{CBRN}} +$$

$$\frac{w_{CBRN} \mathrm{e}^{-\frac{r_a-\log\left(\frac{w_{conv}\delta_{CBRN}}{w_{CBRN}\delta_{conv}}\right)\delta_{conv}+\delta_{conv}{}^2 g_{conv}-\delta_{CBRN}{}^2 g_{conv}+\delta_{CBRN}{}^2 r_g}{\delta_{conv}+\delta_{CBRN}}}\delta_{conv}\left(\delta_{conv}{}^2-\delta_{CBRN}{}^2\right)}{\delta_{conv}+\delta_{CBRN}} -$$

$$\frac{w_{CBRN} \mathrm{e}^{-\frac{r_a-\log\left(\frac{w_{conv}\delta_{CBRN}}{w_{CBRN}\delta_{conv}}\right)\delta_{conv}+\delta_{conv}{}^2 g_{conv}-\delta_{CBRN}{}^2 g_{conv}+\delta_{CBRN}{}^2 r_g}{\delta_{conv}+\delta_{CBRN}}}\delta_{CBRN}\left(\delta_{conv}{}^2-\delta_{CBRN}{}^2\right)}{\delta_{conv}+\delta_{CBRN}}$$

(C21)

We evaluate this numerically in Appendix C, Table 26 and Table 27 to determine if it is less than zero in each circumstance, testing if g_{conv}* is indeed a maximum for the government.

The value of λ_g is found by looking at the derivative of the Lagrangian with respect to g_{conv} without substitution, and inserting the appropriate values.

$$w_1\left(\mathrm{e}^{-g_{conv}\delta_{conv}}\delta_{conv} - \mathrm{e}^{-\frac{r_a+\log\left(\frac{w_{conv}\delta_{CBRN}}{w_{CBRN}\delta_{conv}}\right)\delta_{CBRN}+\delta_{conv}{}^2 g_{conv}+\delta_{CBRN}{}^2 g_{CBRN}}{\delta_{conv}+\delta_{CBRN}}}\delta_{conv} + \frac{\mathrm{e}^{-\frac{r_a+\log\left(\frac{w_{conv}\delta_{CBRN}}{w_{CBRN}\delta_{conv}}\right)\delta_{CBRN}+\delta_{conv}{}^2 g_{conv}+\delta_{CBRN}{}^2 g_{CBRN}}{\delta_{conv}+\delta_{CBRN}}}\delta_{conv}\delta_{CBRN}}{\delta_{conv}+\delta_{CBRN}}\right) -$$

$$\frac{\delta_{conv}{}^2 w_{CBRN}\mathrm{e}^{-\frac{r_a-\log\left(\frac{w_{conv}\delta_{CBRN}}{w_{CBRN}\delta_{conv}}\right)\delta_{conv}+\delta_{conv}{}^2 g_{conv}+\delta_{CBRN}{}^2 g_{CBRN}}{\delta_{conv}+\delta_{CBRN}}}}{\delta_{conv}+\delta_{CBRN}} = \lambda_g \qquad \text{(C22)}$$

Appendix D: Search for Best Threshold Value

In the QQ plots Figure 12 and Figure 13, the threshold of 10 casualties, shown in the first rows, does not produce a good fit. As can been seen from the two rows, the General Pareto model with a threshold of 10 casualties overestimates the bulk of conventional casualties while fitting that same model to the CBRN attacks underestimate the bulk of CBRN casualties. This threshold choice, therefore does not fit either data set particularly well.

The next natural threshold choice, 25 casualties, shown in the second rows, matches the QQ plot well for both conventional and CBRN attacks, and is able to capture a small number of large casualty events that are relevant in light of its highly right skewed shape. The fact that a threshold of 25 casualties seems to fit both conventional and CBRN attacks makes it a particularly appealing choice as our threshold for both, reducing empirical differences between each half of the model, and giving an equivalent definition of "substantial" to both types of attack.

We also tried a threshold level of 50 casualties, shown in the last row of Figures 12 and 13. This seems to be a poor threshold choice because it leaves very few (only eight) CBRN data points for use. For this reason, we reject 50 casualties as an appropriate choice, and use 25 casualties. This leaves us with approximately the upper 10% of our out-the-door CBRN attacks, and the upper 5% of our out-the-door conventional attack data.

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Endnotes

[1] In addition to student safety, 26% of safe ride programs list good publicity as a reason for the creation of the program (Harding et al., 1988).
[2] Lacey, et al. (October 2000) study the influence of safe rides on drunk driving, but do not examine other types of crime.
[3] The yearly cost of BOSS averaged over the period of the study is $425,000.60, which was then divided by the number of yearly rides to get the cost per ride (University of Wisconsin Accounting Services, 2013).
[4] Due to the ending date, some only extend to 181 days, so there are only 180 observable changes. Thus, there are 30,684 (≈168x182) entries for each combination of date and hour of the week.
[5] The COMPASS system does not have any information about the victim or suspected perpetrator.
[6] Note that the service region includes a small neighboring suburb, and data is not available for that suburb. A few crime entries have insufficient geographic detail to identify the location, and are excluded. Finally, prior to the COMPASS data in 2005, there is no way to match crime to the service region of the safe ride program.
[7] Simple regressions of crime counts on trend return a significant positive coefficient while regressions of open hours on trend returns a near zero and insignificant coefficient.
[8] Maximum temperature was also collected, and used, but did not impact results significantly and so it was subsequently removed for brevity.
[9] The percentage change in crime from an increase in z is $e^{\gamma\Delta z} - 1$, which is approximately γ for small γ.
[10] After testing if measures for overdispersion are needed, a simple comparison shows that the variance of crime is about three times larger the mean, which suggests overdispersion (Cameron and Trivedi, 1998). Another test of overdispersion indicates that it is not important, with residual deviance (51876) being less than twice that of the degrees of freedom (30463) (Palmer et al., 2007; Lindsey, 1999). Erring on the side of caution, bootstrapping is used.
[11] The other regressions in the paper have been examined with OLS and the results have been found to be very similar.
[12] A final threat to identification would be the creation of other campus crime programs. In January 2008, a small safe walk escort program began in the two blocks immediately around campus. Yet, removing all of the observations after its establishment does not diminish the coefficient of the safe ride program or its significance.
[13] In fact, in the typically open sample a zero-inflated Poisson (ZIP) model is shown to be preferred to the Poisson by a Vuong Test (Vuong, 1989), with a test statistic from the normal distribution of 14.63, and a p-value indistinguishable from 0.
[14] It may be worth noting that while STATA discards estimations in an APE that do not converge, instead this algorithm repeated the estimation process until 200 successful convergences occurred.
[15] Uniquely, this bias may be minimized in this data set because the number of fixed effects that must be calculated was limited. Instead of having many different individuals,

this data set has a substantial number of time periods (182) per fixed effect, which may greatly mitigate the bias of incidental parameters, it is expected to be on the order of 1/182 (Greene, 2002)

[16] A breakdown of the crime categories, and the frequency in which they occur, is in Table 12, placed in the Appendix.

[17] A number of other definitions of weekend were examined, and no meaningful variation occurred.

[18] The program is committed to sending a van to all who ask for a ride during the hours of operation.

[19] This estimation was repeated in the Bay View data set yielding a coefficient of 0.0001, with a standard error of 0.0016, again suggesting that the significance of the estimates are not an accident.

[20] Over the hours the program is open, 1,352 crimes of the type reported to the UCR a year were reported to local police. These types of crimes are labeled, along with their frequency in the data set, in Table 12, found in the Appendix. If the program causes a 14% reduction in crime while operating, in accordance with the Poisson estimates, the actual crime count would have been 1,572 without the program. This is a reduction of 220 crimes associated with the program.

[21] The estimates of elasticity of police per capita to nonviolent crime per capita was used, -0.501, the larger of the two broad crime categories, and a constant population was assumed for the sake of simplicity.

[22] There are currently 2,586 officers, and a new officer is salaried at $42,563 (City of Milwaukee , 2013), A quick calculation shows 2,586*1.2%*$42,563 = $1,318,179.

[23] As with the falsification test, the coefficient of -0.152 for the treated neighborhood is more than two standard deviations greater than this estimate.

[24] UWM maintains its own set of sworn officers.

[25] While data on the mix of transport programs across universities is not regularly collected, as early as the 1990s 34% of public four-year universities and 24% of private four-year universities reported operating a student transport program (Lewis et al., 1997).

[26] There is a related suggestion that interstate highways through rural areas increase crime by bringing criminals and potential victims more easily together (Marton 2013).

[27] The campus consolidation and expansion in student housing predate the time window we use to examine the advent of campus bus service.

[28] COMPASS is the Community Mapping, Planning and Analysis for Safety Strategies and it can be accessed at http://www.city.milwaukee.gov/compass.

[29] Indeed, as a privacy restriction, the police withhold addresses for sexual assaults and so these crimes are dropped from the sample.

[30] The terms differ slightly between universities and the three dummies for the relevant weeks of each university's term are entered as a determinants of crime only for the respective university neighborhood.

[31] The weeks in which class is not in session receive a zero for all three dummies.

[32] We even experimented with allowing for four time trends, control and university neighborhood both before and after the bus service. Including these simply do not reduce the magnitude of the coefficient or its significance, maintaining the suggestion of a large reduction in crime associated with the advent of the bus service.

[33] The addition of two or four time trends leaves the coefficient of interest essentially unchanged.
[34] It is worth noting that if the policy date is used in a placebo treatment of the MSOE vs. the Bay View neighborhoods, it emerges as insignificant.
[35] The dropped crimes are arson, bribery, burglary/breaking and entering, counterfeiting/forgery, credit card/ATM fraud, false pretenses/swindle/confidence game, impersonation, incest, weapon law violations, wire fraud and not classified.
[36] These additional specifications are available upon request.
[37] The phrasing of "successful" is in keeping with existing crime literature. In our case, we call an attack "successful" if it has incurred casualties.
[38] Later we will account for information asymmetries.
[39] If one believes that the behavior of government and adversary should entail risk-averse or precautionary behavior, δ can be defined to incorporate such parameters. If one believes the true parameter is, say, δ' but $\delta'$is subject to a shock $\epsilon \sim N(0, \sigma^2)$, then define δ such that $\delta = F(\delta', \sigma^2)$. Note that it must be the case that $E(\delta' + \varepsilon) \neq \delta$ due to its position in the exponent.
[40] While we have assumed a linear utility, there remains only one unique solution to the game. We note that, the utility is strictly concave in effort level, and the sites are heterogeneous. Thus the solution remains unique, despite the linearity of utility in expected damage (Zhuang and Bier, 2007).
[41] Zhuang and Bier (2007) have described some single-target circumstances where adversaries respond to an increase in government expenditures by increasing their own effort, as strategic complements. They find that a particular family of multiple-target games decompose into single-target games. They note such a breakdown will not, and should not, occur in model like ours because both parties are strictly bound by their budget constraints. In short, we assume there are not enough resources to treat each attack as completely independent, and participants cannot expand their budget as a response to changes.
[42] See endnote 3, where the government is not risk neutral to shocks in δ' by construction.
[43] We have explored a variety of levels for $r_g = \{1,10,20,30\}$, in order to consider the fact that government expenditures are substantially larger than those of the terrorists. We have found that the model fit is dramatically better, by a factor of 5, when they are both normalized to 1. These results are shown in Table 3.
[44] This can be established by evaluating $e^{-\delta g}$, from equation 3, at e^{-1}.
[45] For example, GTD also includes some CBRN data including those originally complied by Mohtadi and Murshid (2006). We remove these and other CBRN data to avoid double counting.
[46] See also Mohtadi and Ruediger (2011) for a survey for extreme value literature as applied to finance.
[47] Note that μ and σ are related to, but not identical to the mean or standard deviation of this distribution. It is possible to have well defined values of μ and σ, but have no finite mean or standard deviation for a Pareto distribution as the asymptotic decay of the distribution may be too slow for defined mean or variance. Such a case has occurred in our estimations, as shown in Table 5.
[48] We remind that we have already dropped attacks of the type that are deliberately low-casualty: kidnappings, assassinations, and hostage-taking, and hope to mitigate this

problem by doing so. We admit the importance of such impacts, but note that it is impossible to quantify each of them. Without being able to explore such details, we rely on the thought that adversaries prefer attacks with over 25 casualties rather than less.

[49] We note that once an attack has made it out the door, the probability of successful substantial attacks, P(Casualties>25) , is 0.047 for conventional attacks and 0.097 for CBRN attacks.

[50] For example, using least absolute deviation instead, would have led to a fit in only one dimension.

[51] The square root of 0.0007/2 is 1.8%

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Education

- PhD Candidate, UW-Milwaukee, Economics, Expected August 2015
- MA, UW-Milwaukee, Economics, 2011
- BA, UW-Milwaukee (Honors College), Economics and Philosophy, Cum Laude, 2009

Honors

- Fellowship Summer School in International Economics, *Justus-Liebig University Giessen, Germany*, 2010
- Best New Tutor, *Tutoring and Academic Resource Center, UW-Milwaukee*, 2009
- Magnatek Scholarship for Academic Merit, 2005-2009

Dissertation

- "Essays in the Economics of Crime"

Publication

- "Can Safe Ride Programs Reduce Urban Crime?" *Regional Science and Urban Economics*, September 2014 Vol. 48, pp. 1-11. (Lead Article)

Working Papers

- University Bus Services and Urban Crime
- Phased Entry and Spatial Price Discrimination for N Firms
- Modeling Adversary Decisions and Strategic Response

Presentations

- "Modeling Adversary Decisions and Strategic Response," University of Maryland: National Consortium for the Study of Terrorism and Responses to Terrorism, *College Park, Maryland*, February 2015
- "Modeling Adversary Decisions and Strategic Response," Domestic Nuclear Detection Office, Homeland Security Annual Grantees Program Review, *Leesburg, Virginia*, June 2014
- "Can Safe Ride Programs Reduce Urban Crime?" Annual Potsdam Conference in Empirical Economics, *University of Potsdam, Germany*, March 2014
- "Can Safe Ride Programs Reduce Urban Crime?" University of Milwaukee-Wisconsin Labor Economics Seminar, *University of Milwaukee-Wisconsin*, October 2013

Research Assistant Positions

- Modeling the targeting preferences of terrorist groups, for Professor Hamid Mohtadi, *National Science Foundation, Grant No. 1348416*, 2014-2015
- "The Economic Impact of the Milwaukee Brewers," for Professor Swarnjit S. Arora, *Institute for Survey and Policy Research, University of Wisconsin-Milwaukee*, 2011

Referee

- Regional Science and Urban Economics, 2014

Consulting

- Independently assessed both the costs of terrorist attacks, and the consequences of government counter-terrorism policy, *University of Maryland: National*

Consortium for the Study of Terrorism and Responses to Terrorism, College Park, Maryland, 2015.

- Proposed and conducted a research study of the effectiveness of the university safety programs, *UW-Milwaukee Department of Student Services*, 2012

Teaching Positions

- Visiting Instructor of Economics, teaching introductory and intermediate microeconomics, *5 courses, class size 25 to 120 students, College of William and Mary*, 2015
- Instructor, independently teaching and grading introductory microeconomics, *6 semesters, including summers, class size 25 to 50 students, University of Wisconsin-Milwaukee*, 2011-2015
- Teaching Assistant, leading sections in a mass lecture taught by a professor, *2 semesters, University of Wisconsin-Milwaukee*, 2011-2012
- Tutoring and Academic Resource Center, *Subjects: Economics, Calculus, Statistics, (often online), University of Wisconsin-Milwaukee,* 2009-2011

Professional Associations

- American Economics Association, 2014-Present
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