The Impact of the Safe and Successful Youth Initiative (SSYI) on City-Level Youth Crime Victimization Rates

An Interrupted Time Series Analysis with Comparison Groups

October 1, 2014

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EXECUTIVE SUMMARY

Background

The physical, emotional and financial costs on individuals and neighborhoods resulting from youth violence are well documented. According to the U.S. Centers for Disease Control (2013), the third leading cause of death for young people between the ages of 10-24 is homicide; for black males, it is the leading cause of death.

To address serious youth violence, particularly that involving guns, Massachusetts initiated the Safe and Successful Youth Initiative (SSYI) in 2011, providing a comprehensive public health approach to addressing young men, between the ages of 14-24, believed to be at "proven risk" for being involved in firearms.

Eleven cities with the highest violent offenses reported to the police in 2010 were selected for SSYI funding in 2011 and started implementing the program. Although there are variations across sites, there are some components that are mandatory and must be included in each SSYI program at the city level:

- Specific identification of young men, 14-24, at highest risk for being involved in firearms violence
- Use of street outreach workers to find these young men, assess their current needs, and act as brokers for services to address unmet needs
- The provision of a continuum of comprehensive services including education, employment, and intensive supervision

Research Questions

An important question asked of the SSYI at this early stage is whether the intervention makes a difference on city-level violent crime victimization rates. This report describes analyses conducted to answer this question, using a quasi-experimental design known as an interrupted time series (ITS). The analyses were guided by three main research questions:

- *What is the impact of SSYI on monthly city-level violent crime victimization rates (per 10,000 citizens) for persons ages 14-24?*
- *What is the impact of SSYI on monthly city-level aggravated assault victimization rates (per 10,000 citizens) for persons ages 14-24?*

- *What is the impact of SSYI on monthly city-level homicide victimization rates (per 10,000 citizens) for persons ages 14-24?*

Methodology

The ITS design uses the trend data before an intervention such as a law, policy or program starts to establish a projection about how the trend will continue for the period after the intervention began. It compares that prediction of the trend to the actual observed results. In an ITS design, researchers examine these two trends to determine if the difference between the prediction and the observed results is large enough that it is likely not due to chance fluctuation or error. Further strengthening the ITS design is the introduction of a comparison group.

The data used in these analyses come from the victim file of the National Incident-Based Reporting System (NIBRS), as reported to the Massachusetts State Police (or from the local police directly in the case of Boston and Lawrence). The data are represented by monthly crime victimization rates per 10,000 citizens for persons ages 14-24 for three offense categories: all Group A violent crime, homicide, and aggravated assault.

In this study, the 11 cities that received SSYI funding and have implemented the program comprise the treatment group. The results for the SSYI cities are compared to two different comparison groups:

(1) *Total Comparison Group*: the next 23 cities in reported violent crime incidents in 2010

(2) *Non-funded cities:* the six cities in the Total Comparison group that did not receive Shannon funding (and reported sufficient data to NIBRS)

The data file contains monthly crime rate data over 60 months, from January 2009 to December 2013. The period includes 24 months of pre-intervention data and 36 months of post-intervention data (if one identifies the start of SSYI funding, or the “interruption,” as January 1, 2011) or 36 months of pre-intervention data and 24 months of post-intervention data (if one identifies the start of SSYI implementation, or the “interruption,” as January 1, 2012). Analyses were conducted comparing the trend of SSYI cities to the two different comparison groups. They were also conducted using two different “interruption” points (January 2011 and January 2012) to account for variation in implementation timelines between sites.

Findings

According to the analyses presented here:

- **SSYI had a statistically significant and positive impact in reducing the number of monthly victims of violent crimes reported to the police.** This was true regardless of which of the two comparison groups were used, or which of the two interruption points were used.

- **SSYI had a statistically significant and positive impact in reducing the number of monthly victims of homicide reported to the police**. Again, this was regardless of the comparison group or interruption point included in the analysis.

- **SSYI had a statistically significant and positive impact on reducing the number of monthly victims of aggravated assault reported to the police**. Again, this was regardless of the comparison group or interruption point included in the analysis.

- **A city with SSYI had approximately 5.0-5.7 fewer victims of violence each month, ages 14-24, for every 100,000 citizens,[1] over the entire post-intervention period. This represents 60 fewer victims of Group A violent crimes per year, per 100,000 citizens in each SSYI city.**

Table ES-1 summarizes these results. All 12 comparisons were statistically significant. What does this mean in terms of public safety in the Commonwealth? Table ES-1 presents the number of victims that would be prevented for each crime outcome, comparison group and interruption period.

TABLE ES-1. SUMMARY OF SSYI IMPACT ON ALL MONTHLY CITY-LEVEL CRIME VICTIMIZATION RATES OF YOUNG PERSONS AGES 14-24 OVER TIME, BOTH COMPARISON GROUPS AND INTERRUPTION POINTS					IMPACT ON MONTHLY NUMBER OF VICTIMS, 14-24, PER 100,000 CITIZENS OVER THE POST-INTERVENTION PERIOD
GROUPS	**Interruption 2011**		**Interruption 2012**		
	Full Comparison	**Non-Funded Sites**	**Full Comparison**	**Non-Funded Sites**	
All Group A Violent Crimes	YES	YES	YES	YES	**5.0-5.7 FEWER VICTIMS PER MONTH**
Homicide	YES	YES	YES	YES	**.10-.15 FEWER VICTIMS PER MONTH**
Aggravated Assault	YES	YES	YES	YES	**2.1-2.4 FEWER VICTIMS PER MONTH**

[1] Rates in the tables and analyses were based on crime victimization per 10,000 citizens. However, to help provide more interpretable findings at the city-level, and particularly given the very small rates for homicide, we converted the impact estimate to the anticipated number of victims prevented each month per 100,000 citizens.

Conclusion

It is encouraging that monthly crime victimization rates for young persons (ages 14-24) is decreasing across the Commonwealth. This is true for the 11 SSYI cities, the 23 cities making up the full comparison group, and the six cities that did not receive any Shannon funding. However, the decrease in crime victimization rates for young persons in SSYI cities from the pre-intervention to post-intervention period is larger than that observed for the two comparison groups. This was true whether looking at victimization rates for all Group A violent crimes, homicides, or aggravated assaults. The observed effect for the SSYI cities, in relation to the two comparison groups, was statistically significant for all 12 of the main analyses.

The encouraging results from this analysis are consistent with earlier research we did on behalf of EOHHS to analyze the effectiveness of other urban gun violence interventions that also used a list to target high impact offenders (Campie, et al., 2013). In this previous report, we identified three evaluations of "list-driven" initiatives, the Indianapolis Violence Reduction Partnership (IVRP), the Philadelphia Youth Violence Reduction Partnership (YVRP), and the Cincinnati Initiative to Reduce Violence (CIRV). In addition to using a targeted list, these three interventions use street outreach workers to engage youth and provide a range of supportive services to address unmet needs associated with greater risk for offending. Unlike SSYI, these interventions sometimes include aggressive policing and suppression activities through notifying previous offenders that they are being closely monitored.

Our earlier study showed that two of these three studies reported that the interventions were associated with decreases in community violence indicators (the Philadelphia YVRP did not report positive impact at the community level[2]), but because study methods and data sources vary across all of these studies, there are no means to directly compare the outcomes from these interventions with SSYI's results. It is important to note that the evaluations of these other interventions as well as the current analysis of SSYI did not test the individual effects of single intervention components (such as street outreach) on individual or community-level outcomes. These three studies also included measuring criminal justice outcomes (i.e., arrests and homicides) at the community level, like the study described in this report. As a next step, we recommend that SSYI be evaluated at the programmatic level to see how changes in individual youth behaviors may be driving the victimization decreases we present in this report.

[2] The Philadelphia YVRP did include a propensity score matching study of individual offenders that did indicate a positive impact on identified offenders (McClanahan, et al. 2012).

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INTRODUCTION

The physical, emotional and financial costs on individuals and neighborhoods resulting from youth violence are well documented. For example, nearly 100,000 persons in the country are killed or injured by guns in the United States each year (Joyce Foundation, 2014). According to the U.S. Centers for Disease Control (2013), the third leading cause of death for young people between the ages of 10-24 is homicide; for black males, it is the leading cause of death. Schlosser (1997) estimated that 10 million Americans had endured the murder of a family member or a close friend. Besides the human toll for victims and their families, such violence can increase health care costs, decrease property values and disrupt social services in certain neighborhoods (U.S. Centers for Disease Control, 2012). The Violence Policy Center (2012) estimated that a single gunshot injury can have a social cost of about $1 million. This included intangible costs like longtime residents leaving hard hit communities to avoid living in fear of shootings and other violence. Not surprisingly, the federal government and many large urban jurisdictions have directed resources towards addressing gun violence.

Massachusetts Safe & Successful Youth Initiative

Massachusetts is the only state, to our knowledge, to employ a consistent public health approach to address gun violence across its most vulnerable cities, through its Safe and Successful Youth Initiative (SSYI), which targets 14-24 year old young men at "proven risk" for being involved in firearms violence (Campie, et al. 2013). Rather than focus exclusively on criminal justice responses to gun violence such as heavy reliance on suppression, arrest and incarceration, Massachusetts has followed the route taken by several large cities in the U.S. to implement its own cross-system, multi-agency approach.

In May 2011, Governor Deval Patrick's administration announced the start of the SSYI. Eleven cities were selected for state-level SSYI funding in 2011 and started implementing the program (see Figure 1). Although there are variations across sites, there are some components that are mandatory and must be included in each SSYI program at the city level:

- Specific identification of young men, 14-24, at highest risk for being involved in firearms violence
- Use of street outreach workers to find these young men, assess their current needs, and act as brokers for services to address unmet needs
- The provision of a continuum of comprehensive services including education, employment, and intensive supervision

Figure 1. Cities Implementing SSYI

Important questions have been asked about the impact of SSYI. For example, does SSYI reduce recidivism among youth specifically identified by the program? This is a question that was recently addressed in a companion study by our research team, examining outcomes for SSYI youth and a matched group of similar young men not involved in the program (Campie, Vriniotis, Read, Fronius, & Petrosino, 2014).

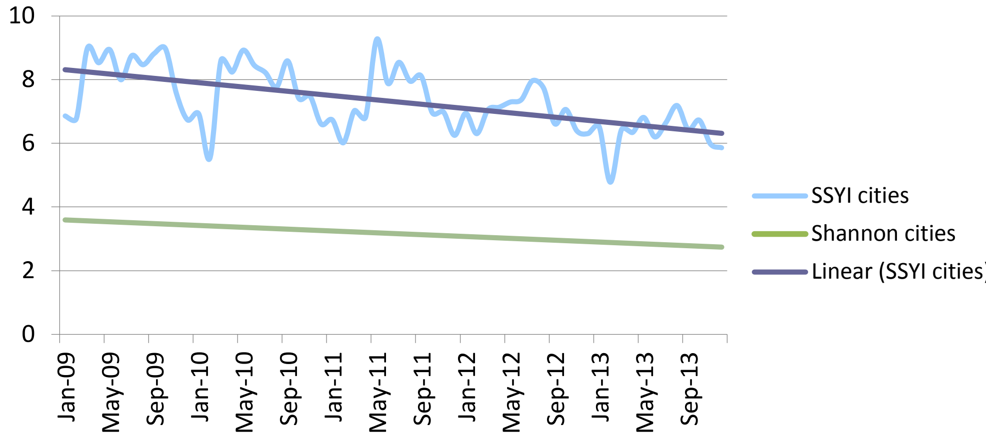
Trend Data

Another question asked of the SSYI at this early stage in the program, is whether the intervention makes a difference on city-level violent crime victimization rates. As a precursor to the more formal statistical analysis described here, EOHHS asked for preliminary data on trends to be presented in August 2014. Figure 2 presents the trends in violent crime victimization among persons ages 14-24 for two groups: (1) SSYI funded cities; and (2) non-SSYI cities receiving Shannon Grants.[3]

As Figure 2 highlights, the trend in violent crime victimization of youth (ages 14-24) in SSYI-funded cities (the blue line) is on a decline. This is also true for non-SSYI cities receiving Shannon grants (the green line), although the decline for SSYI cities is larger. Although this decline for SSYI cities, by itself, could be interpreted as encouraging news, Figure 2 also indicates that the start of these trends preceded the advent of formal SSYI funding.

[3] The Senator Charles E. Shannon Community Safety Initiative (Shannon CSI) is a state grant program administered by the Executive Office of Public Safety and Security (EOPSS) to "support regional and multi-disciplinary approaches to combat gang violence through coordinated programs for prevention and intervention" (EOPSS website, 2014). Note that we also presented the trends at the August 2014 meeting on a third group of non-SSYI cities that did not receive Shannon Grants, but there was a data error that distorted the trend line, that we have corrected here for these analyses.

Figure 2. Violent Crime Victimization Rate



Although illustrations such as Figure 2 using trend data can be illuminating, it is sometimes difficult to establish by visual inspection alone whether changes in these trends are due to random fluctuation or are large enough that we do not consider it to be due to the play of chance. It may also be that while the SSYI and non-SSYI cities both declined, one may have declined at an even greater rate. This report describes a more formal analysis of the impact of SSYI. It does so by employing a quasi-experimental design known as an Interrupted Time Series (ITS). The design is further strengthened by including two comparison groups:

- The full set of comparison cities is comprised of all 23 cities that were next in ranking in 2010 violent crimes reported to the police (after the 11 SSYI cities). Approximately 17 of these cities also received Shannon grants.
- Non-funded sites include only those six cities that did not receive Shannon funds.

RESEARCH QUESTIONS

Guiding the analyses are the following three main research questions. These are:

- *What is the impact of SSYI on monthly city-level violent crime victimization rates (per 10,000 citizens) for persons ages 14-24?*

- *What is the impact of SSYI on monthly city-level aggravated assault victimization rates (per 10,000 citizens) for persons ages 14-24?*

- *What is the impact of SSYI on monthly city-level homicide rates (per 10,000 citizens) for persons ages 14-24?*

We also conducted a supplemental analysis to answer the following question:

- *What is the impact of SSYI on monthly city-level non-violent crime victimization rates (per 10,000 citizens) for persons ages 14-24?*

METHODOLOGY

As mentioned above, the methodology employed in this study to determine if city-level trends in monthly crime victimization for persons ages 14-24 can be attributed in some part to the introduction of the SSYI program is called the ITS design. The ITS design is a commonly used design in studies of jurisdiction-level outcomes. A more detailed explanation of the specific ITS approach we took here is provided in Appendix A. Our review of prior research for EOHHS in 2013, indicated that ten of the 11 studies of multi-sector, multi-agency programs used an ITS design (Campie, et al. 2013).

Generally, the ITS design uses the trend data before the start of an intervention such as a law, policy or program to establish a projection about how the trend will continue for the period after the intervention began. It compares that prediction of the trend to the actual observed results. In an ITS design, researchers examine these two trends to determine whether the difference between the prediction and the observed results is large enough that it is likely not due to chance fluctuation or error. Further strengthening the ITS design is the introduction of a comparison group. The use of a comparison group can help to rule out alternative explanations for observed results, such as changes in statewide policies or economic conditions, during the same time period.

Data Sources

The data come from the National Incident-Based Reporting System (NIBRS), as reported to the Massachusetts State Police. NIBRS collects information on different types of data on each crime incident, including on the offense (known as the incident file), the offender, and the victim. It provides a more fine-grained picture of reported crime than the Uniform Crime Report (UCR). The data analyzed in the current study comes from the victim file, and, include monthly victimization rates for persons ages 14-24 in each city in the study sample. These data were provided by the Massachusetts Executive Office of Public Safety and Security's Office (EOPSS) of Grants and Research (OGR).

Since it is a voluntary system, not all police departments currently report NIBRS data. Of the 11 cities receiving SSYI funding, nine cities report NIBRS data to the Massachusetts State Police. Lawrence and Boston do not submit NIBRS data to the Massachusetts State Police, but do provide "proxy data" that can be used to create monthly counts of data. These were included by the EOPSS OGR in the data file that was the subject of the analyses described below. Also note that not all cities in the comparison sample voluntarily submit to NIBRS. Two of the comparison cities, Framingham and Salem, did not report data to NIBRS until 2011 and 2012 respectively. Because they did not contribute data to the pre-intervention trends, they were both dropped from the analyses.[4]

Only Group A Offenses were included in the data file that the research team received from EOPSS OGR. The eight Group A Offenses, as defined by both the UCR and NIBRS systems include homicide, aggravated assault, forcible rape, robbery, simple assault, burglary and breaking and entering (B&E), all other larceny, and motor vehicle theft.

Because the offenders included in the SSYI program are males 14-24, and because much of the violence perpetrated by this group on others is directed toward persons of a similar age group, EOPSS OGR provided data from the victim file on persons ages 14-24. No other age groups were included in the file.

Key Components of the Interrupted Time Series Design

The Treatment Group

In this study, the 11 cities that received SSYI funding and have implemented the program comprise the treatment group. These cities are identified in Figure 1 and are repeated here: Boston, Brockton, Chelsea, Fall River, Holyoke, Lawrence, Lowell, Lynn, New Bedford, Springfield, and Worcester. These 11 cities had the highest number of

[4] Note, however, that sensitivity analyses were done including the post-intervention data from both Framingham and Salem in the analyses. We did this to determine if there were any differences in the estimates with or without them. The differences were negligible.

violent crime incidents of all jurisdictions in Massachusetts that reported these data to the police in 2010.

The Comparison Group

For the analyses described below, we included two comparison groups. These are (See Appendix 1 for a list of all comparison cities):

(1) *Total Comparison cities*: the next 23 cities in reported violent crime incidents in 2010.

(2) *Non-SSYI, non-Shannon cities*: the six cities in the Total Comparison group that did not receive Shannon funding (and reported sufficient data to NIBRS).

The Time Frame

The EOPSS OGR provided monthly data for a period of five years (60 months). This includes the time period January 2009 to December 2013. The period includes 24 months of pre-intervention data and 36 months of post-intervention data (using the start of SSYI funding as January 1, 2011) or 36 months of pre-intervention data and 24 months of post-intervention data (using the start of SSYI implementation as January 1, 2012). It should be noted that not all cities in the study sample reported all 60 months of data. For example, Wareham began reporting to NIBRS in 2010. But all cities can be included in the model as long as they provide some pre-intervention data; months that have no data values are coded as missing and are not included in the analysis.

The Interruption

As mentioned above, the ITS uses data before an intervention to predict what the trend will be after the intervention is introduced. The predicted trend is compared to the actual observed trend. The intervention in the design is called “the interruption” and it is usually plotted in figures and graphs as the point in time when the intervention began..

In this study, we used two different interruptions. The first set of analyses examines the impact of the advent of SSYI funding, established as January 1, 2011. However, although cities may have been selected for funding to begin in January 2011, the jurisdictions differ as to when they began to formally implement the SSYI program. Thus, the second set of analyses sets the interruption point as January 1, 2012 to capture sites beginning implementation in this later timeframe.

In an ITS design, the interruption represents the key explanatory factor. In short, the analytical model is designed to determine if the observed time period after the interruption has varied from the predicted trend. The introduction of a comparison group strengthens the conclusions that are drawn from the predicted and observed trends.

Controlling for Pre-Existing Differences

The 11 SSYI cities were likely to be different than the non-SSYI cities on other factors besides whether or not the jurisdiction has received funding for the program. Studies such as this often seek to control (or separate out the influence) of variables or factors for which the treatment group may differ from the comparison group. Controlling for a factor means that we include the data on that factor in the analytical model.

In this analysis, we include two variables to help control for pre-existing differences. The first is poverty level. Using available data from the U.S. Census, we added the percentage of persons living in poverty in the jurisdiction to the model.

Essentially this helps to reduce the influence of poverty when examining data on victimization, if there are pre-existing differences between the study groups on poverty. We also included data from the Massachusetts Department of Elementary and Secondary Education (DESE), on the percentage of high school completers. This is considered an important variable because many of the SSYI youth are non-completers.

We had introduced another variable relevant to poverty to the analysis: the percentage of students considered to be from lower-income households. We added this percentage, also using data from the MA DESE to the data file. However, our analyses indicated that this variable was highly correlated with the percentage of persons living in poverty and the percentage of high school completers, and it did not increase the explanatory power of the model. Thus, only the first two covariates were included in the analytic models that follow. (Note that we did run models with additional covariates for a sensitivity analysis in Appendix B, Table B-3). This should help control for the fact that the 11 cities that received SSYI funding are dealing with a much more challenging set of circumstances than the comparison cities, in terms of persons living in poverty and the number of youth completing high school.

To provide the most accurate picture of baseline differences, we strove to obtain data from 2010. We were successful in obtaining high school completion rates. For data on persons living in poverty, we relied on data from the U.S. Census Bureau, which is reported as an average over the years 2008-2012.

Victimization Rates for Persons Ages 14-24

Because EOPSS OGR provided data from the victim file, the outcome data are based on the number of victims. For each outcome measure, we created a rate. The rates are based on the number of victims (ages 14-24) per 10,000 persons. It should be noted that these rates are based on number of victims per offense. Although many offenses have just one victim, there are incidents that include multiple victims. Thus, this rate should not be confused with an incident rate, but rather it represents a rate based on the total number of victims.

Outcome Measures

Violent crimes include the five Group A offenses reported to the police. These are: homicide, forcible rape, aggravated assault, robbery, and simple assault. Again, a rate per 10,000 persons was created to standardize data across all cities in the study sample. For example, in Boston, July 2011, there were 6 homicides reported. The rate is calculated as ((6/617,594)*10000) = .097 homicides per 10,000 persons. The outcome measure is best interpreted as the monthly violent crime victimization rate for persons ages 14-24.

We analyzed two of these Group A violent offenses separately: homicide and aggravated assault. This is because the SSYI program targets young men at grave risk for being involved in firearms violence, and these offenses are the most relevant of the Group A offenses. Again, both of these were converted to similar rates per 10,000 persons. These can best be interpreted as the homicide victimization rate for persons ages 14-24 and the aggravated assault victimization rate for persons ages 14-24.

For the supplemental analysis, we used non-violent crimes; these include the remaining three Group A offenses reported to the police. These are: burglary and breaking and entering (B&E), all other larceny incidents, and motor vehicle thefts. This outcome is best interpreted as the monthly non-violent crime victimization rate for persons ages 14-24. Although the SSYI targets youth at grave risk for being involved in gun violence, offenders included in the program may not just be involved in violence but also in non-violent offenses; thus it is conceivable that the program, if it has impact, could also impact Group A offenses like burglary and motor vehicle theft. Thus, non-violent crime victimization rates per 10,000 citizens are analyzed as another outcome.

Statistical Significance

Although there is a more complex explanation for what researchers mean when they use the phrase "statistically significant," the common understanding is that the observed result is large enough, given the sample size and other factors, that it is likely not random. Researchers often use a traditional significance level of .05, meaning that the size of the impact is large enough that it would be expected to occur by chance only once in 20 tries. This is the level used in the analyses reported here to determine if an observed result is statistically significant.

Sensitivity Analyses

There are a number of assumptions that researchers make when conducting any analysis. Sensitivity analyses are conducted to test whether changing those assumptions would greatly influence the results. Appendix B provides the results of those sensitivity tests.

FINDINGS

In this section, we summarize the results from analyses conducted using the ITS design to answer the three research questions posed above. For each of the following four sections, there are four analyses: (1) SSYI versus the full comparison sample, with interruption as 2011; (2) SSYI versus the non-funded sites, with interruption as 2011; (3) SSYI versus the full comparison sample, with interruption as 2012; and (4) SSYI versus the non-funded sites, with interruption as 2012.

1. *What is the impact of SSYI on monthly city-level violent crime victimization rates (per 10,000 citizens) for persons ages 14-24?*

TABLE 1. CITY-LEVEL MONTHLY VIOLENT CRIME VICTIMIZATION RATES OF YOUNG PERSONS AGES 14-24 OVER TIME, ALL GROUPS (2009-2013), INTERRUPTION OCCURRING IN 2011

GROUPS	**Prior to January 2011**	**After January 2011**
SSYI (N=11)	7.91	6.91
All Comparison Cities (N=23)	3.46	3.05
Non-Funded Sites (N=6)	3.46	3.09

This outcome measure includes homicide, aggravated assault, forcible rape, robbery and simple assault. As Table 1 indicates, the rates for monthly violent crime victimization of young people, ages 14-24, are approximately double in SSYI cities than in the two comparison groups. These rates have been decreasing for all 3 groups, if the interruption is considered to be 2011. These declines are similar if 2012 is considered the start of SSYI (all descriptive tables can be found in Appendix 3). This mirrors statewide and national trends in violent crime victimization. The question is whether that trend in the SSYI group is different than that observed for the other groups.

The results from our analysis using the ITS design indicates that being in a SSYI city is associated with a statistically significant and positive effect on monthly violent crime victimization of young persons. Table 4A-1 in Appendix 4 provides the detailed analytic table for the comparison between SSYI and all comparison cities, using 2011 as the interruption period. According to these results, being in a SSYI city during the post-intervention period is associated with a reduction in the rates of violent crime victimization of persons ages14-24 of -.57 (the effect in all the tables in Appendices 4-7 is represented (including Table A4-1) by the interaction term, *IintXcom*, which is the interaction between the pre and post intervention periods and whether a city was in the treatment or comparison group). This result is large enough that we do not believe it is random (that is, the effect is statistically significant). The estimate means that a city being in SSYI experiences the prevention of approximately 5.7 victims of violent crimes every month, ages 14-24, for every 100,000 citizens over the three year post-intervention period.[5]

When the analysis is rerun using an interruption point of 2012, there is a slight difference in the estimate (it rounds to -.53). The detailed analytic table can be located in Table A4-2 in Appendix 4. We also conducted comparisons of SSYI to the non-funded sites (the six cities that did not receive Shannon or SSYI funding). Again, we ran separate analyses using 2011 and 2012 as the interruption point. Similarly, the estimate of effect is -.55 and -.50 respectively for the two interruption periods (see Tables A4-3 and A4-4 in Appendix 4). Table 2 summarizes the results of the ITS on the rates of monthly violent crime victimization of young persons, ages 14-24.

[5] Rates in the tables and analyses were based on crime victimization per 10,000 citizens. However, to help provide more interpretable findings at the city-level, and particularly given the very small rates for homicide, we converted the impact estimate to the anticipated number of victims prevented each month per 100,000 citizens. This was done for all analysis tables.

TABLE 2. SSYI IMPACT ON MONTHLY CITY-LEVEL VIOLENT CRIME VICTIMIZATION RATES OF YOUNG PERSONS AGES 14-24 OVER TIME, BOTH COMPARISON GROUPS AND INTERRUPTION POINTS			
GROUPS	**Interruption 2011**	**Interruption 2012**	**Corresponding to**
Compared to All Comparison Cities (N=23)	-.57	-.53	5.3 to 5.7 fewer youth victims of violent crime per month during 3 year post-intervention period, per 100,000 citizens
Compared to Non-Funded Sites (N=6)	-.55	-.50	5.0-5.5 fewer youth victims of violent crime per month during 3 year post-intervention period, per 100,000 citizens

2. *What is the impact of SSYI on city-level homicide rates (per 10,000 citizens) for persons ages 14-24?*

TABLE 3. CITY-LEVEL MONTHLY HOMICIDE VICTIMIZATION RATES OF YOUNG PERSONS AGES 14-24 OVER TIME, ALL GROUPS (2009-2013), INTERRUPTION OCCURRING IN 2011		
GROUPS	**Prior to January 2011**	**After January 2011**
SSYI (N=11)	.027	.017
All Comparison Cities (N=23)	.003	.004
Non-Funded Sites (N=6)	0	.005

In this section, we examine the impact of SSYI on monthly homicide victimization rates of young persons, ages 14-24. No matter what period we examine, homicide is an extremely rare event (ranging from 0 for the six non-funded sites during 2009-2010 to .027 per 10,000 citizens in SSYI cities during the same period). Table 3 provides the average rates for the pre-intervention and post-intervention periods for the three study groups, assuming 2011 as the interruption point. The rate goes down in SSYI cities, but increases slightly in both comparison groups.

The results from our analysis using the ITS design indicates that being in a SSYI city is associated with a statistically significant effect on the rates of monthly homicide victimization of young persons. Detailed analysis tables can be found in Appendix 5. Table 5A-1 in Appendix 5 shows the comparison between SSYI and all comparison cities, using 2011 as the interruption period. According to these results, being in a SSYI city during the post-intervention period is associated with a reduction in the monthly rates of homicide victimization of youth ages 14-24 of -.010. This result is large enough that we do not believe it is due to chance (that is, it is statistically significant). The estimate means that a city being in SSYI, experiences the prevention of approximately .10 victims of a homicide each month, between the ages 14-24, for every 100,000 citizens (or one victim each month, ages 14-24, of homicide over 1 million citizens) over the three year post-intervention period.

When the analysis is rerun using an interruption point of 2012, there is trivial difference in the estimate (and it rounds to .016). The detailed analytic table can be located in Table A5-2 in Appendix 5. We also conducted comparisons of SSYI to the non-funded sites (the six cities that did not receive Shannon or SSYI funding). Again, we ran separate analyses using 2011 and 2012 as the interruption point. The estimate of effect is slightly larger (-.014 and -.016 respectively; see Tables A5-3 and A5-4 in Appendix 5). Table 4 summarizes the results of the ITS on the rates of monthly homicide victimization of young persons, ages 14-24.

TABLE 4. SSYI IMPACT ON MONTHLY CITY-LEVEL HOMICIDE VICTIMIZATION RATES OF YOUNG PERSONS AGES 14-24 OVER TIME, BOTH COMPARISON GROUPS AND INTERRUPTION POINTS

GROUPS	**Interruption 2011**	**Interruption 2012**	**Corresponding to**
<u>Compared to</u> All Comparison Cities (N=23)	-.010	-.016	.10-.16 fewer youth victims of homicide per month during 3 year post-intervention period, per 100,000 citizens
<u>Compared to</u> Non-Funded Sites (N=6)	-.014	-.016	.14-.16 fewer youth victims of homicide per month during 3 year post-intervention period, per 100,000 citizens

3. *What is the impact of SSYI on monthly city-level aggravated assault victimization rates (per 10,000 citizens) for persons ages 14-24?*

TABLE 5. MONTHLY CITY-LEVEL AGGRAVATED ASSAULT VICTIMIZATION RATES OF YOUNG PERSONS AGES 14-24 OVER TIME, ALL GROUPS (2009-2013), INTERRUPTION OCCURRING IN 2011		
GROUPS	**Prior to January 2011**	**After January 2011**
SSYI (N=11)	2.16	1.75
All Comparison Cities (N=23)	1.00	.82
Non-Funded Sites (N=6)	1.03	.90

In this section, we examine the impact of SSYI on monthly aggravated assault victimization rates of young persons, ages 14-24. As Table 5 indicates, aggravated assault occurs twice as much in SSYI cities (2.16 per 10,000 persons prior to 2011) than in the two comparison groups (1.00 for all comparison cities and 1.03 for non-funded sites prior to 2011). Table 5 provides the average monthly rates for the pre-intervention and post-intervention periods for the three study groups, assuming 2011 as the interruption point. The rate goes down in all three groups, although the decrease is larger in the SSYI cities.

The results from our analysis using the ITS design indicates that being in a SSYI city is associated with a statistically significant and positive effect on the monthly rates of aggravated assault victimization of young persons. Detailed analysis tables can be found in Appendix 6. Table 6A-1 in Appendix 6 shows the comparison between SSYI and all comparison cities, using 2011 as the interruption period. According to these results, being in a SSYI city during the post-intervention period is associated with a reduction in the monthly rates of aggravated assault victimization of youth ages 14-24 of -.21. This result is large enough that we do not believe it is due to the play of chance (that is, it is statistically significant). The estimate means that a city being funded through SSYI experiences the prevention of approximately 2.1 youth victims of aggravated assault per month, between the ages 14-24, for every 100,000 citizens, over the three year post-intervention period.

When the analysis is rerun using an interruption point of 2012, the estimate is slightly smaller (-.18). The detailed analytic table can be located in Table A6-2 in Appendix 6. We also conducted comparisons of SSYI to the non-funded sites (the six cities that did not receive Shannon or SSYI funding). Again, we ran separate analyses using 2011 and 2012 as the interruption point. The estimate of effect is slightly larger (-.20 and -.24 respectively; see Tables A6-3 and A6-4 in Appendix 6). Table 6 summarizes the results of the ITS on the monthly rates of aggravated assault victimization of young persons, ages 14-24.

TABLE 6. SSYI IMPACT ON MONTHLY CITY-LEVEL AGGRAVATED ASSAULT VICTIMIZATION RATES OF YOUNG PERSONS AGES 14-24 OVER TIME, BOTH COMPARISON GROUPS AND INTERRUPTION POINTS

GROUPS	**Interruption 2011**	**Interruption 2012**	**Corresponding to**
Compared to All Comparison Cities (N=23)	-.21	-.18	1.8-2.1 fewer youth victims of aggravated assault per month during 3 year post-intervention period, per 100,000 citizens
Compared to Non-Funded Sites (N=6)	-.24	-.20	2.0-2.4 fewer youth victims of aggravated assault per month during 3 year post-intervention period, per 100,000 citizens

Supplemental Analysis: What is the impact of SSYI on monthly city-level non-violent crime victimization rates (per 10,000 citizens) for persons ages 14-24?

TABLE 7. MONTHLY CITY-LEVEL NON-VIOLENT CRIME VICTIMIZATION RATES OF YOUNG PERSONS AGES 14-24 OVER TIME, ALL GROUPS (2009-2013), INTERRUPTION OCCURRING IN 2011		
GROUPS	**Prior to January 2011**	**After January 2011**
SSYI (N=11)	4.24	3.55
All Comparison Cities (N=23)	2.30	1.87
Non-Funded Sites (N=6)	2.29	1.96

In this section, we conduct a supplemental analysis to examine the impact of SSYI on monthly non-violent crime victimization rates of young persons, ages 14-24. Though it may seem strange that the non-violent crime rates are smaller than those observed for violent crimes in Table 1, this measure is made up of just three offenses: the UCR Group A offenses burglary and breaking and entering, larceny, and motor vehicle theft. As Table 7 indicates, the rate of such victimization is nearly twice as large in SSYI cities than in the two comparison groups. Table 7 provides the average rates for the pre-intervention and post-intervention periods for the three study groups, assuming 2011 as the interruption point. The rate goes down in all three groups.

The results from our analysis using the ITS design indicates that being in a SSYI city is associated with a statistically significant and positive effect on the monthly rates of non-violent crime victimization of young persons. Detailed analysis tables can be found in Appendix 7. Table 7A-1 in Appendix 7 shows the comparison between SSYI and all comparison cities, using 2011 as the interruption period. According to these results, being in a SSYI city during the post-intervention period is associated with a reduction in the monthly rates of non-violent crime victimization of youth ages 14-24 of -.24. The result is large enough that we do not believe it is due to the play of chance (that is, it is statistically significant). The estimate means that a city being in SSYI experiences the prevention of approximately 2.4 youth victims of non-violent crimes per month, between the ages 14-24, for every 100,000 citizens, over the three year post-intervention period.

When the analysis is rerun using an interruption point of 2012, the estimate is smaller (-.15) and is not significant. The detailed analytic table can be located in Table A7-2 in Appendix 7. We also conducted comparisons of SSYI to the non-funded sites (the six cities that did not receive Shannon or SSYI funding). Again, we ran separate analyses using 2011 and 2012 as the interruption point. The estimate of effect is -.30 (for 2011 interruption) and -.25 (for 2012). The effect assuming a 2011 interruption is statistically significant; the effect using the 2012 interruption is just below the threshold (See Tables A7-3 and A7-4 in Appendix 7). Table 8 summarizes the results of the ITS on the monthly rates of non-violent crime victimization of young persons, ages 14-24.

TABLE 8. SSYI IMPACT ON MONTHLY CITY-LEVEL NON-VIOLENT CRIME VICTIMIZATION RATES OF YOUNG PERSONS AGES 14-24 OVER TIME, BOTH COMPARISON GROUPS AND INTERRUPTION POINTS

GROUPS	**Interruption 2011**	**Interruption 2012**	**Corresponding to**
Compared to All Comparison Cities (N=23)	-.24	-.15*	1.5-2.4 fewer youth victims of non-violent crime per month during 3 year post-intervention period, per 100,000 citizens
Compared to Non-Funded Sites (N=6)	-.30	-.25*	2.5-3.0 fewer youth victims of non-violent crime per month during 3 year post-intervention period, per 100,000 citizens
*Not statistically significant (assuming two tailed, p<.05).			

LIMITATIONS OF THE STUDY

Although this study used an interrupted time series design with a comparison group, considered to be a very rigorous type of quasi-experiment, there are potential limitations to the study that should be taken into account when interpreting the findings. These are:

- *The interruption*: The best condition for using the interrupted time series design is when there is a clear interruption or start to the intervention. However, most social programs and policies do not have such clear “start dates” but often take time to get implemented. It is sometimes difficult to even determine when the “clock should start ticking” on the intervention. In addition, there is variation in when each of the 11 cities implemented the SSYI program, and the degree to which each was implemented. Further complicating the “interruption” is that some cities build their SSYI programs on similar violence prevention initiatives already operating in the jurisdiction.
- *Sensitivity of the outcome measure*: Many of the prior studies that evaluated the impact of multi-agency, multi-sector programs similar to SSYI used outcome measures that may have been more sensitive to the offenders targeted by the intervention. These outcomes included such refined measures such as “gang-involved shootings” or “gang-involved homicides.” It was not possible, using the existing NIBRS data provided by EOPSS OGR to create more fine-grained outcomes

- *NIBRS proxy data*: Lawrence and Boston did not submit to NIBRS, but they provided proxy data to EOPSS OGR that were included in the analyses presented here. Different definitions may have been used in Lawrence and Boston than what were used in the NIBRS data reported by the other jurisdictions.
- *Lack of randomization*: The safest way to ensure that the SSYI cities and the comparison cities were similar on both known and unknown factors would be to establish a pool of eligible cities and then randomize them to two different groups (assign them in such a way that the city has equal probability of getting assigned to SSYI or non-SSYI). We cannot rule out the possibility that there are other rival explanations than SSYI to account for any of the observed results.
- *Statistical dependence*: Also note that having 60 pre-intervention and post-intervention time points could have resulted in dependence among the data that were not controlled for statistically. In general, such dependence would result in lower probability levels (the threshold used by researchers to determine if a results is statistically significant) than those observed here.

CONCLUSIONS

It is encouraging that monthly crime victimization rates for young persons (ages 14-24) are decreasing across the Commonwealth. This is true for the 11 SSYI cities, the 23 making up the full comparison group, and the six cities that did not receive any Shannon funding. However, the decrease in monthly crime victimization rates for young persons in SSYI cities from the pre-intervention to post-intervention period is larger than that observed for the two comparison groups. This was true whether looking at monthly victimization rates for violent crime, homicides, or aggravated assaults.

The observed effect for the SSYI cities, in relation to the two comparison groups, was statistically significant in all 12 of the main analyses. This means that, all things being equal, it is large enough that we do not believe that chance fluctuation is a good explanation for the observed results. The supplemental analyses also indicate statistically significant and positive impacts on monthly non-violent crime victimization, but only when the 2011 interruption period is used. It was beyond the scope of this study to examine alternatives to SSYI to determine if there were other policy choices that could reduce violent and non-violent offenses further than SSYI demonstrated here.

What does this mean in terms of public safety in the Commonwealth? Table ES-1 also presents the number of victims that would be prevented each month according to these analyses for each crime outcome, for each comparison group and for each interruption period. For example, a city with SSYI has approximately 5.0-5.7 fewer victims of violence per month, ages 14-24, for every 100,000 citizens, over the entire post-intervention period. That could result, for example, in 60-68 fewer victims of violent crime per year, per 100,000 citizens. A companion benefit to cost study conducted by members of the research team based on the ITS findings in this report, estimate that in Boston and Springfield alone (MA' two largest cities), the preventive benefit of the SSYI program was close to $15M for the roughly $2M investment in program costs (Bradham & Campie, 2014).

The encouraging results from this analysis are consistent with earlier research we did on behalf of EOHHS to analyze the effectiveness of other urban gun violence interventions that also used a list to target high impact offenders (Campie, et al. 2013). In this previous study, we identified three evaluations of "list-driven" initiatives, the Indianapolis Violence Reduction Partnership (IVRP), the Philadelphia Youth Violence Reduction Partnership (YVRP), and the Cincinnati Initiative to Reduce Violence (CIRV). In addition to using a targeted list, these three interventions use street outreach workers to engage youth and provide a range of supportive services to address unmet needs associated with greater risk for offending. Unlike SSYI, these interventions sometimes include aggressive policing and suppression activities through notifying previous offenders that they are being closely monitored.

Our earlier study showed that two of these three studies reported that the interventions were associated with decreases in community violence indicators (the Philadelphia YVRP did not report positive impact at the community level[6]), but because study methods and data sources vary across all of these studies, there are no means to directly compare the outcomes from these interventions with SSYI's results. It is important to note that the evaluations of these other interventions as well as the current analysis of SSYI did not test the individual effects of single intervention components (such as street outreach) on individual or community-level outcomes. These three studies also included measuring criminal justice outcomes (i.e., arrests and homicides) at the community level, like the study described in this report. As a next step, we

[6] The Philadelphia YVRP did include a propensity score matching study of individual offenders that did indicate a positive impact on identified offenders (McClanahan, et al. 2012).

recommend that SSYI be evaluated at the programmatic level to see how changes in individual youth behaviors may be driving the victimization decreases we present in this report.

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APPENDIX A. INTERRUPTED TIME SERIES METHODOLOGY

A short interrupted time series analysis with a comparison group was used to more rigorously assess whether there was a statistically significant difference between the SSYI cities and two sets of comparison cities in changes on four measures of crime victimization rates (see Bloom, 2003; Shadish, Cook & Campbell, 2002). The interrupted time series design was meant to determine whether there was any change in the trend from pre-intervention period to the post-intervention period because of the "interruption" (program implementation).

There are several approaches to the short interrupted time series design. The method for short interrupted time series in Bloom (2003) formed the basis of the analysis strategy. The Bloom paper examines the short interrupted time series approach using educational data, but is perfectly suitable for other fields. Bloom (p. 5) argues that the approach can "measure the impact of a reform as the subsequent deviation from the past pattern of student performance for a specific grade." The method establishes the trend in an outcome measure over time and analyzes the post-intervention data to determine whether there was a departure from that trend. Bloom notes that the introduction of a comparison group can greatly strengthen conclusions using the short interrupted time series design.

A series of models analogous to Bloom's (2003) recommendations were then run. Bloom's paper provides three different models to account for assumptions we make about the baseline or pre-intervention trend in the data: (1) linear trend (in which the outcome variable increases or decreases incrementally over time); (2) the baseline mean trend (in which the outcome variable appears to be a flat line during the pre-intervention period); and (3) the nonlinear baseline trend (in which the outcome scores may be moving in a curvilinear or other pattern).

To project post-implementation impact on crime rates for each city, a linear baseline trend model was assumed (see Bloom, 2003). Estimates of impact then come from differences-in-differences in observed and predicted post-implementation crime rates between program and comparison cities.

APPENDIX B. SENSITIVITY CHECKS

There are a number of assumptions that researchers make when conducting any analysis. Sensitivity analyses are conducted to test whether changing those assumptions would greatly influence the results. We conducted three sensitivity tests to determine if changing our assumptions would influence the results: (1) using a smaller aggregate series (using quarterly rather than monthly data); (2) assuming a baseline mean model rather than the linear baseline model; and (3) introducing more covariates into the analytic model.

Using a smaller aggregate series

Because the approach used here often includes a smaller series of time points (for example, Bloom [2003] uses 10 years of annual data for one school), we tested to see if the results would change if we only had quarterly rather than monthly data. To conduct this sensitivity test, we created a file averaging violent crime rates by quarter (the average for the three months comprising that quarter), and aggregating the observations at the quarter level. This provided 20 quarterly observations per city, compared to 60 monthly observations. We then repeated the analysis with the quarterly data that we initially conducted using the monthly data.

The results in Table B-1 are nearly identical to the results in Table A4-1. The model using quarterly data estimates that being funded through SSYI would prevent 5.6 victims of violent crime (indicated by the factor _IIntXcom and coefficient -.5635277), ages 14-24, for every 100,000 citizens over the three year post-intervention period. Table A4-1, using monthly data, indicates that being funded through SSYI prevents 5.7

victims of violent crime (indicated by the coefficient -.569656), ages 14-24, for every 100,000 citizens over the three year post-intervention period. The possibility that either result is due to the play of chance is remote (p=.000).

Table B-1. Linear Baseline Model Full Comparison Interruption 2011, Using Quarterly Data

```
. xi: xtreg viocrimrate_sum quarter_time1 Percent_HS_Completion Percent_Living_Poverty i.Int_quart1*i.comparison1,i(city_id )
i.Int_quart1      _IInt_quart_0-1     (naturally coded; _IInt_quart_0 omitted)
i.comparison1     _Icompariso_0-1     (naturally coded; _Icompariso_0 omitted)
i.Int~1*i.com~1   _IIntXcom_#_#       (coded as above)
warning: existing panel variable is not city_id

Random-effects GLS regression                   Number of obs      =       656
Group variable: city_id                         Number of groups   =        33

R-sq:  within  = 0.2082                         Obs per group: min =        16
       between = 0.8018                                        avg =      19.9
       overall = 0.7338                                        max =        20

                                                Wald chi2(6)       =    281.94
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000

------------------------------------------------------------------------------------------
       viocrimrate_sum |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------------+------------------------------------------------------------------
         quarter_time1 |  -.0748677   .0104209    -7.18   0.000    -.0952923   -.0544431
 Percent_HS_Completion |  -10.08195   3.626475    -2.78   0.005    -17.18971   -2.974187
Percent_Living_Poverty |   10.96219   7.371056     1.49   0.137    -3.484813     25.4092
         _IInt_quart_1 |   .3062293   .1307482     2.34   0.019     .0499676    .5624911
         _Icompariso_1 |   1.403237   .7642491     1.84   0.066    -.0946641    2.901137
         _IIntXcom_1_1 |  -.5635277   .1373492    -4.10   0.000    -.8327272   -.2943282
                 _cons |   9.717325   3.452177     2.81   0.005     2.951181    16.48347
-----------------------+------------------------------------------------------------------
               sigma_u |  1.1303674
               sigma_e |  .81228038
                   rho |  .65946361   (fraction of variance due to u_i)
------------------------------------------------------------------------------------------
```

Assuming a baseline mean model rather than a linear baseline model

As mentioned earlier, Bloom (2003) provides three different models to account for assumptions we make about the baseline or pre-intervention trend in the data: (1) linear trend (in which the outcome variable increases or decreases incrementally over time); (2) the baseline mean trend (in which the outcome variable appears to be a flat line during the pre-intervention period); and (3) the nonlinear baseline trend (in which the outcome scores may be moving in a curvilinear or other pattern). For this sensitivity analysis, we compare the results for the model assuming a baseline mean trend versus the results for the linear baseline trend that we assumed. The only difference between the two models is that the factor representing the trend over time in the outcome (“time1”) in omitted when assuming a baseline mean trend. The results, highlighted in Table B-2, show a negligible difference when compared to the results when assuming a linear baseline trend (Table A4-1).

The results of running the model assuming a baseline mean trend indicates that being funded through SSYI would prevent 5.7 victims of violent crime (indicated by the factor _IIntXcom and coefficient -.5733976), ages 14-24, for every 100,000 citizens over the three year post-intervention period. Table A4-1, assuming a linear baseline trend, also indicates that being funded through SSYI prevents 5.7 victims of violent crime (indicated by the coefficient -.569656), ages 14-24, for every 100,000 citizens over the three year post-intervention period. The possibility that either result is due to the play of chance is remote (p=.000).

Table B-2. Baseline Mean Model Full Comparison Interruption 2011, Using Quarterly Data

```
. xi: xtreg viocrimrate_sum i.interruption1*i.comparison1 Percent_HS_Completion Percent_Living_Poverty, i(city_id)
i.interruption1   _Iinterrupt_0-1     (naturally coded; _Iinterrupt_0 omitted)
i.comparison1     _Icompariso_0-1     (naturally coded; _Icompariso_0 omitted)
i.int~1*i.com~1   _IintXcom_#_#       (coded as above)

Random-effects GLS regression                  Number of obs      =      2028
Group variable: city_id                        Number of groups   =        34

R-sq:  within  = 0.0635                        Obs per group: min =        48
       between = 0.7894                                       avg =      59.6
       overall = 0.6264                                       max =        60

                                               Wald chi2(5)       =    249.03
corr(u_i, X)   = 0 (assumed)                   Prob > chi2        =    0.0000

----------------------------------------------------------------------------------------
       viocrimrate_sum |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------------+----------------------------------------------------------------
         _Iinterrupt_1 |  -.4325778   .0709466    -6.10   0.000    -.5716305   -.2935251
         _Icompariso_1 |   1.686492   .7607276     2.22   0.027     .1954939    3.177491
         _IintXcom_1_1 |  -.5733976   .1240445    -4.62   0.000    -.8165203   -.3302748
 Percent_HS_Completion |  -9.574366   3.698801    -2.59   0.010    -16.82388   -2.324848
Percent_Living_Poverty |   10.00171   7.519718     1.33   0.183    -4.736664    24.74009
                 _cons |   9.616058   3.527022     2.73   0.006     2.703223    16.52889
-----------------------+----------------------------------------------------------------
               sigma_u |   1.160693
               sigma_e |  1.2805037
                   rho |  .45103926   (fraction of variance due to u_i)
----------------------------------------------------------------------------------------
```

Introducing more covariates into the analytic model

We only selected two covariates, or other factors, in the analytic models to help control for differences between the SSYI cities and the two comparison groups of jurisdictions. Those factors were the percentage of high school completers in 2010 in each city, and the average percentage of persons living in poverty 2008-2012 in each city. We asked how the results would change, if at all, if more covariates were introduced into the model. For this sensitivity analysis, we introduced the total population size for each city in 2012 (“population”), the number of police working in the municipal police department for every 1,000 citizens in 2012 (“num_police”) and the percentage of students in 2010 identified as low income by the Massachusetts DESE. The results of this analysis are provided in Table B-3.

The results of running the model with these three additional covariates indicates that being funded through SSYI would prevent 5.7 victims of violent crime (indicated by the factor _IIntXcom and coefficient -.5695353), ages 14-24, for every 100,000 citizens over the three year post-intervention period. Table A4-1, assuming a linear baseline trend, is nearly identical, indicating that being funded through SSYI prevents 5.7 victims of violent crime (indicated by the coefficient -.569656), ages 14-24, for every 100,000 citizens over the three year post-intervention period. The possibility that either result is due to the play of chance is remote (p=.000).

Table B-3. Using Additional Covariates, Full Comparison Interruption 2011

```
. xi: xtreg viocrimrate_sum time1 i.interruption1*i.comparison1 Percent_HS_Completion Percent_Living_Poverty Percent_Students_Low
> _Income population num_police ,i(city_id)
i.interruption1   _Iinterrupt_0-1     (naturally coded; _Iinterrupt_0 omitted)
i.comparison1     _Icompariso_0-1     (naturally coded; _Icompariso_0 omitted)
i.int~1*i.com~1   _IintXcom_#_#       (coded as above)

Random-effects GLS regression                   Number of obs      =      2028
Group variable: city_id                         Number of groups   =        34

R-sq:  within  = 0.0884                         Obs per group: min =        48
       between = 0.8281                                        avg =      59.6
       overall = 0.6614                                        max =        60

                                                Wald chi2(9)       =    323.20
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000

---------------------------------------------------------------------------------------------
           viocrimrate_sum |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------------------+-----------------------------------------------------------------
                     time1 |  -.0225648   .0030604    -7.37   0.000     -.028563   -.0165667
             _Iinterrupt_1 |   .2405054   .1150554     2.09   0.037      .015001    .4660098
             _Icompariso_1 |   2.191963   .7880183     2.78   0.005     .6474756    3.736451
             _IintXcom_1_1 |  -.5695353    .122403    -4.65   0.000    -.8094408   -.3296298
     Percent_HS_Completion |  -12.18481    3.72313    -3.27   0.001    -19.48202   -4.887614
    Percent_Living_Poverty |   7.706232   8.390981     0.92   0.358    -8.739788    24.15225
Percent_Students_Low_Income |  -1.778421   1.909171    -0.93   0.352    -5.520327    1.963486
                population |  -4.90e-06   2.44e-06    -2.01   0.045    -9.68e-06   -1.15e-07
                num_police |   .7601465   .5307242     1.43   0.152    -.2800538    1.800347
                     _cons |   11.22241   3.703783     3.03   0.002     3.963125    18.48169
---------------------------+-----------------------------------------------------------------
                   sigma_u |  1.1121801
                   sigma_e |   1.263671
                       rho |  .43649542   (fraction of variance due to u_i)
---------------------------------------------------------------------------------------------
```

APPENDIX 1. LISTING OF CITIES IN THE THREE COMPARISON GROUPS

Total Comparison Cities Not Receiving SSYI Funds (N=25)	Comparison Cities Receiving Shannon Funding (N=17)	Comparison Cities Not Receiving Shannon Funding (N=6)[7]
Attleboro	Attleboro	Barnstable
Barnstable	Brookline	Marlborough
Brookline	Cambridge	Waltham
Cambridge	Everett	Wareham
Chicopee	Chicopee	West Springfield
Everett	Fitchburg	Weymouth
Fitchburg	Gardner	
Framingham	Haverhill	
Gardner	Leominster	
Haverhill	Malden	
Leominster	Methuen	
Malden	Pittsfield	
Marlborough	Quincy	
Methuen	Revere	
Pittsfield	Somerville	
Quincy	Taunton	
Revere	Winthrop	
Salem		
Somerville		
Taunton		
Waltham		
Wareham		
West Springfield		
Weymouth		
Winthrop		

[7] Framingham and Salem were removed due to their lack of submissions to NIBRS through 2011 and 2012 respectively.

APPENDIX 2. COVARIATE DATA FOR EACH CITY IN THE STUDY SAMPLE

City	% completing high school (2010)	% of population living in poverty (average 2008-2012)	% of students defined as low income (2009-2010 academic year)[8]
	SSYI CITIES		
Boston	.53	.21	.76
Brockton	.67	.17	.72
Chelsea	.53	.25	.91
Fall River	.66	.23	.75
Holyoke	.53	.31	.74
Lawrence	.47	.29	.87
Lowell	.69	.17	.70
Lynn	.69	.21	.79
New Bedford	.54	.22	.66
Springfield	.53	.29	.81
Worcester	.72	.20	.72
	COMPARISON GROUP CITIES		
Attleboro	.82	.08	.28
Barnstable	.82	.11	.30
Brookline	.90	.12	.12
Cambridge	.85	.14	.46
Chicopee	.68	.14	.61
Everett	.77	.13	.69
Fitchburg	.69	.19	.66
Gardner	.67	.13	.46
Haverhill	.66	.13	.42
Leominster	.87	.10	.36
Malden	.72	.15	.59
Marlborough	.84	.08	.36
Methuen	.79	.09	.36
Pittsfield	.75	.16	.50
Quincy	.83	.10	.45
Revere	.69	.16	.71
Somerville	.73	.16	.68
Taunton	.76	.13	.43
Waltham	.73	.11	.32
Wareham	.78	.10	.46
West Springfield	.72	.13	.43
Weymouth	.82	.07	.24
Winthrop	.78	.09	.26

[8] Because this variable was highly correlated with the other two, we did not leave it in the analytic models. Running it with or without the percentage of low income students made no difference in the results.

APPENDIX 3. DESCRIPTIVE DATA ON YOUTH CRIME VICTIMIZATION RATES

VIOLENT CRIME RATES PER 10,000

	Full Comparison	SSYI
Before 2011	3.456157	7.911326
After 2011	3.04547	6.905351

	Non-Funded Sites	SSYI
Before 2011	3.46071	7.911326
After 2011	3.085801	6.905351

	Full Comparison	SSYI
Before 2012	3.46071	7.911326
After 2012	3.085801	6.90535

	Non-Funded Sites	SSYI
Before 2012	3.437442	7.733363
After 2012	2.931587	6.669307

HOMICIDE RATES PER 10,000

	Full Comparison	SSYI
Before 2011	.0033354096	.0273212407
After 2011	.0035678928	.0172438293

	Non-Funded Sites	SSYI
Before 2011	0	.0273212407
After 2011	.0051420439	.0172438293

	Full Comparison	SSYI
Before 2012	.004029871	.028108278
After 2012	.0026575394	.0110245676

	Non-Funded Sites	SSYI
Before 2012	.003489758	.028108278
After 2012	.0027276973	.0110245676

AGGRAVATED ASSAULT RATES PER 10,000

	Full Comparison	SSYI
Before 2011	1.00473047	2.156292991
After 2011	.8187629564	1.747573048

	Non-Funded Sites	SSYI
Before 2011	1.024860206	2.156292991
After 2011	.9023179089	1.747573048

	Full Comparison	SSYI
Before 2012	.9786146469	2.072037576
After 2012	.7643851987	1.669596198

	Non-Funded Sites	SSYI
Before 2012	1.017666246	2.072037576
After 2012	.8513238467	1.669596198

NON-VIOLENT CRIME RATES PER 10,000

	Full Comparison	SSYI
Before 2011	2.303241	4.243024
After 2011	1.872851	3.558633

	Non-Funded Sites	SSYI
Before 2011	2.28823	4.243024
After 2011	1.964474	3.558633

	Full Comparison	SSYI
Before 2012	2.235621	4.088913
After 2012	1.757617	3.447604

	Non-Funded Sites	SSYI
Before 2012	2.231287	4.088913
After 2012	1.883942	3.447604

APPENDIX 4. DETAILED ANALYSIS TABLES:

SHORT INTERRUPTION TIME SERIES,

VIOLENT CRIME VICTIMIZATION RATES FOR YOUNG PERSONS, AGES 14-24, PER 10,000 CITIZENS

Table A4-1. Linear Baseline Model Full Comparison Interruption 2011

```
. xi: xtreg viocrimrate_sum time1 Percent_HS_Completion Percent_Living_Poverty i.interruption1*i.comparison1,i(city_id)
i.interruption1   _Iinterrupt_0-1     (naturally coded; _Iinterrupt_0 omitted)
i.comparison1     _Icompariso_0-1     (naturally coded; _Icompariso_0 omitted)
i.int~1*i.com~1   _IintXcom_#_#       (coded as above)

Random-effects GLS regression                   Number of obs      =      2028
Group variable: city_id                         Number of groups   =        34

R-sq:  within  = 0.0884                         Obs per group: min =        48
       between = 0.7890                                        avg =      59.6
       overall = 0.6318                                        max =        60

                                                Wald chi2(6)       =    306.99
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000
```

viocrimrate_sum	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
time1	-.0225625	.0030607	-7.37	0.000	-.0285614	-.0165636
Percent_HS_Completion	-9.580426	3.69887	-2.59	0.010	-16.83008	-2.330774
Percent_Living_Poverty	9.97638	7.519853	1.33	0.185	-4.762261	24.71502
_Iinterrupt_1	.240556	.1150686	2.09	0.037	.0150258	.4660862
_Icompariso_1	1.684498	.7606469	2.21	0.027	.1936571	3.175338
_IintXcom_1_1	-.569656	.1224171	-4.65	0.000	-.809589	-.329723
_cons	9.368071	3.527239	2.66	0.008	2.45481	16.28133
sigma_u	1.1610027					
sigma_e	1.263671					
rho	.45773263	(fraction of variance due to u_i)				

Table A4-2. Linear Baseline Model Full Comparison Interruption 2012

```
. xi: xtreg viocrimrate_sum time2 Percent_HS_Completion Percent_Living_Poverty i.interruption2*i.comparison1,i(city_id)
i.interruption2   _Iinterrupt_0-1     (naturally coded; _Iinterrupt_0 omitted)
i.comparison1     _Icompariso_0-1     (naturally coded; _Icompariso_0 omitted)
i.in~n2*i.com~1   _IintXcom_#_#       (coded as above)

Random-effects GLS regression                   Number of obs      =      2028
Group variable: city_id                         Number of groups   =        34

R-sq:  within  = 0.0894                         Obs per group: min =        48
       between = 0.7890                                        avg =      59.6
       overall = 0.6320                                        max =        60

                                                Wald chi2(6)       =    309.27
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000
```

viocrimrate_sum	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
time2	-.0152189	.0030737	-4.95	0.000	-.0212433	-.0091944
Percent_HS_Completion	-9.580403	3.69887	-2.59	0.010	-16.83006	-2.330751
Percent_Living_Poverty	9.976478	7.519853	1.33	0.185	-4.762163	24.71512
_Iinterrupt_1	-.0783767	.1150326	-0.68	0.496	-.3038365	.1470831
_Icompariso_1	1.554348	.7586702	2.05	0.040	.0673822	3.041315
_IintXcom_1_1	-.5291137	.1221721	-4.33	0.000	-.7685665	-.2896608
_cons	9.31336	3.527288	2.64	0.008	2.400002	16.22672
sigma_u	1.1610147					
sigma_e	1.2630115					
rho	.45799695	(fraction of variance due to u_i)				

.

Table A4-3. Linear Baseline Model NON-FUNDED SITES Interruption 2011

```
. xi: xtreg viocrimrate_sum time1 Percent_HS_Completion Percent_Living_Poverty i.interruption1*i.comparison2,i(city_id)
i.interruption1   _Iinterrupt_0-1     (naturally coded; _Iinterrupt_0 omitted)
i.comparison2     _Icompariso_0-1     (naturally coded; _Icompariso_0 omitted)
i.int~1*i.com~2   _IintXcom_#_#       (coded as above)

Random-effects GLS regression                   Number of obs      =      1068
Group variable: city_id                         Number of groups   =        18

R-sq:  within  = 0.1050                         Obs per group: min =        48
       between = 0.8140                                        avg =      59.3
       overall = 0.6344                                        max =        60

                                                Wald chi2(6)       =    184.90
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000
```

viocrimrate_sum	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
time1	-.024878	.0046175	-5.39	0.000	-.0339281	-.0158279
Percent_HS_Completion	-3.871829	5.979418	-0.65	0.517	-15.59127	7.847615
Percent_Living_Poverty	19.92129	11.1847	1.78	0.075	-2.000328	41.8429
_Iinterrupt_1	.2849779	.1963827	1.45	0.147	-.0999252	.669881
_Icompariso_1	1.231107	1.055355	1.17	0.243	-.8373512	3.299566
_IintXcom_1_1	-.5446133	.1794466	-3.03	0.002	-.8963221	-.1929045
_cons	4.085023	5.623401	0.73	0.468	-6.93664	15.10669
sigma_u	1.1842515					
sigma_e	1.384496					
rho	.42251675	(fraction of variance due to u_i)				

Table A4-4. Linear Baseline Model NON-FUNDED SITES Interruption 2012

```
. xi: xtreg viocrimrate_sum time2 Percent_HS_Completion Percent_Living_Poverty i.interruption2*i.comparison2,i(city_id)
i.interruption2   _Iinterrupt_0-1     (naturally coded; _Iinterrupt_0 omitted)
i.comparison2     _Icompariso_0-1     (naturally coded; _Icompariso_0 omitted)
i.in~n2*i.com~2   _IintXcom_#_#       (coded as above)

Random-effects GLS regression                   Number of obs      =      1068
Group variable: city_id                         Number of groups   =        18

R-sq:  within  = 0.1069                         Obs per group: min =        48
       between = 0.8139                                        avg =      59.3
       overall = 0.6348                                        max =        60

                                                Wald chi2(6)       =    187.40
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000
```

viocrimrate_sum	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
time2	-.01842	.004655	-3.96	0.000	-.0275437	-.0092963
Percent_HS_Completion	-3.872334	5.979445	-0.65	0.517	-15.59183	7.847162
Percent_Living_Poverty	19.91896	11.18475	1.78	0.075	-2.002756	41.84067
_Iinterrupt_1	-.013264	.1949538	-0.07	0.946	-.3953665	.3688385
_Icompariso_1	1.103056	1.052151	1.05	0.294	-.9591221	3.165233
_IintXcom_1_1	-.4981913	.1775635	-2.81	0.005	-.8462094	-.1501732
_cons	3.9997	5.623309	0.71	0.477	-7.021783	15.02118
sigma_u	1.1842808					
sigma_e	1.3830114					
rho	.42305246	(fraction of variance due to u_i)				

APPENDIX 5. DETAILED ANALYSIS TABLES:

SHORT INTERRUPTION TIME SERIES,

HOMICIDE VICTIMIZATION RATES FOR YOUNG PERSONS, AGES 14-24, PER 10,000 CITIZENS

Table A5-1. Linear Baseline Model Full Comparison Interruption 2011

```
. xi: xtreg homicide time1 Percent_HS_Completion Percent_Living_Poverty i.interruption1*i.comparison1,i(city_id)
i.interruption1   _Iinterrupt_0-1     (naturally coded; _Iinterrupt_0 omitted)
i.comparison1     _Icompariso_0-1     (naturally coded; _Icompariso_0 omitted)
i.int~1*i.com~1   _IintXcom_#_#       (coded as above)

Random-effects GLS regression                   Number of obs      =      2028
Group variable: city_id                         Number of groups   =        34

R-sq:  within  = 0.0074                         Obs per group: min =        48
       between = 0.5640                                        avg =      59.6
       overall = 0.0598                                        max =        60

                                                Wald chi2(6)       =     58.84
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000
```

homicide	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
time1	-.0001859	.0000935	-1.99	0.047	-.0003691	-2.74e-06
Percent_HS_Completion	-.0387976	.0255461	-1.52	0.129	-.088867	.0112717
Percent_Living_Poverty	.0437234	.0519573	0.84	0.400	-.058111	.1455579
_Iinterrupt_1	.0055996	.0035141	1.59	0.111	-.001288	.0124871
_Icompariso_1	.0122929	.0056884	2.16	0.031	.0011438	.0234421
_IintXcom_1_1	-.0100992	.0037379	-2.70	0.007	-.0174254	-.002773
_cons	.0258918	.0244222	1.06	0.289	-.0219748	.0737584
sigma_u	.00637676					
sigma_e	.03856486					
rho	.0266135	(fraction of variance due to u_i)				

Table A5-2. Linear Baseline Model Full Comparison Interruption 2012

```
. xi: xtreg homicide time2 Percent_HS_Completion Percent_Living_Poverty i.interruption2*i.comparison1,i(city_id)
i.interruption2   _Iinterrupt_0-1     (naturally coded; _Iinterrupt_0 omitted)
i.comparison1     _Icompariso_0-1     (naturally coded; _Icompariso_0 omitted)
i.in~n2*i.com~1   _IintXcom_#_#       (coded as above)

Random-effects GLS regression                   Number of obs      =      2028
Group variable: city_id                         Number of groups   =        34

R-sq:  within  = 0.0163                         Obs per group: min =        48
       between = 0.5668                                        avg =      59.6
       overall = 0.0680                                        max =        60

                                                Wald chi2(6)       =     77.02
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000
```

homicide	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
time2	.0000989	.0000935	1.06	0.290	-.0000843	.000282
Percent_HS_Completion	-.0387311	.0255451	-1.52	0.129	-.0887985	.0113364
Percent_Living_Poverty	.0440016	.0519551	0.85	0.397	-.0578286	.1458318
_Iinterrupt_1	-.0044415	.003499	-1.27	0.204	-.0112993	.0024164
_Icompariso_1	.012474	.005435	2.30	0.022	.0018216	.0231263
_IintXcom_1_1	-.0156084	.003716	-4.20	0.000	-.0228916	-.0083252
_cons	.030262	.0244278	1.24	0.215	-.0176156	.0781396
sigma_u	.00639415					
sigma_e	.03839298					
rho	.02698857	(fraction of variance due to u_i)				

Table A5-3. Linear Baseline Model NON-FUNDED SITES Interruption 2011

```
. xi: xtreg homicide time1 Percent_HS_Completion Percent_Living_Poverty i.interruption1*i.comparison2,i(city_id)
i.interruption1   _Iinterrupt_0-1     (naturally coded; _Iinterrupt_0 omitted)
i.comparison2     _Icompariso_0-1     (naturally coded; _Icompariso_0 omitted)
i.int~1*i.com~2   _IintXcom_#_#       (coded as above)

Random-effects GLS regression                  Number of obs      =      1068
Group variable: city_id                        Number of groups   =        18

R-sq:  within  = 0.0123                        Obs per group: min =        48
       between = 0.4837                                       avg =      59.3
       overall = 0.0598                                       max =        60

                                               Wald chi2(6)       =     27.51
corr(u_i, X)   = 0 (assumed)                   Prob > chi2        =    0.0001

------------------------------------------------------------------------------------------
              homicide |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------------+------------------------------------------------------------------
                 time1 |  -.0003128   .0001507    -2.08   0.038    -.0006081   -.0000175
 Percent_HS_Completion |  -.0641196   .0574106    -1.12   0.264    -.1766423    .0484031
Percent_Living_Poverty |   .0256934   .1073943     0.24   0.811    -.1847955    .2361823
         _Iinterrupt_1 |   .0135704   .0064068     2.12   0.034     .0010132    .0261275
         _Icompariso_1 |   .0119728   .0106942     1.12   0.263    -.0089875    .0329331
         _IintXcom_1_1 |  -.0142627   .0058512    -2.44   0.015    -.0257309   -.0027946
                 _cons |   .0440333   .0540921     0.81   0.416    -.0619852    .1500517
-----------------------+------------------------------------------------------------------
               sigma_u |  .00990503
               sigma_e |  .04516031
                   rho |  .04589785   (fraction of variance due to u_i)
------------------------------------------------------------------------------------------
```

.

Table A5-4. Linear Baseline Model NON-FUNDED SITES Interruption 2012

```
. xi: xtreg homicide time2 Percent_HS_Completion Percent_Living_Poverty i.interruption2*i.comparison2,i(city_id)
i.interruption2   _Iinterrupt_0-1     (naturally coded; _Iinterrupt_0 omitted)
i.comparison2     _Icompariso_0-1     (naturally coded; _Icompariso_0 omitted)
i.in~n2*i.com~2   _IintXcom_#_#       (coded as above)

Random-effects GLS regression                  Number of obs      =      1068
Group variable: city_id                        Number of groups   =        18

R-sq:  within  = 0.0237                        Obs per group: min =        48
       between = 0.4873                                       avg =      59.3
       overall = 0.0704                                       max =        60

                                               Wald chi2(6)       =     39.93
corr(u_i, X)   = 0 (assumed)                   Prob > chi2        =    0.0000

------------------------------------------------------------------------------------------
              homicide |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------------+------------------------------------------------------------------
                 time2 |   .0002395   .0001511     1.58   0.113    -.0000567    .0005356
 Percent_HS_Completion |  -.0640804    .057409    -1.12   0.264    -.1765999    .0484391
Percent_Living_Poverty |   .0258745   .1073911     0.24   0.810    -.1846082    .2363571
         _Iinterrupt_1 |  -.0083201    .006332    -1.31   0.189    -.0207306    .0040903
         _Icompariso_1 |    .009838   .0103505     0.95   0.342    -.0104486    .0301245
         _IintXcom_1_1 |  -.0159483    .005765    -2.77   0.006    -.0272475    -.004649
                 _cons |   .0546784   .0540773     1.01   0.312    -.0513111    .1606679
-----------------------+------------------------------------------------------------------
               sigma_u |  .00992501
               sigma_e |  .04489988
                   rho |  .04658576   (fraction of variance due to u_i)
------------------------------------------------------------------------------------------
```

APPENDIX 6. DETAILED ANALYSIS TABLES:

SHORT INTERRUPTION TIME SERIES,

AGGRAVATED ASSAULT VICTIMIZATION RATES FOR YOUNG PERSONS, AGES 14-24, PER 10,000 CITIZENS

Table A6-1. Linear Baseline Model Full Comparison Interruption 2011

```
. xi: xtreg aggassault time1 Percent_HS_Completion Percent_Living_Poverty i.interruption1*i.comparison1,i(city_id)
i.interruption1   _Iinterrupt_0-1     (naturally coded; _Iinterrupt_0 omitted)
i.comparison1     _Icompariso_0-1     (naturally coded; _Icompariso_0 omitted)
i.int~1*i.com~1   _IintXcom_#_#       (coded as above)

Random-effects GLS regression                   Number of obs      =      2028
Group variable: city_id                         Number of groups   =        34

R-sq:  within  = 0.0626                         Obs per group: min =        48
       between = 0.6552                                        avg =      59.6
       overall = 0.3476                                        max =        60

                                                Wald chi2(6)       =    197.24
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000

------------------------------------------------------------------------------------------
            aggassault |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------------+------------------------------------------------------------------
                 time1 |  -.0080735   .0014997    -5.38   0.000    -.0110128   -.0051343
 Percent_HS_Completion |  -.8644988   1.111644    -0.78   0.437     -3.04328    1.314283
Percent_Living_Poverty |   1.699226   2.260078     0.75   0.452    -2.730445    6.128898
         _Iinterrupt_1 |   .0402845   .0563808     0.71   0.475    -.0702198    .1507889
         _Icompariso_1 |   .7999539   .2303572     3.47   0.001      .348462    1.251446
         _IintXcom_1_1 |   -.206798   .0599804    -3.45   0.001    -.3243574   -.0892385
                 _cons |   1.385137   1.060304     1.31   0.191    -.6930202    3.463295
-----------------------+------------------------------------------------------------------
               sigma_u |  .34286387
               sigma_e |  .61863699
                   rho |  .23498561   (fraction of variance due to u_i)
------------------------------------------------------------------------------------------
```

Table A6-2. Linear Baseline Model Full Comparison Interruption 2012

```
. xi: xtreg aggassault time2 Percent_HS_Completion Percent_Living_Poverty i.interruption2*i.comparison1,i(city_id)
i.interruption2   _Iinterrupt_0-1     (naturally coded; _Iinterrupt_0 omitted)
i.comparison1     _Icompariso_0-1     (naturally coded; _Icompariso_0 omitted)
i.in~n2*i.com~1   _IintXcom_#_#       (coded as above)

Random-effects GLS regression                   Number of obs      =      2028
Group variable: city_id                         Number of groups   =        34

R-sq:  within  = 0.0619                         Obs per group: min =        48
       between = 0.6551                                        avg =      59.6
       overall = 0.3473                                        max =        60

                                                Wald chi2(6)       =    195.77
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000

------------------------------------------------------------------------------------------
            aggassault |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------------+------------------------------------------------------------------
                 time2 |  -.0068966   .0015073    -4.58   0.000    -.0098508   -.0039423
 Percent_HS_Completion |  -.8646405   1.111646    -0.78   0.437    -3.043427    1.314146
Percent_Living_Poverty |   1.698634   2.260083     0.75   0.452    -2.731048    6.128316
         _Iinterrupt_1 |  -.0184048   .0564121    -0.33   0.744    -.1289705    .0921609
         _Icompariso_1 |   .7467365   .2287897     3.26   0.001     .2983169    1.195156
         _IintXcom_1_1 |  -.1771388   .0599131    -2.96   0.003    -.2945663   -.0597113
                 _cons |   1.326477   1.060347     1.25   0.211     -.751765    3.404718
-----------------------+------------------------------------------------------------------
               sigma_u |  .34285741
               sigma_e |  .61885001
                   rho |  .23485509   (fraction of variance due to u_i)
------------------------------------------------------------------------------------------
```

Table A6-3. Linear Baseline Model Non-Funded Sites Interruption 2011

```
. xi: xtreg aggassault time1 Percent_HS_Completion Percent_Living_Poverty i.interruption1*i.comparison2,i(city_id)
i.interruption1   _Iinterrupt_0-1     (naturally coded; _Iinterrupt_0 omitted)
i.comparison2     _Icompariso_0-1     (naturally coded; _Icompariso_0 omitted)
i.int~1*i.com~2   _IintXcom_#_#       (coded as above)

Random-effects GLS regression                   Number of obs      =      1068
Group variable: city_id                         Number of groups   =        18

R-sq:  within  = 0.0687                         Obs per group: min =        48
       between = 0.6607                                        avg =      59.3
       overall = 0.3143                                        max =        60

                                                Wald chi2(6)       =    110.94
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000
```

aggassault	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
time1	-.0083554	.0022674	-3.69	0.000	-.0127994	-.0039115
Percent_HS_Completion	1.106387	1.688551	0.66	0.512	-2.203113	4.415887
Percent_Living_Poverty	3.080916	3.158527	0.98	0.329	-3.109682	9.271515
_Iinterrupt_1	.0790361	.0964286	0.82	0.412	-.1099605	.2680327
_Icompariso_1	.8963257	.3012718	2.98	0.003	.3058439	1.486807
_IintXcom_1_1	-.2370939	.0881032	-2.69	0.007	-.4097729	-.0644149
_cons	-.2101412	1.58858	-0.13	0.895	-3.323701	2.903419
sigma_u	.3261338					
sigma_e	.67884014					
rho	.18752761	(fraction of variance due to u_i)				

Table A6-4. Linear Baseline Model Non-Funded Sites Interruption 2012

```
. xi: xtreg aggassault time2 Percent_HS_Completion Percent_Living_Poverty i.interruption2*i.comparison2,i(city_id)
i.interruption2   _Iinterrupt_0-1     (naturally coded; _Iinterrupt_0 omitted)
i.comparison2     _Icompariso_0-1     (naturally coded; _Icompariso_0 omitted)
i.in~n2*i.com~2   _IintXcom_#_#       (coded as above)

Random-effects GLS regression                   Number of obs      =      1068
Group variable: city_id                         Number of groups   =        18

R-sq:  within  = 0.0675                         Obs per group: min =        48
       between = 0.6595                                        avg =      59.3
       overall = 0.3132                                        max =        60

                                                Wald chi2(6)       =    109.46
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000
```

aggassault	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
time2	-.0077972	.0022896	-3.41	0.001	-.0122846	-.0033098
Percent_HS_Completion	1.105903	1.688596	0.65	0.513	-2.203685	4.415491
Percent_Living_Poverty	3.078684	3.15861	0.97	0.330	-3.112079	9.269446
_Iinterrupt_1	.0332965	.0958983	0.35	0.728	-.1546606	.2212537
_Icompariso_1	.8342616	.2985701	2.79	0.005	.2490749	1.419448
_IintXcom_1_1	-.2018221	.0873374	-2.31	0.021	-.3730003	-.030644
_cons	-.27189	1.588526	-0.17	0.864	-3.385344	2.841564
sigma_u	.32611877					
sigma_e	.67926748					
rho	.18732188	(fraction of variance due to u_i)				

APPENDIX 7. DETAILED ANALYSIS TABLES:

SHORT INTERRUPTION TIME SERIES,

NON-VIOLENT CRIME VICTIMIZATION RATES FOR YOUNG PERSONS, AGES 14-24, PER 10,000 CITIZENS

Table A7-1. Linear Baseline Model Full Comparison Interruption 2011

```
. xi: xtreg nonviocrimrate_sum time1 Percent_HS_Completion Percent_Living_Poverty i.interruption1*i.comparison1,i(city_id)
i.interruption1   _Iinterrupt_0-1     (naturally coded; _Iinterrupt_0 omitted)
i.comparison1     _Icompariso_0-1     (naturally coded; _Icompariso_0 omitted)
i.int~1*i.com~1   _IintXcom_#_#       (coded as above)

Random-effects GLS regression                   Number of obs      =      1968
Group variable: city_id                         Number of groups   =        33

R-sq:  within  = 0.0728                         Obs per group: min =        48
       between = 0.6706                                        avg =      59.6
       overall = 0.4415                                        max =        60

                                                Wald chi2(6)       =    213.58
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000

------------------------------------------------------------------------------------------
    nonviocrimrate_sum |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------------+------------------------------------------------------------------
                 time1 |  -.0085416   .0024054    -3.55   0.000    -.0132561   -.0038272
 Percent_HS_Completion |  -3.789318   2.407056    -1.57   0.115    -8.507062    .9284262
Percent_Living_Poverty |   12.24277   4.861327     2.52   0.012     2.714739    21.77079
          _Iinterrupt_1 |  -.1929337   .0899365    -2.15   0.032     -.369206   -.0166614
          _Icompariso_1 |   .0410583   .4926464     0.08   0.934    -.9245109    1.006628
          _IintXcom_1_1 |   -.235208   .0979125    -2.40   0.016    -.4271129    -.043303
                 _cons |   3.644566   2.276266     1.60   0.109    -.8168327    8.105965
-----------------------+------------------------------------------------------------------
               sigma_u |  .74167654
               sigma_e |  .97809695
                   rho |  .36507799   (fraction of variance due to u_i)
------------------------------------------------------------------------------------------
```

Table A7-2. Linear Baseline Model Full Comparison Interruption 2012

```
. xi: xtreg nonviocrimrate_sum time2 Percent_HS_Completion Percent_Living_Poverty i.interruption2*i.comparison1,i(city_id)
i.interruption2   _Iinterrupt_0-1     (naturally coded; _Iinterrupt_0 omitted)
i.comparison1     _Icompariso_0-1     (naturally coded; _Icompariso_0 omitted)
i.in~n2*i.com~1   _IintXcom_#_#       (coded as above)

Random-effects GLS regression                   Number of obs      =      1968
Group variable: city_id                         Number of groups   =        33

R-sq:  within  = 0.0735                         Obs per group: min =        48
       between = 0.6710                                        avg =      59.6
       overall = 0.4419                                        max =        60

                                                Wald chi2(6)       =    215.06
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000

------------------------------------------------------------------------------------------
    nonviocrimrate_sum |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------------+------------------------------------------------------------------
                 time2 |  -.0070868   .0024164    -2.93   0.003    -.0118228   -.0023508
 Percent_HS_Completion |  -3.787714   2.407032    -1.57   0.116    -8.505411    .9299832
Percent_Living_Poverty |   12.25013   4.861279     2.52   0.012     2.722202    21.77806
          _Iinterrupt_1 |   -.278199   .0899365    -3.09   0.002    -.4544712   -.1019267
          _Icompariso_1 |  -.0399522   .4906889    -0.08   0.935    -1.001685    .9217805
          _IintXcom_1_1 |  -.1505047   .0977423    -1.54   0.124    -.3420761    .0410667
                 _cons |   3.543033   2.276296     1.56   0.120    -.9184258    8.004492
-----------------------+------------------------------------------------------------------
               sigma_u |  .74168401
               sigma_e |  .97775971
                   rho |  .36524255   (fraction of variance due to u_i)
------------------------------------------------------------------------------------------
```

Table A7-3. Linear Baseline Model Non-Funded Sites Interruption 2011

```
. xi: xtreg nonviocrimrate_sum time1 Percent_HS_Completion Percent_Living_Poverty i.interruption1*i.comparison2,i(city_id)
i.interruption1   _Iinterrupt_0-1     (naturally coded; _Iinterrupt_0 omitted)
i.comparison2     _Icompariso_0-1     (naturally coded; _Icompariso_0 omitted)
i.int~1*i.com~2   _IintXcom_#_#       (coded as above)

Random-effects GLS regression                   Number of obs      =      1008
Group variable: city_id                         Number of groups   =        17

R-sq:  within  = 0.0857                         Obs per group: min =        48
       between = 0.7164                                        avg =      59.3
       overall = 0.4954                                        max =        60

                                                Wald chi2(6)       =    126.65
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000

------------------------------------------------------------------------------------------
    nonviocrimrate_sum |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------------+------------------------------------------------------------------
                 time1 |  -.0101486   .0033873    -3.00   0.003    -.0167875   -.0035096
 Percent_HS_Completion |  -2.394809   4.194532    -0.57   0.568    -10.61594    5.826324
Percent_Living_Poverty |   17.31199    7.63756     2.27   0.023     2.342651    32.28134
          _Iinterrupt_1 |  -.0803811    .141946    -0.57   0.571    -.3585903     .197828
          _Icompariso_1 |  -.5281957   .7349865    -0.72   0.472    -1.968743    .9123514
          _IintXcom_1_1 |  -.2995533   .1302817    -2.30   0.021    -.5549008   -.0442059
                 _cons |   2.200439   3.898111     0.56   0.572    -5.439719    9.840597
-----------------------+------------------------------------------------------------------
               sigma_u |  .80598489
               sigma_e |   .9866352
                   rho |  .40023867   (fraction of variance due to u_i)
------------------------------------------------------------------------------------------
```

Table A7-4. Linear Baseline Model Non-Funded Sites Interruption 2012

```
. xi: xtreg nonviocrimrate_sum time2 Percent_HS_Completion Percent_Living_Poverty i.interruption2*i.comparison2,i(city_id)
i.interruption2   _Iinterrupt_0-1     (naturally coded; _Iinterrupt_0 omitted)
i.comparison2     _Icompariso_0-1     (naturally coded; _Icompariso_0 omitted)
i.in~n2*i.com~2   _IintXcom_#_#       (coded as above)

Random-effects GLS regression                   Number of obs      =      1008
Group variable: city_id                         Number of groups   =        17

R-sq:  within  = 0.0818                         Obs per group: min =        48
       between = 0.7162                                        avg =      59.3
       overall = 0.4939                                        max =        60

                                                Wald chi2(6)       =    122.16
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000

------------------------------------------------------------------------------------------
    nonviocrimrate_sum |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------------+------------------------------------------------------------------
                 time2 |   -.012138   .0034275    -3.54   0.000    -.0188557   -.0054202
 Percent_HS_Completion |  -2.395004   4.194544    -0.57   0.568    -10.61616    5.826152
Percent_Living_Poverty |   17.31084   7.637581     2.27   0.023     2.341459    32.28023
          _Iinterrupt_1 |  -.0272507    .141436    -0.19   0.847    -.3044603    .2499588
          _Icompariso_1 |  -.6082233   .7325775    -0.83   0.406    -2.044049    .8276022
          _IintXcom_1_1 |  -.2499194   .1293674    -1.93   0.053    -.5034749    .0036361
                 _cons |   2.031029   3.898058     0.52   0.602    -5.609024    9.671082
-----------------------+------------------------------------------------------------------
               sigma_u |  .80594233
               sigma_e |  .98868868
                   rho |  .39921558   (fraction of variance due to u_i)
------------------------------------------------------------------------------------------
```

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