

MPRA

Munich Personal RePEc Archive

Is There a 1033 Effect? Police Militarization and Aggressive Policing

Olugbenga Ajilore

30 October 2017

Online at <https://mpra.ub.uni-muenchen.de/82543/>

MPRA Paper No. 82543, posted 17 November 2017 15:26 UTC

Is there a 1033 Effect? Police Militarization and Aggressive Policing

Author: Olugbenga Ajilore
Affiliation: University of Toledo
Address: 2801 Bancroft St.
Department of Economics
Toledo, OH 43606-3390
Phone: (419) 530-2113
E-mail: gbenga.ajilore@utoledo.edu

Abstract

Events in Ferguson and Baltimore in the United States in the past 3 years have brought to light issues related to the militarization of police and adverse police–citizen interactions. Through federal programs and grants, local law enforcement agencies have been able to acquire surplus military items to combat terrorism and drug activity. The acquisition of these items has accelerated over the past 10 years. These agencies acquired nearly \$1 billion worth of property in 2014 alone through the Pentagon’s 1033 Program, a program that distributes excess military surplus to law enforcement agencies. This study seeks to determine whether the increased acquisition of these items has led to more police use-of-force incidents. We create a dataset merging administrative data from the Pentagon’s 1033 Program database and survey data from the Bureau of Justice Statistics. Using a binary treatment effects estimator, we show that there is little evidence of a causal link between general military surplus acquisition and documented use-of-force incidents. In fact, the acquisition of military vehicles leads to fewer use-of-force incidents. The results also show that more diverse departments have fewer incidents, while agencies with SWAT team have more incidents.

JEL Codes: H70, H76, K42

Keywords: Police Militarization, Excessive Force, Law Enforcement Management and Administrative Statistics (LEMAS), 1033 Program, Treatment Effects

1. INTRODUCTION

Recent incidents of adverse police–public interactions have become national news in the United States as a result of seemingly unnecessary escalations to violence. The names Eric Garner, Alton Sterling, Tamir Rice, and Sandra Bland are well known to the public. The increasing militarization of the police is also at the forefront of media attention. Local law enforcement agencies have been acquiring items previously commissioned for use in Iraq and Afghanistan to help combat terrorism and drug-related activities in the United States (Grasso, 2013). Although many programs have contributed to the increasing militarization of local law enforcement, the 1033 Program, a program that distributes excess military surplus to law enforcement agencies, is the most well known of these programs. Through the work of several institutions, including MuckRock (Musgrave, 2014) and National Public Radio (Rezvani et al., 2014), data on 1033 Program acquisitions have been made available through the Pentagon. Many in the #BlackLivesMatter movement argue there is a connection between the increasing militarization of police and the excessive use of force by officers.¹ From a (social) media perspective, the militarization of police may appear to have had a causal impact on the seemingly growing number of incidents of use of force by police.

In economic literature, studies of police behavior tend to focus on racial profiling and bias in policing (Knowles et al., 2001; Anwar and Fang, 2006; Close and Mason, 2007; Antonovics and Knight, 2009). Research on the use of force is scarce, although a recent National Bureau of Economic Research working paper by Roland Fryer looks at whether there are racial differences in the treatment of citizens by police officers (Fryer, 2016). His findings show race is a factor in use-of-force incidents, but not in officer-involved shootings. Ajilore and Shirey

¹ <http://www.joincampaignzero.org/solutions/#solutionsoverview>

(2017), in a study of citizen complaints to the Chicago Police Department, finds that African Americans who live in Chicago's South Side are less likely to have their complaints sustained.

In criminal justice literature, the determinants of police use of force have been analyzed by many scholars (Friedrich, 1980; Garner et al., 2002; Worden, 1995). These determinants fall into four broad categories: individual, situational, organizational, and community. The consensus is that the primary factor in use-of-force incidents is situational, depending on a suspect's characteristics and the seriousness of the crime (Riksheim and Chermak, 1993). However, one difficulty in analyzing the issue is the consideration of the interactions between factors (Sun et al., 2008). Another issue in studying the use of force is that most studies use incident and arrest data for only one or several cities (Hickman et al. (2008) Appendix). Few nationally representative databases are available, for which the findings can be generalized.

The question posed in this study is whether local law enforcement agencies that request military surplus items are more likely to have more incidents of confrontational police behavior than those agencies that do not. This is not a study of individual police–citizen interactions in which a use of force has occurred but rather an agency-level study on the total number of use-of-force incidents. In this study, we examine the relationship between the acquisition of surplus military items and the number of use-of-force incidents by law enforcement officers using survey data from the Bureau of Justice Statistics (BJS) and the Pentagon's 1033 Program database.

2. BACKGROUND

Law enforcement agencies can acquire military items through various programs administered by the Department of Defense (DOD), the Department of Justice (DOJ), and the Department of Homeland Security (DHS). Programs administered through the DOD include the

1033 Program and the 1122 Program, which allow for the acquisition of military surplus either at no cost (1033) or through the purchase of new equipment (1122). The DOJ programs are grants to states and localities to assist in law enforcement activity. These funds are mostly used for the hiring of new police officers to combat the illegal drug trade and gang-related activity. The DHS programs deliver funds to localities to combat terrorism. In each of these programs, the “War on Drugs” or “War on Terror” has been used as justification for procurement, regardless of whether there have been incidents related to drugs, gang activity, or terrorist activity (Hall and Coyne, 2013).

One of the more well-known programs, the 1033 Program, has become a conduit for a significant increase in the acquisition of military surplus items. This program began in 1990 but was formalized in 1997 through the National Defense Authorization Act, which enabled all local law enforcement agencies to acquire surplus property. The law enforcement agencies must request items with the approval of a state officer, appointed by the governor, and Law Enforcement Support Office staff. Preference is given to counter-drug and counter-terrorism activities. This program is popular because these local agencies can acquire these items without cost. Two recent papers have attempted to estimate the effect of police militarization on a number of policing outcomes. Bove and Gavrilova (2017) find that militarization has lowered crime rates, and Harris et al. (2017), using distance to field activity centers as an instrument, reach the same result. However, police militarization may have other impacts beyond that on crime. The acquisition of military surplus may be driven by demographic changes, such as race and immigration, instead of criminal activity. Ajilore (2015) finds that more ethnically segregated counties are more likely to acquire mine-resistant ambush protected (MRAP) vehicles.

To understand how the acquisition of military items can lead to excessive use-of-force incidents, we need to explain why individuals with punitive preferences are more likely to have law enforcement jobs. Individuals with a given set of preferences will self-select into certain institutions. For example, people who love children are more likely to become elementary school teachers or daycare providers. Individuals who care about the environment are more likely to work at the Environmental Protection Agency or the Sierra Club. Likewise, individuals with interests in justice or punishment will self-select into law enforcement jobs that offer the opportunity to catch criminals and punish wrongdoers.

Prendergast (2007) develops a principal–agent model to explain the motivation of bureaucrats. In the model, a principal hires an agent to enact the preferences of a client. For example, law enforcement agencies hire police officers to enforce laws on behalf of citizens. If citizens in a jurisdiction have strong preferences for justice, the agency needs to hire officers that will enforce laws in a way that aligns with citizens’ preferences. The outcome of the model is that those who self-select into certain bureaucracies will accept lower wages because these individuals can act upon their preferences. Based on the wage offered, the model predicts that two types of individuals will self-select into law enforcement: people who seek justice and people who want to punish others.

Dharmapala et al. (2016) extend this research and model how law enforcement can consist of individuals who have punitive preferences. These researchers cite literature from experimental economics that supports the existence of punitive preferences. We can regard the excessive use of force as representing a preference for “extreme punishment.” Individuals with punitive preferences may self-select into law enforcement jobs, and the acquisition of military items may intensify these preferences, which translate into a greater number of excessive use-of-

force incidents. If individuals with punitive preferences have a tendency to become police officers, the following question arises: does access to night vision equipment, tanks, body armor, and tactical weapons embolden these individuals to be more confrontational? In Section 4, we specify an empirical model to test the hypothesis that agencies that acquire more surplus military items have more use-of-force incidents.

3. DATA

3.1 Sample

The data to estimate our model are obtained from the Law Enforcement Management and Administrative Statistics (LEMAS) survey for 2013. This survey is conducted by the DOJ's BJS, and is a nationally representative survey of law enforcement agencies. This survey is conducted periodically, although the last survey conducted prior to 2013 was in 2007. The data include information on agency responsibilities, operating expenditure, salaries, education and training requirements, agency demographics, technology use, and weapon policies. The survey primarily covers local police departments but also includes sheriffs' offices and state law enforcement agencies. LEMAS is not the most comprehensive database on use-of-force incidents. The Police-Public Contact Survey (PPCS), a supplement to the National Crime Victimization Survey, has more detailed data on the nature of police-citizen interactions. However, the PPCS does not have geographic identifiers that would enable the linking of that data to military surplus acquisitions from the 1033 Program.

Data on the acquisition of military surplus items is taken from the Pentagon's website,² which states all acquisitions requested by local law enforcement agencies. The data are listed by agency, item requested, the original acquisition value,³ and the date the item was shipped to the agency. The Pentagon data were aggregated by agency to facilitate a merger with LEMAS data. While the LEMAS survey data is from 2013, the information references 2012; therefore, the Pentagon data are aggregated through to the end of 2011.

3.2 Variables

The dependent variable is the number of use-of-force incidents per 100 officers. In the survey, most agencies have use-of-force forms to document incidents, but only approximately one-third of the agencies document use of force within arrest reports. In addition, most agencies file only one report per incident rather than separate reports for each officer involved. Some agencies did not have exact counts of incidents; hence, these counts were estimated. We include a dummy variable for agencies that estimated the number of incidents.

The primary independent variable is the quantity of military surplus acquisitions through the 1033 Program for an agency in 2011. This measure is not normalized by the number of officers because we transform it into a dichotomous variable that takes the value of one if the agency acquired surplus, and zero otherwise. We use a binary treatment effects estimator, which is why we use a binary specification of the independent variable. Although the program has existed since 1990, large-scale acquisitions did not begin until 2006. This measure is based on

² <http://www.dispositionservices.dla.mil/leso/Pages/default.aspx>. The program is operated by the Defense Logistics Agency.

³ As these items were originally purchased by the U.S. Military, this does not reflect the costs borne by the agency. The only costs to the agency are the transportation and transaction costs incurred in the acquisition of the item.

the DOD’s collection of items acquired through the Pentagon’s 1033 Program. The agencies have access to all types of military items including vehicles, tools, weapons, and electronic systems. The second independent variable details four different categories: tactical items,⁴ vehicles (including tracked and wheeled), surveillance items (including night vision items), and clothing (e.g., body armor and camouflage outfits). Table 1 outlines the surplus acquisitions by category for the time period.

Table 1. Distribution of Surplus Acquisition by Category

	Total Surplus	1033 Only
Total Acquisitions	46.5%	100.0%
2011 Acquisitions	11.0%	23.6%
Tactical	40.4%	86.8%
Weapons	40.3%	86.6%
Vehicles	8.0%	17.3%
Vehicles (tracked)	1.3%	2.9%
Vehicles (wheeled)	1.6%	3.3%
Surveillance	7.7%	16.6%
Night Vision	7.0%	15.1%
Clothing	2.6%	5.7%
Body Armor	1.2%	2.7%
Number of Agencies	1,928	897 (46.5%)

Table 1 shows that less than 50% of the sample acquired some type of surplus item through the 1033 Program. The primary items received by these agencies are tactical items, of which the majority are guns, followed by vehicles and surveillance items. One item that has received considerable media attention is MRAP vehicles. This item would be categorized as a tracked vehicle and Table 1 shows that it accounts only for 2.9% of all acquisitions.

⁴ In addition to weapons, tactical items include fire control items, ammunition and explosives, grenade launchers, aircraft accessories, and ships.

The control variables include measures pertaining to the agency and characteristics of the community that the agency serves. The agency measures are taken from the LEMAS, while the demographic data are taken from the 2011 5-year sample of the American Community Survey (ACS). In the principal–agent model, agencies that offered higher wages would be less likely to only have individuals with punitive preferences apply for openings. Therefore, we include a measure of entry-level salary for officers in the model. Agencies that offer a higher entry salary should attract a wider variety of applications with diverse preferences. Based on previous studies, enforcement culture plays a large role in use of force incidents (Miller, 2015). Explanatory variables to measure culture include whether the agencies have dedicated task forces to combat terrorism, gang activity, or drug activity. Although this study focuses on the 1033 Program, many federal government programs direct resources toward combating the “War on Terror” or the “War on Drugs.” Federal grants and surplus items are purposed for these activities. If such agencies have dedicated task forces devoted to these wars, this may suggest a culture with norms towards enforcement. We include a dummy variable whether the agency has a SWAT task force.⁵ SWAT teams have been linked to many incidents where an excessive use of force occurred (ACLU, 2014). We include a dummy variable whether the agency’s budget includes money from asset forfeiture. Agencies that receive revenue from asset forfeiture may be more aggressive in terms of enforcement (Benson, Rasmussen, and Sollars, 1995). We also examine whether officers have body cameras or cameras in their cars. We seek to determine whether these items could potentially mitigate the number of use-of-force incidents. We include the share of the police force that is African American and the share of the police force that is

⁵ The SWAT, gang, and drug task forces are multi-jurisdictional. The terrorism unit is agency specific.

Hispanic or Latino. Finally, we include whether the agency requires at least eight hours of community policing training, whether the officer is a new recruit, or if it was in-service⁶.

Other explanatory variables include demographic characteristics that would affect the demand for police services at the county level. We use the county as the geographic level for the demographics because it more accurately resembles the population an agency serves, as people travel in and out of the jurisdiction. Demographic variables include median income, unemployment rate, crime index, Gini index, elderly population, youth population, and owner-occupied housing. Racial and ethnic diversity has been shown to be an important factor in policing outcomes and therefore we include the African-American share, Latino share, and residential segregation. Residential segregation is measured by the dissimilarity index, which is shown in (1):

$$D = \sum_{m=1}^M \sum_{j=1}^J \frac{t_j}{2TI} |\pi_{jm} - \pi_m|. \quad (1)$$

Measure (1) is a multi-group segregation index aggregating data for multiple ethnic groups (Reardon and Firebaugh, 2002), where T is the total population, M is the number of ethnic groups m , J is the number of census tracts, and I is Simpson's interaction index (the Simpson's interaction index is given by $I = \sum_{m=1}^M \pi_m(1 - \pi_m)$ and measures the basic diversity of a population). Furthermore, t_j is the number of individuals in the census tract, π_{jm} is the proportion in group m , and π_m is the proportion in group m in census tract j . We include dummies for agencies that are not local police: sheriffs' departments or state agencies. The total number of observations is 1,928. Table 2 presents the descriptive statistics.

⁶ This refers to experienced officers completing their training.

Table 2. Descriptive Statistics

Variable	Mean	Mean	Std. Dev.	Min	Max
<i>Dependent Variable</i>	(Total)	(Incidents only)			
Incidents per 100 officers	33.9	77.5	196.2	0	6,960
<i>Acquisitions</i>					
Total Acquisitions	7.3	9.5	44.0	0	2,504
Acquisitions in 2011	4.0	5.8	42.2	0	2,504
Tactical items (total)	5.0	6.4	25.8	0	1,119
Vehicles (total)	0.1	0.1	0.4	0	10
Surveillance items (total)	0.6	0.8	7.8	0	317
Clothing items (total)	0.7	1.1	16.6	0	1,311
<i>Controls (Agency)</i>					
Entry-level Wage	46,217.41	48,163.77	18,045.05	17,160.00	195,247.00
Asset Forfeiture (Budget)	35.8%	41.3%	0.48	0	1
Body Camera	30.0%	30.4%	0.46	0	1
Dash Camera	70.7%	70.2%	0.46	0	1
Share of force that is Black	3.8%	4.1%	0.09	0	78.5%
Share of force that is Latino	5.1%	5.3%	0.14	0	100%
Community Policing (8 hours)	57.0%	60.3%	0.50	0	1
<i>Agency Task Forces</i>					
SWAT (multijurisdictional)	30.8%	35.9%	0.46	0	1
Gangs (multijurisdictional)	15.1%	17.2%	0.36	0	1
Drugs (multijurisdictional)	54.8%	60.0%	0.50	0	1
Terrorism Unit	47.8%	50.4%	0.50	0	1
<i>Controls (County Demographics)</i>					
Share Elderly	14.8%	14.3%	0.04	5.6%	42.2%
Share Owner-Occupied Housing	71.8%	71.1%	0.08	22.7%	90.2%
Share Youth	13.5%	13.7%	0.03	5.4%	34.8%
Gini Index	0.436	0.436	0.03	0.334	0.601
Unemployment Rate	5.1%	5.3%	0.02	0.3%	10.7%
Median Household Income	50,418.62	51,599.14	13,944.68	22,982.00	120,096.00
Crime Index	2,622.69	2,779.5	1,217.6	0	8,040.1
African-American Share	8.6%	9.1%	0.12	0	74.1%
Latino Share	9.5%	10.1%	0.13	0	90.4%
Segregation (Dissimilarity) Index	0.338	0.339	0.12	0	0.705
Population	39,194	55,137	319,809	196	19,200,000

The first column provides the means for all agencies in the sample. The second column shows the means for the agencies that had at least one incident. These agencies were more likely to have task forces dedicated to combating terrorism, gang activity, and drug activity. In addition, the agencies with incidents had higher entry-level salaries and used asset forfeiture. These agencies were in counties with a higher median income but a lower elderly population and less owner-occupied housing. Furthermore, these agencies were in counties with higher crime rates and larger populations.

4. METHODOLOGY

4.1 Basic Regressions

Our baseline model provides an initial estimate of the relationship between surplus acquisition from the 1033 program and use of force incidents. In the estimation, incidents and acquisitions are normalized by the number of sworn officers so that comparisons across agencies can be made. The model is provided as shown:

$$Y_i = \beta_0 + \beta_1 Acquisitions_i + \beta_2 X_i + \varepsilon_i, \quad (2)$$

where Y_i is the number of incidents per 100 officers and X_i are the explanatory variables described in Table 2. The coefficient β_1 indicates whether there is correlation between the cumulative acquisition of surplus items and the number of incidents. Table 3 provides the estimates of the regression of surplus acquisitions including specific categories of acquisitions on use-of-force incidents.

Table 3. Ordinary Least Squares Estimates

	Total	Tactical	Vehicles	Surveillance	Clothing
Surplus Acquisitions	0.021	0.070+	0.135+	0.116+	0.110+
	(0.021)	(0.036)	(0.075)	(0.062)	(0.062)

Note: + p<0.10, * p<0.05, ** p<0.01, *** p<0.001; robust standard errors in parentheses.

The acquisition of surplus items throughout 2011 is positively correlated with use-of-force incidents in the ordinary least squares (OLS) regressions. This mildly significant effect is consistent across all types of surplus acquisitions.

4.2 Endogeneity

The results of these previous regressions show a correlation between the acquisition of surplus military items and the number of use-of-force incidents. However, these estimates assume that acquiring the surplus items and the number of incidents are independent actions, which may not be the case. Certain agency-related factors might lead them to want to acquire military items. As mentioned in Section 2, individuals with preferences toward punishing criminals may self-select into law enforcement. Agencies that have officers with punitive preferences that lead to excessive use-of-force incidents may want to acquire military items because of these preferences. In this case, that agency acquires surplus items and will have more incidents, although it is not a causal link. The question that needs to be answered is whether police departments that want to behave more aggressively acquire more military surplus items or whether the acquisition of military surplus causes more aggressive behavior. A method needs to be implemented to establish causality and address the selection issue. To address these issues, we can place the model within an evaluation framework using a treatment effects estimator. If we view the acquisition of military surplus as a treatment, we can estimate the average treatment effect using a binary treatment estimator. That is, we can ask the question, what would happen to the number of incidents at an agency if it acquired surplus military items?

We transform the specification given in (2) into a potential outcomes specification for which the binary treatment is where an agency makes the choice to acquire surplus through the 1033 Program:

$$Y_i = \beta_1 S_i + \beta_2 X_i + \varepsilon_i, \quad (3)$$

where Y_i is the number of incidents per 100 sworn officers, $S_i = 1$ if the agency acquired surplus items and 0 if they did not, and X_i is a vector of explanatory variables (from Table 1) with effects given by β_2 . Our goal is to estimate the average treatment effect (ATE), which is the difference between the average effect if an agency is treated and the average effect for an agency that is not treated. In addition, we can estimate the average treatment effect on the treated (ATET), which is the average treatment effect for the subsample of individuals that are treated. We can also estimate the average treatment effect on the non-treated (ATENT), which is the average treatment effect for the subsample of individuals that are not treated. Furthermore, ATE is the weighted average of ATET and ATENT.

The standard treatment effects estimators make the following three assumptions: (1) the conditional mean independence assumption, which restricts the dependence between the treatment model and potential outcomes; (2) the overlap assumption, which requires each individual to have a positive probability of receiving the treatment; and (3) the assumption that errors are independently and identically distributed. Assumption (1) may be too strong and in the case that it does not hold, we employ an estimator that allows for the treatment effects to be heterogeneous. There may be reasons for an agency acquiring surplus items that are not random, as would be the assumption using standard treatment effects estimators. In this case, we need to estimate an ATE that is conditioned on variables that could drive the heterogeneity. We use several agency-level measures that may drive a heterogeneous response to the treatment. We

include task force dummies, an asset forfeiture dummy, and race and ethnicity variables. These variables would drive heterogeneous responses because the existence of these task forces provides an avenue by which the surplus items would be employed in the community.⁷

4.3 Instruments

Great care must be taken when finding instruments that pass the exclusion restriction. An instrument must be correlated with the treatment variable but conditionally independent of the outcome measure. Bove and Gavrilova (2017) use national-level military expenditures weighted by the probability of receiving surplus equipment that provide variation by region and time. While fluctuations in national-level military expenditures should impact the amount of available surplus, Harris et al. (2017) use the location of distribution centers as an instrument. They use the distance between the county centroid and one of 18 field activity centers (FAC). The 18 FACs are a part of 76 distribution centers interspersed throughout the country.⁸ This study uses the distance to the distribution center from the agency as an instrument. The further away a center is, the less likely an agency will acquire surplus military equipment. To account for the center being a FAC, we include a dummy regarding whether that distribution center is a FAC. This study is a cross-sectional analysis, so we do not have to worry about the fact that the instrument is time invariant.

Harris et al. (2017) use knowledge gained from conversations with Pentagon officials to include two other instruments, a High Intensity Drug Trafficking Area (HIDTA) designation and county land area. Because one of the justifications for the 1033 Program is to help local law

⁷ For example, agencies with SWAT teams would use night vision goggles differently than agencies without SWAT teams.

⁸ <http://www.dla.mil/DispositionServices/Contact/FindLocation.aspx>

enforcement departments combat drug activity, priority is given to regions with high levels of drug trafficking. Agencies in HIDTA regions and agencies in larger counties are given special consideration for surplus items. Land area in terms of square footage and a dummy that designates whether an agency is located in a HIDTA region are also included as instruments.⁹ In Appendix Table 2A, diagnostics show the instruments perform well. The Kliebergen-Paap F Statistic is 15.322 and the Hansen J-statistic has a p-value of 0.385.

5. RESULTS

5.1 Probit Two-Stage Least Squares Regressions

We employ a probit two-stage least squares (probit-2sls) estimator, as developed by Cerulli (2014). In the first stage, we apply a probit of the treatment (S_i) on the explanatory variables and the instruments described in section 4.3. From this, we obtain the predicted probability of being treated. The second step is to run an OLS regression of the treatment on the explanatory variables X_i and the predicted probability from the first step. The third step is to run a second OLS of incidents on the explanatory variables, the predicted probability from the first step, and fitted values from the second step. The final step is the use of the estimated parameters to recover the causal effects and obtain standard errors for the ATET and ATENT using a bootstrap method. This procedure produces a more efficient and consistent estimator of the ATE. The three average treatment effects are provided in Table 4. The results of the first stage probit and the complete results are given in the Appendix Table 2A.

⁹ In 2011, there were 28 HIDTA designated regions. These are collapsed into 16 regions because some regions have small sample sizes. See Figure 1A in the Appendix for the regions.

Table 4. Average Treatment Effects

	Surplus	2011 only
ATE(X_i)	0.772 (0.794)	-0.294 (1.721)
ATET(X_i)	0.752 (0.816)	-0.187 (1.882)
ATENT(X_i)	0.772 (0.794)	-0.294 (1.721)

Note: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Standard errors in parentheses; Standard errors for the ATET and ATENT are calculated using a bootstrap with 100 replications.

ATE(X_i) is the average treatment effect conditioned on the explanatory variables X_i . We can consider these as individual specific average treatment effects. The results obtained show that surplus acquisitions do not have significant effects on use-of-force incidents.

In Appendix table 2A, the results of the control measures show the largest driver of incidents is population size. Agencies with a SWAT team see a higher prevalence of incidents. This fits with the anecdotal evidence of excessive force by units devoted to combating terrorism or drug activity (ACLU, 2014). Counties with a larger elderly population and higher median income see a lower prevalence of use-of-force incidents. These results are intuitive as counties with a higher socioeconomic status are less likely to experience use-of-force incidents. Finally, agencies with a larger share of African-American officers also see a lower prevalence of use-of force-incidents. This provides evidence that having a more diverse agency can lower the level of excessive use-of-force incidents.

As a robustness check, we re-estimate the models using different estimation procedures. In addition to the probit-2sls model, there is the direct two-stage least squares (direct-2sls) method, which is an instrumental variables (IV) regression fit directly with two-stage least squares, the probit-OLS method, which is an IV two-step regression fit by probit and OLS, and finally, the Heckit method, which is a Heckman two-step selection model. We also include a simple unconditional difference in means t-test.

Table 5. Comparison of ATE from Binary Treatment Estimation Methods

	T-test	Direct-2sls	Probit-2sls	Probit-OLS	Heckit
Acquired Items ($S_i = 1$)	1.991*** (0.079)	0.933 (0.630)	0.761 (0.729)		0.810 (0.595)
G_fv ¹⁰				0.558 (0.631)	

Note: + p<0.10, * p<0.05, ** p<0.01, *** p<0.001; robust standard errors in parentheses.

The results in Table 5 show that the treatment of surplus acquisition does not lead to a greater number of incidents and this finding is robust.

5.2 Categories

The previous models looked at total acquisition as a dependent variable. Now we estimate models in various categories to see if the type of acquisition matters for use-of-force incidents. It is plausible that the acquisition of guns will affect officers differently than the acquisition of military vehicles.

Table 6. Estimate of Effect of Acquisitions on Use of Force by Item Category (N=1,928)

	Tactical	Vehicles	Surveillance	Clothing
Acquired Items ($S_i = 1$)	0.356 (0.644)	-2.887+ (1.484)	-1.438 (2.391)	7.150 (7.399)

Note: + p<0.10, * p<0.05, ** p<0.01, *** p<0.001; robust standard errors in parentheses.

Table 6 shows that only vehicles have a mildly significant effect on incidents. Agencies that acquired vehicles are less likely to have incidents. While given the media coverage of MRAPs and other large combat and assault vehicles, this category also includes smaller passenger vehicles, trailers, and motorcycles.

¹⁰ This represents the predicted probability from the probit regression, conditional on the observable confounders.

We can break this category down further. In Table 7, we separate vehicles into tracked vehicles and wheeled vehicles.¹¹ We also focus more closely on tactical items (looking only at weapons, surveillance items), night vision items, and clothing (specifically body armor).

Table 7. Estimates of Surplus Acquisitions on Incidents by Smaller Category

	Weapons	Vehicles (Tracked)	Vehicles (Wheeled)	Night Vision	Body Armor
Acquired Items ($S_i = 1$)	0.317 (0.639)	1.437 (10.21)	-40.295 (142.74)	-0.920 (2.30)	27.231 (27.72)
N	1,928	1,346	1,843	1,928	1,557

Note: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; robust standard errors in parentheses.

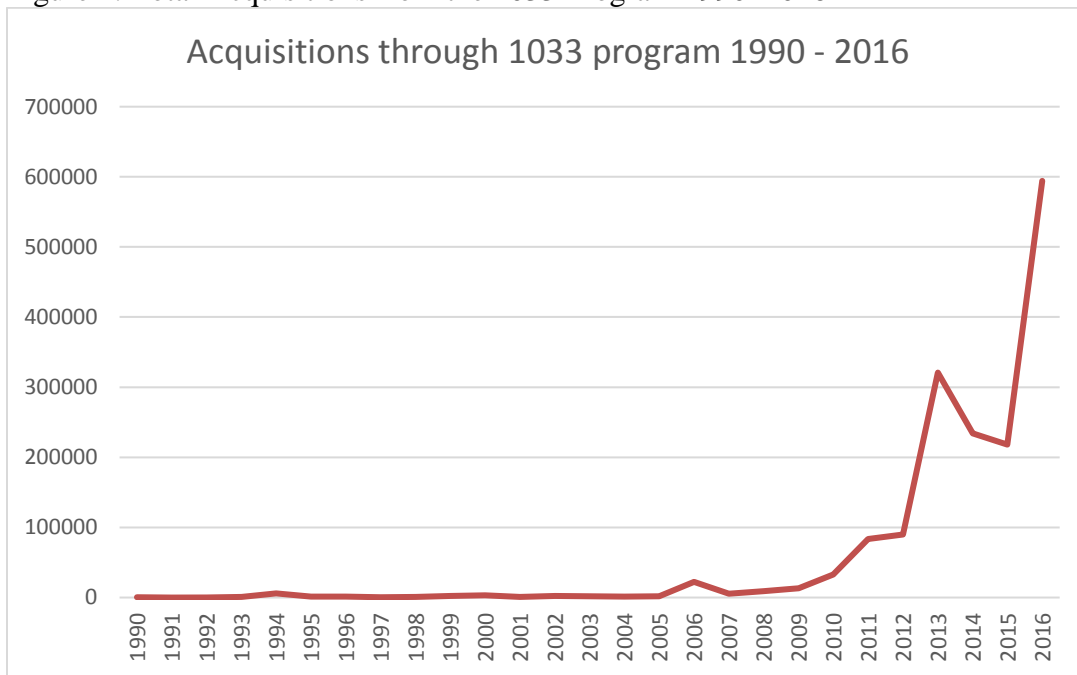
Tracked vehicles have a positive coefficient while wheeled vehicles have a negative coefficient, though neither measure is significant. One reason for the insignificant effects is that portioning the categories into smaller categories incurs a sample size issue. During this period, there were few acquisitions of vehicles and these other categories as they barely represent 3% of total acquisitions.

6. DISCUSSION

The results in the previous section show that the militarization of police through the Pentagon's 1033 Program does not lead to more use-of-force incidents. In the specific case of vehicles, it lowers the rate of use-of-force incidents. This result can be explained through the fact that vehicles are used during rescue operations and natural disasters (Shaw, 2015). Another explanation is that as of 2012, surplus acquisition was a relatively new phenomenon.

¹¹ Tracked vehicles were initially banned by the Obama administration in 2015, but were reinstated by the Trump Administration in August 2017.

Figure 1. Total Acquisitions from the 1033 Program 1990–2016



(Source: Author’s calculations from the Pentagon’s website)

As shown in Figure 1, interest in and the use of the 1033 Program is a recent phenomenon. There was an initial increase in acquisitions in 2006, followed by a large spike in 2013, and the number of acquisitions has continued to increase. Any dynamic between acquisitions and crime and negative externalities may not be evident in an analysis that uses a time sample prior to 2012.

The recent literature on police militarization and their effects have consistently shown that increased militarization lowers crime at the county level. Bove and Gavrilova (2017) find that higher-value military surplus acquisitions lower various arrest rates. They argue that militarization has a deterrent effect that increases the cost of criminal activities. Harris et al. (2017) find that militarization has similar effects on crime, even though those authors use different instruments and a different set of controls. There have been other studies addressing the relationship between police militarization and crime. McQuoid and Haynes, Jr. (2017), in their working paper using a panel of states, find a negative relationship between crime and militarization. In another working paper, Masera (2016) uses agency-level analysis and finds

militarization lowers crime. However, he is able to show that one-third of this effect is due to the shifting of crime to neighboring regions.

Few of these studies, however, address the potential adverse outcomes of police militarization. As described in the Data section, the lack of quality data, both in terms of validity and breadth, limits the degree to which rigorous analysis can occur. While Bove and Gavrilova (2017) and Harris et al. (2017) find that increased police militarization has no significant effect on citizen complaints or excessive use-of-force incidents, only Harris et al. (2017) mentions the issue of faulty data when it comes to collecting a nationally representative database of use-of-force incidents. Furthermore, using data from the Federal Bureau of Investigations (FBI), Masera (2016) finds that police militarization does increase officer-involved shootings.¹² Thus, there is more work to be done to better understand how police militarization affects local communities.

Another issue we need to think about when we discuss police militarization is how the items that are disbursed are employed in communities throughout the country. We need to consider whether, once deployed, they are disproportionately used against people of color or in low-income communities. Police militarization became an issue after the unrest in Ferguson, Missouri following the death of Michael Brown, an 18-year old African-American male, at the hands of Officer Darren Wilson. Images of the National Guard looking like an occupying force struck many in the public and media as problematic. Furthermore, after the recent acquittal of Officer Jason Stockley in the death of Anthony Lynn Smith, the St. Louis Police Department was already prepared in riot gear in anticipation of protests. However, earlier in the year there was minimal police presence during the Women's March, conducted a day after the Presidential

¹² As with other data, the FBI count of fatal encounters has been shown to undercount the actual numbers of police killings.

Inauguration (Blay, 2017). Further research, with available data, can help us to understand whether there are racial disparities in where and how military surplus items are used.

7. CONCLUSIONS

Images of police in U.S. towns deploying high-tech weaponry and tanks normally observed in war-torn nations have raised questions regarding the purpose of heavily arming civilian police. In addition, law enforcement officials have engaged in behavior more similar to that of the military as opposed to community policing. It has been argued that this blurring of the lines between the military and police is an outcome of the militarization of local law enforcement (Den Heyer, 2014; Kraska, 2007). The acquisition of military-type equipment has led to military-style tactics, such as the establishment of SWAT teams and no-knock raids. Instead of using these items in a reactive manner, police agencies use them proactively, which has sometimes led to fatal mistakes (Balko, 2013). The findings in this study show a causal link between the militarization of police and excessive use-of-force incidents.

Concern regarding the militarization of police is not new, but discussions in this regard have become more prevalent given the public incidents in Ferguson, Baltimore, and in many other U.S. cities. Such concerns are the subject of significant debate in the criminal justice literature (Den Heyer, 2014; Kappeler and Kraska, 2015). This study aimed to estimate whether the militarization of police, measured by the acquisition of military surplus through the Pentagon's 1033 Program, impacts on use-of-force incidents. Using a treatment effects estimator to identify a causal link, this study did not find evidence that the increased militarization of police is associated with a greater incidence of excessive force. In fact, the acquisition of vehicles lowered the prevalence of incidents. The concern of many groups about the growing

militarization of police is that it further damages the poor community relationship between police and citizens. The issues associated with police militarization are increasingly recognized as a problem at both the federal and local levels. In January 2015, former U.S. President Barack Obama established the Law Enforcement Working Group to find solutions to the police militarization problem. Many local agencies have started to return military items to the federal government. In February 2016, the Los Angeles Unified School District returned all of its acquired military surplus items (Kohli and Blume, 2016). However, the current U.S. President Donald Trump reversed the restrictions of the prior administration on specific types of military surplus.

An important issue emphasized in this study is the need for better data to conduct more conclusive research on excessive force. One limitation of this study is that it lacked detailed information on the nature of excessive force incidents. Currently, two national-level datasets, the PPCS from the BJS and the International Association of Chief of Police database, collect information on use-of-force incidents. However, these datasets are not nationally representative.¹³ Hickman et al. (2008) use the PPCS and the Survey of Inmates in Local Jails to generate aggregate numbers. Alpert and Smith (1999) argue that better organization and documentation of use-of-force incidents could improve policing. In Utah, agencies have begun requiring the collection of data on the deployment of tactical teams (Kaste, 2015). California has collected data on three types of police–citizen interactions: officers killed or assaulted, arrest rates, and deaths in custody.¹⁴ These data date back to 1980 and are updated continuously. Finally, the previous White House administration established the Public Safety Open Data

¹³ Fryer (2016) creates a detailed dataset on police-citizen interactions, but this is for a limited number of cities.

¹⁴ The website can be found at <http://openjustice.doj.ca.gov/>.

Portal¹⁵ for law enforcement agencies to voluntarily submit data on use-of-force incidents, officer-involved shootings, traffic stops, and other relevant data. As we gain access to more data, we can improve our understanding of police–citizen interactions, police behavior, and use-of-force incidents.

¹⁵ This website is now run by the Police Foundation: <https://publicsafetydataportal.org/>

REFERENCES

- Ajilore, O., 2015. The militarization of local law enforcement: is race a factor? *Appl. Econ. Lett.* 22(13), 1089–1093.
- Ajilore, O. and Shirey, S., 2017. Do# AllLivesMatter? An Evaluation of Race and Excessive Use of Force by Police. *Atlantic Economic Journal*, pp.1-12.
- Alpert, G.P., Smith, M.R., 1999. Police use-of-force data: where we are and where we should be going. *Police Q.* 2(1), 57–78.
- ACLU, 2014. War come home: the excessive militarization of American policing.
- Antonovics, K., Knight, B.G., 2009. A new look at racial profiling: evidence from the Boston Police Department. *Rev. Econ. Stat.* 91(1), 163–177.
- Anwar, S., Fang, H., 2006. An alternative test of racial prejudice in motor vehicle searches: theory and evidence. *Am. Econ. Rev.* 96(1), 127–151.
- Balko, R. 2013. Rise of the warrior cop: The militarization of America's police forces. Public Affairs Books.
- Benson, B. L., D. W. Rasmussen, and D. L. Sollars. 1995. "Police bureaucracies, their incentives, and the war on drugs." *Public Choice* 83.1-2 (1995): 21-45.
- Blay, Z. "Before You Celebrate The Zero Arrests At The Women's March..." The Huffington Post. January 23, 2017. Accessed October 19, 2017.
https://www.huffingtonpost.com/entry/before-you-celebrate-the-zero-arrests-at-the-womens-march_us_588617e4e4b0e3a7356a3ee4
- Bove, V. and Gavrilova, E. 2017. Police Officer on the Frontline or a Soldier? The Effect of Police Militarization on Crime. *American Economic Journal: Economic Policy*, 9(3), 1-18.
- Cerulli, G., 2014. `ivtreatreg`: A command for fitting binary treatment models with heterogeneous response to treatment and unobservable selection. *Stata J.* 14(3), 453–480.
- Close, B.R., Mason, P.L., 2007. Searching for efficient enforcement: officer characteristics and racially biased policing. *Rev. Law Econ.* 3(2), 263–321.
- Den Heyer, G., 2014. Mayberry revisited: a review of the influence of police paramilitary units on policing. *Polic. Soc.* 24(3), 346–361.
- Dharmapala, D., Garoupa, N., McAdams, R.H., 2016. Punitive police? Agency costs, law enforcement, and criminal procedure. *The J. of Leg Stud* 45(1): 105–141
- Friedrich, R.J., 1980. Police use of force: individuals, situations, and organizations. *Ann. Am. Acad. Political Soc. Sci.* 452(1), 82–97.
- Fryer, Jr., R. 2016. An Empirical Analysis of Racial Differences in Police Use of Force. National Bureau of Economic Research Working Paper No. 22399
- Garner, J.H., Maxwell, C.D., Heraux, C.G., 2002. Characteristics associated with the prevalence and severity of force used by the police. *Justice Q.* 19(4), 705–746.
- Grasso, V.B., 2013. Defense surplus equipment disposal: background information. Library of Congress, Washington, DC Congressional Research Service.

- Hall, A. R., Coyne, C.J. 2013. The Militarization of US Domestic Policing. *The Indep. Rev.* 17(4), 485-504
- Harris, M.C., Park, J., Bruce, D.J. and Murray, M.N., 2017. Peacekeeping force: Effects of providing tactical equipment to local law enforcement. *American Economic Journal: Economic Policy*, 9(3), pp.291-313.
- Hickman, M.J., Piquero, A.R., Garner, J.H., 2008. Toward a national estimate of police use of nonlethal force. *Criminol. Public Policy* 7(4), 563–604.
- Kappeler, V.E., Kraska, P.B., 2015. Normalising police militarisation, living in denial. *Polic. Soc.* 25(3), 268–275.
- Kaste, M. Why Utah is the Only State Trying to Track and Limit SWAT-Style Tactics. NPR Morning Edition. August 31, 2015
- Kohli, S., Blume, H. 2016. L.A. Schools Have Given up the Last of their Defense Department-issued Rifles. *Los Angeles Times*. February 23, 2016.
- Knowles, J., Persico, N., Todd, P., 2001. Racial bias in motor vehicle searches: theory and evidence. *J. Political Econ.* 109(1), 203–229.
- Kraska, P.B., 2007. Militarization and policing—its relevance to 21st century police. *Polic.* 1(4), 501–513.
- McQuoid, A.F. and Haynes, J.B., 2017. *The Thin (Red) Blue Line: Police Militarization and Violent Crime*. United States Naval Academy Department of Economics.
- Masera, F., Bringing War Home: Violent Crime, Police Killings and the Overmilitarization of the US Police (October 12, 2016). Available at SSRN: <https://ssrn.com/abstract=2851522>
- Musgrave, S. Every Item Distributed to Local Law Enforcement by the Pentagon’s 1033 Program Over Two Years. *MuckRock*. August 15, 2014
- Prendergast, C., 2007. The motivation and bias of bureaucrats. *Am. Econ. Rev.* 97, 180–196.
- Reardon, S.F., Firebaugh, G., 2002. Measures of multigroup segregation. *Sociol. Methodol.* 32(1), 33–67.
- Rezvani, A., Pupovac, J., Eads, D., Fisher, T. MRAPs and Bayonets: What We Know About the Pentagon’s 1033 Program. NPR. September 2, 2014
- Riksheim, E.C., Chermak, S.M., 1993. Causes of police behavior revisited. *J. Crim. Justice* 21(4), 353–382.
- Shaw, Adam. "Outrage as military vehicles, equipment taken from officers in wake of Obama order." *Fox News*. November 23, 2015. Accessed October 20, 2017. <http://www.foxnews.com/politics/2015/11/23/outrage-as-military-vehicles-equipment-taken-from-officers-in-wake-obama-order.html>.
- Smith, B.W., Holmes, M.D., 2014. Police use of excessive force in minority communities: a test of the minority threat, place, and community accountability hypotheses. *Soc. Probl.* 61(1), 83–104.
- Sun, I.Y., Payne, B.K., Wu, Y., 2008. The impact of situational factors, officer characteristics, and neighborhood context on police behavior: a multilevel analysis. *J. Crim. Justice* 36(1), 22–32.

Worden, R.E., 1995. The causes of police brutality: theory and evidence on police use of force. in W. A. Geller, & H. Toch, eds., *And Justice for All: Understanding and Controlling Police Abuse of Force*. Washington, DC: Police Executive Research Forum

APPENDIX TABLES

Table 1A. Ordinary Least Squares Estimates

	Total	Tactical	Guns	Vehicles	Surveillance	Clothing
Surplus Acquisitions	0.021 (0.021)	0.070+ (0.036)	0.070+ (0.036)	0.135+ (0.075)	0.116+ (0.062)	0.110+ (0.062)
Entry-level wage	-0.071 (0.257)	-0.067 (0.255)	-0.067 (0.255)	-0.054 (0.254)	-0.056 (0.254)	-0.059 (0.255)
Asset Forfeiture (Budget)	0.097 (0.133)	0.098 (0.132)	0.098 (0.132)	0.113 (0.132)	0.109 (0.132)	0.107 (0.132)
Body Camera Use	-0.003 (0.102)	0.002 (0.103)	0.003 (0.103)	0.003 (0.102)	0.001 (0.102)	-0.005 (0.102)
Dash Camera Use	-0.008 (0.090)	-0.014 (0.091)	-0.014 (0.091)	0.001 (0.091)	-0.006 (0.091)	-0.001 (0.091)
Share of Black Officers	-0.549 (0.404)	-0.508 (0.405)	-0.507 (0.405)	-0.444 (0.407)	-0.479 (0.408)	-0.460 (0.414)
Share of Hispanic Officers	-0.190 (0.543)	-0.175 (0.540)	-0.175 (0.540)	-0.174 (0.530)	-0.183 (0.537)	-0.177 (0.530)
8 Hrs. of Comm. Policing	0.136+ (0.080)	0.139+ (0.080)	0.139+ (0.080)	0.144+ (0.078)	0.146+ (0.078)	0.145+ (0.078)
Elderly Share	-2.683 (1.954)	-2.666 (1.958)	-2.666 (1.958)	-2.660 (1.971)	-2.703 (1.953)	-2.586 (1.958)
Owner-Occupied Share	-0.849 (0.865)	-0.858 (0.862)	-0.859 (0.862)	-0.834 (0.863)	-0.821 (0.859)	-0.814 (0.860)
Youth Share	-2.847 (2.107)	-2.930 (2.102)	-2.931 (2.102)	-2.950 (2.132)	-2.928 (2.115)	-2.866 (2.134)
Gini Index	-2.794 (2.035)	-2.584 (1.996)	-2.582 (1.996)	-2.563 (2.039)	-2.578 (2.029)	-2.635 (2.029)
Unemployment Rate	-0.318 (3.562)	-0.281 (3.560)	-0.282 (3.561)	0.091 (3.572)	-0.048 (3.542)	0.044 (3.563)
Median Household Income	-0.559+ (0.310)	-0.533+ (0.305)	-0.533+ (0.305)	-0.536+ (0.304)	-0.541+ (0.301)	-0.538+ (0.302)
Crime Index	0.041 (0.057)	0.040 (0.058)	0.040 (0.058)	0.059 (0.059)	0.059 (0.060)	0.056 (0.059)
Census Population	0.296*** (0.060)	0.328*** (0.059)	0.328*** (0.059)	0.379*** (0.070)	0.366*** (0.068)	0.363*** (0.061)
Share Black	-0.218 (0.404)	-0.194 (0.405)	-0.193 (0.405)	-0.224 (0.416)	-0.214 (0.412)	-0.209 (0.416)
Share Latino	-0.078 (0.786)	-0.088 (0.789)	-0.088 (0.789)	-0.145 (0.775)	-0.129 (0.787)	-0.116 (0.779)
Segregation Index	-0.857* (0.404)	-0.859* (0.405)	-0.859* (0.405)	-0.859* (0.416)	-0.877* (0.412)	-0.855* (0.416)

	(0.399)	(0.399)	(0.399)	(0.401)	(0.402)	(0.402)
SWAT team	0.194 (0.117)	0.191 (0.117)	0.191 (0.117)	0.193 (0.118)	0.191 (0.117)	0.191 (0.117)
Gang Taskforce	-0.072 (0.102)	-0.071 (0.101)	-0.071 (0.101)	-0.055 (0.097)	-0.062 (0.099)	-0.061 (0.099)
Drug Taskforce	0.064 (0.084)	0.070 (0.084)	0.070 (0.084)	0.079 (0.083)	0.076 (0.082)	0.080 (0.085)
Terrorism Special Unit	0.214+ (0.111)	0.216+ (0.111)	0.216+ (0.111)	0.219+ (0.112)	0.216+ (0.111)	0.217+ (0.111)

Table 2A. Full Estimation Results of Binary Treatment Model

	Total Surplus	1st Stage Probit		
Acquired Items ($S_i = 1$)	0.761 (0.729)			
			<i>Instruments</i>	
Entry-level wage	0.175 (0.175)	0.125 (0.175)	Distance to Center	0.067 (0.060)
Asset Forfeiture (Budget)	-0.232 (0.233)	0.110 (0.082)	Field activity center	0.154 (0.112)
Body Camera Use	-0.025 (0.093)	0.013 (0.088)	County area	0.107+ (0.058)
Dash Camera Use	0.127 (0.105)	0.229* (0.089)	<i>HIDTA region</i>	
Share of Black Officers	-0.881+ (0.513)	0.448 (0.506)	Atlantic1	-0.109 (0.201)
Share of Hispanic Officers	-0.260 (0.492)	-0.870+ (0.455)	Atlantic2	-0.246 (0.274)
8 Hrs. of Community Policing	0.039 (0.085)	0.073 (0.077)	California	0.297 (0.283)
			Los Angeles	0.916** (0.334)
Elderly Share	-3.195+ (1.672)	-0.762 (1.737)	Pacific	-0.752* (0.294)
Owner-Occupied Share	0.738 (0.789)	0.705 (0.796)	Rocky Mountain	-0.226 (0.254)
Youth Share	-0.742 (1.712)	2.609 (1.668)	Southwest1	-0.420 (0.256)
Gini Index	1.052 (1.781)	-2.445 (1.590)	Southwest2	0.355 (0.292)
Unemployment Rate	-2.161 (3.644)	4.830 (3.207)	Florida	0.392+ (0.230)
Median Household Income	-0.339+ (0.199)	-0.322 (0.271)	Gulf Coast	-0.193 (0.352)
Crime Index	0.132 (0.103)	0.263** (0.101)	Midwest	0.150 (0.222)
Census Population	0.218*** (0.056)	0.075+ (0.041)	Michigan/Ohio	0.420* (0.209)
Share Black	-0.419 (1.039)	-0.846 (0.526)	Wisconsin/Lake County	0.426 (0.261)
Share Latino	-0.596 (0.835)	-0.888+ (0.539)	Chicago	0.339 (0.271)
Segregation Index	-1.379 (1.001)	-0.527 (0.373)	New York/New Jersey	-0.292 (0.197)

			New England	0.052
SWAT team	0.452+	0.094		(0.217)
	(0.243)	(0.085)		
Gang Taskforce	-0.289	0.152		
	(0.295)	(0.094)		
Drug Taskforce	-0.006	0.014		
	(0.245)	(0.090)		
Terrorism Special Unit	0.150	-0.015		
	(0.206)	(0.077)		
Kliebergen-Paap F Statistic	15.322			
Hansen J-statistic p-value	0.385			

Figure 1A. HIDTA designated regions

High Intensity Drug Trafficking Areas Program Counties 2011 with Intelligence and Information Sharing Initiative Locations

