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Author
Eusterbrock, Matias

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Undergraduate

The Black Box of the Blue Lights: Investigating Police Militarization Through Participation in the 1033 Program

Matias Eusterbrock

Olivier Deschenes, PhD

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Abstract:

As handheld cameras and social media increase the visibility of officer involved shootings and excessive use of force, the use of advanced military technology by police has raised important questions on the war on crime. While aggrieved citizens decry this militarization, limited data and a lack of nationally homogenous accountability procedures prohibits systemic analysis of these concerns. Utilizing unique data on department acquisitions of military gear from 1996-2017, we assess the influence of demographic and economic factors on police militarization. Using a series of robust regression models, we find that rural areas are much more likely to acquire military-grade weapons and vehicles. Additionally, county political affiliation and minority population may also be predictive of these outcomes. This study is among the most rigorous efforts to identify causal relationships of an increasingly militarized police force, and informs the growing debate on law enforcement methods in the 21st century.

Introduction:

Politicians and the public increasingly scrutinize excessive use of force and militarization by the police. As jarring videos of officer involved shootings circulate social media and news outlets, large protests have erupted in towns such as Ferguson, MO and Charlotte, NC. Departments have responded to these protests clad in riot gear and mounted in heavily armored vehicles, further compounding perceptions of an overly militant police force. Aggrieved citizens claim these police-related tragedies intentionally target communities of color and other marginalized groups, and have formed sizeable coalitions to mobilize against this. The social dialogue fostered by these issues invokes central questions about the proper role of law enforcement, and has involved lawmakers and advocacy groups across the political spectrum

Limited access to information regarding LEA practices, policies, and equipment purchases has stymied greater levels of research into this topic. Due to the potentially volatile nature of citizen oversight, LEAs and their political advocates have historically resisted the intrusion of the public into their affairs. Furthermore, the lack of organizational homogeneity across departments has challenged systemic study of this issue.

Utilizing a unique dataset on military acquisitions from 1996-2017 by LEAs across the country, we are able to peer into the "black box" of policing and assess the predictive ability of a host of demographic and economic factors on utilization of military equipment. The 1033 Program, authorized by Congress in 1996, allows the Department of Defense (DoD) to excess military gear to interested LEAs. Thanks to a plethora of requests by lawyers and journalists for information on this program pursuant to the Freedom of Information Act (FOIA), the Defense Logistics Agency (DLA) currently publishes a list of current inventors held by participating LEAs. We combine this data with economic and demographic factors in order to assess the ability of these factors to predict participation in the 1033 Program.

There exists a small body of research on causal relationships of increased police militarization. Radil, Dezzani, and McAden (2017) find statistically significant differences in participation in the 1033 Program across the country, but perform limited quantitative analysis to explore this more completely. Ajilore (2015) identifies statistically significant relationships between vehicle acquisition and race, but fails to utilize appropriate controls. We build off of this work, as well as other studies on human capital distribution in police departments, to construct robust models to identify factors that contribute to increased participation in the 1033 Program.

Our estimates find that rural counties are substantially more likely to utilize the 1033 Program across a broad array of models. Additionally, race and political affiliation may impact departmental decisions.

This paper contributes to the literature on police militarization by providing a statistically robust analysis of participation in the 1033 Program. By merging data from the DLA with important demographic and economic variables, we are able to conduct a comprehensive, rigorous analysis of this Program.

Literature Review:

Throughout the second half of the 20th century, law enforcement agencies across the United States increasingly utilized military operational strategy and equipment. Using an independent, nationally representative survey on police departments, Kraska and Kappeler (1997) find that the use of Paramilitary Police Units (PPUs), units within police departments that explicitly utilize combat tactics derived from the military, nearly doubled in medium to large cities from 1980 to 1996. This trend was even more pronounced in small jurisdictions, which experienced more than 150% growth in the presence of PPUs between 1985 and 1995 (Kraska & Cubellis, 1997). Furthermore, departments increased their use of these units nearly tenfold between 1985 and 1995. In addition to adopting operational dimensions of traditional militaries, Kraska finds that civilian police have also increasingly adopted material dimensions of the military by utilizing combat weapons and advanced technology to achieve objectives of social control (Kraska, 2007).

The material militarization of the police is currently facilitated in part by the National Defense Authorization Act (NDAA), also known as the "1033 Program". As part of a politicized response to concerns in the late 1980s over a growing drug trade, Congressional enactment of the NDAA in 1990 allowed police departments and other law enforcement agencies to request access to excess military equipment stored in warehouses throughout the country by the Department of Defense (DoD). This equipment includes a broad range of military gear such as weapons and armored vehicles, as well as mundane items such as office supplies and athletic gear. Otherwise scrapped after 40 days, this equipment was made available to qualifying departments for only the cost of transportation. The savings offered to police departments are considerable: mine-resistant anti personnel (MRAP) vehicles with an original acquisition value of over $700,000 can be transported for less than $7,000 (C. McCarty, 2017). Remaining operable to date, this program has provided over $4 billion in equipment to law enforcement agencies since its inception, with $2.4 billion worth of equipment currently held in police inventories (Bove & Gavrilova, 2017; own calculations).

Public outcry in response to this militarization has erupted as videos of excessive use of police force and military equipment circulate social media and news sources. Police clad in riot gear brandishing automatic rifles while mounted on mine resistant armored vehicles met protestors in Ferguson responding to the killing of unarmed African American Michael Brown. The widespread circulation of images of this response further fanned the flames of discontent, and catapulted this discourse on this issue to the national level

Opponents of militarization claim that this level of response is excessive, and targets minority communities and increases police aggression. In response to the protests of Ferguson, former President Barack Obama declared that "equipment made for the battlefield is not appropriate for local police departments," (Nakamura & Lowery, 2015) and signed an executive order restricting LEA access to the most militarized gear. Activist organizations such as Black

Lives Matter (BLM) and the Movement for Black Lives (M4BL) connect police militarization and officer related shootings of African Americans with the racist historic legacy of the United States. Corroborating this understanding, Jacobs and O'Brien (1998) observe that greater levels of racial inequality has a statistically significant relationship with police killings of African Americans. In a study of four states - Connecticut, Maine, Nevada, and New Hampshire – Delehanty, et al (2017) find that equipment transfers through the 1033 Program has a statistically significant and positive impact on police aggression and civilian casualties from officer-involved shootings. However, in-depth quantitative analysis of the cause of this militarization remains sparse.

Proponents of increased police militarization cite increased officer safety and a reduction in crime rates as key considerations. Bove and Gavrilova (2017) identify significant decreases in a host of crimes in counties that received excess military equipment from 2006-2012. Additionally they identify substantial financial benefits to society as a result of the 1033 Program, albeit under rudimentary cost benefit analysis assumptions. Harris, et al (2017) find that the reception of military equipment results in a reduction in civilian complaints and assaults on police officers, as well as an increase in conviction rates for violent and drug-related crimes. Importantly, both analyses reject a relationship between equipment acquisitions and increased police aggression. This perspective is shared by current US Attorney General Jeff Sessions, who lifted Obama-era restrictions on departmental access to grenade launchers, armored vehicles, and other "lifesaving gear" through the 1033 program (Sessions, 2017).

Given the positive and negative implications of police militarization, researchers should look into the regional demographic characteristics that predict it. Geographers Radil, Dezzani, and McAden (2017) find that equipment acquisitions through the 1033 Program varied significantly throughout the continental United States and that counties were more likely to utilize the program if neighboring counties did so. Maps generated by the authors appear to show indicate that rural LEAs utilized greater levels of equipment per capita, though quantitative methods were not utilized to examine this distinction. In an analysis of transactions under the 1033 Program from 2006 to 2014, Ajilore (2015) finds that acquisition of MRAP vehicles is negatively correlated with the share of African-Americans and positively correlated with residential segregation within a county. However, this analysis errantly lacked appropriate fiscal controls due to a misperception of the program's administration. Additionally, research on police force size has found it to be positively associated with the power of the Republican party (Jacobs & Helms, 1997), economic inequality (Jacobs & Helms, 1997), and Black population (McCarty, Ren, & Zhao, 2012; Stults & Baumer, 2007).

The aim of this research is to unify existing research on the spatial geography of police resource distribution with new data on material increases in police militarization. The utilization of advanced military technology to achieve law enforcement objectives is a relatively recent phenomenon, and research should distinguish this from studies on police force size. Guided by past research, in the following paper we work to identify predictive relationships between military equipment acquisitions and political, racial, criminal, and economic factors of counties.

Data:

Dependent Variables

To operationalize Kraska's definition on material militarization (Kraska, 2007), we use data recently released by the DLA of excess military property currently held by law enforcement agencies. These data include information on the type, quantity, shipping date, and original acquisition value of military gear held by these agencies, and excludes equipment that was retired or returned after transferring. The total value of property held by all local police departments has an original acquisition value over $2.4 billion. Using NATO Stock Numbers (NSN), this property was classified into one of three categories: weapons (guns, batons, and grenade launchers), military vehicles (including aircraft, mine resistant vehicles, and armored personnel carriers), and body armor (cite articles that use similar categories). Items not included in one of these categories were excluded for the purpose of this study. Department possession of these items was then aggregated to the county level to identify total current equipment stocks of each of these categories. Heat maps of the location of weapons and vehicles are displayed in Figure 1, and descriptive statistics are summarized in Table 1. Similar to maps presented in Radil, Dezzani, and McAden (2017), it appears weapon acquisitions are clustered by proximity. Counties receive an average of almost 24 weapons and over 2 militarized vehicles.

<Insert Table 1 Here>

<Insert Figure 1 Here>

Independent Variables

Data on crime rates and police department characteristics are publically available through the Interuniversity Consortium for Political and Social Research (ICPSR). In order to focus on determinants of local decision-making, only local police departments were included in this study, thus excluding LEAs such as Park Rangers and State Police. Police force size was estimated using the total number of full time sworn officers from the 2008 Census of State and Local Law Enforcement Agencies (CSLLEA08), a quadrennial study published by the Bureau of Justice Statistics (BJS). As shown in Table 1, the average county employed nearly 200 full-time law enforcement officers. Crime data from 2011-15 was drawn from the Uniform Crime Reports (UCR) Annual Summary Reports and Offenses and Clearances published by the BJS. This data includes the total number of reported crimes, arrests, and clearances in all US county equivalents for a broad range of crimes. Our total crime metric is an aggregation of murder, assault, rape, robbery, burglary, and grand theft auto. The average county experienced 1521 crimes per 100,000 residents.

Data on police and 1033 Program utilization were merged with demographic data from a variety of sources. County population characteristics including race, share male, and population size were drawn from 5-year Census estimates for 2011-15. Regional urbanicity estimates are drawn from the 2010 US Census estimates, and incorporate regional development type, density, and location. As depicted in the leftmost heat map in Figure 2, rural areas appear to be concentrated in the Southwest and Midwestern states, though there exists considerable heterogeneity. Political affiliation is determined by 2012 presidential election results for the Republican (Romney) and Democratic (Obama) candidates, data published by the US Geological Survey. Depicted in the rightmost heat map in Figure 2, counties with the highest percentage of votes for the Republican candidate appear concentrated in the middle of the United States, though includes large swathes of the Southeast and eastern portion of the Western region.

<Insert Figure 2 Here>

Economic variables were also merged to this dataset. Annual unemployment rates published by the Bureau of Labor Statistics were used to generate a 5-year county average from 2011-15. 5-year estimates of the percentage of the county population at or below poverty were provided by the American Community Survey. Annual per capita income estimates provided by the Bureau for Economic Analysis were used to generate 5-year averages for 2011-15. Local government tax revenue during the 2001-02 fiscal year is published by the US Department of Commerce and Census Bureau, and made available by ICPSR. All financial metrics adjust for inflation using updated CPI values published by the BLS.

Empirical Strategy:

In order to test which counties are more likely to militarize, we operationalize Kraska's definition of material militarization by aggregating military equipment acquisitions by local police departments through the 1033 Program. Given that requirements are very low for police departments to qualify for access to the 1033 Program[1], by assessing differences in program participation we can identify departmental distinctions that may predict increased militarization. If exogenous variation in our independent variables is correlated with a change in the level of departmental participation in the 1033 Program, this may indicate that these factors play a role in material processes of militarization. Using a host of reliable quantitative estimates for county political beliefs, crime rates, and racial composition, we will analyze the impact of a range of cultural differences on increased militarization from 1990-2016.

Before beginning our analysis, several steps were taken to homogenize our sample. County observations for which information on all independent variables was not present were dropped, leaving a final analytic sample size of 2,982. To avoid unintentional downward bias on select variables, independent and dependent variables were weighted by the population size.

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[1] Indeed, the US Government Accountability Office was able to request over $1 million in equipment using fabricated information for a nonexistent LEA. https://www.wired.com/story/gao-sting-defense-department-weapons/

Additionally, equipment transactions were aggregated by unit and not item value. Although information regarding the original price paid by the military is available in our dataset, it need not reflect the prices facing LEAs. For example, the high level of technology present in night vision goggles contribute to a high original price paid for by its original consumers within the military. However, given their light weight and the nature of the 1033 Program, these items are likely to be much cheaper than other items such as scrap metal for vehicle repair which had a lower original acquisition value. Therefore, we determine that quantity of items is a more appropriate metric for our analysis, though we observe little qualitative differences in analysis when using quantity or cost.

We analyze the impact of county level demographic factors on militarization using several multivariate regressions. First, we utilize the following baseline model:

$$Y_c = \alpha + \beta M_c + \delta_c + \varepsilon \qquad (1)$$

where Y_c is the quantity of military equipment transferred to local police departments for county c, β represents the coefficient of one of our explanatory variables of interest M_c, and δ represents state-level fixed effects. By including a vector of binary variables for each state in our analysis, we control for county-invariant differences between states such as state-specific laws that may introduce endogeneity into our model and bias our estimates. Heteroskedasticity robust standard errors are clustered at the state level to address intra-state treatment heterogeneity.

Coefficient estimates from our baseline model may be biased due to the omission of variables correlated to both our independent and dependent variables. For example, economic factors such as poverty and unemployment are likely to result in increased levels of crime. These economically depressed counties are also likely to have lower general revenue to invest in policing equipment, resulting in a negative bias on our crime coefficient. To address this, we use a host of controls from existing economic literature on crime and public spending: poverty rate, unemployment rate, per capita income, population, population density, share of males in the population, and local governmental tax revenue (ie. Bove & Gavrilova, 2017; Levitt, 1997). Employing these controls gives us the following model:

$$Y_c = \alpha + \beta M_c + \gamma E'_c + \delta_c + \varepsilon \qquad (2)$$

where *E*' represents the vector of control variables for county *c* discussed above. Robust standard errors are clustered at the state level to address intra-state treatment heterogeneity.

While our explanatory variables may be predictive of increased utilization of the 1033 Program, correlation between our explanatory variables will bias separate linear regressions. Therefore, we utilize the following model to address this issue:

$$Y_c = \alpha + \beta M'_c + \delta_c + \varepsilon \qquad (3)$$

where *M*' represents a vector of all explanatory variables used in this study. Standard errors are clustered at the state level and robust to heteroskedasticity.

However, given the likely sources of omitted variable bias discussed above, our most rigorous model is as follows:

$$Y_c = \alpha + \beta M'_c + \gamma E'_c + \delta_c + \varepsilon \qquad (4)$$

in which vectors for all of our explanatory variables, *M*', all of our control variables, *E*', and state fixed effects are included jointly. As in all models, standard errors are robust to heteroskedasticity and are clustered at the state level.

Results:

The results for our baseline model using only one of our key variables at a time are presented in Table 2. All regressions utilize state-level fixed effects, and robust standard errors are clustered at the state level and reported beneath their respective coefficients. Odd-numbered columns represent regressions in which only state fixed effects were used. Even-numbered columns represent OLS coefficient estimates in which economic and demographic controls are also included. Both dependent and independent variables have been standardized, meaning coefficients represent effect size of the relationships.

Using our baseline model, we find consistent statistically significant relationships between many of our explanatory variables and acquisition of excess military gear through the 1033 Program.

<Insert Table 2 Here>

Regressions with and without controls estimate statistically significant negative effect sizes for total crime rate on per capita levels of weapons and vehicles. With no controls, total crime rates show an effect size of -0.0604 on weapons per capita and -0.0913 on military vehicles per capita. The magnitudes of these effects appear to increase slightly once more rigorous controls are utilized, with weapons and vehicles showing effect sizes of -0.0722 and -0.096 respectively. However, it is likely that crime rate is endogenous to military equipment utilization by law enforcement officers, and thus this estimated relationship might suffer from considerable bias. Given a lack of appropriate instrumental variables this cross-sectional data, we acknowledge that interpretation of effect size estimates of crime on 1033 Program utilization are not feasible. Effect sizes for body armor per capita were negative but not statistically significant.

Racial demographics of the county population showed consistently negative and statistically significant relationships with our outcome variables. A one standard deviation increase in the non-white percentage of county population was related to a corresponding decrease in weapons per capita by .0509 standard deviations when uncontrolled regressions were utilized, although this estimate was only significant at the 10% level. This estimated effect size grew in magnitude following the use of more robust controls, although it remained insignificant at the 5% level. Non-white population showed an effect size of -.0714 on vehicle acquisition, a finding that was significant at the 1% level. This finding increased in magnitude to -.0738 following the addition of control variables, while remaining significant at the 5% level. These findings do not support anecdotal claims of racialized implementation of military tactics, though increasingly robust models will shed more light on this question. There appears to be no statistical relationship between body armor per capita and county racial demographics.

The effects of minority population on weapons per capita appear heterogeneous across different races and ethnicities. Counties with greater percentages of Hispanics appear to acquire less weapons and vehicles, with respective effect sizes of -.0752 and -.041 in models utilizing state fixed effects and additional controls. These estimates are robust at the 5% level, and do not support hypotheses of racialized motivation for police militarization. Counties with higher percentages of Blacks showed negative relationships with weapon and vehicle acquisitions, although these effect sizes are not significant at the 10% level. While this does not support historically prevalent patterns of increased policing resources in Black communities, a lack of statistical significance does not allow us to infer further. Percentage of Asians in the county population show the largest effect sizes, with estimated coefficients of -.1388 for weapons and -.0849 for vehicles using fixed effects and our additional control variables. While these findings are not corroborated by previous research, they remain comparatively large and robust at the 5% level.

The percent of the population that voted for the Republican presidential candidate in the 2012 election was statistically significantly related to equipment acquisitions. GOP voting percentage shows an estimated effect size of 0.0891 for weapons per capita and 0.0821 for vehicles per capita in models that only utilized state fixed effect controls. These results were significant at the 1% level. After utilizing additional controls these effect sizes strengthened to 0.107 for weapons per capita and 0.0822 for vehicles per capita, both of which were significant at the 5% level. Although we were unable to find rigorous academic research that identified a connection between political ideology and police militarization, surveys by Cato Institute and YouGov in 2016 indicated that only 40% of conservatives believed that police militarization was excessive, as compared to 75% of liberals (Ekins, 2016). Given that causal factors leading to GOP voting percentage are likely endogenous to our models, we will explore this relationship further in subsequent estimates. There was no observable relationship between GOP voting patterns on body armor per capita.

LEOs per capita appear to have no statistically significant relationship with equipment acquisitions per capita. In regressions utilizing only state fixed effects, LEOs per capita showed a positive effect size of 0.0755 on weapon acquisitions, although this effect size is not significant at the 5% level. An effect size of .0361 was found on LEOs per capita and vehicle acquisitions, although this estimate was also insignificant at the 5% level. Although the inclusion of additional control variables increases these effect sizes, they remain insignificant at the 5% level. This result is perplexing, as it strikes us that greater police force size would have greater equipment needs. However, this may indicate some level of substitution effect, where human capital is replaced by physical capital. There also appeared to be no observable relationship between LEOs per capita and body armor acquisitions.

The percent of the housing stock in the county that was considered rural was statistically significantly related to equipment acquisitions. In regressions using only state fixed effects, rural housing in the county showed an effect size of 0.1638 on weapons per capita and an effect size of 0.1641 on vehicles per capita. These effect sizes were considerably larger than those of any other explanatory variable in our study, and were significant at the 0.1% level. Following additional controls, our OLS effect size estimates grew to .1692 for weapons and .1745 for vehicles while remaining significant at the 0.1% level. These results are comparatively quite large, and corroborate qualitative assessments by Radil, et al (2017) regarding the distribution of 1033 Program resources. As with all of our explanatory variables, there was no observable relationship between rural housing stock and body armor acquisitions.

The Gini index of economic inequality did not appear to have a meaningful impact on equipment acquisitions per capita. Utilizing only state fixed effects, OLS estimates find LEOs per capita have an effect size of -.0158 for weapons acquisitions, .0072 for vehicle acquisitions, and -.0202 for body armor acquisitions. None of these findings are significant at the 10% level. Additional controls appear to increase the magnitude of the respective effect sizes, although all estimates remain insignificant at the 90% level.

Despite the consistent direction and statistical significance of these results, our explanatory variables appear to be statistically significantly correlated with themselves. While this may be observed qualitatively from Figure 2, OLS regressions using state fixed effects presented in Table 3 estimate large and highly significant effect sizes of rural housing stock on our other explanatory variables. Given that rural housing stock shows positive impacts on both weapons and vehicle acquisitions, negative effect sizes of rural housing stock on crime, presence of racial minorities, and the Gini index of economic inequality will result in downward bias on the model estimates for these variables if rural variables are omitted. Conversely, the positive relationship between rural housing and GOP votes means estimates that omit rural housing will bias the effect size estimates of GOP voting percentage on equipment acquisitions. To address this concern of bias, we next include rural housing as a control for separate OLS regressions.

<Insert Table 3 Here>

Table 4 shows the results of expanding our controls to include rural housing stock. Odd-numbered columns represent effect sizes for separate regressions using state fixed effects and all controls from regressions in Table 2. Even numbered columns display effect sizes from regressions utilizing the same fixed effects and controls as well as controls for rural housing stock in the county. As predicted, effect sizes on weapons and military vehicles for the crime rate, racial demographics, and Gini index of a county become more positive following inclusion of rural controls. Excepting the presence of Asians, all of these variables lose statistical significance once this more robust model is utilized. Additionally, the inclusion of rural controls greatly lessens the estimated effect size of Republican voters on all equipment acquisitions. In addition to a substantially reduced effect size estimate, the estimate for weapon acquisition is only statistically significant at the 10% level, and not statistically significant at all for vehicle and body armor acquisitions.

<Insert Table 4 Here>

In addition to the bias on our effect size estimates caused by omitting rural housing controls, correlation between other explanatory variables will also bias our regressions. As shown in Table 5, pairwise Pearson's correlation tests show that there are indeed sizable and statistically significant relationships between most of our independent variables. Given the bias that separate regressions of these variables will induce on our estimates, we next estimate joint regressions by including all of our explanatory variables within a single model.

<Insert Table 5 Here>

Table 6 shows our model estimates once all of our explanatory variables are included. Body armor acquisitions have been excluded, as none of our explanatory variables are able to predict changes in this outcome. Odd numbered columns represent regression estimates including state fixed effects but no further controls. Even numbered columns represent OLS estimates including both state fixed effects and a host of economic and demographic controls.

<Insert Table 6 Here>

In the model utilizing only state fixed effects, we see that nearly all variables fail tests of statistical significance except rural housing stock. Indeed, the effect size for rural housing appears virtually unchanged from original estimates, and remains statistically significant at the 0.1% level. Including our economic and demographic control variables addresses the potential for omitted variables bias. Following the inclusion of these controls, Asian population is no longer statistically significant, and GOP voting population becomes statistically significant at the 5% level. Rural housing stock continues to remain the strongest predictor of military equipment acquisition after a series of rigorous controls are implemented, and remains at statistical significance at the 0.1% level across all model specifications.

Given the importance of rural indicators in predicting equipment acquisitions, in Table 7 we assess heterogeneous effects of other explanatory variables across different levels of rural indicators. In Table 7(a), we use our most rigorous models to identify changes in the explanatory ability of our independent variables across the top 50% most rural counties and the bottom 50% of rural counties. As a robustness check, in Table 7(b) we present effect size heterogeneity across counties in which less than 50% of housing is rural and counties with more than 50% of housing classified as urban. Odd numbered columns represent joint OLS estimates of all explanatory variables, utilizing state fixed effects but no controls. Even numbered columns present joint regression estimates using state fixed effects as well as economic and demographic control variables.

<Insert Table 7 Here>

There appears to be effect size heterogeneity in some of our explanatory variables across the most and least rural counties. Hispanic population in the most rural half of counties has an effect size of -.1346 on weapon acquisitions in models utilizing controls. This finding is statistically significant at the 5% level, and corroborated by estimates of similar magnitude and significance in uncontrolled models. This finding also withholds the alternate rural specification in Table 7(b), in which the percent of Hispanics in the counties with over 50% of housing classified as rural shows an effect size of -.1158 after utilizing both state fixed effects and controls. This finding is significant at the at the 1% level, and corroborated in uncontrolled models. The effect size of Hispanic population on military vehicle acquisitions also appears to be negative in rural counties, though this finding is not significant at the 10% level. Conversely, urban counties appear to have a positive relationship between Hispanic population and equipment acquisitions, although this finding does not retain statistical significance following inclusion of our control variables.

Political affiliation appears to have a tenuous positive relationship with weapon and vehicle acquisition. Although the effect size remains positive across all specifications, only in counties in which over 50% of the housing stock are considered rural do these estimates retain statistical significance at the 5% level. While this variable appeared statistically significant in earlier models, it appears correlated covariates absorb much of this effect.

In both rural and urban counties, rural housing stock continues to have a substantial impact on equipment acquisitions. Comparisons across both specifications of urbanicity indicate that increases in rural housing stock in relatively urban counties has a greater impact on weapons than on vehicles. Given that we control for land area and population density, this variation cannot be explained by greater traveling distance.

Conclusion:

It appears that indicators of urbanicity have substantial ability to predict the utilization of military technology by LEAs. However, the USGS metric is an imperfect metric, as it obscures the distinctions between urbab, suburban, and rural. While these areas may indeed have distinct law enforcement cultures that differentially affect the likelihood of acquiring military weapons and vehicles, the broad strokes painted by our metric do not allow for finer analysis to occur. Falcone et al (2002), Meeks 2015,

As discussed by Kraska, Cubellis, and Kappeler (Kraska & Cubellis, 1997; Kraska & Kappeler, 1997), considerable militarization of the police occurred prior to the implementation of the 1033 Program in 1990. Therefore, utilization of the 1033 Program may represent a "catching up" effect, whereby communities that did not militarize in earlier generations are now taking advantage of discounted prices. This would have substantial impacts on the interpretation of our estimates. More accurate assessments of the factors leading to militarization must therefore take into account total existing equipment utilized by LEAs. As lawmakers and public interest groups advocate for sensible police practices, gathering data that is more representative of these inventories must be gathered.

It is also noted that most research identified in our literature review analyzed militarization at the level of individual cities or metropolitan statistical areas (MSAs). It is plausible that variables relevant to LEA decision making such as race or political affiliation may be diluted at the county level, since most departments in our sample our local city police departments. Future research should work on select departments to assess these impacts at the city level, conditional on the availability of relevant data.

Table I: Summary Statistics for Key Variables

	Mean	SD	Min	Max	Observations
Dependent Variables					
Quantity					
Weapons	23.8	63.59	0	2,314	3,116
Vehicles	2.27	5.28	0	105	3,116
Body armor	5.3	50.35	0	2,266	3,116
Acquisition Value					
Weapons	$8,633	$24,185	$0	$699,760	3104
Vehicles	$313,617	$698,141	$0	$10,200,000	3104
Body armor	$696	$5,316	$0	$141,149	3104
Independent Variables					
Crime rate	1,521	978	0.4	8,437	3,020
% GOP vote in 2012	59.7	14.8	6.0	96.2	3,113
Total population*	101,467	324,454	85	10,038,388	3,112
% Male*	50.0	2.4	40.6	73.2	3,112
% Minority*	14.2	16.0	0.0	87.9	3,112
% Hispanic*	8.9	13.6	0.0	98.7	3,112
% Black*	9.8	14.7	0.0	85.9	3,112
% Asian*	1.6	3.1	0.0	60.5	3,112
% Population at or below poverty*	16.7	6.5	1.4	48.7	3,112
FT sworn personnel	194.3	993.8	0.5	36,243	3,104
% Housing units rural**	59.4	31.5	0.0	100.0	3,114
Unemployment rate*	7.1	2.4	1.5	25.9	3,104
Income per capita*	$39,260	$10,994	$15,985	$184,794	3,059
General revenue per capita***	$3,009	$1,438	$102	$43,774	3,134
Gini Index	0.44	0.03	0.33	0.62	2,982

*5-year average from 2011-15
** 2010 estimates
***2001-2002 fiscal year

Figure 1- Heat maps of select dependent variables

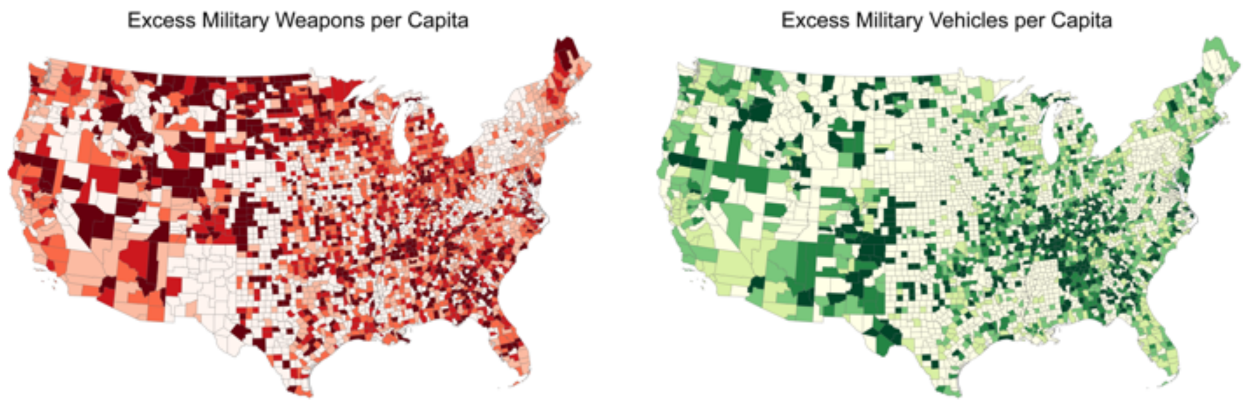

Figure 2- Heat maps of select independent variables

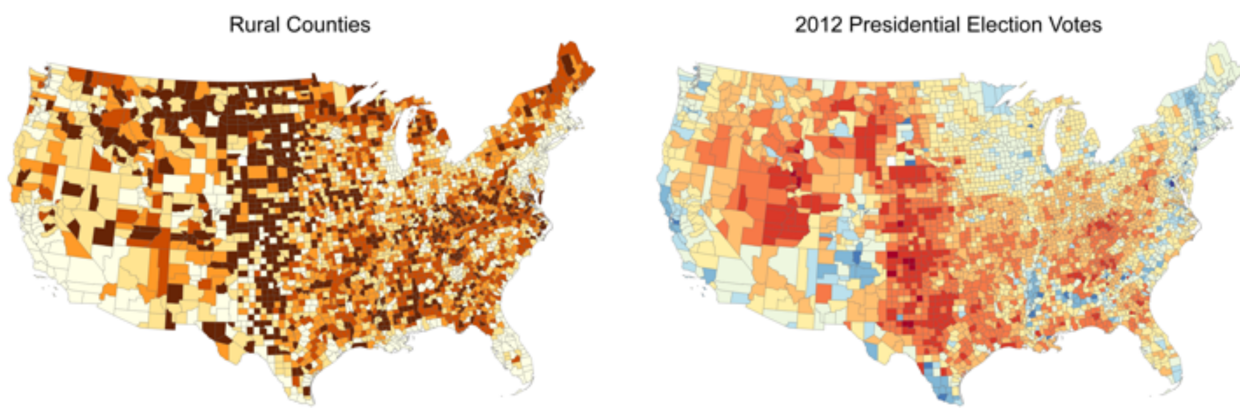

Table II: Separate OLS estimates of all key variables on excess military equipment acquisition by LEAs

	I	II	III	IV	V	VI
	Weapons per capita		Military vehicles per capita		Body armor per capita	
Crime rate	-.0604*	-.0722*	-.0913***	-.096**	-.0216	-.0207
	(.0226)	(.0255)	(.0236)	(.0277)	(.0179)	(.0213)
% Minority	-.0509+	-.0638+	-.0714**	-.0738*	.0275	.0603
	(.0262)	(.032)	(.0233)	(.0324)	(.0364)	(.0523)
% Hispanic	-.079*	-.0752**	-.0475+	-.041*	-.0381+	-.0347
	(.0298)	(.024)	(.0241)	(.0203)	(.0224)	(.0218)
% Black	-.013	-.0087	-.0484+	-.0381	.0518	.0812
	(.0244)	(.0303)	(.0266)	(.0322)	(.0514)	(.0651)
% Asian	-.1495***	-.1388***	-.1027**	-.0849*	-.0195	-.0188
	(.0359)	(.0386)	(.0326)	(.0295)	(.0174)	(.0221)
% GOP vote in 2012	.0891**	.107*	.0821**	.0822*	-.0211	-.0421
presidential election	(.0293)	(.0365)	(.0262)	(.0296)	(.0312)	(.0403)
LEOs per capita	.0755	.089	.0361+	.0371	.0129	.0249
	(.0542)	(.0569)	(.02)	(.027)	(.0172)	(.0263)
% Rural	.1638***	.1692***	.1641***	.1745***	.0178	.0204
	(.0266)	(.0315)	(.0309)	(.0359)	(.0137)	(.0161)
Gini index of	-.0158	-.0376	.0072	.0265	-.0202	-.0086
economic inequality	(.0188)	(.0272)	(.0317)	(.0446)	(.0278)	(.0481)
Observations	2,982	2,982	2,982	2,982	2,982	2,982
Controls?	No	Yes	No	Yes	No	Yes

Dependent and independent variables are standardized to report effect sizes. All regressions include state-level fixed effects. Robust standard errors clustered at the state level are reported in parentheses. Control variables: income per capita, poverty rate, unemployment rate, local government tax revenue, population, population density, and share of males.

*** p<0.001, ** p<0.01, * p<0.05, + p<0.10

Table III: Separate univariate OLS effect size estimates of rural housing stock on all key variables

Crime rate	% Non-white	% Hispanic	% Black	% Asian	% GOP vote in 2012 presidential election	LEOs per capita	Gini index of economic inequality	Weapons per capita	Military vehicles per capita
-.418***	-.166***	-.192***	-.118***	-.341***	.257***	-.010	-.099***	.164***	.164***
(.034)	(.024)	(.047)	(.023)	(0.038)	(.025)	(-.045)	(.028)	(.027)	(.031)

Dependent and independent variables are standardized to report effect sizes. All regressions include state-level fixed effects. Robust standard errors clustered at the state level are reported in parentheses.

*** p<0.001, ** p<0.01, * p<0.05, + p<0.10

Table IV: Identifying OVB for separate OLS estimates of all key variables on excess military equipment acquisition by LEAs

	I	II	III	IV	V	VI
	Weapons per capita		Military vehicles per capita		Body armor per capita	
Crime rate	-.0708*	.0135	-.0944**	-.0136	-.021	-.0137
	(.0259)	(.021)	(.0273)	(.0197)	(.0217)	(.0202)
% Minority	-.0633*	-.0166	-.0749*	-.0254	.0574	.0691
	(.0313)	(.0296)	(.0313)	(.0291)	(.0494)	(.0574)
% Hispanic	-.0708*	-.0237	-.0391+	.0146	-.035	-.0303
	(.0248)	(.0161)	(.0208)	(.0147)	(.0223)	(.0203)
% Black	-.0126	.0337	-.0409	.0048	.0796	.0889
	(.03)	(.0312)	(.032)	(.0333)	(.0634)	(.0693)
% Asian	-.1403***	-.0641*	-.0927**	-.002	-.0192	-.01
	(.0358)	(.0243)	(.0299)	(.014)	(.0208)	(.0196)
% GOP vote in 2012 presidential election	.1097**	.0548+	.0867*	.0259	-.0399	-.0532
	(.0371)	(.0314)	(.0305)	(.0287)	(.0381)	(.0466)
LEOs per capita	.1287*	.0902	.0496	.0383	.0269	.0251
	(.057)	(.059)	(.0311)	(.0303)	(.0263)	(.0265)
Gini index of economic inequality	-.0406	-.0257	.0245	.039	-.009	-.0072
	(.0264)	(.0265)	(.0442)	(.044)	(.0483)	(.0483)
Observations	2,982	2,982	2,982	2,982	2,982	2,982
Rural control?	No	Yes	No	Yes	No	Yes

Dependent and independent variables are standardized to report effect sizes. All regressions include state-level fixed effects. Robust standard errors clustered at the state level are reported in parentheses. Control variables for all columns include: income per capita, poverty rate, unemployment rate, urbanicity, local government tax revenue, population, population density, and share of males. Even-numbered columns additionally control for % rural.

*** p<0.001, ** p<0.01, * p<0.05, + p<0.10

Table V: Pariwise Pearson's Correlations of Explanatory Variables

Variable	X1	X2	X3	X4	X5	X6	X7
X1: Crime rate	1						
X2: % Hispanic	.138***	1					
X3: % Black	.430***	-.104***	1				
X4: % Asian	.125***	.173***	.036+	1			
X5: % GOP vote in 2012 presidential election	-.208***	-.069***	-.357***	-.335***	1		
X6: LEOs per capita	.209***	.139***	.208***	-.0007	-.035+	1	
X7: % Rural	-.394***	-.262***	-.107***	-.509***	.312***	-.035+	1

Table VI: Joint OLS estimates of all key variables on excess military equipment acquisition by LEAs

	I	II	III	IV
	Weapons per capita		Military vehicles per capita	
Crime rate	.0093	-.0066	-.0132	-.0192
	(.0193)	(.022)	(.0189)	(.0207)
% Hispanic	-.0129	-.0006	.0165	.0268
	(.0226)	(.0227)	(.0172)	(.0192)
% Black	.0519	.0692	.0164	.0351
	(.0414)	(.0451)	(.0426)	(.047)
% Asian	-.0408+	-.0383	.0122	.011
	(.0222)	(.0267)	(.0135)	(.0147)
% GOP vote in 2012	.0649	.0831*	.0434	.046
presidential election	(.0402)	(.0409)	(.0428)	(.0399)
LEOs per capita	.0769	.0888	.0422	.0412
	(.0592)	(.0585)	(.0278)	(.0313)
% Rural	.1415***	.1480***	.1571***	.1672***
	(.0276)	(.0307)	(.0307)	(.0331)
Observations	2,982	2,982	2,982	2,982
Controls?	No	Yes	No	Yes

Dependent and independent variables are standardized to report effect sizes. All regressions include state-level fixed effects. Robust standard errors clustered at the state level are reported in parentheses. Control variables: income per capita, poverty rate, unemployment rate, local government tax revenue, population, population density, and share of males.

*** p<0.001, ** p<0.01, * p<0.05, + p<0.10

Table VII (a): Testing heteronegeous effect of explanatory variables across top 50% of rural countiesand top 50% of urban counties using joint OLS regression

	Most rural counties				Most urban counties			
	I	II	III	IV	V	VI	VII	VIII
	Weapons per capita		Military vehicles per capita		Weapons per capita		Military vehicles per capita	
Crime rate	-.0059	.0058	-.0379	-.0221	.0161	.0036	-.0045	-.0079
	(.0358)	(.0392)	(.0386)	(.0387)	(.0196)	(.0202)	(.018)	(.021)
% Hispanic	-.1259*	-.1346*	-.0602	-.0694	.0365+	.0283	.0309*	.0319+
	(.0579)	(.055)	(.0398)	(.0435)	(.0187)	(.0197)	(.0147)	(.018)
% Black	.0577	.0763	.0226	.0336	.0405	.0333	.0234	.0165
	(.0601)	(.0658)	(.0571)	(.0582)	(.0332)	(.0329)	(.0387)	(.0414)
% Asian	-.1844	-.1264	.2628+	.3081+	-.0263	-.0176	-.0204	-.0187
	(.1865)	(.2003)	(.1542)	(.1583)	(.0193)	(.0217)	(.0169)	(.0176)
% GOP vote in 2012 presidential election	.091	.1114+	.0759	.0656	.0297	.0377+	.028	.0338
	(.0677)	(.0629)	(.0701)	(.0626)	(.0193)	(.0213)	(.0182)	(.0204)
LEOs per capita	.0773	.1141+	.0481	.0351	.0548	.0525	.023	.0321
	(.068)	(.0613)	(.0318)	(.0411)	(.0532)	(.0622)	(.0253)	(.0289)
% Rural	.1117*	.0641	.2036**	.1362*	.1899***	.1598***	.1015***	.089**
	(.0472)	(.059)	(.0681)	(.063)	(.0353)	(.0326)	(.0225)	(.0262)
Observations	1,491	1,491	1,491	1,491	1,491	1,491	1,491	1,491
Controls?	No	Yes	No	Yes	No	Yes	No	Yes

Table VII (b): Testing heteronegeous effect of explanatory variables across counties with majority rural or urban development using joint OLS regression

	>50% Rural				>50% Urban			
	I	II	III	IV	V	VI	VII	VIII
	Weapons per capita		Military vehicles per capita		Weapons per capita		Military vehicles per capita	
Crime rate	-.0023	-.0048	-.0319	-.0254	.0096	-.0055	-.0054	-.0048
	(.0279)	(.0296)	(.0316)	(.0306)	(.0234)	(.023)	(.0149)	(.0175)
% Hispanic	-.1128*	-.1158**	-.045	-.0546	.0464*	.0357	.026	.0265
	(.04)	(.0385)	(.0399)	(.0409)	(.0216)	(.0234)	(.0161)	(.0205)
% Black	.0613	.0855	.0361	.0457	.0421	.0297	-.0131	-.02
	(.0572)	(.0614)	(.0554)	(.0568)	(.0338)	(.0359)	(.0254)	(.0296)
% Asian	-.1616	-.0969	.1396	.2112+	-.0109	-.0076	-.0106	-.0122
	(.1262)	(.1389)	(.0979)	(.1086)	(.0138)	(.0176)	(.0133)	(.0146)
% GOP vote in 2012 presidential election	.084	.095	.0639	.0558	.0335	.0478*	.0211	.0248
	(.0587)	(.0568)	(.0632)	(.0569)	(.0204)	(.0228)	(.016)	(.0214)
LEOs per capita	.0812	.1045+	.0491	.0371	.0471	.0416	.0238	.0317
	(.0661)	(.0599)	(.0322)	(.0393)	(.0532)	(.0619)	(.0273)	(.0302)
% Rural	.1153*	.0987+	.2006***	.1495**	.2459***	.2036***	.1447***	.1384***
	(.0463)	(.0537)	(.055)	(.0481)	(.0436)	(.0393)	(.0352)	(.0389)
Observations	1,832	1,832	1,832	1,832	1,149	1,149	1,149	1,149
Controls?	No	Yes	No	Yes	No	Yes	No	Yes

Dependent and independent variables are standardized to report effect sizes. All regressions include state-level fixed effects. Robust standard errors clustered at the state level are reported in parentheses. Control variables: income per capita, poverty rate, unemployment rate, local government tax revenue, population, population density, and share of males.
*** p<0.001, ** p<0.01, * p<0.05, + p<0.10

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