Evaluating the Determinants of Support for Police Militarization among Officers

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Abstract
We evaluate the determinants of officer support for their agency participating in the 1033 Program: a program that facilitates the flow of military hardware to local law enforcement agencies. In doing so, we provide insight into why officers demand such equipment, which in turn, may partially explain patterns of Program participation and equipment usage. We utilize a series of random forest models to examine survey data collected from officers in a large police department, finding that being white and exhibiting animus towards minority communities are highly predictive of officer support across models. Our findings validate long-held public concerns regarding the distributional patterns and consequences of 1033 transfers: concerns that have led to a number of proposed policy changes at the state and federal levels meant to restrict Program usage (e.g., EO-13688, HR-1694; MO HB-330). Policymakers should consider how out-group animus may drive distributional patterns and usage when considering policy reform.

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Research on police militarization demonstrates that the use of military equipment (e.g., weapons, military vehicles, apparel, etc.) by law enforcement agencies (LEAs) promotes police violence (Carriere & Encinosa, 2017; Delehanty et al., 2017; Lawson Jr., 2019; Masera, 2021), degrades community trust in LEAs (Mummolo, 2018), and fails to promote LEA crime-reduction capacity (Gunderson et al., 2020; Lowande, 2020).[1] The steady rise in the use of military equipment by LEAs (Radil, Dezzani, & McAden, 2017)—despite such documented effects and ever-increasing public scrutiny (Tolan & Hernandez, 2020)—has resulted in a new line of research seeking to understand why and in what contexts militarization proliferates (Ramey & Steidley, 2018). To date, such studies have largely focused on isolating how agency-specific and community-specific factors impact the rate by which LEAs acquire such equipment (e.g., Burkhardt & Baker, 2019), largely ignoring how individual-level features shape officer support for equipment acquisition. This is an important omission given that: i) actor-level features of police-leadership (officers that make choices regarding whether and how to militarize) may drive patterns of equipment acquisition and usage; ii) why street-level officers desire such equipment likely impacts how they intend to (and eventually do) use it. Do officers support militarization? If so, what officer attributes explain more or less support?

In this paper, we seek to identify the factors that influence officer support for their department acquiring military hardware. We do so by surveying officers in a large LEA about the U.S. Department of Defense (DoD) 1033 Program: a program that supplies LEAs with surplus DoD equipment at little or no cost. The data we collect allows us to address topics largely missing from social science research, ranging from how officers feel about the

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1033 Program in general, to which items they think their department should acquire. Potential predictors are derived by viewing police militarization through multiple theoretical lenses. We use a machine-learning technique known as random forests to determine the most predictive covariates from the data.

The strongest and most consistent predictors are related to race. White officers and those who exhibit racial animus towards non-whites exhibit higher levels of support for the Program in general and are more likely to support their department receiving both weapons and military vehicles through the Program. Variables capturing officers' access to resources, their experience in the department, their connection to the region, and various demographic features also affect sentiment towards militarization, though these effects are less consistent.

This paper contributes to the academic community, the public, and practitioners alike. First, we present an original, publicly available dataset on individual officers and their favorability towards different aspects of their job including, but not limited to, police militarization. Second, we begin to build a scaffolding for micro-level theorizing and hypothesis testing by shifting focus from aggregate organizational behavior to individual attitudes (cf. Ramey & Steidley, 2018; Burkhardt & Baker, 2019). Third, by drawing on multiple theories to guide our research, we help direct the growing literatures on police militarization toward the most promising theoretical avenues to explain the determinants of demand for militarized equipment. Finally, and perhaps most pragmatically, the findings highlight potential equity issues associated with the 1033 Program which should be used to inform ongoing debates regarding the Program's future (e.g., debates surrounding the "Stop Militarizing Law Enforcement Act" currently under consideration in the US House of Representatives). Extending the well-established link between desire, intention and behavior in social psychology research (Ajzen & Madden, 1986; Sheeran, 2002), we anticipate that why officers want equipment serves as a credible signal for how they intend to, and eventually do, use it. Among police leadership, racial animus may not only drive whether a department makes use of the Program, but also, the types and quantity of equipment requested, as well as protocols for equipment use. Concurrently, racial animus may not only impact whether a street-level officer wants the equipment, but also, how they plan to use it (or *who* they plan to use it against). While our current study cannot disentangle i) the extent to which animus drives demand for higher-level vs. street-level officers, ii) whether such trends extend to other LEAs across the US, and iii) whether the determinants of demand do in fact affect behavior, these findings do give some credence to long held concerns that militarization facilitates out-group oppression (Lawrence & O'Brien, 2021; Ramey & Steidley, 2018).

The paper proceeds as follows. First, we introduce the DoD 1033 Program. Then we discuss the relevant theories and describe the data collection process. Next, we describe the statistical methods used to identify the most predictive beliefs and attributes of individual officers and present those results. We conclude by discussing our findings' implications and avenues for future research.

1. THE 1033 PROGRAM

President Clinton signed into law H.R. 3230 (National Defense Authorization Act of Fiscal Year 1997) containing section 1033. Though 1990-91 were the first years that excess DoD property could be transferred to LEAs for counter-drug activities, the 1997 law transformed the relationship between the military and the police.[2] The law allows LEAs to acquire excess equipment from the US military at no cost.[3] While the policy has existed since the 1990s, the militarized police response in Ferguson, MO to protests over Michael Brown's

[2] Predecessor laws occasionally came up in the 1940s until their abolition in 1949 (https://www.archives.gov/research/guide-fed-records/270.html#270.1).
[3] Though receiving equipment is not totally free as receiving LEAs have to pay for transport and maintenance of material (Masera, 2021)

death in 2014 led media and elected officials to scrutinize the Program (e.g., Holland & Shalal, 2014; Paul, 2014; Shesgreen, 2014).

The spotlight on the 1033 Program led to detailed media attention of 1033 receipts for the 2006-2014 fiscal years (Rezvani et al., 2014). During that time, over 80% of US counties received military items (Radil, Dezzani, & McAden, 2017, p. 208). Though the military transfers are intended to aid in counter-drug and counter-terrorism activities, the geographical distribution does not follow a discernable pattern. Measured by acquisition value per capita, the lowest levels are clustered in the Midwest, Mississippi, Pennsylvania, and central Texas, with high pockets of acquisition in Montana, the Southeast, and a few other scattered locations (Radil, Dezzani, & McAden, 2017).[4]

Received items range from innocuous goods that can subsidize day-to-day activities (e.g., utility vans, computers, and exercise equipment) to items capable of inflicting harm. Following Kraska, (2007), we refer to the latter items as "militarized". Between 2006 and 2014, LEAs received an array of militarized transfers including, but not limited to, 79,288 assault rifles, 205 grenade launchers, 11,959 bayonets, 3,972 combat knives, 422 helicopters, and 605 Mine-Resistant Armored Protection Vehicles (Rezvani et al., 2014). Receiving militarized transfers may have a transformative effect on departments, such as establishing elite units that use these weapons (e.g., SWAT teams) and increasing the likelihood that officers see themselves as "soldiers" rather than "peace-officers" (Balko, 2013). Surveying officers in both large cities and small towns, Peter Kraska and colleagues find such a shift in policing culture (Kraska & Cubellis, 1997; Kraska & Kappeler, 1997). Almost 20 years later,

[4] Though in raw total acquisition value, the Southwest and northeast Maine stand out as particularly high (Radil, Dezzani, & McAden, 2017).

these issues have not only continued but accelerated (Kiker, 2014).[5] Such changes can lead to more violent police-citizen interactions (Delehanty et al., 2017; Lawson, 2019, Masera, 2021).

2. PREDICTORS OF MILITARIZATION

In this section, we draw from various social science literatures to derive expectations regarding the individual-level determinants of officer support for 1033 transfers. We solely derive expectations for militarized transfers. While predicting support for non-militarized transfers (e.g., computers, furniture, vans, etc.) is a potentially important subject matter, it is beyond this paper's scope.[6]

2.1 *Resources*

Scholars often conceptualize police officers as "street-level bureaucrats" ("SLBs": Chaney & Saltzstein, 1998; Levi, 1977; Wilson, 1989)—government representatives who directly interact with the public on behalf of the state (Prottas, 1978). SLBs provide government services to citizens (i.e., "clients"), whether collecting refuse, issuing drivers' licenses, or in the case of officers, "maintaining public order" (Lawson Jr., 2019, p.179). Though the public expects SLBs to accomplish various tasks, they often lack the resources to effectively do so (e.g., training, materials, and time). Unsurprisingly, SLBs with fewer resources struggle to effectively provide client services (Mewhirter, Coleman, & Berardo, 2019).

Problematically, SLBs often develop counter-productive and potentially harmful shortcuts to deal with resource shortages, which further reduces their service-provision

[5] Though see den Heyer (2014) for a counterargument that increased militarization represents increased professionalism. See Stavro & Welch (2023, p. 11-14) for a skeptical response to the professionalization argument.
[6] That said, we did collect whether officers support receiving these types of materials from the 1033 Program.. Although outside of the scope of the paper, we estimated models predicting that outcome, as well. Interested readers can find those results in the Appendix.

effectiveness (Lubell et al., 2022; Merritt, 2019; McLaughlin, Mewhirter & Lubell, 2022; Goodsell, 1981). More so, resource-strapped SLBs often blame clients for the service-provision inadequacies (Lipsky, 2010; Riccucci, 2005) and view clients with indifference, or even contempt (Lindhorst & Padgett, 2005; McLaughlin et al., 2021).

For law enforcement officers, the link between resource shortages and an adversarial view of clients elicits concern given use of force is, at times, a possible (and potentially legitimate) response to SLB-client interactions. Research in organizational psychology provides evidence of this link, showing resource-strapped officers often become disconnected from their work and develop resentment towards the clients they serve (Martinussen, Richardsen & Burke, 2007). These officers often view violence against civilians in a more favorable light (Lindhorst & Padgett, 2011) and engage in violent behaviors more often while on the job and at home (Johnson, Todd, & Subramanian, 2005).

We argue the relationship between resource scarcity and sentiment towards/engagement in violence should parallel the relationship between resource scarcity and support for militarized transfers. This logic leads us to the following hypothesis:

H1: The more officers perceive resource shortages, the more they will support their department receiving militarized transfers.

2.2 *Perceived Threat*

Instead of SLBs, the comparative politics and political violence literatures view officers in a different light, suggesting when governments experience increased threat, they rely on coercion, often by police, to maintain power and order (e.g., Moore, 1998; Poe, 2004; Davenport, 2007, della Porta, 2011). The government, acting on the state's behalf, controls a relative advantage over the legitimate use of violence, which it uses to maintain order (Weber, 1965). Different governmental agents use coercion for different purposes. For example, the military deters and repels external threats. LEAs, on the other hand, perform a similar function for domestic threats. When thinking about interactions between the government and potential dissidents threatening the status quo, a simple relationship exists: as the perceived threat to the government increases, state violence increases (Poe, 2004). Empirically, this relationship is so ubiquitous Davenport (2007) labeled it the “Law of Coercive Responsiveness.” Although this literature usually conceives of the state as a unitary actor, LEAs in the US exhibit marked decentralization. However, the theoretical relationship should hold in each jurisdiction as the government presiding over that geography assesses a threat and decides whether to respond with force (Earl, Soule and McCarthy, 2003; Soule & Davenport, 2009).

Whereas the on-average relationship between threat and government coercion has been borne out many times at the macro-level, we know less about threat’s effects at the individual level. Individuals within the coercive apparatus possess agency themselves (e.g., DeMeritt, 2015; Mitchell, 2004). When agents sense threats to law and order, and thus their own ongoing safety, they should be more willing to use physical coercion. This is true whether or not they act as faithful agents (in a principal-agent sense). If so, the government senses threat and delegates coercion to the agents who, in turn, fulfill their obligation. But, even without the explicit government order, agents can act on the perceived threat in their personal jurisdiction (Soule & Davenport, 2009). Given the nature of their positions, many LEAs possess considerable autonomy (Brogden, 1982) allowing them to make threat assessments in their own territories separate from the overall threat levels. The argument leads to a testable proposition. The more threat officers perceive, the more attractive force becomes as a tool to perform their jobs, thus we expect an increase in the desire for coercive tools.

H2a: The more officers perceive threat, the more they will support their department receiving militarized transfers.

The origin of the perceived threat can stem from various sources. Group threat theory (Blalock, 1967; Blumer, 1958; Liska, 1992) suggests majority groups exhibit prejudice and hostility towards minority groups based on perceived threat from those groups. [7] Jackson (1989) successfully applied the theory to policing in the United States. Others followed her work showing perceived threat originating from minority communities leads to social control of those minority groups whether through arrest (Eitle, D'Alessio, & Stolzenberg, 2002), incarceration (Jacobs & Carmichael, 2001), and/or criminal justice expenditures (Jacobs & Helms, 1999). Others show police mobilization increases in the presence of minority groups (Earl, Soule, & McCarthy, 2003), and police take more coercive action against minority protests (Davenport, Soule, & Armstrong, 2011). Several studies show police use violence disproportionately against minorities (e.g., Chamlin, 1989; Jacobs & O'Brien, 1998). If bias against outgroups can lead to higher mobilization rates and more violent behavior, then those of the ingroup or those that show animus towards racial minorities should support programs

[7] Relatedly, conflict theories of policing suggest the state protects the majority's interests which can lead to repression of minority groups (Turk, 1969).

that increase access to militarized equipment. Further, outgroup bias can lead to support for more extreme policies (Andrews & Seguin, 2015), perhaps including the 1033 Program.

H2b: Officers who are in group members will more likely support their department receiving militarized transfers.

H2c: The more officers exhibit animus towards minorities, the more they will support their department receiving militarized transfers.

3. RESEARCH SITE

Both the department and city remain anonymous throughout the paper. However, we give general information to provide context about the research site. The department in question acts as the primary law enforcement agency for one of the 100 largest US cities which sits at the center of a major metropolitan statistical area (one of the 50 largest; US Census 2019). Over 90% of city residents are either white or black, with the white population being ~5% larger (PolicyLink and the USC Equity Research Institute, 2020). The city has historically grappled with high levels of poverty and crime. Currently, over 25% of the city's population falls under the poverty line (PolicyLink and the USC Equity Research Institute, 2020). The city's property crime and violent crime rates fall within the top 15th percentile of cities with populations over 100,000 (United States Department of Justice, 2018). While significant socioeconomic-based disparities exist between black and white residents, they do not differ much from other large US cities. The Racial Equity Income score places it in the 40th to 60th percentile of 100 largest US cities (PolicyLink and the USC Equity Research Institute, 2020). The department has been involved in several high-profile killings of black citizens, giving rise to civil unrest. Studies examining police-community relations in the city find that, on average, black residents exhibit low trust in police and believe officers often engage in racial profiling.[8]

The department's officer per resident rate places it in the top 10th percentile of cities with populations over 100,000 (United States Department of Justice, 2018). Whites are largely overrepresented in the department, with white officers outnumbering black officers by a 2:1 ratio. To date, the department in question has *not* acquired items through the 1033 Program, though it has used alternate federal grant programs to procure military equipment. LEAs in the state have used the Program extensively, making it among the largest recipients in terms of transfer value. Other departments in the region—including the county sheriff's office, a major university's police department, and other LEAs operating within the metro region—have received weapons and armored vehicles through the Program, some of which has been used within city limits (Defense Logistics Agency, 2020).

Neighboring LEAs' 1033 use increases the likelihood officers know of the Program's existence. Officer sentiment towards the Program should not be significantly influenced by past departmental actions since the department has yet to participate in the Program. That said, the Program as presented in the survey should not be a totally alien concept since the department has received equipment from related, federal programs.

4. DATA & MEASUREMENT

Officer-level data comes from two sources. First, the city's Human Resources Department provided all personnel files for current officers (as of July 2018). These files contain demographic data on each officer (e.g., salary, birthdate, date of initial employment, race, gender, and education level). Second, we collected survey data from officers.[9] We

[8] We cannot cite such studies because it would allow readers to identify the study site.
[9] This study was reviewed by the Institutional Board at an author's university. As the study was (partially) funded by the city in question, it was not deemed subject to institutional oversight. The survey was administered online via emails provided by the city Human Resources Department. Once opened,

provide the survey instrument in the Appendix. The surveys—completed as part of a larger city-funded project by one of the authors[10]—were distributed via email from 6/18-7/27/2018. Reminder emails were sent to non-respondents every Monday, Wednesday, and Friday. City leaders repeatedly urged LEA leadership to encourage participation from employees. Of 1,386 potential respondents, 459 completed the survey (response rate=33.12%). Of the 459 respondents, 350 were officers and the remainder were department staff (dispatchers, typists, IT support staff, etc.). We only include officers in our analyses. Survey questions directly related to police militarization represented roughly 3.5% of the survey instrument. Below, we describe the variables used in our analyses.

4.1 *Dependent Variables*

The dependent variables capture the extent to which officers support their department's participation in the 1033 Program generally, as well as the types of militarized items they would support receiving.[11] We utilize three dependent variables generated through the survey. Before receiving the relevant survey questions, respondents received the following prompt: "The 1033 Program is a federal program that makes a wide range of

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participants were presented with a cover sheet indicating that their participation was entirely voluntary, and that the responses would remain anonymous. Participants consented by continuing to the survey after reading the cover letter detailing data use and renumeration. No payment (direct or otherwise) was offered for their participation.

[10] The city funded (in part) a self-study which involved surveying employees in multiple departments. The self-study's goal was unrelated to the 1033 Program. As such, it is highly unlikely that officer sentiment towards the 1033 Program (or police militarization more broadly) directly impacted response rates.

[11] We follow several other studies using the 1033 Program to proxy militarization, but recognize LEAs can obtain militarized equipment from other federal programs, philanthropies, or by using their own budgets. Records of these sources remain opaque. Future studies should explore ways to collect and analyze those data. One might wonder whether officers are evaluating militarization more generally, rather than the 1033 Program, specifically. Since we use 1033 support to proxy for militarization support, we view this as appropriate and consistent with our research question.

surplus military equipment available to state and local law enforcement agencies at little or no cost."

The first dependent variable, *Overall Support*, captures each respondent's level of support for the agency receiving equipment through the 1033 Program in general. Respondents were asked the following: "Using the sliding scale below, please respond to the following question: how supportive are you of the [REMOVED] Police Department accessing surplus military equipment through the 1033 Program?" Values range from 0-10, where 0= "not at all supportive" and 10= "very supportive".

In Table 1, we provide summary statistics for all variables used in our analyses. As shown in Table 1, officers tend to be highly supportive of their department receiving 1033 transfers. The mean of *Overall Support* is 8.43, with roughly 54% of respondents indicating that they are "very supportive" (=10). These results echo Turner and Fox's (2019) and Meitl, Wellman and Kinkade's (2020) findings that police officers overwhelmingly support militarizing their departments.

We also asked respondents to identify the specific types of military items they would support their department receiving. We constructed two dependent variables—*Weapons* and *Military Vehicles*—using the following question: "In your opinion, which of the following should [REMOVED] PD be requesting through this program?" Respondents indicate support for each of the following: "Weapons"; "Military vehicles (for example: Mine-Resistant Ambush Protected Vehicles)". These variables take a value of 1 when the respondent supports receiving these items, and 0 if not.

As shown in Table 1, while officers exhibit extremely high levels of *Overall Support*, they are largely split on whether their department should be receiving specific militarized transfer items. Roughly 61% of officers support their department receiving weapons while only 47% feel their department should receive military vehicles.[12] Officers generally support the 1033 Program, but when primed to consider the equipment's specific nature, their support weakens. These statistics differ from Turner & Fox (2019) who found roughly 85 – 90% support for weapons and vehicles in their departments. Their sample included officers and executives across the U.S. based on professional membership rolls, while we focus on one department and all its employees regardless of their extracurricular activities. Our combined results suggest interesting variation in support for each equipment type, and we seek to understand that variation on the individual level in the analyses below.

[INSERT TABLE 1 AROUND HERE]

4.2 *Independent Variables*

We use several independent variables, described below.

<u>Resources</u>

We consider that officers who feel as though they lack sufficient resources to perform their assigned tasks will be more likely to support their department receiving militarized transfers. To test this proposition, we rely on three independent variables labeled *Resources, Workload,* and *Training.* The variable *Resources* captures officer sentiment regarding access to/lack of resources more generally (e.g., material resources, up-to-date technology, support staff, etc.). *Workload* specifically measures the time-crunch officers feel when performing their duties. *Training* captures the extent to which officers feel they have received adequate training to perform their duties correctly and efficiently.

To capture these concepts, we ask participants to respond to the following statements: "In general, I have sufficient resources (people, materials, budget, etc.) to get my job done"; "In general, my workload is reasonable"; "In general, my training needs are met." Responses

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[12] The majority of military veterans, though, support receiving vehicles. More research should explore this difference given the military-to-police pipeline (Hussey, 2020, p. 7-11).

range from 0-10, where 0= "completely disagree" and 10= completely agree." The argument suggests a negative relationship between these independent variables and the dependent variables.

Perceived Threat

According to the perceived threat approach outlined above, officers who view community members with which they regularly interact as a threat—either to themselves or to society—will exhibit more support for their department receiving militarized transfers. *Safety* captures how safe officers feel when performing their work-related duties. Officers with lower feelings of safety exhibit higher perceived threat levels. We asked participants to respond to the following statement: "In general, I feel physically safe while performing my work-related duties." Values range from 0-10, with 10 indicating complete agreement, and 0 complete disagreement. We expect a negative relationship between *Safety* and all dependent variables.

We generated two additional expectations based on group threat theory. Given the majority of officers and a plurality of residents are white, we expect individual attitudes towards minorities to predict support for militarized transfers from the 1033 Program. *White* takes a value of 1 when an officer's personnel file lists her/him as "white," and 0 otherwise. We also measure the extent to which an officer views non-whites as a threat. To construct the variable, *Racial Animus*, we asked individuals to respond to the following statement: "On average, non-whites are often given more advantages than white people."[13] Values range from 0-10, where 0 indicates complete disagreement and 10 indicates complete agreement.

[13] Alternative survey questions can tap into the racial animus concept. This question represents one of the four most common. We chose to employ only one due to survey space constraints. Kinder & Sanders (1996) provide evidence for the measure's validity.

As support for that statement increases, we expect an increase in support for militarized transfers from the 1033 Program.

4.3 *Other Variables*

Based on past work surveying police officers (Meitl, Wellman, & Kindade, 2020; Turner & Fox, 2019) and the public (Lockwood, Doyle, & Comiskey, 2018; Moule et al., 2019; Moule, Fox, & Parry, 2019) about police militarization, we include several other variables.[14]

We include a number of demographic variables that could impact 1033 Program support. Leveraging officer personnel files, we account for each officer's *Birth Year* (year), whether they are *Male* (0=No; 1=Yes), and whether they are a *College Graduate* (1=Yes; 0=No). We use survey data to capture the number of *Children* (count) an officer has, whether they are *Married* (1=Yes; 0=No), and their *Military Rank* (1=Veteran; 0=Non-veteran).

We use survey data to account for an officer's connection to the community/region. To do so, we include the variables *Native* and *Local Years.* The former captures whether the officer was born in the metropolitan area in which they are employed, whereas the latter measures the number of years one has lived in the metropolitan area (if any).[15]

Finally, we include a number of variables that capture an officer's role and experience in the department. The variable, *Role*, was constructed using city-provided personnel files: all other variables were collected via the survey instrument. *Role* accounts for one's current position in the department: it takes a value 1 for street-level officers, 2 for department leadership (e.g., chief, sergeants, etc.), and 3 for specialists (e.g., detectives,

[14] We remain agnostic as to their direction, allowing our machine learning model to inform us about the relationships.
[15] The LEA in our study does not maintain residency requirements for officers.

school officers, etc.). We include variables that capture the number of *Promotions* respondents have received since joining the department (count), and the year that they joined the department (*Start Year)*. We also include variables that capture the extent to which respondents agree that "In general,": "I have enough information to do my job well" (*Information*) "the physical conditions (furniture, lighting, etc.) allow me to perform my job well (*Physical Conditions*)"; "I am happy working in my current department (*Happiness*); "the work I do is important" (*Work-Important*); Each variable take values between 0 and 10, where 0 indicates complete disagreement and 10 indicates complete agreement.

5. METHODS & FINDINGS

To make full use of the collected data, we rely on the machine learning-technique known as random forests (RFs).[16] RFs are an ensemble method[17] that allow us to determine how much predictive power each covariate adds to a statistical model (Breiman, 2001a). Given we did not artificially weight any of the theoretical lenses used to motivate data collection and our inclusion of several additional covariates, RFs offer an attractive way to explore the data and determine which of the many covariates explain variation in support for the 1033 Program. After discovering each variable's importance, we create partial dependence plots (Hastie, Tibshirani, & Friedman 2009) to explore *how* these important

[16] Others have used RFs to predict a wide range of outcomes from human rights abuses (Hill & Jones, 2014), crime (Oh et al., 2021), and Covid-19 vaccine hesitancy (Mewhirter. Sagir, & Sanders, 2022).
[17] Bagging represents another popular ensemble method. It is a special case of random forests in which the set of predictors from which the algorithm chooses is constrained to the full set of variables in the model. Random forests show improved prediction compared to bagging due to the higher diversity in single trees involved in the averaging (Hastie, Tibshirani, & Friedman, 2009).

variables affect support for the Program. These plots visualize realistic, non-linear relationships between the predictors and the outcomes.

5.1 *Random Forests*

We use RFs to analyze the collected data. RFs base predictions of an outcome of interest on an ensemble of classification or regression trees. The tree type depends on the nature of the dependent variable—classification trees for discrete variables and regression trees for continuous variables. In our case, overall support for the 1033 Program requires regression trees, while the yes/no responses about support for specific items requires classification trees. Classification/regression trees create binary splits in predictor variables based on what values best predict the outcome. This is done one variable at a time, choosing the variable most strongly associated with the outcome variable to make the first split. Then, the same process occurs in the resultant daughter nodes until a stop rule is reached. Figure 1 presents the trees for two of the three dependent variables.[18]

[INSERT FIGURE 1 AROUND HERE]

To build these trees, we used the conditional inference framework (Hothorn, Hornik, & Zeileis, 2006). Simply, the algorithm tests the null hypothesis that every predictor is independent from the outcome variable. Each time it rejects the null ($p < 0.05$), it creates a binary split using the predictor variable with the strongest relationship as measured by the lowest p-value. For example, looking at the top tree in Figure 1, we see the variable that most strongly predicts overall 1033 support is whether the respondent is white ($p = 0.002$). If so,

[18] Notice how each of these trees has only one split. Although regression trees can have (and are often presented with) more than one split i.e., another variable splitting the resultant subsamples from the first split, and so on, in each of our DVs, the most important variable (race or racial animus) partitions the data, and then none of the others reach the $p < 0.05$ level to partition the subsamples further. One might wonder if any other variable can be important in these models, then. However, we describe the process later in the manuscript that would potentially allow other variables to enter the trees as important (i.e., each tree in the forest is built from a subsample of the data). Each of the trees then creates the ensemble called the forest.

the average response is around a 10; if not, the average response is around an 8. In the bottom classification tree in Figure 1, racial animus most strongly predicts support for weapons ($p = 0.045$). If the respondent registered her/his support that non-white people receive more advantages than white people in society higher than a 4 of 10, s/he supported weapons transfers about 75% of the time. Those who agreed with a score of 4 or less supported receiving weapons a little over 40% of the time.[19] These binary partitions continue until $p \geq 0.05$ for the relationship between the remaining predictor variables and the response variable. In the regression/classification trees using all of the independent variables as potential predictors, a single variable predicts the variation in each dependent variable (see Figure 1). However, we may miss some important variables due to the order in which the data partitioning occurs. Strong competitor variables may keep other variables out of the model. These other variables may affect the outcome variable, especially as an interaction with other predictors (Strobl, Malley, & Tutz, 2009).

RFs help solve this problem. RFs allow us to make more accurate predictions using an ensemble of regression/classification trees.[20] However, when building RFs, each tree in the forest includes a subset of randomized variables drawn from all predictor variables.[21] Restricting the included variables allows for locally suboptimal splits that improve the global performance of the ensemble of trees. Further, the process allows the trees in RFs to grow very large without stopping. Combining the predictions from the diverse trees allows for

[19] The classification tree for receiving military vehicles looks similar to the weapons tree. We exclude it to save space. Racial animus again predicts support ($p = 0.033$). Officers who disagreed strongly with the statement that non-whites receive more advantages than white people (0 or 1), supported receiving vehicles about 20% of the time. Those who agreed at a higher level than 1 (2 – 10) supported receiving vehicles almost 60% of the time.

[20] We build our RFs with 1000 trees. Increasing the number of trees from 1000 to 10000 does not meaningfully change the prediction rate.

[21] Svetnik et al. (2003) show restricting the number of predictors from the full set (V) used to build the individual trees equal to $\sqrt{V}$ yields optimal prediction accuracy. Our model contains 22 predictors; thus, each tree is built from a randomly selected five variables. Increasing the number of subsampled variables from 5 to 10 does not meaningfully change the prediction rate.

better overall predictions (Breiman, 2001a; Büchlmann & Yu, 2002). RFs also possess other attractive qualities compared to traditional methods including the incorporation of unknown flexible functional forms (i.e., non-linear with complex interactions) and the avoidance of overfitting (Breiman, 1996a; Strobl, Malley, & Tutz, 2009). Table 2 presents the model performance. Each model predicts the response variable accurately about 70 to 82% of the time.[22] The baseline prediction rate may be high since it predicts in-sample observations.

[INSERT TABLE 2 AROUND HERE]

For more conservative rates, we rely on the out-of-bag predictions (Breiman, 1996b). Each tree in the RF is built on a bootstrap sample that acts as a training set. Those observations not used in the training set are known as out-of-bag observations. We can then use those out-of-bag observations as a test sample to test the prediction accuracy on data not used to create the RF. The out-of-bag prediction rates range from 56 to 62% depending on the dependent variable. These represent conservative rates given out-of-bag error rates can sometimes be overestimated (Janitza & Hornung, 2018). Therefore, the true prediction rate probably lies somewhere between the in-sample and out-of-bag predictions. Although the prediction rates suggest an opportunity for future work to identify even more important covariates, 56 to 82% prediction rates represent a marked improvement over naïve models.

5.2 *Variable Importance*

RFs allow us to decide which variables contribute most to predicting the response variable. To do so, we perform permutation accuracy importance whereby we randomly alter each variable in each tree, while the others remain unchanged. The relative variable importance represents the average difference (over each tree) of how accurately the variable predicts the outcome before and after permutation. If a variable does not predict the outcome,

[22] Since we use regression trees for overall support, we create a dichotomous variable for predicting high values (greater than the mean) of the response.

permuting it will not meaningfully change its ability to predict the outcome.[23] Strobl et al. (2008) show conditional permutation variable importance performs best when multicollinearity exists between predictor variables. The proportion of independent variables significantly correlated in our data ($p < 0.05$) is 0.47. Figures 2 - 4 show the variable importance and its uncertainty[24] for each outcome of interest. We consider those predictor variables with positive variable importance and whose 95% confidence interval does not overlap zero as important predictors of support for the 1033 Program (or some aspect of it).

[INSERT FIGURES 2-4 AROUND HERE]

An officer's race, time living in the city, racial animus, whether s/he is married, promotions, whether s/he is a city native, age, role, how important s/he views her/his work, happiness in her/his current department, and belief that physical conditions facilitate her/his ability to do their job best predict an officer's overall support for the 1033 Program (Figure 2). An officer's racial animus, race, promotions, satisfaction with resources, satisfaction with workload, number of children, and employment length predict support for receiving weapons through the 1033 Program (Figure 3). Racial animus, the extent to which s/he believes her/his work is important, training, whether s/he is a city native, military veteran status, and race predict officer support for receiving military vehicles through the 1033 Program (Figure 4).

Only race and racial animus predict all three outcomes. Variables that predict two outcomes include whether an officer finds her/his work important (*Overall Support; Military Vehicles*), the number of officer promotions (*Overall Support; Weapons*), and whether the

[23] Permuting the values could even make the variable more predictive. Those variables with a negative variable importance score represent this relationship. They are not considered predictively important. See Strobl, Malley, & Tutz (2009) for more.

[24] We acquire the 95% confidence intervals by generating 100 random permutations and summarizing their distribution (Strobl, Malley, & Tutz, 2009).

officer is a city native (*Overall Support; Military Vehicles*). We place these results into context below. But first, we must discover *how* the variables affect support for the Program.

5.3 *How Are the Variables Important?*

The previous exercise tells us which variables predict the outcome of our choosing. It does not, however, tell us how those variables predict the outcome. For example, does more racial animus lead to more or less support? Although RFs allow us to discard several rigid assumptions normally employed in linear regression, they create a problem of how to simply present results.

To understand the relationship between the predictor variables and support for the 1033 Program, we present partial dependence plots (PDPs). PDPs present the complex estimated nonparametric prediction function as a low-dimensional graph (Greenwell, 2017). PDPs allow us to visualize the average marginal effect between each predictor variable and individual support for the Program (Friedman, 2001). Figures 5 – 7 present PDPs for each outcome of interest. Though the PDPs do not represent constant effects over predictor variables' ranges, many are *generally* positive or negative. To make interpretation analogous to linear regression results, one can view the PDPs as direction of effect and the variable importance as significance.

[INSERT FIGURES 5-7 AROUND HERE]

Table 3 lists how each variable in the model affects each dependent variable *if it is important* (refer to Figures 2-4). If deemed unimportant by the variable importance exercise, the cell is left blank. As shown, when the variables meant to capture the resource distribution and threat arguments show up as important predictors, they generally do so in the expected direction. We find strong evidence supporting Hypotheses 2b and 2c—white officers and officers who exhibit racial animus show higher support for the 1033 Program, including military weapons and vehicles. The substantive effect of being white increased support for the program, overall, almost a whole point, from 7.8 to 8.6. Being white increased officers' support for weapons and military vehicles by five to six percentage points. Interestingly, the effect of being white pushed the support for receiving military vehicles from a minority view (less than 50%) to a majority view (over 50%). Whereas racial animus' substantive effect is relatively small when predicting overall 1033 support (~0.5 points on a 10-point scale), moving across the values of racial animus increase the support for receiving weapons and military vehicles by 15 to 20 percentage points, again moving support for vehicles from below 50% to above 50%. These represent substantively large effects of racial attitudes' effects on receiving militarized hardware.

We find weaker (or no) support for the other hypotheses. Resource constraints (H1) do not predict overall 1033 support but do partially predict support for receiving weapons and military vehicles. The extent to which officers feel individually threatened (H2a) does not predict support at all. We explore the results further in the proceeding section.

[INSERT TABLE 3 AROUND HERE]

5.4 *Alternative Model Specifications*

We estimate a series of alternate models to assess the robustness of our results. First, we consider whether our findings are impacted by selection bias: if non-respondents and respondents vary in some meaningful way, then it is possible that the findings observed in our sample are not reflective of broader trends within the department (Barclay et al. 2002; Schouten, Cobben, & Bethlehem, 2009). To test for this potentiality, we estimate a logistic regression predicting whether the variables that we possess for both respondents and non-respondents (variables obtained through personnel files)—*Birth Year, Start Year, Role, Male, White, College-Graduate*—impact the likelihood of survey response. The results, presented in Table A3 in the Appendix, demonstrate that *Birth Year, Start Year, Role* and *Male* all significantly impact the likelihood of response. To adjust for this, we utilize an inverse propensity score weighting approach.[25] Using the results from the logistic regression, we construct a propensity score that estimates each respondent's likelihood of response. We then re-estimate the original RF models using the inverse of each propensity score (1/propensity score) as a weight. The results are presented in Figures A3-A5 in the Appendix. As shown, the weighting process did not meaningfully impact our estimates. Note that this procedure only corrected for factors observed across respondents and non-respondents. It is possible that other, unobserved differences could be impacting our estimates.

Second, we consider whether the use of RFs is truly advantageous relative to more-traditional linear-regression models (LRs). While RFs offer a number of advantages over LRs—RFs allow for flexible functional forms (i.e., non-linear effects with complex interactions) and are robust to multicollinearity—it is possible that RFs do not outperform LRs (Na et al., 2021). If such is the case, then our approach may be needlessly overcomplicated and suboptimal. In the Appendix, we i) provide a more thorough discussion of the advantages and disadvantages of our approach and ii) compare the results of our RF models against a series of competing LRs. As shown in the Appendix, RFs outperform the LRs: switching from a LR to a RF reduces the root mean standard error by of 1.01% (*Overall Support*), 58.00% (*Weapons*), and 72.55% (*Military Vehicles*). While many of our predictor variables yield similar results across approaches (e.g., *Racial Animus* is a significant predictor in 2 of 3 LRs), differences exist. Together, this suggests that LRs in this context would generate suboptimal and potentially misleading results.

6. DISCUSSION & CONCLUSION

[25] For a description of the process, see Rosenbaum & Rubin (1983), Schonlau et al. (2004), McLaughlin, Mewhirter, & Sanders (2021), Uttermark et al. (2022), and/or Valliant & Dever (2011).

Recently, LEAs, large and small, have become more militarized. This increased militarization unsurprisingly tracks with the militarized way American society tends to tackle social problems—the Wars on Crime, Drugs, and Terror, for example. The 1033 Program represents one important driver of increased militarization, justified as a means to fight these "wars."[26] Contributing to the growing literature examining police militarization's causes and consequences, this article provides one of the first empirical assessments of the determinant of demand for militarized tools among officers. As one would expect from the growingly pervasive warrior model of policing (as opposed to a guardian model e.g., Stoughton, 2015), we found officers overwhelmingly supported the 1033 Program. However, in line with McLean et al. (2020), we find a more nuanced picture of officer attitudes where support for the 1033 Program, while high, is not ubiquitous. Specifically, officers exhibit reduced, though still high, support for receiving weapons and military vehicles.

Drawing from various literatures, we derived two theoretical reasons officers would support receiving equipment from the 1033 Program—perceived lack of resources (H1) and perceived threat (individual threat (H2a); group threat (H2b and H2c)). Of these, only the perceived-threat approach produced consistent results (H2) and only in a group-threat context rather than individual threat (H2b and H2c, not H2a). More specifically, for resource shortages, officer beliefs about available resources, training, and workload do not predict overall 1033 support or support for receiving militarized vehicles. Though, officers who perceive their workload as burdensome and who feel under-resourced do support receiving weapons from the 1033 Program.

[26] Importantly, though, this is not exclusively an American issue. Globally, LEAs are increasing militarization (De Bruin, 2021), and that militarization is associated with more violent repression (Stavro & Welch, 2023).

Lastly, although officers' perceived threat to their person did not predict support for militarization, group threat does for each outcome. For all three dependent variables, officer race and racial animus predicted support in the hypothesized direction. White officers and those officers displaying higher racial animus more strongly support receiving any military equipment from the federal government, including those objects most prone to violence—weapons and military vehicles.[27] Further, race and racial animus are among the two or three most important variables in predicting overall 1033 support and support for weapon acquisition, respectively. For military vehicle acquisition, racial animus is most important, and race is sixth. Ramey & Steidley (2018) find support for minority threat arguments by testing the effects of the policed area's racial makeup on departmental acquisition of militarized equipment. Our research supplements their findings by showing officer race and racial attitudes increase individual support for militarization.

While these findings provide lessons relevant to the study of police militarization, they also raise several questions. First, we cannot say whether and to what extent our findings would hold in different LEAs. For instance, would racial animus play such an important role in LEAs serving less diverse communities or in LEAs where officer demographics better match the city's? Would resource scarcity play a larger role in LEAs with significantly fewer officers per resident? Would racial animus play a lesser role in an area not plagued by years of tension between the police and Black community? How do distinct LEA subcultures shape the factors that drive demand? While we anticipate context matters, our current dataset precludes us from examining variation in effects. Future research should replicate our study

[27] These two variables also predict receiving office equipment from the 1033 Program (results in the Appendix, Figures A1 and A2). We did not have expectations about when officers would support receiving this material, but it strikes us as interesting, if not surprising. Future research should seek to better understand when officers support militarized vs. non-militarized equipment. Conjoint experiments represent a feasible tool for better understanding how officers rank the importance of receiving different types of equipment from the 1033 Program.

across different LEAs to elucidate how these different contexts affect support for militarization. Second, while we sought to include a wide array of variables that could predict support for militarization, it should by no means be considered an exhaustive list. Researchers should continue to comb social science literatures to identify alternative predictors of support. This is especially important in light of considering confounders to establish causality more confidently. Although we included several covariates, the risk remains, as with all observational studies, that we omitted an unobserved confounder.[28] As more science accumulates on this topic, researchers will be able to more precisely specify models with this in mind. Third, while our study highlights the determinants of individual officers' desire for military equipment, it is unclear as to whether such determinants also impact their behavior. While social psychology research has long established that *why* someone desires an object ultimately drives *how* they use it (see Sheeran, 2002), more research is needed to understand how the determinants of demand manifest into actions in this context. Finally, our study focuses on officer support for one of several programs (but potentially the most well-known and controversial program) that facilitate the flow of military goods to LEAs. Future studies should seek to replicate and extend our study in the context of alternate programs.

As the science accumulates, we can gain a better understanding of the types of officers who support receiving militarized equipment. Since receiving militarized equipment represents a danger to officers (Carriere & Encinosa, 2017; Masera, 2021) and those they encounter (Delehanty et al., 2017; Lawson, 2019), this information can help target training efforts designed to decrease violence in society. Further, our results provide clues to the types

[28] We also note that observational studies always carry with them the challenge that the explanatory variables were not administered at random, which also represents potential threats to establishing causality. Future research should take the lessons from our work and carefully design experiments that can more effectively isolate causal relationships.

of training to conduct. For example, the implicit bias training described by Eberhardt (2019) may decrease violence by changing officer attitudes with respect to communities policed,[29] but training should also seek to change officer attitudes towards the tools they use to police those communities.

[29] Though research suggests solely identifying biases does not cause one to introspect on whether they themselves fall prey to them (e.g., Pronin & Schmidt, 2012). More research needs to be done on bias training and its effects.

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TABLES

Table 1: Summary Statistics

Variable	N	Mean	SD	Min	Max
Overall Support	253	8.38	2.46	0	10
Weapons	291	0.61	0.49	0	1
Military Vehicles	291	0.47	0.50	0	1
Resources	272	5.89	2.90	0	10
Workload	265	6.91	2.65	0	10
Training	274	7.42	2.46	0	10
Start Year	319	2000.16	8.15	1985	2016
Work-Important	284	8.46	2.19	0	10
Happiness	302	6.56	2.84	0	10
Safety	253	6.79	2.78	0	10
White	358	0.71	0.45	0	1
Racial Animus	256	4.80	3.50	0	10
Birth Year	358	1972.32	8.20	1952	1994
Male	358	0.75	0.43	0	1
Promotions	319	0.82	1.07	0	6
Local Years	329	30.64	17.28	0	66
Native	343	0.60	0.49	0	1
Married	336	0.69	0.46	0	1
Children	296	2.15	1.85	0	15
Information	280	7.76	2.24	0	10
Physical Conditions	261	6.45	2.89	0	10
Veteran	345	0.32	0.47	0	1

	N	Percentage
Role		
Officers	209	58.38
Leadership	114	31.84
Specialist	35	9.78

Table 2: Prediction Rates for 1033 Program Support

	Overall	**Weapons**	**Military Vehicles**
In-sample Prediction	0.70	0.76	0.82
Out-of-bag Prediction	0.62	0.61	0.56

Table 3: Direction of Effects for Important Variables on Officer Support for the 1033 Program.

		1033	**Weapons**	**Military Vehicles**
H1: Resources	Resources		-	
	Workload		-	
	Training			-
H2: Threat	Safety			
	White	+	+	+
	Racial Animus	+	+	+
Other Variables	Birth Year	+		
	Male			
	Role	-		
	College Grad			
	Promotions	-	-	
	Local Years	-		
	Native	-		-
	Married	+		
	Children		+	
	Military Rank			+
	Information			
	Physical Conditions	+		
	Start Year		∩	
	Work-Important	+		+
	Happiness	+		

Each symbol represents the general relationship between the listed predictor variable and officer support – positive (+); negative (-); or inverted-U curvilinear (∩). A blank cell indicates the variable was found to be unimportant in predicting the outcome.

FIGURES

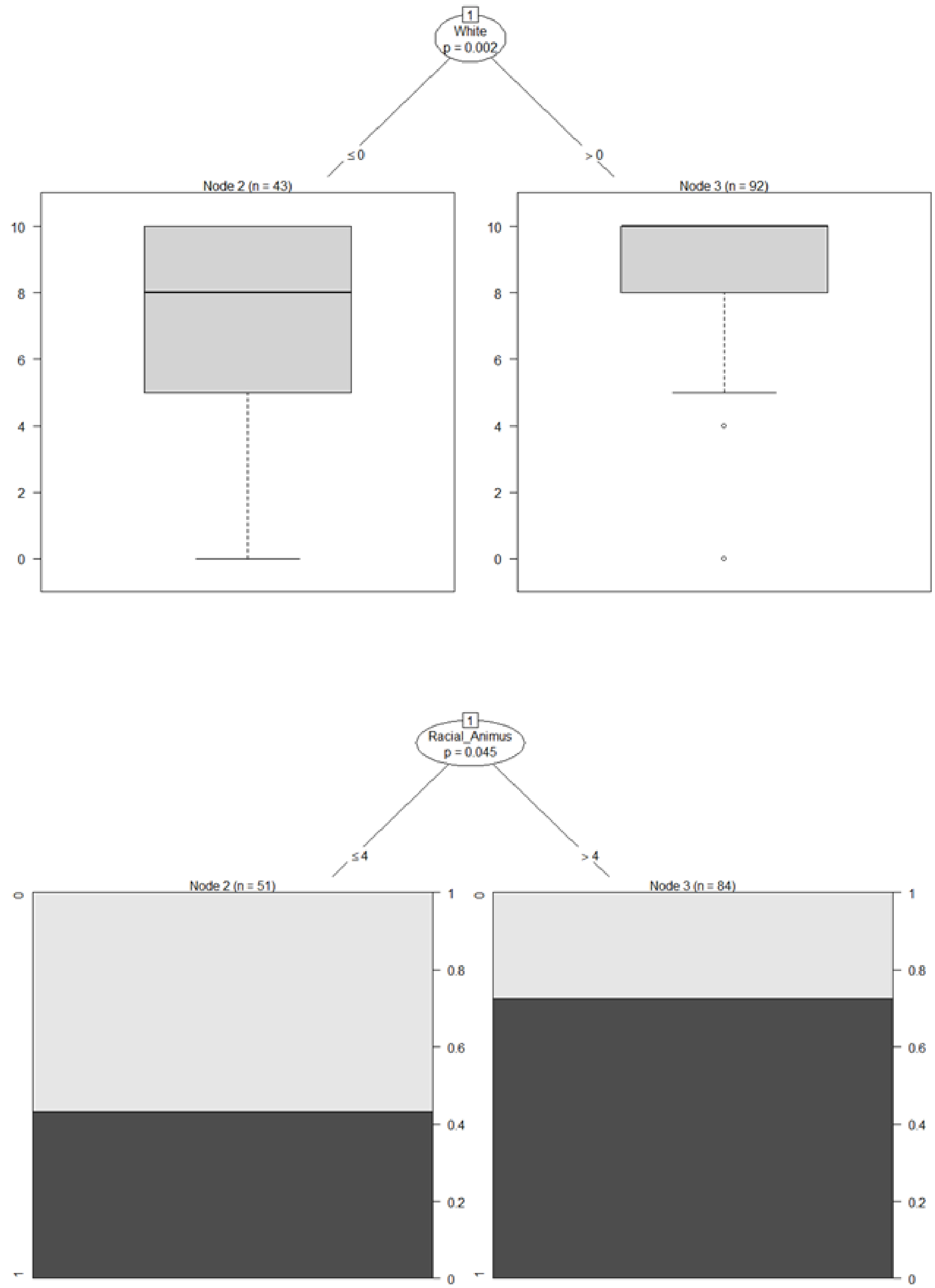

Figure 1: Individual Regression/Classification Trees.
The top regression tree predicts overall 1033 Program support. The bottom classification tree predicts support for receiving weapons from the 1033 Program.

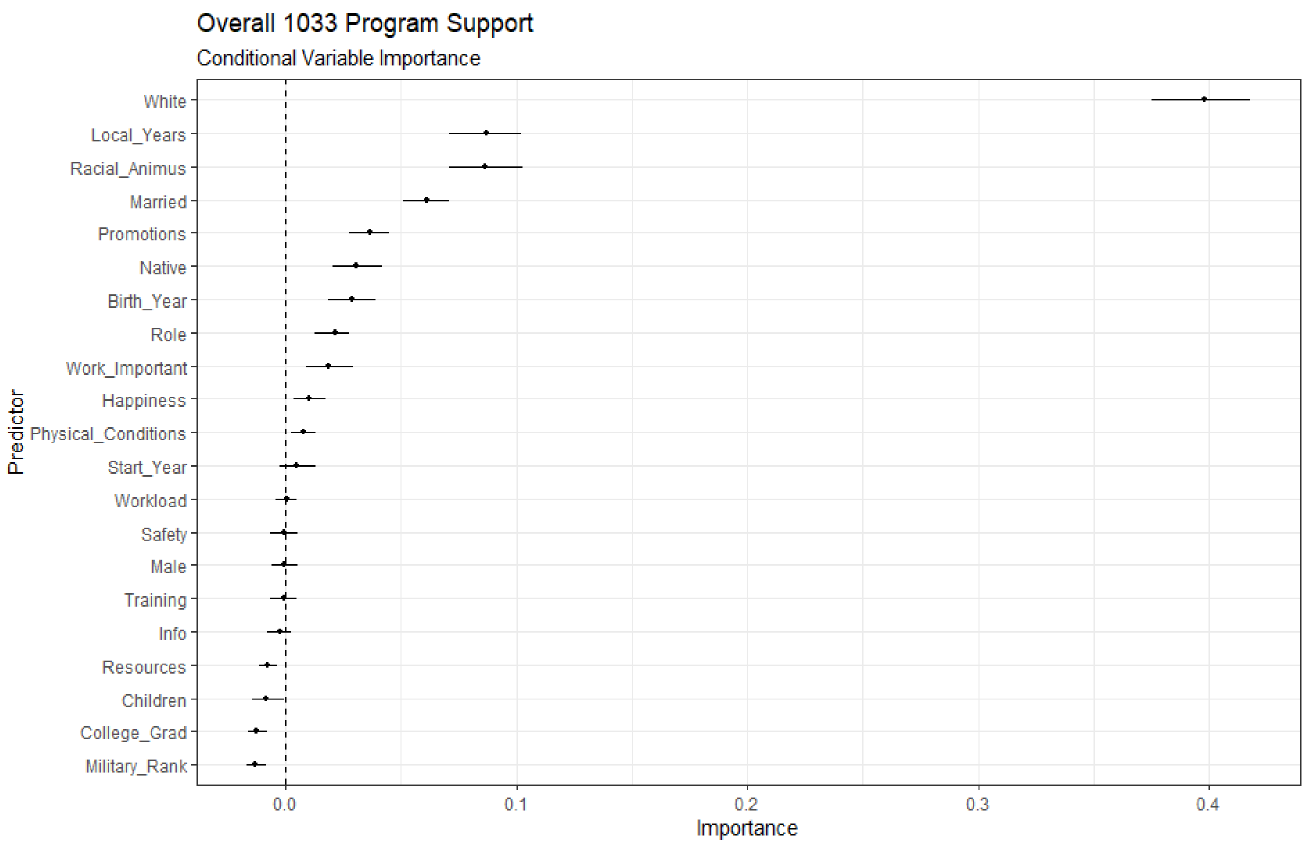

Figure 2. Conditional Variable Importance Plots, Overall 1033 Support

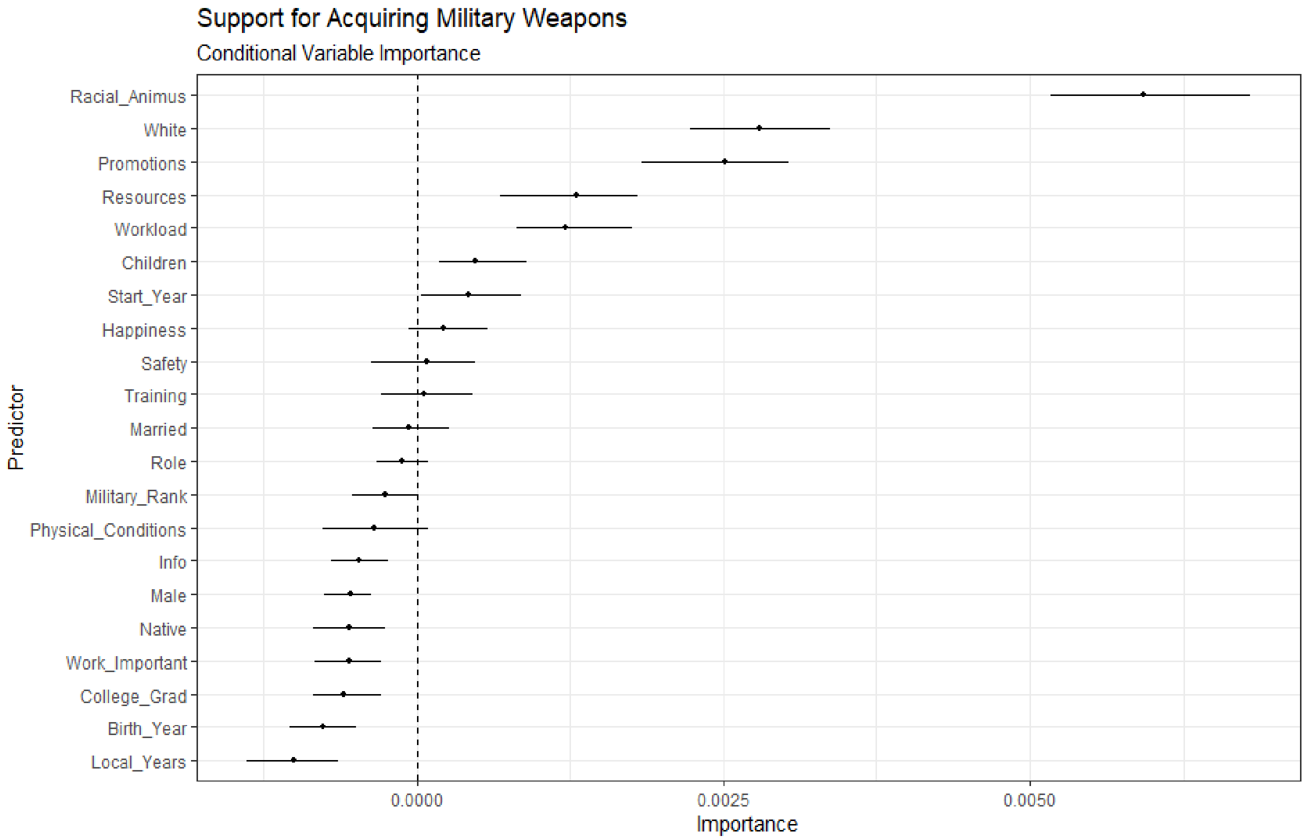

Figure 3. Conditional Variable Importance Plot, Military Weapons

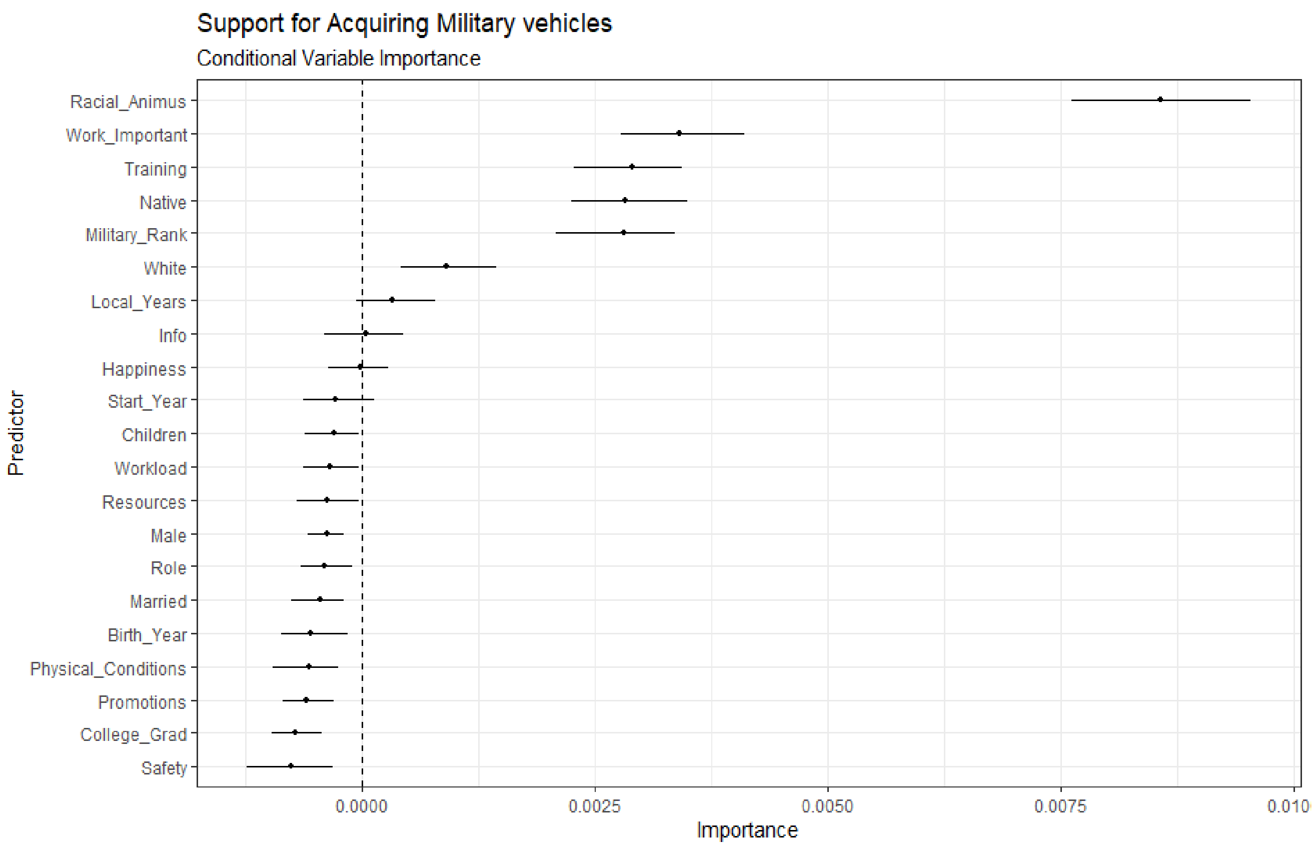

Figure 4. Conditional Variable Importance Plot, Military Vehicles

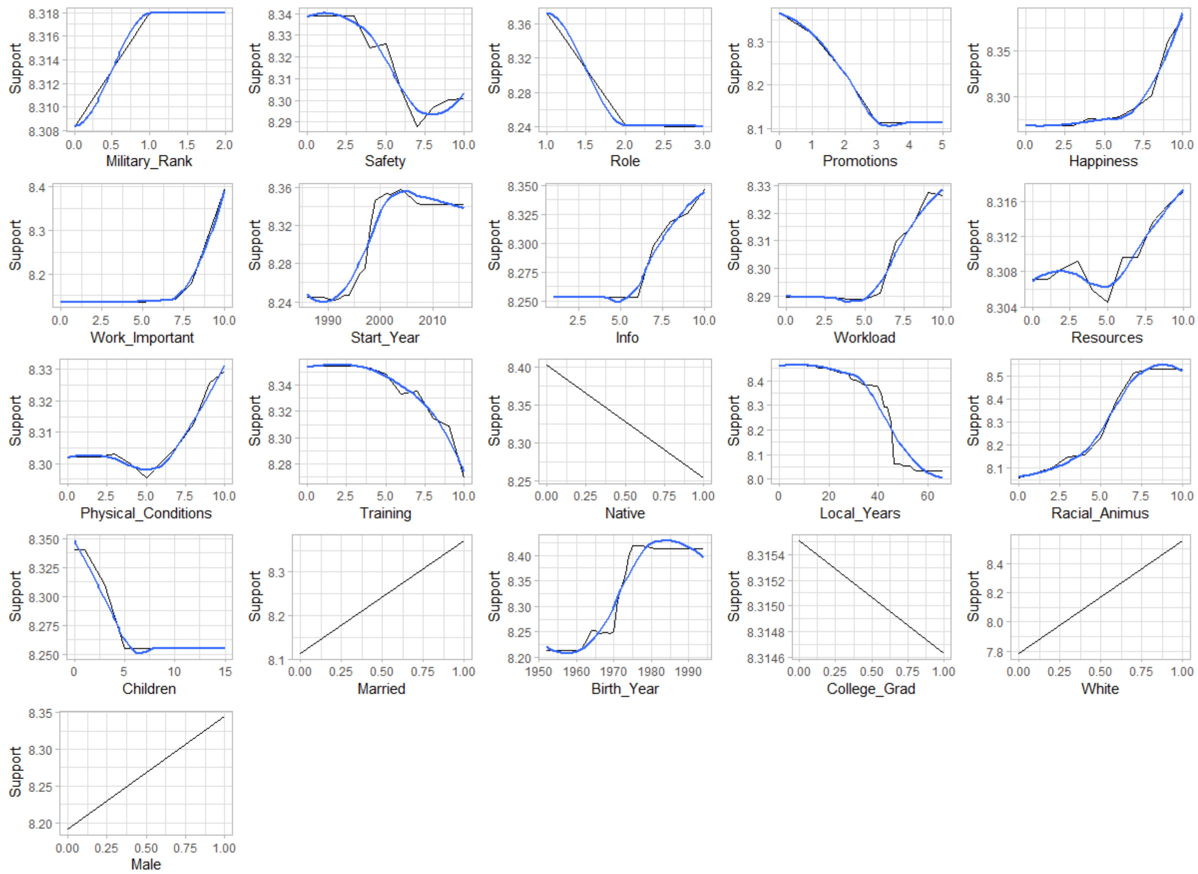

Figure 5: Partial Dependence Plots, Overall 1033 Support
Black lines are linear connections between each plotted point. Blue lines use LOESS to smooth those lines. Variables deemed important by the variable importance exercise are: Role, Promotions, Work-Important, Start Year, Native, Local Years, Racial Animus, Married, Birth Year, and White

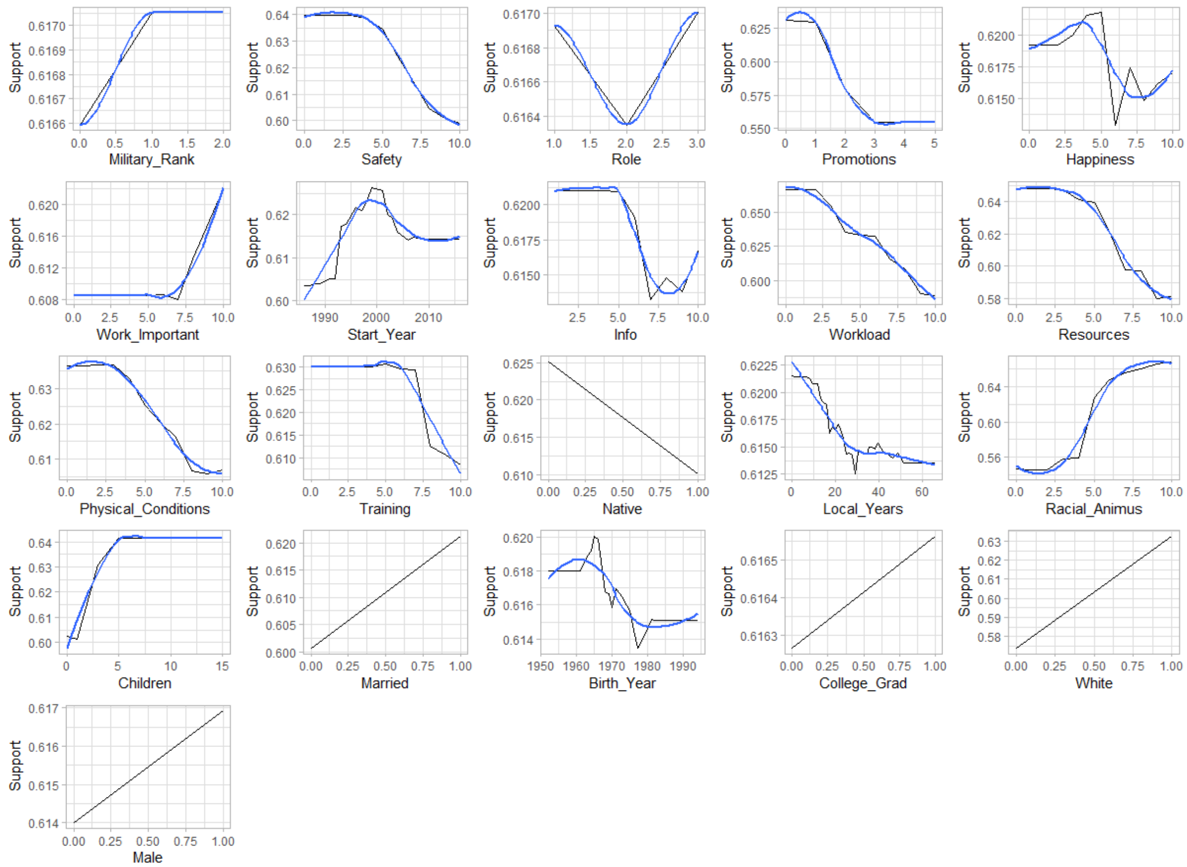

Figure 6: Partial Dependence Plots, 1033 Weapons Support
Black lines are linear connections between each plotted point. Blue lines use LOESS to smooth those lines. Variables deemed important by the variable importance exercise are: Promotions, Start Year, Workload, Resources, Racial Animus, Children, and White.

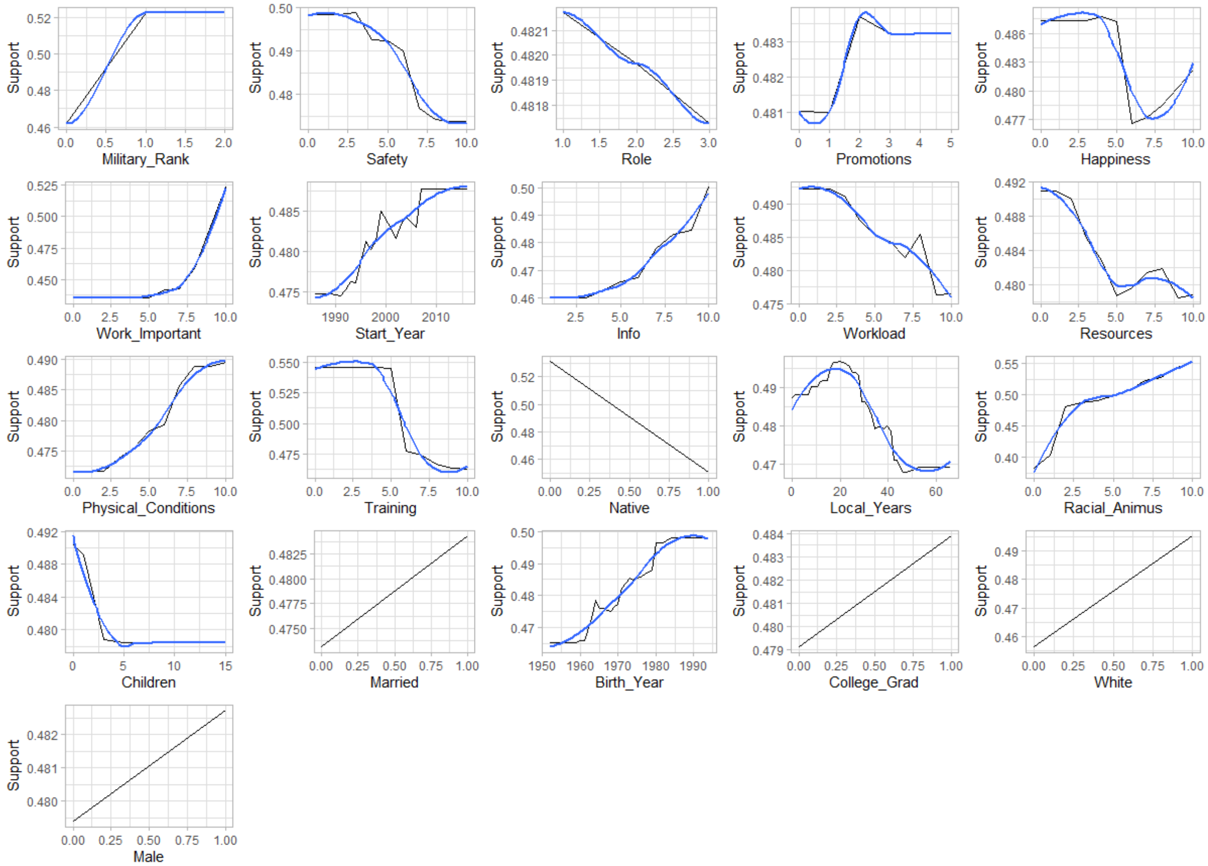

Figure 7: Partial Dependence Plots, 1033 Military Vehicle Support
Black lines are linear connections between each plotted point. Blue lines use LOESS to smooth those lines. Variables deemed important by the variable importance exercise are: Military Rank, Work-Important, Training, Native, Racial Animus, and White.