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Vulnerabilities to Terrorism

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Abstract

Is our nation safe from terrorist attacks? This paper examines the effectiveness of U.S. federal grants in reducing domestic vulnerability to terrorism since the 9/11 attacks. I derive a model for allocating federal funds to States based on targets within the State, the government budget, and three parameters specific to a target type - the probability of attack, the expected damage upon attack, and the effectiveness of grant funds on mitigating risk. The damage mitigation function captures the effectiveness of grant funding toward reducing expected damage - a feature that is ignored in the current policy environment. My comparison of the optimal allocations to the government formula by which $19 billion has been allocated exposes three distortions. Empirical results suggest that the government formula over-compensates for population-based vulnerabilities leaving unsystematic vulnerabilities exposed. Chemical plants, oil and gas pipelines and livestock facilities may be particularly at risk.

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Vulnerabilities to Terrorism

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I. Introduction

As we commemorate the five year anniversary of the 9/11, is our nation safer from terrorist attacks? Federal authorities have spent over $19 billion in state and local homeland security efforts since 9/11, yet the question of how effective they have been in reducing our domestic vulnerability to terrorism is debatable. Intuitively, one could measure effectiveness by assessing whether federal funds have been allocated to areas that risk being attacked.[2] Practice has not followed intuition, however, and evidence suggests that federal authorities have not been effective in reducing vulnerability because federal grant funds have not been allocated to areas based on risk.

Since the attacks of 9/11, the Department of Homeland Security (DHS) has overseen funding to state and local homeland security programs for preventing, preparing for and responding to acts of terrorism. The Patriot Act of 2001 authorized grants for the purchase of equipment and training and mandated that 40% of the funds be distributed equally among States. The remaining 60% has been distributed according to DHS discretion. From 2002-2005, DHS allocated the 60% based solely on population. In 2006, DHS began allocating the 60% based on risk, but the formula remains classified. With this as a backdrop to the policy environment, we can ask what an economic model of a formula that is based 100% on risk would look like. Only then can we compare the optimal risk allocations with the allocations distributed by DHS since 2002 to see which risks are not being protected.

The implications of this are large. The paper focuses on the Homeland Security Grant Program, the program responsible for $11 billion of the $19 in spending since 9/11. Since the first allocations in fiscal year 2002, controversy over the funding formula has escalated. Interstate bickering over who receives “too much” or “too little” is endemic. A case in point is the claim by California that Wyoming receives more than it deserves in per capita funding ($35.31 as opposed to California’s $4.68 per capita), and

[2] The 9/11 Commission Report urged that spending to local police departments, firefighters and emergency medical technicians “be based strictly on an assessment of risks and vulnerabilities”

the rebuttal by Wyoming that California receives too much total funding resulting in a sizeable share of the total budget ($164 million or nearly 10% of the total appropriation, compared to Wyoming's $17.6 million) (Ransdell, 2005). I show that they may both be right, to a degree.

The Patriot Act requires that funds be used to increase the capabilities of jurisdictions to prepare for terrorist attacks, but provides little guidance to DHS on how to do so. Should jurisdictions equally prepare against loss of life, damage to property, disruptions of economic activity, and attacks on national icons? How much should the private sector contribute to prepare? These questions fueled multiple bills in Congress, which have all died in political wrangling[3], and we are left with no established systematic framework to assess what risks are covered, and what risks are missed. In addition, there has been no consensus on a ranking of factors which make one State more or less vulnerable to terrorism. According to a recent Government Accounting Office (GAO) report, 3,400 chemical plants in the U.S. pose a grave hazard to human life and health (GAO, 2006). Without a ranking of risk factors (i.e., chemical plants versus nuclear facilities) and *how funds can be used to dissipate or mitigate risk*, it is futile to debate which areas are the "neediest".

In this paper, I provide an economic framework for the optimal allocation of homeland security grants to State governments based 100% on risk. The optimal allocations result from societal welfare optimization of a benevolent social planner with a fixed budget facing terrorists who seek to maximize expected damage. A relationship between grant funding and expected damage, the *damage mitigation function*, is the first of two key innovations of the analysis. The model predicts that allocations should be increasing in three parameters characterizing each type of target:[4] (i) the probability of attack, (ii) the expected damage given a successful attack, and (iii) the efficiency of a dollar granted to ameliorate the expected damage of an attack (damage mitigation).

The second key innovation of the analysis is the insight that the original formula can be related to the optimal allocation by separating targets, or portions of targets, into three classes. The original formula used between 2002-2005 allocated 40% equally

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[3] See e.g., H.R. 91, H.R. 228, H.R. 1419/S.308, S. 140

[4] Types of targets include water input sources, power generation, airports, pipelines, livestock feeding lots, chemical plants, etc.

among all States and 60% based on share of population. Because the 2006 grant formula remains classified, I compare the optimal risk-based allocations with the original formula only. The comparison is made by sorting all targets into three categories according to those that are equally distributed across states (covered by the 40% allocation), those that are perfectly correlated with population (covered by the 60% allocation) and those that are unsystematically dispersed across states (uncovered). A simple *government excess formula* comparing the original *40/60 formula* and the risk based formula highlights three distortions created by the current policy environment. First, the 40% that is distributed equally among states may be too large or too small relative to the number of targets that are distributed evenly. Second, the 60% that is distributed based on population may be too large or too small relative to the number of targets that are correlated with population. Finally, there may be non-coverage of unsystematic targets.

As an example of the implications of our model, consider California's argument that Wyoming is over-funded by the 40% equal allocation. Even if Wyoming has a small number of evenly distributed assets such as interstate highway miles, Wyoming may also have a large number of unsystematic and thus uncovered targets, such as its large system of pipelines and livestock facilities. Since the DHS allocates money in a federalist system whereby funds are allocated to states and not directly to targets, a distortion in over-allocation by the 40% lump sum allocation may be, in the specific case of Wyoming, offset by the failure of DHS to provide risk funding to cover pipelines. A critical implication is that as DHS begins to assess risk for re-allocating the 60% funds, it must consider any over- or under-allocations of the 40% equal grant allocations mandated by the Patriot Act.

To examine these distortions, I use data from the State of Indiana as a reduced form of risk weighting among targets. Applying these to the nation at large, I calculate the optimal risk-based allocations for all States from the known distribution of targets and compare them to the government allocations. The results suggest that the government over-compensates to population-based vulnerabilities leaving unsystematic vulnerabilities exposed. Unsystematic vulnerabilities include chemical plants, oil and gas pipelines and livestock facilities. California is the most over-funded of all states.

The remainder of the paper proceeds as follows. The next section presents a model of damage mitigation in which a social planner distributes funds across jurisdictions given a budget constraint for homeland security. Section III introduces an implementation framework and Section IV introduces data which can be used in comparing optimal risk-based allocation framework with the original allocation mechanism. Section V compares the allocations from the original formula to those using the optimal risk-based formula, using reduced form expected damage parameters from the state of Indiana. Section VI concludes with implications of the analysis.

II. Model of Terrorism Damage Mitigation

Consider a social planner sitting in Washington D.C., charged with the task of distributing Federal Homeland Security funds to States for terrorism preparedness. The social planner understands that terrorists are rationally minded actors relying on violence or its threatened use to promote their political goals (Frey and Luechinger, 2004).[5] Terrorists select attacks on targets to maximize the expected damage inflicted (Lakdawalla and Zanjani, 2002; Kunruther, Michel-Kerjan and Porter, 2003). The social planner must construct a plan to assist jurisdictions in their efforts to prevent, prepare for and respond to terrorist attacks which minimizes the expected damage across all possible attacks.

A. The Basic Model

I begin by characterizing the level of terrorist inflicted damage in the benchmark case in which there is no government intervention. In this case, a terrorist attack will cause a level of expected damage, calculated across all jurisdictions $j = 1,...,N$ and across all targets $i=1,...M$. The total expected damage is simply the probability of a successful attack, p_i, times the terrorist-inflicted damage, d_i, given an attack, times total number of targets in a jurisdiction, s_{ij}:

$$E[D] = \sum_{i}^{M} \sum_{j}^{N} p_i \, d_i \, s_{ij} \tag{1}$$

[5]The Al Queda operational training manuals state that economic disruption and mass casualties are its central goals (Woo, 2002).

The expected damage formula makes three assumptions. (i) Targets are a fixed number installations or structures which can be observed, categorized and counted. (ii) Non-pecuniary damage (e.g., psychological damage such as fear) can be monetized. (iii) Both the probability of a successful attack and the damage upon attack are the same for a given target type, irrespective of location. For instance, Yankee Stadium in New York City, NY, has the same probability of a successful attack and the same damage upon attack as an attack on the University of Kansas Stadium in Manhattan, KS.

The first assumption is that targets can be observed and counted. Targets are defined consistent with the definition in Homeland Security Presidential Directive No. 7, "Critical Infrastructure Identification, Prioritization (HSPD-7)." [6] The 17 sectors identified in HSPD-7 are defined as Critical infrastructure and key resources provide the essential services that underpin American society whose incapacitation, exploitation, or destruction, through terrorist attack, could have a debilitating effect on security and economic well-being. The HSPD-7 sectors are: Agriculture and Food, Public Health and Health Care, Drinking Water and Wastewater Treatment Systems, Energy, Banking and Finance, National Monuments and Icons, Defense Industrial Base, Information Technology, Telecommunications, Chemical, Transportation Systems, Emergency Services, Postal and Shipping, Dams, Government Facilities, Commercial Facilities, Nuclear Reactors, Materials, and Waste. This is consistent with what others have listed as possible targets: stadiums, bridges, dams, airports, nuclear power plants, marine terminals, defense installations, banking and financial targets, water supplies, chemical plants, food and agricultural resources, police and fire departments, hospitals and public health systems, and government offices (Willis, H., Morral, A., Kelly, T. and J. Medby, 2005). Symbolic targets, defined as ones associated with the American way of life or with name recognition -- such as national symbols, high profile skyscrapers and major corporate headquarters – have also been listed as attractive to terrorists. In what follows,

[6] Consistent with HSPD-7, "Critical Infrastructure Identification, Prioritization, and Protection," the NIPP reflects the 17 individual CI/KR sectors http://www.whitehouse.gov/news/releases/2003/12/20031217-5.html (last accessed 12/26/06)

we ignore security externalities such as target shifting[7], whether hardening one target diverts an attack to another target (Shavell, 1991; Lakdawalla and Zanjani, 2005), and interdependent security[8], whether individuals or firms have incentives to carry out socially appropriate levels of security investment (Kunreuther and Heal, 2003).

The probability of successful attack (p_i) is a function of the accessibility of the target, mode of attack and methods used for the attack (bomb, nuclear, biological). Terrorist-inflicted damage, (d_i), is defined as the severity resulting from a strike or the monetized destabilization from a successful terrorist attack, where destabilization can include disruption of normal activities, loss of life, fear and media attention as well as purely economic impacts (Kunreuther H., E. Michel-Kerjan, and B. Porter, 2003;Luechinger, 2004) such as tourism (Enders et al, 1992), foreign direct investment (Enders and Sandler, 1996), gross domestic income and stock (Abadie and Gardeazabal, 2003), and trade (Nitsch and Schumacher, 2004). To illustrate the different types of impacts from a terrorist attack, consider the terrorist attacks of 9/11, which killed nearly 3000 people and inflicted damage currently estimated at $80 billion and growing (Kunreuther and Heal, 2003). This illustrates that economic consequences can be both direct and cascading. As another example, pipelines are important on a national level, due to interdependencies and system effects (downstream and upstream), even if they are not perceived as highly consequential by the jurisdictions which possess them. For example, during Hurricane Katrina one Louisiana Parish ignored protection of a nationally critical pipeline, one which provides two-thirds of eastern U.S. petroleum production, because the pipeline traverses but is not critical to the Parish. Together, $p_i d_i$ represents the base level of expected damage in monetarized property and human loss for a given target, with no federal spending considered. The loss figure is multiplied by the total number of that given target in the jurisdiction, s_{ij}, otherwise known as the

[7] The empirical literature on risk-shifting and deterrence in crime is reviewed by Cameron (1988) and Hesseling (1994). Shavell (1991) explains that an individual, who invests in observable protection such as iron bars on his windows, discourages rational thieves from attempting to enter. However, by discouraging thieves from entering his house, he diverts them to other houses without any visible defenses. This represents the risk-shifting external effect of protection – a negative externality that has obvious analogues in the case of terrorism. (Lakdawalla and Zanjani, 2005)

[8] Kunreuther and Heal (2003), self-protection by one target directly reduces risk of other targets. An example is screening by airlines, where effective screening by one airline yields benefits to other airlines.

vulnerability exposure in that jurisdiction, to arrive at a loss figure for a given target in a given jurisdiction.

In the spirit of Bergstrom and Goodman (1973), the model generates optimal spending allocations for homeland security as an outcome of a decision that considers the likelihood of an attack on an asset, subsequent damage upon attack, and a budget which constrains government spending. The benevolent social planner seeks to minimize the expected damage, $E[D]$, of a terrorist attack by providing funding to jurisdictions to prepare, prevent and respond to terrorist acts.[9] All social welfare models focus on inequality and have one of several distributive goals (Musgrave, 1959). One goal is equalization of cost differences in the provision of public safety services, a goal that can be justified in that without intergovernmental aid, some local communities would not be able to afford to provide their communities with the levels of protection provided in affluent neighboring jurisdictions (Ladd, 1994). So, similar to the way in which a social planner allocates funding for federal education and healthcare programs, in our framework, homeland security grants are allocated with the goal of maximizing social welfare across jurisdictions (Ladd, 1994; Oates,1999).

Certainly other motivations influence spending decisions on homeland security. The public choice school of thought and assumes that government officials pursue their own interests and maximize other non-economic goals, such as size of bureaucracy or probability of election (Niskanen, 1971; Fiorina and Noll, 1978). In a separate paper, Brunet (2006), I consider the political economy impact on homeland security funding in the context of this public choice framework.

The social planner in Washington knows all the p_i and d_i parameters as well as targets, s_{ij}. She has a fixed budget G for homeland security, of which a portion g_j is distributed to each jurisdiction j. Since we assume (for simplicity) that there is no role for

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[9] This goals and objectives of the model correspond nicely to the goals and objectives of DHS. According to the Homeland Security Act of 2002, http://www.dhs.gov/xabout/laws/law_regulation_rule_0011.shtm (last accessed 12/27/06) "The primary mission of the Department is to (A) prevent terrorist attacks within the United States; (B) reduce the vulnerability of the United States to terrorism; and (C) minimize the damage, and assist in the recovery, from terrorist attacks that do occur within the United States."

State decision-making[10], we can temporarily abstract from the g_j to model the allocation of terrorism funds to cover each target. The budget constraint can be re-written as:

$$G = \sum_{j=1}^{N} g_j = \sum_{i=0}^{M} \sum_{j=1}^{N} a_{ij} s_{ij} \ , \tag{2}$$

where the a_{ij} are the allocations of funds to cover targets s_{ij}. There are $N+1$ targets i and M jurisdictions j. A standard non-negativity constraint applies to a_{ij}.

The relationship between grant funding and expected damage, the *damage mitigation function*, is the key innovation of our model. The amount of damage, $p_i d_i s_{ij,}$ is offset by the damage mitigation function, $f(a_{ij})$. Federal efforts to mitigate expected damage are captured by $f(a_{ij})$:

$$f(a_{ij}) = \frac{1}{1 + k_i a_{ij}} \qquad \text{where } k_i > 0 \text{ and } a_{ij} \geq 0 \tag{3}$$

In this framework, k_i is a parameter describing damage mitigation effectiveness by target i. This parameter describes the benefit of spending on a target in terms of mitigating future expected damage upon a target. The overall damage mitigation function, $f(a_{ij})$, measures the mitigation of risk (in percentage terms) for every dollar mitigation investment per target in a jurisdiction.

The damage function possesses three key properties, (i) allocation spending, $a_{ij,}$ reduces expected damage, $f'(a_{ij})<0$, (ii) there are diminishing returns to investment in damage mitigation, $f''(a_{ij})>0$, and (iii), the damage function is benchmarked to the original damage parameter, namely when $a_{ij,}=0$, the damage mitigation function is not infinity, $f(0)=1$. When there is no government spending, damage is the original $p_i d_i s_{ij.}$

Having introduced the effect of the damage mitigation function, the social planner chooses the a_{ij} to minimize the expected damage of terrorism subject to the budget constraint in (2):

$$\underset{a_{ij}}{Min}\ E[D] = \sum_{i}^{M} \sum_{j}^{N} p_i d_i s_{ij} f(a_{ij}) \tag{4}$$

[10]In reality, the Federal government distributes disbursements of $g_{j,}$ to each State j. In turn, the State allocates its grant, $g_{j,}$ to sub-state governmental entities (local governments, Indian tribes, parishes and the like) in the form of mitigation allocations , a_{ij},. Our simplifying assumption is that state and local-level governmental decisions regarding the allocation of a_{ij} are equivalent to how the Federal government would allocate. One could imagine the alternative view where multiple social planners represent potential barriers to the effectiveness of complimentary forms of public participation.

Solving the social planner's expected damage minimization problem subject to the governmental budget constraint yields several results. The multiplier, known as the shadow value of an extra dollar of the government budget for terrorism protection, λ, is given by:

$$\lambda = \frac{p_i d_i k_i}{\left(1 + k_i a_{ij}\right)^2} \quad \forall\, ij \tag{5}$$

The key insight is that, since only a_{ij} vary across jurisdictions j in the multiplier equation, it must be that $a_{ij} = a_i\ \forall ij$. Optimal allocations do not vary by jurisdiction -- they are target specific and not jurisdiction-target specific. Allocations among states vary by the types and number of targets that each state has.[11] This result alone suggests that funding should be allocated based on the dispersion of targets and not by jurisdiction. Equating λ across targets yields a relationship across any two a_i , a_0 combination

$$a_i = \frac{1}{k_i}\left[\left(1 + k_0 a_0\right)\sqrt{\frac{p_i d_i k_i}{p_0 d_0 k_0}} - 1\right]. \tag{6}$$

The resulting optimal allocation to target, a_0, is:

$$a_0^* = \frac{G + \sum_{i=1}^{N} \frac{S_i}{k_i}\left(1 - \sqrt{\frac{p_i d_i k_i}{p_0 d_0 k_0}}\right)}{\sum_{i=0}^{N} \frac{k_0}{k_i} S_i \sqrt{\frac{p_i d_i k_i}{p_0 d_0 k_0}}} \tag{7}$$

where the total number of one particular target across all jurisdictions is the endowment of that target: $S_1 = \sum_{j=1}^{M} s_{ij}$.

Intuitively, a target's allocation, a_0^*, depends on the Government budget G, all efficiency parameters k_i, the probability of attack on all targets i, and the damage upon attack, d_i. The resulting optimal allocations a_{ij} should be subject to a non-negativity constraint. Rather than impose the necessary Kuhn-Tucker conditions to ensure non-negative allocations, I assume that the number of targets whose probability of attack, damage upon attack and/or mitigation efficiency is sufficiently low relative to other

[11] This paper only considers that each State contains targets in it's jurisdiction, and does not distinguish between public or private ownership or management of the target per se.

targets, such that allocations which would optimally be negative are not included in the set of targets which the government would try to protect. The non-negativity constraint imposed on an asset to be considered a target is:

$$G+\sum_{i=1}^{N}\frac{S_i}{k_i}\left(1-\sqrt{\frac{p_i d_i k_i}{p_0 d_0 k_0}}\right)>0 \tag{8}$$

Targets not meeting (8) are excluded from government consideration.

To interpret a_0^*, begin under the unrealistic scenario that all targets have the same expected damage times the efficiency parameter, $p_i d_i k_i$, are equal across all targets. In this case, $a_0^* = \dfrac{G}{\sum_{i=0}^{N}\frac{k_0}{k_i}S_i}$, indicating that an optimal allocation to a target 0 is the government budget G divided equally among all targets s_{ij}, normalized by mitigation efficiency of target 0, $\frac{k_0}{k_i}$. In this way, funding is distributed with allocations varying by degree of effectiveness. Of course, it is unrealistic that the expected damage times the efficiency parameter would be equal across targets. Realistically, the allocation to target 0 decreases (increases) depending on whether the mitigation of the expected damage, $p_i d_i k_i$, for each target i is larger (smaller) than that of the base target 0. It is worth noting that an allocation to a target depends on relative damage exposure and mitigation efficiency of all other targets. Thus, a government program with a fixed budget for each target will not equally protect all risks over time if new sources of risk (new targets) arise.

B. Incorporating the Original 40/60 Government Formula

This section begins with a description of the original government formula used to distribute homeland security grants across States from fiscal year 2002-2005. I combine this with the risk-based formula and call it the *government excess* formula.

Since the 1990s, states have relied on federal funds to purchase equipment and specialized training to aid in the prevention and response to terrorist events. The terrorist attacks of 9/11 sparked efforts to codify and expanded previous mechanisms to distribute homeland security funds for counterterrorism. Section 1014 of the U.S. Patriot Act codified a grant program for states and local governments to allocate a minimum, lump sum amount (40%) of the year's appropriation for homeland security to each U.S. State and territory to prevent, prepare, and respond to acts of terrorism.[12] The remainder (60%) would be distributed according to agency discretion. From fiscal year 2002 to 2005, grants have been distributed according this formula with 40% of the annual appropriation distributed to States in equal shares with the remaining 60% distributed based on a state's population (pop_j) relative to total U.S. population ($TPop$). This distribution is formalized as:

$$\tilde{g}_j = 0.4G\left(\frac{1}{50}\right) + 0.6G\left(\frac{Pop_j}{TPop}\right) \tag{9}$$

Where $\tilde{g}_j$ is the Federal grant amount for State j, and G is the government budget for homeland security. We refer to (9) as the original *40/60 formula*,[13] and describe two key characteristics of this formula.

To be sure, the original *40/60 formula* communicates a strong equity consideration consistent with democratic principles. Similarly, the ideology behind the *40/60 formula* closely parallels voter representation in the U.S. Congress: equal state representation in the Senate and population-based representation in the House of Representatives. Finally, the original formula also parallels sentiment regarding the distribution of risk. States with large populations presumably perceive their States' vulnerability to terrorism as correlated with population, and those from small States would perceive exposure as more evenly distributed across States.

Next, examining the original formula reveals that it implicitly groups targets into three classes: (i) those evenly distributed among states (represented by the 40% amount), (ii) those correlated with population (represented by the 60% amount), and most importantly, (iii) those not covered by the formula (all else not covered by either the 40%

[12] For this paper, distributions to the territories – Virgin Islands, Mariana Islands, Samoa, Guam - are not discussed.

[13] A formula with a minimum amount is not uncommon for federal grants. In fiscal 2001, 12 of the largest federal grant programs provided small-state minimums from 0.05 to 0.50 percent of appropriations for the program year. The SHSP minimum amount for each state, (0.75 percent) is larger than most minimums. For example: 0.05 percent for Technology Literacy Challenge Fund Grants and also the School Renovation Grants (DOL); 0.25 percent for the Byrne Formula Grant Program(DOJ); 0.50 percent for the Special Programs for aging and the community service block grant programs(DHHS), the Workforce Investment Act (DOL), and the Special Education Grants for Infants and Families with Disabilities (DOE).

or the 60%). Of course, the government may realize that targets in the third class exist, but the legislative process may impede the funding of targets outside of the 40/60 framework. These three classes will enable us to simplify the model and compare the allocations to States using the original formula ($\tilde{g}_j$) with the optimal risk-based State allocations (g_j).

Since the original formula implicitly establishes three classes of targets, the next step is to transform the targets into comparable units. I assume that all targets s_{ij} fall into one of these government classes. It is important to note that this assumption is made without loss of generality because any specific target can be decomposed into 3 parts according to:

$$s_{ij} = \frac{1}{50}\sum_j s_{ij} + m_i \ pop_j + \mu_{ij} \tag{10}$$

In this formulation, m_i is a transformation common to all jurisdictions that maps population to units of the target. For example, for pipelines, m_{pipe} might be in units of miles per population. A full example of how each target can be decomposed into three parts helps to make these concepts concrete. States might average 1,000 miles of pipelines. In addition, pipelines might increase at the rate of 500 miles per one million people. Finally there is a noise term, μ_{ij}, which captures the unsystematic nature of targets. The unsystematic term is particularly appropriate for states such as Oklahoma, which has a low relative population but large stocks of oil which have been naturally unsystematically distributed across the continent by forces of nature.[14] While I assume that targets fall into one of the three categories, later I show techniques that can be used to categorize targets. For example, linear regression techniques can be used on equation (10) to determine what percentage of the target is related to the target class.

Using the transformation approach from above, I develop the risk-based formula assuming three target types $\{s_{1j}, s_{2j}, s_{3j}\}$. Class 1 targets ($s_{1j}=S_1/50$) are evenly

[14] We admit that there may be some characteristic that defines unsystematic assets as something other than unsystematic. Unsystematic assets could be described as assets that are located in "mineral rich areas" or based on "system functionality". For example, oil reserves are located in high carbon areas which were at one point in time, forests or sea beds. Liquefied natural gas storage plants are not located near population, nor are they evenly distributed across the country, but they may be located adjacent to a port simply because natural gas is transported by cargo ship.

distributed across States. Class 2 targets ($s_{2j} = m*pop_j$) are perfectly correlated with population. Class 3 targets (s_3) are unsystematically distributed across all States. Optimal allocations are distributed across the three types in this way:

$$g_j = a_1^* \frac{S_1}{50} + a_2^* s_{2j} + a_3^* s_{3j} \tag{11}$$

To compare the original formula, $\tilde{g}_j$, in (9), with the risk-based model, g_j, in (11), I take two steps. First, I substitute $pop_j = \frac{s_{2j}}{m}$ into (9). Second, I impose public choice parameters, δ_1 and δ_2, to gauge the distortion between the original formula model and the risk-based formula.

To examine how the distortions δ_1 and δ_2 work, note that the original model allocates $0.4G\left(\frac{1}{50}\right)$ to protect the evenly-distributed targets. The risk-based model allocates $a_1 \frac{S_1}{50}$ for the same purpose. Thus, we can equate these numbers with a correction term δ_1:

$$0.4G\left(\frac{1}{50}\right) = a_1^* \frac{S_1}{50}(1+\delta_1)\ , \tag{12}$$

When $\delta_1 > 0$, on the right hand side of (12), the original model over-funds the evenly-distributed targets for reasons outside of the social welfare maximizing framework, perhaps due to public choice reasons such as overrepresentation in Congress (Mueller, 1992; Atlas, C. M., Gilligan, T.W., Hendershott, R.J., and M.A. Zupan, 1995). The same procedure is applied to the population-based targets:

$$0.6G\left(\frac{s_{2j}}{m\,Tpop}\right) = a_2^* s_{2j}(1+\delta_2)\,. \tag{13}$$

When $\delta_2 > 0$ on the right hand side of (13), the government over-funds the population-based targets, again perhaps due to public choice reasoning.

After some simple algebra, I define a *government excess* formula as the difference between the risk-based formula and the original *40/60* formula.

$$\widetilde{g}_j - g_j = \delta_1 a_1^* \frac{S_1}{50} + \delta_2 a_2^* s_{2j} - a_3^* s_{3j} \qquad (14)$$

When the *government excess* is positive for a State, the State is over-funded compared to the optimal risk-based model. The *government excess* formula is positively related to the amounts of public choice distortion in the evenly distributed and population based allocations.

The *government excess* formula facilitates an analysis of whether States are over or under-funded by the original *40/60 formula* relative to their respective sets of targets. Equation (14) introduces three possible sources of distortion that cause the original formula to deviate from the optimal risk-based allocation. These distortions are analyzed in the next section.

It is important to note that the formula does not address the fact that all targets could be under-protected if the overall budget *G* is simply not sufficiently large for the task of mitigating expected damage. Rather, the optimal formula simply ensures that the allocation of funds results in the marginal mitigation of expected damage being equal across target types. This means that, for two assets such as a stadium and a bridge, the mitigation of expected damage from an extra dollar of spending will be the same – they all mitigate expected damage – irrespective of the size of the budget *G*.

C. Three Distortions

Before empirically implementing the *government excess* formula to compare the original formula and the risk based formula, I use the model in (14) to draw insights for the subsequent calculations and to contribute to the current policy debate regarding alterations to the original formula. I first look in isolation at the distortions and then try to understand how the distortions interact. The distortions to the current formula are:

Distortion 1: $\delta_1 \neq 0$

Distortion 2: $\delta_2 \neq 0$

Distortion 3: $s_{3j} \neq 0$, *for any j*

Distortion 1 says that all States are either over- or under-funded for targets equally distributed across all States. Since by definition each State has an equal amount of these targets, and there is no cross-sectional dispersion of these targets, it is tautologically irrelevant to consider the change in *government excess* for an increase in an evenly distributed target, (i.e., $\frac{\partial\left(\tilde{g}-g_j(a_1^*)\right)}{\partial s_{1j}}$ does not make sense since $s_{1j}=\frac{S_1}{50}$). However, Distortion 1 is important as it relates to different state perspectives. For instance, California claims that Wyoming receives too much funding based on $\delta_1>0$ (too much funding for evenly distributed targets.). I return to this example momentarily.

Distortion 2 says that all States are either over- or under-funded for targets correlated with population. Here the comparative statics of the *government excess formula* with respect to the exposure of each jurisdiction to the targets in Class 2 is: $\frac{\partial\left(\tilde{g}-g_j(a_2^*)\right)}{\partial s_{2j}}$. It is important to note that we are not looking at increases in targets, but rather only examining the dispersion of targets among jurisdictions. Because I only look within the cross-section of dispersion in funding, I can take the optimal allocations a_i^* as fixed. The change in *government excess* for an increase in population-based targets, $\frac{\partial\left(\tilde{g}-g_j(a_2^*)\right)}{\partial s_{2j}}=\delta_2 a_2$, is greater than zero if the $\delta_2>0$ holds. This result is obvious. States with more targets that are population-based will be over-funded by the original *40/60 formula* relative to the risk-based funding formula if the government over-funds population-based risks.

It is possible that the 40% and 60% provisions to equally-distributed and population-distributed targets are too large relative to the optimal (positive signs on δ_1 and δ_2). For instance, it is plausible that 25% of targets in the U.S. are unsystematically distributed across States and thus not optimally covered by the original *40/60* formula. Examples of targets which are distributed unsystematically across States are chemical plants. If 25% of the homeland security budget is captured by unsystematic targets, the sum of all a_3s_{3j}, then the Class 1 and Class 2 targets should only be entitled to 75% of the budget. Under this scenario, it is likely but not necessary that both the 40% and the 60% of the original *40/60* formula are too large.

Distortion 3 states that there are targets not covered by the original *40/60 formula* because they are either neither correlated with population nor evenly distributed across States. The comparative static for this, $\frac{\partial\left(\tilde{g} - g_j(a_3^*)\right)}{\partial s_{3j}}$, is also simplistic. The *40/60* formula in $\tilde{g}$ does not cover Class 3 targets, which are unsystematically distributed across jurisdictions. Therefore, the more Class 3 targets that a State has, the more under-funded it will be under the original *40/60 formula* : $\frac{\partial\left(\tilde{g}_j - g_j(a_3^*)\right)}{\partial s_{3j}} = -a_3$. For example, even if Wyoming is correct in alleging that California is over-funded because it receives too much funding for population related targets, California has a large number of Class 3 targets which may make it under-funded.

The above analysis of the three distortions is complicated by the fact that governments fund States, not targets as the model suggests. The distinction is critical because one distortion may under-fund a particular set of targets in a State, while another distortion may over-fund a second set of targets in the same State. These distortions must be analyzed as the sum of all funding received from the federal government. We assume that a State corrects the flaws in the original *40/60 formula* by not thinking in the 40/60 categories at all. A State receives a federal lump sum and allocates it efficiently in line with the optimal allocation formula given in (11).

Two examples serve to elucidate this effect. Because allocations go to States and not to targets, it may be that the original *40/60 formula* over-compensates a State based on the equal distribution of targets or on population relative to what it needs for unsystematic targets. Members of Congress have argued for changing the original *40/60 formula* arguing that States like Wyoming are over-compensated because the 40% is too large (Cox, 2002; Feinstein, 2005). However, compared to a similarly populous state Maine, Wyoming may have a large set of unsystematic targets (in this case, pipelines and oil wells) that go under-funded by the formula. Compared to Maine, Wyoming may be under-funded if the Class 3 targets are not covered, even if evenly-distributed or population-based risks are over-funded.

Wyoming may be a good counter-example to New York. Wyoming, argues that the 60% is too large, resulting in too much funding for New York. Of course, Wyoming has less political clout (fewer U.S. Representatives) than New York, so the allegations that population related targets are over-funded is less considered. Take for example a state with similar population, New Jersey. New Jersey has potentially more unsystematic assets than New York. Even if Wyoming is right, and the 60% is too large making it possible that New Jersey is also under-funded if it endowed with many unsystematic targets.

In sum, the distortions highlight several key insights of this model. The first insight is that while it is likely that $\delta_1>0$ and $\delta_2>0$, we need to know the relative size of each public choice parameter. The second insight is that a State's overall grant amount is not just a function of δ_1 and δ_2 making the distribution of s_3 critical to this study. Clearly, the over-or-under-funding analysis has to consider all three distortions. The third insight is the public choice parameter δ_1 is fixed by the Patriot Act Section 1014(c), and will remain in place until there is an act of Congress mandating a change. This means that the optimal allocation calculations must continue to incorporate the δ_1 and δ_2 distortions, even if the simulated optimal allocations become available and politically feasible to implement

III. Implementation

Our theoretical model assumes that the social planner knows the probability of attack, damage upon attack, and efficiency of mitigation for each target (the p_i, d_i and k_i parameters for each target type). Ideally to compare original *40/60 formula* allocations with optimal risk-based allocations, we would use simulation to calibrate each of the parameters and then use the parameters to calculate the a_i as shown in (7).[15] Combining the a_i with the s_{ij} would yield the allocation to each state from which we can directly calculate the difference in the original *40/60 formula* and the risk-based formula.

If one were to calibrate the optimal allocations for homeland security, how would it be done? Current approaches adopted by the federal government and the insurance

[15] The U.S. Department of Homeland Security and the Sandia National Labs are doing work similar to this suggestion.

industry in their terrorism risk models provide insights into estimating the probability of attack, the damage upon attack, and the effectiveness of each dollar spent on homeland security (the p_i, and d_i and k_i parameters)

Since the 9/11 terrorist attacks, the federal government has leveraged different capabilities and techniques to model risks and consequences associated with terrorism. Typically associated with providing research related to the consequences of naturally occurring disruptions or network failures upon sectors of our economy (e.g., transportation, telecommunications, electricity, finance), national laboratories (Sandia, Los Alamos, Argonne) and universities have been asked to model the damages resulting from intentional acts of terrorism. The reports that they provide to the federal government are, sadly for our purposes, for official use only or classified and unavailable to the general public. The inherent problem with the government studies, as best is to the understanding to the authors, is in coordination of modeling results. Simulation models of attacks on types of infrastructure must be made comparable across infrastructures. We believe the simple expected damage with mitigation formula given in (4) offers a framework.

Similar to the approach used by the national labs, private insurance firms are applying models originally developed for pricing natural hazard insurance (e.g., for hurricanes and tornados) to estimate the expected losses from terrorism.[16] Prior to 9/11, terrorism coverage was available for different policies (workers compensation, life, accident and health, disability, property and casualty compensation lines of insurance). After 9/11, insurance companies began charging a premium for terrorism coverage, with some insurers dropping this form of coverage altogether. In response, Congress passed (and recently extended[17]) the Federal Terrorism Risk Insurance Act (TRIA) of 2002 requiring all property/casualty insurers writing commercial lines policies to offer coverage for losses caused by international terrorism within the United States (TRIA, 2002). To comply with the law, insurers separately report the portion of the premium

[16] To date, there are four terrorism risk models: The National Council on Compensation Insurance (workman's compensation), and The Insurance Services Office (property and casualty), have their own risk modeling team. In 2002, AIR Worldwide, a subsidiary of the Insurance Service Office, launched a Loss Estimation Model (ISO, 2004). Other models were developed by EQECAT, for the National Council on Compensation Insurance (NCCI), and by Risk Management Solutions (RMS).

[17] Terrorism Risk Insurance Extension Act of 2005 (the Act). President Bush affixed his signature to the bill on Dec. 22, 2005. Thus, Senate Bill Number 467 became Public Law 109-144.

being charged a policyholder to cover possible acts of terrorism. In this way, TRIA spurred the development of a market for terrorism risk insurance and for the development of models to price these risks. While these models are critical to a discussion on terrorism risk, it is important to note that private sector objectives differ from public sector objectives. Private models focus on maximizing profits of supplying terrorism risk coverage and do not necessarily capture goals desired in a public distribution mechanism, such as equity and welfare maximization.

Private sector terrorism models estimate the probability of terrorist attack and damage upon terrorist attack borrowing techniques for modeling natural hazards. Terrorism risk is assessed according to the most likely locations or targets for the hazard, the probability of the event occurring based on historical time-series data, and the severity (Kunreuther et al, 2003). Target identification is the first step. Targets vary depending on the nature and goals of the individual terrorist groups (Kunreuther et al, 2003). One insurer of terrorism risk keeps a database of over 300,000 potential targets that include commercial, industrial, educational, medical, religious, and governmental facilities, with a subset of trophy targets (such as stadiums and convention centers) carrying a higher probability of attack (ISO, 2004).

The probability of a certain event is more difficult to determine. While there is a long history of naturally occurring events, data on terrorism attacks is limited, and where it is available, it is usually classified for national security reasons (Kunreuther and Heal, 2003). Another complicating factor is that probabilities change. News reports have cited a higher threat to softer, but still high-value targets, such as transportation facilities and prominent commercial buildings, and a lowered threat to well-protected sites, such as federal facilities and nuclear plants (AIR, 2004). Nonetheless, popular methods for overcoming the uncertainty of probability in modeling terrorism include assuming that one terrorism event will occur per year (NCCI, 2004), or relying on the "delta method" -- subjective assessments of subject matter experts or individuals (e.g., military and intelligence personnel) with expertise (ISO, 2003).

The expected damage caused by a particular impact (such as a bomb blast) is an area in which modelers have more expertise. The severity of a terrorist attack is modeled using data on the types of weapons used, and it is a function of the attack mode and weapon type (the weapon used is a function of the organization initiating the attack). These data are more accessible based on U.S. military testing and impact on assessments post-attack.

To the best of my knowledge, there are no publicly available studies which even conceptualize, much less calibrate the k_i parameter, or the effectiveness of each dollar spent on homeland security targets. One key obstacle is a lack of understanding of the derived benefit of additional homeland security expenditure in terms of risk mitigation. Complicating matters is that much of our nation's critical infrastructure is owned by private owner-operators who are generally reluctant to share information on homeland security spending. Some will spend more private funds on protection, mitigation, response and recovery from terrorist attacks than others.

This is not to say that a mitigation measure cannot be derived. A revealed preference approach, hereafter called 'revealed mitigation', can be used to implement a model of terrorism risk mitigation. Lacking an official mandate to report cost information or willingness to volunteer information, owner-operators will not provide information without an incentive to do so. If we are able to provide owner-operators with an incentive to reveal how they value mitigation measures, or how each would spend his next dollar, then this can be used to derive the risk mitigation value of each homeland security investment. Equivalently, if owner-operators were presented with an opportunity whereby the federal government would match each dollar expended on a security investment, dollar-by-dollar, then this would also reveal the value that owner-operators place on mitigation. This 'revealed mitigation' approach would provide federal authorities with valuation measures for mitigation investments.

IV. Data

In order to compare the current and risk based allocations, we need data on current federal allocations and data on allocations based on a risk based model. If the social planner is unable to implement the first-best scenario, a second approach is to calibrate the parameters using state-level data. I use the State Homeland Security Grant Program (SHSP). For any State, the SHSP is based on the application of a federal formula originating from the Patriot Act, to a congressionally-appropriated amount for the SHSP program for that year. The SHSP allocations in this study are taken from the DHS website for fiscal years 2003 and 2004. Fiscal 2005 allocations are calculated based on the Patriot Act formula and the SHSP funding amount in the DHS Appropriation Bill signed in October 2004 (DHS, 2004). Since data for risk-based allocations at the federal level do not exist at this time, we need to devise the methodology for collecting data for a risk based model. I use the theoretical results to guide the estimation of risk-based allocations.

Without the data to calculate a_i at the national level,[18] I use state-level data as a reduced form, to measure the parameter levels (the p_i, and d_i and k_i parameters). As enacted, the Patriot Act dictated that the original *40/60 formula* be used to allocate federal funds to States. States, in turn, were given flexibility to develop their own formulas for distributing funds to local entities. I selected the formula used by the State of Indiana both to calculate allocations at the state-level and used their formula to develop a methodology for allocating to all states. I fully recognize that the Indiana formula is one formula among others that States utilize to distribute funding to local governments, and that the risk-based allocation system is therefore an approximation to an optimal solution. However, Indiana was selected due to data availability and because the state of Indiana includes terrorism risks representative of a number of states, such as nuclear power plants, natural gas and oil pipelines, and so on. This section introduces the framework used to develop a national formula using one states' formula (Indiana) and risk assessment. No claim is being made that the Indiana allocations are optimal, only that they represent one solution to allocating funds based on terrorism risk.

To a great extent, the targets selected by the State of Indiana draw upon guidance from the federal government through definitions for critical infrastructure and resemble the 16 factors currently examined by the federal government in its new allocation based on risk: agriculture and food, banking and finance, chemical industries, the defense industrial base, emergency services, energy, government facilities, postal and shipping, public health and health care, information technology, telecommunications, transportation systems, water, dams, commercial facilities, national monuments and

[18] The Federal government is capable of calculating the ai at the national level, but has not done so to date.

icons. Table 1 juxtaposes the 11 factors used by Indiana with the factors currently used by the federal government.

The State of Indiana identifies 11 risk targets: population, hazardous chemical facilities, federal facilities, hospitals, interstate highways, pipeline miles, power plants, public water usage, airports, major universities and concentration of livestock. Table 2 describes the Indiana factors along with the means, standard deviations, and sources. In order to employ the Indiana factors to calibrate a system of federal allocations, we need to accomplish two steps. First, we need to understand the system that Indiana used to determine county-level allocations. Next, we need to make adjustments to the Indiana data to reconcile the differences between the 11 Indiana factors with the factors introduced to the Patriot Act Reorganization Bill of 2005[19] and in the Fiscal Year 2006 Homeland Security Grant Program (DHS, 2006).

As mentioned above, the Indiana formula is comprised of 11 risk targets. The importance of the Indiana data is not in identification of the risk targets however, but in Indiana's assessment of the weight given to each target. Indiana gave each county a maximum of five discrete points (P) for each of its risk targets. For example, a county c with one interstate crossing it was given one point; two interstates yield two points;… ; five or more interstates yield five points. While Indiana no longer uses this method, for security reasons, we hesitate to provide the point breakdown for all the targets. The thresholds used by Indiana all have the feature of making quintiles of the counties' distribution of targets. By creating 'buckets' of discrete point assignment, the method does not over-fund points to the large city (Indianapolis), which would naturally capture a higher share of points if the scale were continuous.

The discrete points (P) are then weighted by a prioritization factor for the target type. Adding up to one, the prioritization weights are given by:

[19] To read the factors see H. Amdt. 507 (introduced by Rep. Lowey, D-NY) to H.R. 3199 (USA Patriot Improvement and Reauthorization Act of 2005) http://www.govtrack.us/congress/bill.xpd?bill=h109-3199 (last accessed 1/6/05)

$$
\begin{aligned}
v_c = {} & 0.286\,\mathrm{P}_{Pop,c} + 0.143\,\mathrm{P}_{HazFacilities,c} + 0.036\,\mathrm{P}_{FederalFacilities,c} + \\
& 0.036\,\mathrm{P}_{StateFacilities,c} + 0.036\,\mathrm{P}_{Hospitals,c} + 0.071\,\mathrm{P}_{Pipelines,c} + \\
& 0.071\,\mathrm{P}_{UtilityGeneration,c} + 0.071\,\mathrm{P}_{WaterSupply,c} + 0.071\,\mathrm{P}_{WaterIntake,c} + \\
& 0.071\,\mathrm{P}_{Universities,c} + 0.071\,\mathrm{P}_{FeedingLots,c}
\end{aligned} \tag{15}
$$

In this formulation, v_c is called the risk point valuation for the Indiana county. The total allocation to each county, α_c, is its share of the total state's point valuations times the total Indiana homeland security funding budget (G_{IN}), or:

$$
\alpha_c = \frac{v_c}{\sum_c v_c} G_{IN} \tag{16}
$$

Equation (16) provides a reduced form of our derived optimal allocations for a given county. The way in which Indiana allocates funding to counties, based on a point system that considers the 11 targets and prioritization factors (weights) can be used to compile federal risk-based allocations.

I would like to use Indiana's methods for assigning points to jurisdictions and for allocating funding based on a target-based point system. Translating Indiana's risk value function and risk point weights into a usable national model involves making two adjustments. First, I need to define Indiana's target types into variables that can be collected on a national scale. Moreover, the list of targets over which I will allocate funds needs to be representative of targets in the nation. For one, translating Indiana's risk value function into a usable national model involves making one alteration regarding the population-based metric that is used in the Indiana formula.

Indiana is not the only state to consider population as an indicator of terrorism risk when allocating funds to sub-state jurisdictions. The logic supporting the inclusion of population in a formula is that population is correlated with consequences from a terrorist attack. Aside from the advantage of being a readily available measure, Indiana selected population as a measure because for a state whose 92 counties are roughly uniform in land area, population and population density are highly correlated. While Indiana used population as a risk measure, it scored population in a way that directed funds to the dense, harder to protect areas as opposed to the farmland and rural areas. Other states strictly use population density as a measure, because density is correlated with terrorist threat. A hybrid approach which includes both arguments is to use a density-weighted population, or a region's population multiplied by its population density (Canada, 2003; Willis et al., 2005). In this study, I deviate from the Indiana model and use population density, as opposed to pure population, as an indicator of terrorism risk.

The next step involves re-calibrating thresholds (cutoffs) for assigning points so that we can use the Indiana risk point valuation weights. For example, Indiana gave 5 points for five or more interstates crossing through a county. Using interstates at the national level requires understanding and correcting for the possibility that another state may have over 20 interstates crossing a particular county. In order to assign points for target levels, several steps need to be followed. After compiling numerical counts of targets for each of the fifty states, the first step involves ranking each state in percentiles according to the quantity of each of target in the jurisdiction. One approach is to rank the percentiles into five quintiles. The percentile is the raw score. Next, the raw score (quintile) is multiplied by the weight assigned to the target (the Indiana weights). The result is a weighted score for each target and each state. Summing across targets results in a total weighted score for the state. Each state's weighted score is normalized by multiplying the state's weighted score by the sum of weighted scores for all states, resulting in a normalized weighted score for the state. The final step is to multiply the normalized weighted score for each state by the Federal funding appropriation for the given year, for the grant program we are examining. This yields the risk-based allocation for each state. The risk-based calculation is based on the Indiana factors and the Indiana weights.

V. Results

We are now in a position to compare the current allocations with the risk-based allocations derived using the Indiana weights and factors. This section first asks whether the risk-based allocations from the risk-based formula differ from the current 40/60 allocations. After concluding that they do in fact differ, the next step is to delve into the question of why they differ. To begin to describe why they differ I propose and develop a simple scheme for classifying risk targets into the three classes (equally distributed, correlated with population, and unsystematically distributed), thereby offering a framework to assess where the greatest biases are in the system. In the final paragraphs of the section, I present some initial tests that showing that the distortions in the *government excess formula* are a natural way to find the vulnerabilities from missing or under-funded risk assets.

Table 7 illustrates the risk-based funding allocations (in millions of dollars) for five states. Two important pieces of information can be extracted from Table 7. First, Table 7 presents the risk-based allocations to targets, the a_i, for a select sample of states. According to the table, the risk-based model predicts that Indiana should allocate $9 million, and Louisiana allocated $12 million, to enhance the capabilities of local governments to protect hazardous material facilities in their respective jurisdictions. Indiana and California should allocate more funding toward protecting agricultural targets, while Maine should allocate more funding to airports, density and hazardous material facilities, than to anything else. One limitation to interpreting these results is that clearly two targets would not receive exactly the same amount of funding, as the table suggests. The approach using percentiles and quintiles eliminates the specificity that is needed for more detailed analysis. Another limitation is that the funding allocations among states are based on estimates for a_i which originate from Indiana's prioritization (weights) of targets; different prioritization mechanisms could be considered as a means of altering the risk-based formula.

I then use the risk-based funding allocations, previewed Table 7, to calculate the government excess and plot the results. Figure 1, a map of the United States, presents the key empirical results of the paper. The map shades states according to how much government excess funding it received in 2003 relative to the optimal calculation using the Indiana weights. Distinctions are made with five levels of funding: those states that are over-funded by 20% more (yellow/light grey), states that are over-funded between 5%-20% (red/dark grey), states that are appropriately funded within 5% more or less (blue/black), states that are under-funded between 5%-20% (white), and states that are under-funded by 20% or more (green/medium grey). Seventeen states are under-funded by 20% or more.[20] Fifteen states are under-funded by 5% to 20%.[21] Eight states are

[20] Most under-funded are Alabama, Alaska, Arkansas, Iowa, Kansas, Kentucky, Mississippi, Montana, New Mexico, North Dakota, Oregon, Rhode Island, South Dakota, West Virginia, and Wyoming

appropriately funded.[22] Five states are over-funded by 5% to 20%.[23] Four states are over-funded by more than 20%.[24] In total, nine states are over-funded; whereas 32 States are under-funded by the original *40/60 formula*. From the Figure, the large population states are the main recipients of over-funding. The South Atlantic states are the most likely to be appropriately funded. The interior states and New England states are almost all under-funded except for the high population states of the Great Lakes.

How can one make sense of Figure 1? Even without a thorough analysis, Figure 1 tells a story of a seemingly large population distortion ($\delta_1 >> 0$). For California, Texas and New York, the three most populated of the fifty states, the original level of funding exceeds the amount predicted by a risk based model. Given this, which States (and which targets) are being penalized (being left exposed) by the over-allocation of 60% of the budget based on population? Clearly some states are under-funded by the original formula, what can we say about which classes of assets are being under-funded? Specifically, is the under-funding due to their endowment of evenly distributed (class 1) and/or unsystematically distributed (class 3) targets? To answer this, we return to the concept of classes of assets.

The simplest way to analyze which classes of assets are being under-funded is to assign each target into one or more of the three classes – equally distributed (class 1), correlated with population (class 2), or unsystematically distributed (class 3). To accomplish this assignment, we consider the correlation with population and the coefficients of variation among targets in a two step procedure. Using the accepted norm that a correlation above 0.75 is highly, I assign all targets with a correlation with population above 0.75 into the population-based, class 2 target group. Table 3 presents the correlation matrix. All correlations among targets are presented, but the relation of interest is found in the first column, the correlation between population and all other variables. Resulting population-based targets are *PUBLIC WATER USE, UNIVERSITIES, HOSPITALS*, *FEDERAL COURTS, POWER PLANTS,* and *INTERSTATES*.

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[21] Somewhat under-funded are Colorado, Connecticut, Idaho, Indiana, Massachusetts, Minnesota, Nebraska, Nevada, New Hampshire, Oklahoma, South Carolina, Tennessee, Utah, Vermont, and Wisconsin.
[22] Appropriately funded are Arizona, Maine, Maryland, Michigan, Missouri, North Carolina, and Virginia.
[23] Somewhat over-funded are Georgia, Illinois, New Jersey, Ohio and Pennsylvania.
[24] Most over-funded are California, Florida, New York, and Texas.

To classify the equally distributed targets, I appeal to each target's coefficient of variation (CV). A low CV implies that the target endowments do not vary greatly among states. The coefficient of variation is measured as the standard deviation divided by the mean. Table 4 shows the target variables and their corresponding CV's. I assign a variable as being at least partially in the class 1 of equally distributed targets if the standard deviation is less than the mean, resulting in a CV less than one. The resulting class 1 targets are *INTERSTATES*, *FEDERAL COURTS*, *HOSPITALS*, and *AIRPORTS*.[25]

Finally, class 3 targets in this model are targets that are neither highly correlated with population or do not have a low CV. These targets are unsystematically distributed across States, and are termed "unsystematically distributed targets". Determining which targets fall under this category involves summing the rankings from the previous two categorizations for each target and then ranking these summation results. The ranking of the summation results is the ranking for the unsystematically distributed targets in descending order. The rationale here is that risk class categories are mutually exclusive: if a target is highly correlated with population, it will not be evenly distributed or unsystematically distributed. In contrast, if a target is not correlated with population, and not evenly distributed, it will be unsystematically distributed.

In sum, the categorization process results in three categories of targets. These results are presented in Table 5. For example, (*PUBLIC WATER USE*) and (*UNIVERSITIES*) are categorized as class 2 assets because they are highly correlated with population. Factors which record low coefficients of variation, such as (*INTERSTATES*), (*FED COURTS*), and (*AIRPORTS*) can be placed in the class 1, evenly distributed targets. Other variables belong in the class 3 unsystematically distributed targets category. For example, (*HAZARD)* ranked high in the correlation analysis (high number means low correlation), and it ranked high in the CV analysis (not evenly distributed), which means that it ranked high in the summation analysis. The result is that (*HAZARD*) ranks low in the summation analysis and can be categorized as a class 3, unsystematically

[25]The CV results are confirmed by a regression which first removes the effect of population and then ranks the residuals of the projection of each variable on population. Regressing the targets on 2002 population, without a constant, yields a set of residuals that explain everything other than population effect. The CV analysis can be recalculated using the residuals and the resulting CVs can be ranked in ascending order for each target. The ranking confirms that federal facilities *(FED COURTS),* hospitals *(HOSPITALS),* interstate highway miles *(INTERSTATES),* and airports *(AIRPORTS),* are evenly distributed among States.

distributed target. Other class 3 assets include (*DENSITY*), (*PIPELINES*) and (*LIVESTOCK*).

Having assigned each target to a class enables us to decompose the relationship between over-funding, under-funding and the different types of targets. We examine the properties of government excess formula in order to draw conclusions concerning the three distortions (the causes of over-funding or under-funding) analyzed previously. Recall, under or over-funding is determined by the government excess formula stated earlier as:

$$\tilde{g}_j - g_j = \delta_1 a_1^* \frac{S_1}{50} + \delta_2 a_2^* s_{2j} - a_3^* s_{3j} \qquad \text{(14-Restated)}$$

A state is over-funded if the right-hand side of the equation is positive; a state is under-funded if the right-hand side is negative. We regress the excess funding for each state on target endowments for each state. If the original *40/60 formula* is over-funding evenly distributed targets (δ_1>0), then we would expect a positive relation between the over-funding calculation and the class 1 assets in the cross-section. Likewise, an over-funding of population-correlated targets (δ_2>0) should yield a positive coefficient for a class 2 target. Finally, I would expect an unambiguous negative relation between unsystematically distributed targets and state funding.

The results for the regression are found in Table 6. Contrary to intuition, the results from regression suggest that class 1 targets (the 40% allocation) are under-funded. (*INTERSTATES*) and (*AIRPORTS*) and have negative and significant coefficients. The coefficient on (*UNIVERSITIES*), a class 2 target, is positive and significant showing us that population-based targets (the 60% allocation) are over-funded as expected. However, note that two additional class 2 target variables, (*PUBLIC WATER USE*) and (*POWER PLANTS*) are not significant, possibly due to the mulitcollinearity of our small-sample (n=50) regression. Finally, the coefficients for unsystematic class 3 targets (*DENSITY*) and (*HAZARD*) are both negative and significant as expected. However, the coefficient for the other class 3 target variable, (*PIPELINES*), is significant and positive to which I can only suggest that the proxy for pipeline miles is not the most accurate measure for pipelines miles throughout the U.S. In sum, the regression findings suggest that the current grant formula under-funds targets that are unsystematically distributed and if anything, it under-funds targets that are evenly distributed. Targets that are correlated with population are over-funded.

VI. Concluding Remarks

This paper models the optimal level of federal allocations to states for terrorism preparedness under the assumption that the federal government acts as a benevolent social planner who allocates funding based on target risk. The optimal allocation is a function of the probability of attack, the damage upon attack, and the effectiveness of each dollar spent on homeland security. After developing the theoretical model, I compare the optimal allocations to the government distributions and test the distortions using risk priorities set by Indiana State officials.

I find that the original grant formula under-funds targets that are unsystematically distributed, implying that targets such as chemical plants, oil and gas pipelines and livestock facilities are more vulnerable to terrorist threat. Conversely, the regression findings suggest that targets that are correlated with population are over-funded.

A more efficient allocation of federal resources would require that the government implement a formula that allocates funds 100% based on risk and incorporates the ability of funds to mitigate risk. The recent decision by DHS to incorporate measures of risk into the 60% share of the allocation is a step in the right direction. But allocating a portion of funding based on risk does not fully solve the distortions created by the Patriot Act requirement that 40% of the funds be evenly distributed across States. Because it does not seem as if the Patriot Act requirement will be repealed any time soon (Strohm, 2006), the optimal allocation calculations must incorporate the public choice distortions.

Some final points result from the fact that allocations go to States and not to targets specifically. Under-funding of jurisdictions and targets may result in geographic weaknesses. In addition, because DHS allocates grants to States and not directly to targets, the burden of correcting the distortions in the government formula lies in States. However, it is not clear that States have the ability, expertise, or access to information to model terrorism risk that Federal authorities have. Finally, even if States allocate the optimal level of funding to, say, a chemical facility, how will public funds be used to mitigate risk to a private facility?

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Table 1: Comparison of Different Model Factors Used

Indiana Critical Infrastructure Factors	Selected Critical Infrastructure Factors [Lowey Amt. to Patriot Act Reorganization Act (Based on H.R. 1544), and FY06 Homeland Security Grant Program]
Hazardous Chemical Sites	Chemical industries
Federal Courts	Government facilities Defense industrial base Postal and shipping
Hospitals	Public health and health care
Interstate Highway Miles Primary Airports	Transportation systems
Power Utility Generation Natural Gas and Oil Pipelines	Dams Energy
Public Water Use	Water
Major Universities	National monuments and icons
Confined Feeding Operations	Agriculture and food
Density	Banking and finance Commercial facilities Emergency services

Table 2: Target Data Sources and Summary Statistics

Variables	*Description*	*Mean*	*Std. Dev.*	*Source*
State Population Density (*DENSITY*)	Person/Sq. mi.	183	263	U.S. Census, 2002
Quantity RCRA Hazardous Waste Generated (*HAZARD*)	Tons	796,736	1,312,887	Quantity of RCRA Hazardous Waste Generated and Number of Hazardous Waste Generators, by State, 2001, tons generated
Federal Courts (*FED COURTS*)	Number	7	6	Federal Law Clerk Information System, 2004
Hospitals (*HOSPITALS*)	Registered Hospitals in U.S.	117	98	American Hospital Association, 2004
Interstate Highway Miles (*INTERSTATES*)	Miles	910	599	State Statistical Abstract: No. 1053. Highway Functional Systems and Urban/Rural: 2000
Pipelines (*PIPELINES*)	Standardized oil production plus gas production	0	2	Energy Information Administration, Department of Energy, 2002 Distribution of Wells by Production Rate,Bracket
Power Utility Generation (*POWER PLANTS*)	Sum gas, coal, nuclear. Per Capita, Million BTU	1,777	1,864	State Statistical Abstract: No. 946. Energy Consumption—End-Use Sector and Selected Source by State, 1997
Water Withdrawl Use: Public Supply (*WATER USE*)	Per Capita, Million Gallons per day	862	1,013	State Statistical Abstract: No. 368. Water Withdrawals and Consumptive Use—State and other areas,1995
Public Primary Airports (*AIRPORTS*)	Number	7	6	Federal Aviation Administration, Primary Airports, CY 2003 Passenger Boarding and All-Cargo Data
Large Universities (*UNIV*)	Number	8	13	Peterson's Thompson Search, undergraduate universities >10,000 students
Confined Feeding Operations (*LIVESTOCK*)	Number	10,374	13,464	Number of livestock operations with confined livestock, 1997

Table 3: Correlations Among Targets and Population

	Population	*Density*	*Chemical Facilities*	*Federal Courts*	*Hospitals*	*Interstates*	*Oil and Gas Pipelines*	*Power Plants*	*Public Water Use*	*Airports*	*Universities*
Population	1.00										
Density	0.09	1.00									
Chemical Fac.	0.46	-0.09	1.00								
Federal Courts	0.85	-0.11	0.68	1.00							
Hospitals	0.91	-0.16	0.68	0.91	1.00						
Interstates	0.81	-0.24	0.59	0.86	0.89	1.00					
Pipelines	0.32	-0.16	0.57	0.52	0.46	0.55	1.00				
Power Plants	0.83	-0.13	0.77	0.91	0.94	0.88	0.59	1.00			
Water Use	0.99	-0.08	0.46	0.84	0.90	0.80	0.34	0.82	1.00		
Airports	0.69	-0.19	0.38	0.73	0.68	0.74	0.70	0.67	0.70	1.00	
Universities	0.92	-0.05	0.25	0.71	0.76	0.67	0.26	0.63	0.94	0.64	1.00
Livestock	0.31	-0.15	0.55	0.47	0.59	0.54	0.38	0.57	0.29	0.28	0.16

Table 4: Coefficient of Variation (CV) results and rankings

Variable	*CV*	*CV Ranking (in ascending order)*
Population Density	3.88	11
Hazardous Chemical Plants	1.65	9
Federal Courts	0.79	2
Hospitals	0.84	3
Interstate Highways	0.66	1
Oil and Gas Pipelines	1.16	6
Power Plants	1.05	5
Public Water Use	1.19	7
Airports	0.85	4
Universities	1.66	10
Livestock	1.30	8

Table 5: Target Rankings into Classes

Target	*Class 1: Evenly Distributed*	*Class 2: Correlated with Population*	*Class 3: Unsystem-atically Distributed*	*Class Designation*
Population Density	11	11	1	Class 3
Hazardous Chemical Plants	9	8	3	Class 3
Federal Courts	2	4	10	Classes 1 (& 2)
Hospitals	3	3	10	Classes 1 & 2
Interstate Highways	1	6	9	Classes 1 (& 2)
Oil and Gas Pipelines	6	9	4	Class 3
Power Plants	5	5	7	Class 2
Public Water Use	7	1	8	Class 2
Airports	4	7	6	Class 1
Universities	10	2	5	Class 2
Livestock	8	10	2	Class 3

Table 6: Excess Government Funding Regressed on Targets by Type

The dependent variable is the excess government funding for each state defined as the actual allocation amount received by each state in 2003 minus the optimal risk-based allocation calculated using the Indiana weighting formula. Significance at the 1%, 5% and 10% levels are denoted by ***, **, and *.

Dependent Variable: Excess Government Funding				
Variable	***Coefficient***		***t - value***	***Class Designation***
DENSITY	-0.187	*	(1.97)	Class 3 (Unsystematic)
HAZARD	-0.091	***	(2.55)	Class 3 (Unsystematic)
FED COURTS	-5.010		(0.40)	**Class 1 (Even)** or Class 2 (Pop)
HOSPITALS	1.684		(1.04)	Class 1 (Even) or Class 2 (Pop)
INTERSTATES	-0.331	***	(3.04)	**Class 1 (Even)** or Class 2 (Pop)
PIPELINES	0.098	***	(2.92)	Class 3 (Unsystematic)
POWER PLANTS	-0.027		(0.43)	Class 2 (Pop)
PUBLIC WATER USE	0.080		(0.49)	Class 2 (Pop)
AIRPORTS	-0.018	*	(1.69)	Class 1 (Even)
UNIVERSITIES	0.044	***	(4.73)	Class 2 (Pop)
LIVESTOCK	0.099		(0.30)	Class 3 (Unsystematic)
R-Square	0.94			
Observations	51			

Table 7: 2003 Vulnerability Score Translated into Allocation Dollars by Target

The numbers are in millions of dollars. The procedure to obtain the dollar values is to allocate 1 to 5 points to each target type according to the quintile of the endowment of that asset in the State. The, using the Indiana weights from equation (14) and the overall government budget, the vulnerability score can be translated into dollar equivalent.

	Indiana	***Maine***	***California***	***New Jersey***	Louisiana
Population Density	13.5	9.0	18.0	22.4	13.5
Hazardous Chemical Plants	9.0	2.2	6.7	6.7	11.2
Federal Courts	1.7	0.6	2.8	1.1	2.2
Hospitals	1.7	0.6	2.8	1.7	2.2
Interstate Highways	2.2	0.6	2.8	0.6	1.7
Oil and Gas Pipelines	3.4	1.1	5.6	1.1	4.5
Power Plants	4.5	1.1	5.6	4.5	4.5
Public Water Use	3.4	1.1	5.6	4.5	3.4
Airports	2.2	2.2	5.6	1.1	3.4
Universities	3.4	1.1	5.6	3.4	3.4
Livestock	3.4	1.1	3.4	1.1	2.2
Risk-based Allocation (mil.$)	48.3	20.8	64.5	48.3	52.2

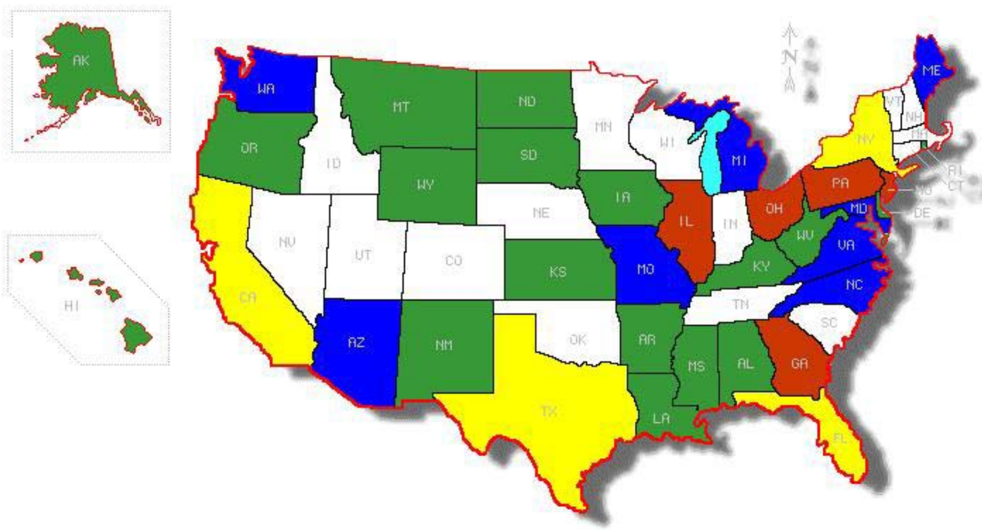

Figure 1: Excess Government Funding by State: Comparison of Risk-Based Formula and Original Formula used from 2002-2005

The colors correspond to over or under-funding according to:
<u>Over-funded by 20% or more (Yellow/Light Grey)</u> are California, Florida, New York, and Texas.

<u>Over-funded by 5-20% (Red/Dark Grey)</u> are Georgia, Illinois, New Jersey, Ohio and Pennsylvania.

<u>Over-funded or Under-Funded by 5% or less (Blue/Black)</u> are Arizona, Maine, Maryland, Michigan, Missouri, North Carolina, and Virginia.

<u>Under-funded by 5-20% (White)</u> are Colorado, Connecticut, Idaho, Indiana, Massachusetts, Minnesota, Nebraska, Nevada, New Hampshire, Oklahoma, South Carolina, Tennessee, Utah, Vermont, and Wisconsin.

<u>Under-funded by 20% or more (Green/Medium Grey)</u> are Alabama, Alaska, Arkansas, Iowa, Kansas, Kentucky, Mississippi, Montana, New Mexico, North Dakota, Oregon, Rhode Island, South Dakota, West Virginia, and Wyoming.