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TECHNICAL REPORT

Using Pattern Analysis and Systematic Randomness to Allocate U.S. Border Security Resources

Joel B. Predd • Henry H. Willis • Claude Messan Setodji • Chuck Stelzner

Sponsored by the Department of Homeland Security

RAND HOMELAND SECURITY AND DEFENSE CENTER

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Cover image: A border patrol agent surveys the U.S. border in Montana. U.S. Customs and Border Protection photo by Gerald L. Nino.

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Preface

The U.S. Department of Homeland Security (DHS) has the responsibility to protect and control U.S. borders against terrorist threats, criminal endeavors, illegal immigration, and contraband. Due to budgetary and other resource constraints, DHS cannot "see and be" everywhere at once along America's long and porous border.

Confronting this reality, DHS is investigating how pattern and trend analysis of historical interdictions and systematic randomness can be used to position border security personnel and equipment in the places and at the times they will be most effective. However, if used improperly, pattern and trend analysis can mislead rather than guide decisionmakers and thus possibly degrade the effectiveness of border security operations. To address this challenge, this report describes how pattern and trend analysis may be coupled with systematic randomness to effectively position border security resources.

The findings presented here are the result of a study supported by DHS through the National Center for Border Security and Immigration under grant number 2008-ST-061-BS0002. However, the study results and this report are the responsibility of the RAND Corporation and the authors and do not necessarily reflect views of DHS.

We expect that this report will be of interest to several audiences. For policymakers and researchers who have limited experience with border security operations, the report provides an overview of the challenges and constraints associated with tactical border security operations. For those who are interested in developing or applying pattern and trend analysis methods to border security problems, the report describes an approach for evaluating the effectiveness of such methods, an assessment of approaches that couple pattern analysis with systematic randomness, and a plan for progressively implementing such approaches using randomized controlled trials.

The RAND Homeland Security and Defense Center

This research was conducted in the RAND Homeland Security and Defense Center, which conducts analysis to prepare and protect communities and critical infrastructure from natural disasters and terrorism. Center projects examine a wide range of risk management problems, including coastal and border security, emergency preparedness and response, defense support to civil authorities, transportation security, domestic intelligence, technology acquisition, and related topics. Center clients include the Department of Homeland Security, the Department of Defense, the Department of Justice, and other organizations charged with security and disaster preparedness, response, and recovery. The Homeland Security and Defense Center is a joint center of the RAND National Security Research Division and RAND Infrastructure, Safety, and Environment.

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Summary

The U.S. Department of Homeland Security (DHS) has the responsibility to protect and control U.S. borders against terrorist threats, criminal endeavors, illegal immigration, and contraband. Unfortunately, due to budgetary and other resource constraints, DHS cannot "see and be" everywhere at once along America's long and porous border. As a result, DHS officials continually face the question of where, when, and how to position people and technology on the border.

Confronting this problem in the context of the land-based border between ports of entry, agents from the Office of Border Patrol (OBP) are investigating how *pattern and trend analysis* and *systematic randomness* can be used to position border security personnel and equipment in the places and at the times they will be most effective. *Pattern and trend analysis* refers to predictive methods that can identify regularities in the times, places, or tactics that interdicted border crossers have historically employed. For example, methods or tools of pattern and trend analysis may identify "hot spots"—i.e., border zones or times of high or increased border activity—to ascertain where more resources could increase interdiction rates. *Systematic randomness*, in a sense the antithesis of pattern and trend analysis, refers to the insertion of unpredictability into planning with the hopes mitigating adversary adaptation by introducing uncertainty into smuggler decisionmaking.

These two tools have potentially significant benefits, as demonstrated by their productive application in other homeland security and law enforcement contexts. But the tools come with risks: Pattern and trend analysis can mislead rather than guide decisionmakers if historical apprehension data do not represent what "we don't know we haven't seen." And randomness can waste precious resources if applied carelessly or in excess. Moreover, no two OBP stations are the same, and we would expect the productive application of these tools to vary accordingly, based on the number of zones at a particular border station, the amount or capability of resources available there, and the local rate of illegal flow.

Research Questions

This report investigates how pattern and trend analysis may be productively coupled with systematic randomness to increase interdiction rates and mitigate smuggler adaptation. We shed light on these issues by addressing three research questions:

- How can OBP leverage pattern and trend analysis and systematic randomness to increase its interdiction rate?

- Under what circumstances would OBP stations benefit from using comparable approaches? Under what circumstances would approaches differ?
- How should OBP start implementing approaches to pattern and trend analysis and systematic randomness?

Approach

Our analysis draws on three data sources. First, we conducted interviews and field studies and gathered feedback on preliminary results through interim briefings to stakeholders at DHS and OBP headquarters. These interviews and field studies provided an understanding of how OBP approaches problems of resource allocation, and they provided opportunities to gather feedback during the early phases of our research.

Second, we developed an agent-based simulation model of the interaction of border patrol agents and illegal smugglers. The model allows us to explore how interdiction rates differ across thousands of scenarios that vary by the number of patrols, the rate of illegal flow, the size of the border, and the approach OBP takes to using pattern and trend analysis and systematic randomness.

Finally, we collected historical data from OBP on interdictions, seizures, and patrol and station configurations. These data provide a basis comparing OBP stations based on metrics suggested by our modeling.

Findings

Several findings emerged from our analysis. First, our model suggests that, in nearly all cases, coupling pattern and trend analysis with systematic randomness yields greater interdiction rates than using either approach alone. The relative benefit of coupled approaches appears particularly strong in circumstances in which the number of available patrols is high relative to the rate of illegal flow but low relative to the size of the border. Such circumstances would seem to resemble those confronted by many OBP stations along the U.S. border.

Second, our analysis further suggests that coupled approaches can yield interdiction rates that are competitive with expensive alternatives, such as surveillance that affords "perfect hindsight" of all historical crossings. This suggests that appropriate combinations of pattern and trend analysis and systematic randomness could, in some cases, mitigate the need for expensive investments in technology and infrastructure.

Third, our analysis suggests that relative measures (e.g., coverage, capacity) are more important than absolute measures (e.g., the rate of illegal flow, the size of the border) in predicting interdiction rates. In fact, we show that some lower-activity, lower-resourced northern border stations are similar to higher-activity, higher-resourced southern border stations when compared using relative measures.

Finally, we offer an implementation plan that OBP could use to experiment with new approaches to using pattern analysis and systematic randomness.

Recommendations

These findings support several recommendations. First, OBP should catalog detections, even those that do not result in interdiction. These data should then be integrated with historical apprehension data to improve the overall representation of illegal flows in pattern and trend analysis.

Next, OBP should institute a plan to schedule patrols based on daily pattern and trend analysis and systematic randomness. As described later, this plan should allow OBP to strike a balance between exploiting existing assessments of border risks and exploring for risks that have yet to be characterized. This plan should include a phase of experimentation using randomized control trials. We outline one approach to experimentation in Chapter Six of this report. A crucial feature of our experimental design is that it does not require knowledge of successful border crossers.

Finally, we recommend that OBP develop a management tool to compare its stations based on relative measures, such as coverage and capacity. We developed a data visualization tool to facilitate these comparisons based on measures that our analysis suggests influence interdiction rates. Such a tool may be useful to OBP sector and station chiefs in comparing stations on operational grounds and in tracking changes over time.

Other Research Outputs

This report also describes products of our research that may hold interest independently of our findings. We present an agent-based simulation model of patrol-smuggler interaction; a data visualization tool for comparing and contrasting OBP stations; and a model of how OBP conceptualizes resource allocation at the headquarters, sector, and station levels.

Acknowledgments

This study benefited from numerous DHS officials, OBP agents, and federal agents who hosted our visits and contributed through discussions to our understanding of the tactical issues of securing the U.S. border. In particular, we thank Mark Borkowski, Pat DeQuattro, David Hoffman, Merv Leavitt, Jerry Martino, Steven McPartland, Francisco Rodriguez, Jaime Salazar, Mickey Valdez, and Michael Webb. A special thanks goes to U.S. Army LTC Eloy Cuevas, whose experiences and insights contributed to our basic understanding of the choices and trade-offs in border security. We also thank our RAND colleague Robert Lempert and University of Southern California Professor Milind Tambe for helpful comments on earlier drafts. Finally, we thank Sarah Hauer and Lauren Skrabala for their help in preparing the document.

This report is the responsibility of the RAND Corporation and the authors and does not necessarily reflect the views of these individuals or DHS.

Abbreviations

CBP	U.S. Customs and Border Protection
DHS	U.S. Department of Homeland Security
FY	fiscal year
GIS	geographic information system
OBP	Office of Border Patrol

CHAPTER ONE

Introduction

Background

The borders of the continental United States span approximately 6,000 miles of land between Canada and Mexico; 5,000 miles of coastline along the Atlantic Ocean, Pacific Ocean, and Gulf of Mexico; and 5,000 miles of the shoreline of the Great Lakes and connecting rivers (Beaver, 2006). The U.S. Department of Homeland Security (DHS) is responsible for securing these vast borders (DHS, 2010). One objective of DHS border security missions is to interdict illegal trafficking, cross-border crime, illegal migration, and potential terrorists (DHS, 2010; Willis, Predd, et al., 2010).

To meet this objective, DHS manages more than 60,000 officers, agents, pilots, civilians, and enlisted personnel (DHS, 2009). Recent investments in technology and infrastructure are designed to "multiply" the capability of the personnel who ultimately form the front line of border security. However, even with these enhanced capabilities, border security agencies face a genuinely complex and enormous task. Moreover, illegal border crossers are able to observe U.S. border security efforts directly or through the consequences of interdictions and use this feedback to avoid the interdiction efforts. Thus, in addition to having to patrol a vast expanse of border with limited resources, DHS must also work to counter continually shifting adversary tactics.

In response to these challenges, agents from the Office of Border Patrol (OBP) face the question of where, when, and how to position people and technology along the border. OBP is investigating a variety of methods and tools to help its decisionmakers determine how its resources should be positioned to be most effective. This report concerns two such methods and tools: pattern and trend analysis and systematic randomness.

Pattern and trend analysis refers to predictive methods that can identify regularities in the times, places, or tactics that interdicted border crossers have historically employed. For example, methods or tools of pattern and trend analysis may identify "hot spots"—i.e., border zones or times of high or increased border activity—to ascertain where more resources could increase interdiction rates. In general, historical data may inform how OBP resources should be positioned under the assumption that the behavior of those who have been interdicted historically is generally representative of the behavior of future border crossers. As discussed in greater detail in Chapter Two, this is a problematic assumption: If historical data are too sparse, or if illegal border crossers adapt too rapidly, then historical data may not be representative of future threats, and using pattern and trend analysis to guide decisions about where to position people and technology may be counterproductive. For example, allocating more patrols to regions with the greatest number interdictions may be counterproductive if the rate actually reflects a high level of OBP presence rather than genuinely high flow. In field studies, described later, OBP agents routinely mention "not knowing what we haven't seen," and their sentiment perfectly captures the challenge of using pattern and trend analysis to position resources: How closely should OBP follow interdiction trends if it cannot determine whether observed trends reflect OBP or smuggler behavior?

OBP is also investigating the role of systematic randomness, the antithesis of pattern and trend analysis. The expressed idea is to inject some amount of unpredictability into planning and thereby mitigate adversary adaptation by introducing uncertainty into smuggler decision-making. Intuitively, there is some wisdom behind this approach, but how much randomness is enough? And, as a practical matter, how should it be implemented?

In fact, conditions across U.S. land borders vary dramatically in ways that could potentially influence the utility of pattern and trend analysis and systematic randomness. In some sectors, OBP has significant resources dedicated to patrolling densely populated and contained segments of the border. In others, it relies on limited personnel to cover hundreds of miles. In some stretches of the southern border, interdictions occur daily or hourly. In contrast, interdictions are relatively rare along some stretches of the northern border. Table 1.1 summarizes some of the dimensions along which OBP stations vary. One would expect each of these dimensions to affect the degree to which historical interdiction data represent current threats and thus how pattern and trend analysis and systematic randomness could be used by OBP. How does the "right" approach vary from station to station?

Research Questions

This report aims to shed light on these issues by addressing three research questions:

- How can OBP leverage pattern and trend analysis and systematic randomness to increase its interdiction rate?
- Under what circumstances would OBP stations benefit from using comparable approaches? Under what circumstances would approaches differ?
- How should OBP start implementing approaches to pattern and trend analysis and systematic randomness?

Table 1.1
Variation Across OBP Stations

Dimension	Range Across OBP Stations	
Miles	Less than 10	More than 100
Apprehensions	Tens annually	Hundreds daily
Agents	Tens	Multiple hundreds
Infrastructure	Fenced barriers and paved roads	Undeveloped land
Technology	Unmanned aircraft, cameras, and radars	People-centric
Environment	Rugged desert	Dense urban
Main threat profile	Drug smugglers	Illegal migrants

Approach

Our analysis draws on three data sources. First, we conducted interviews and field studies and gathered feedback on preliminary results through interim briefings to stakeholders at DHS and OBP headquarters. These interviews and field studies provided an understanding of how OBP approaches problems of resource allocation, and they provided opportunities to gather feedback during the early phases of our research. Specifically, the study team visited OBP sites in the San Diego and Rio Grande Valley sectors and interviewed officials at the Border Intelligence Centers in both sectors, the Air Mobile Unit and Coast Guard Operations Center in the San Diego sector, and the Air Marine Operations Center in Riverside, California. The study team also witnessed aspects of Operation Red Zone, a U.S. Customs and Border Protection (CBP)–led border security operation conducted jointly by DHS, the U.S. Department of Justice, the U.S. Department of Defense, and federal and state law enforcement agencies. We presented preliminary findings of our research to officials in the OBP Office of Strategy, Policy, and Planning and the CBP Office of the Secure Border Initiative.

Second, we developed an agent-based simulation model of the interaction of border patrol agents and illegal smugglers. The model allowed us to quickly and inexpensively explore trade-offs among the different approaches to using pattern and trend analysis and systematic randomness and revealed how these trade-offs depend on conditions that vary from station to station. The model is described in Chapter Three.

Finally, we collected historical data from OBP on interdictions, seizures, and patrol and station configurations. These data, discussed in Chapter Five, provided a basis for our comparison of OBP stations.

Scope

This analysis is limited in scope in two ways. First, our focus is on the resource allocation decisions associated with securing the U.S. land border *between ports of entry*. In principle, some of the findings may generalize to air travel or sea borders, or to border regions at ports of entry. However, the scope of our study did not include these dimensions. OBP is the CBP component agency that is principally responsible for controlling the land border between ports of entry and thus is the focus of our analysis.

Second, our primary focus is on resource allocation decisions that OBP *stations* face when positioning assets across zones. Some of our findings may be relevant to resource allocation decisions that *sectors* face when considering how to position assets across stations or to decisions that DHS faces when considering how to allocate funds across sectors. But our focus is on how station-level decisionmakers make day-to-day choices about how to position agents, sensors, and other elements of operations across border zones. We discuss the difference between station- and sector-level resource allocation in Chapter Two.

Outline

The remainder of this report is organized as follows. In Chapter Two, we describe how OBP conceptualizes resource allocation and how pattern and trend analysis and systematic randomness fit within this conceptual model. In Chapter Three, we present an agent-based simulation model that we designed to explore trade-offs between different approaches to using pattern and trend analysis and systematic randomness. We develop findings from our use of this simulation model in Chapter Four. In Chapter Five, we describe a data visualization tool that we developed to help OBP decisionmakers understand salient differences among OBP stations. Chapter Six presents an experimental design that OBP could use to evaluate the contributions of pattern and analysis and systematic randomness to its mission. In Chapter Seven, we summarize findings and recommended next steps for OBP as it implements new approaches to using pattern and trend analysis and systematic randomness.

CHAPTER TWO

Resource Allocation, Pattern Analysis, and Systematic Randomness

In this chapter, we present results from our field studies that show how OBP conceptualizes resource allocation. We also discuss fundamental relationships between resource allocation, pattern and trend analysis, and systematic randomness.

Conceptualization of Resource Allocation

OBP conceptualizes the border in three levels of spatial resolution. The most elementary unit of the border is termed a *zone*. The size of each zone is chosen based on the operational art of border patrol, but in practice, it might be a few hundred meters or a few miles; it represents a part of the border where individual patrols are positioned. A *station* is a set of contiguous zones, and a *sector* is a set of contiguous stations. For example, the Imperial Beach station in the San Diego sector along the southern border might have a dozen or more zones, depending on the choices of the station officials there.

These different levels of spatial resolution correspond to different resource allocation decisions. DHS and OBP headquarters decide how to position resources across OBP sectors. These national decisions generally concern how to apportion national budgets and thus are made in conjunction with annual budget cycles. These decisions are also made within the strategic planning processes in place at the national level and are subject to national priorities and budget constraints.

OBP sectors decide how to position resources across OBP stations. These decisions may concern how to appropriate funds, but more typically they focus on how to allocate people, infrastructure investments (e.g., fences, roads), and scarce tactical assets, such as unmanned aerial systems or special operations forces. These decisions are often made in response to new intelligence or in the context of sector-level risk assessment and planning processes that may occur on a monthly or quarterly basis.[1] Intelligence, pattern and trend analysis, and the operational experience of border agents are key inputs to these processes. Randomness is less important at the sector level, given the infrequency of decisionmaking and the amount of information that figures into the decisionmaking processes. OBP also staffs sector headquarters that have a variety of roles, including making resource allocation decisions and fusing and distributing intelligence from national and interagency partners.

1 We use *intelligence* in this context to refer to information about specific border crossing events or smugglers. Examples of intelligence in border security could include information that a drug shipment is expected or information about particular drug cartels. A variety of federal and local law enforcement agencies may contribute to collecting information that shapes OBP resource allocation.

Finally, OBP stations decide how to position resources across OBP zones. These decisions concern how to position individual people or station-level assets, such as ground sensors, bike patrols, and mobile towers, on an hourly or daily basis. OBP stations are where discussions of pattern and analysis and systematic randomness are most frequent, reflecting the day-to-day or minute-by-minute demands of law enforcement. These efforts represent initiatives to formalize what has historically been an informal process.

Figure 2.1 presents a descriptive conceptual model of the OBP approach to resource allocation. The figure shows the three different types of resource allocation decisions and the inputs and processes that affect them. Recall that this report focuses on station-level decisions concerning how to position people or technology across zones.

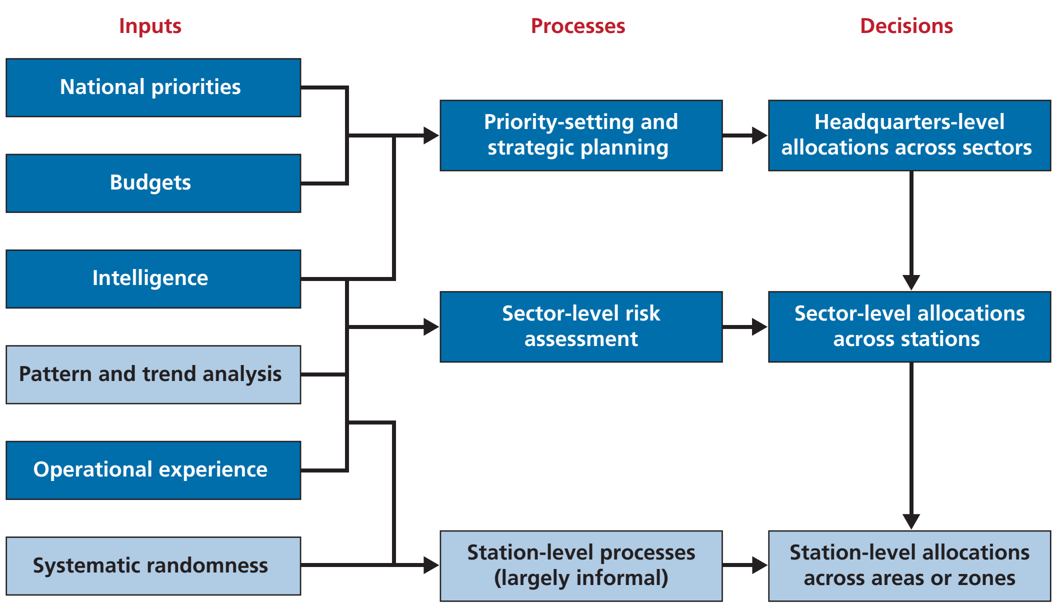
Pattern and Trend Analysis

Our field studies suggest that OBP is investing in methods and tools to conduct pattern and trend analysis of historical cross-border flows and that it is planning to integrate the products of such tools into station- and sector-level decisionmaking about how to allocate people and technology. For the purposes of this discussion, we define pattern and trend analysis as follows:

> *Pattern and trend analysis is the analysis of historical cross-border flows in aggregate for the purpose of identifying regularities in the times, places, or tactics employed by illegal border crossers.*

Methods and tools associated with pattern and trend analysis are relevant to resource allocation because the regularities they identify could be exploited by border enforcement to increase the rate at which illegal flows are interdicted.

Figure 2.1
A Conceptual Model of OBP Resource Allocation Decisionmaking



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Consider a few examples:

- Historical data may reveal "hot spots"—i.e., places and times of high or increased border activity. In some circumstances, repositioning available border agents to zones with high levels of activity may increase interdiction rates.
- Historical data may reveal a relative increase in vehicular versus foot traffic in a particular zone. This information could motivate the allocation of more vehicle-detecting ground sensors to the appropriate region and thereby improve interdiction efforts.
- Historical data may indicate a recent drop in activity in one zone and raise the question of whether OBP should allocate patrols to other zones to which activity may have shifted.

In practice, there are myriad ways to implement pattern and trend analysis, and many tools have been developed for this purpose. COMPSTAT is an example of such a tool, but there are others. Here, we are not as interested in the design of specific tools as we are in the fundamental role and opportunity such tools provide for improving interdiction rates.

Benefits

The benefits of formal pattern and trend analysis should ultimately be measured in terms of their contribution to border security—however border security is measured (see, e.g., Willis, Predd, et al., 2010). These contributions could be assessed through carefully designed randomized controlled experiments and, possibly, through high-resolution modeling and simulation. However, it is worth extolling several of the more theoretical virtues of these methods, particularly in comparison to informal approaches that rely predominantly on operator intuition.

First, such methods typically incorporate a larger set of data than is readily digestible by humans. Larger data sets may reveal patterns that are too subtle to be detected on a smaller scale or by the most observant humans, and they can provide greater confidence in the validity of the resulting conclusions.

Second, formal methods theoretically avoid the cognitive and emotional biases that can characterize human intuition by relying exclusively and systematically on data.

Finally, similar approaches have demonstrated useful results in the context of other law enforcement and military operations; see, for example, Gordon (2010) and Groff and La Vigne (2002). These operations bear some resemblance to those conducted by OBP and thus there is reason to believe that similar results could be achieved in that context.

Risks

These benefits come with the real risk that pattern and trend analysis may in fact mislead—rather than guide—OBP decisionmaking. The reason is that the techniques of pattern and trend analysis are typically applied to historical *interdictions* (i.e., border events that conclude with an apprehension or seizure). And when using these analyses of historical data to guide decisions about future threats, one must make the questionable assumption that the behavior demonstrated in historical interdictions is at least generally representative of the behavior of future illegal crossers.

There are two reasons why this assumption should be questioned. First, historical interdiction data represent apprehensions and seizures but not the complete set of attempted (i.e., interdicted *and* uninterdicted) crossings. The choices and tactics employed by interdicted crossers are, by definition, unsuccessful. Thus, historical interdiction data may not be representative of the nature or type of choices made by successful smugglers. In our field studies, OBP agents stated routinely, "We don't know what we haven't seen." This sentiment perfectly captures the essence of the issue.

Second, smugglers and illegal border crossers are known to change their tactics in response to OBP efforts to thwart them. For sure, historical interdiction data provide clues about these adaptations. But fundamentally, historical interdiction data may not represent the most recent threat adaptations.

Thus, there may be an inherent bias in sampling historical interdictions to represent historical flows, and as a result, the products of historical analyses of interdiction data are often subject to multiple explanations. For example, areas or times with apparently high numbers of apprehensions and seizures may be alternatively explained by a high level of border patrol capability, by genuinely high levels of illegal activity, or both. Low numbers of apprehensions and seizures may be alternately explained by a lower concentration of border patrol resources, genuinely low levels of illegal activity, or threat adaption to other areas. Finally, the use of particular technologies or tactics by interdicted smugglers may reflect a broader capability among border crossers or the feasible strategies of the more incapable border crossers.

Unfortunately, this is not merely academic curiosity, since the explanation for a pattern is often an important factor when deciding how to allocate people and technology. For example, repositioning patrols to an area with historically high numbers of interdictions may be appropriate if the observed trend genuinely reflects the level of illegal activity, but the allocation may be less beneficial if the observations are simply due to the self-fulfilling presence of law enforcement. Repositioning patrols away from areas with low numbers of interdictions may be exactly the wrong strategy if the observation is due to the inability of an already insufficient presence of law enforcement to detect an evasive threat.

Thus, one must be careful when interpreting patterns or trends in historical interdiction data as patterns or trends in illegal flow more generally, since historical interdiction data reflect historically unsuccessful attempts to cross the border and may or may not indicate how border crossers will adapt. Exacerbating this issue, smugglers are widely known to adopt deceptive tactics that exploit strategies that follow historical trends too closely.

Systematic Randomness

OBP is also exploring the role of systematic randomness—in a sense, the antithesis of pattern and trend analysis. *Randomness* refers to the introduction of unpredictability into the resource allocation decision process. This randomness is *systematic* in the sense that it is introduced as part of a repeatable process, such as daily patrol scheduling.

In formal terms, systematic randomness involves specifying a probability distribution over a set of alternatives and selecting among the alternatives by sampling from the distribution. Our interviews did not reveal what, if any, specific approach OBP employs to specify the probability distribution or conduct sampling. But systematic randomness is a concept that our interviewees discussed and seemed to employ in informal and ad hoc ways.[2]

[2] It is important to distinguish systematic randomness from carelessness or arbitrariness. Whereas carelessness or arbitrariness suggest decisionmaking without principles, systematic randomness should be employed with care: The relevant probability distribution should be specified according to a consistent and coherent set of principles, and alternatives should be sampled using appropriate sources of randomness or pseudo-randomness.

There are three main reasons that introducing randomness into resource allocations may be beneficial. The first is that randomness may allow one to sample the border for illegal activity without the bias of historical trends. The idea is that a random strategy may allow one to discover activity that one would not otherwise discover if biased by historical data. This rationale can be supported by statistical arguments about sampling strategies and so-called multi-armed bandit models (see, e.g., Cesa-Bianchi and Lugosi, 2006).

A second rationale for introducing systematic randomness is that it makes it harder for smugglers to exploit patterns in border patrol behavior. The idea is that smugglers cannot exploit OBP behavioral patterns that do not exist. This rationale can be motivated by game-theoretic arguments demonstrating the optimality, under some assumptions, of so-called mixed strategies. In fact, this approach has motivated the introduction of randomness to airport security at Los Angeles International Airport (Pita et al., 2008), the scheduling of federal air marshals (Jain et al., 2010), and U.S. Coast Guard port security patrols.

The third rationale is that randomness introduces uncertainty into smuggler decision-making, thereby increasing risk and possibly deterring illegal activity in the first place. The idea is that smugglers confronting a randomized strategy may perceive higher risk than they would otherwise and may therefore reconsider crossing in the first place, or at least consider crossing at a different location or using a different mode of transport. This rationale is supported by research on smuggler decisionmaking (see, e.g., Decker and Chapman, 2008).

Of course, randomness is useful only when it is used appropriately. A purely or excessively random approach to positioning or configuring resources would not capitalize on what OBP agents know to be true based on historical evidence or what careful analysis suggests is likely.

Exploitation Versus Exploration Trade-Offs

As discussed, pattern and trend analysis and systematic randomness have both risks and potential benefits. Pattern analysis may usefully guide OBP to where resources can be most effective, but only if historical data are representative of the future. Systematic randomness may help OBP explore unseen risks and mitigate adversary adaptation, but excessive randomness will not exploit what OBP knows or expects to be true. Conceptually, the two approaches are related; randomized allocation strategies affect the degree to which historical data can represent future border activity.

In fact, the relationship between pattern and trend analysis and systematic randomness can be characterized in terms of a fundamental trade-off between *exploitation* and *exploration*. In this context, *exploitation* refers to the objective of allocating resources to increase interdiction rates by leveraging what is known or expected to be true today. *Exploration* refers to the objective of gathering information to guide future resource allocations and risk assessments.

Both risk exploitation and exploration are important in the resource-constrained border environment. On one hand, OBP ultimately must interdict illegal border crossing by exploiting best estimates of where and when the risks are greatest. It is well understood that risks vary by location and over time, and decisionmakers must exploit this variation to effectively control the border. However, the quality and availability of the information needed to assess those risks can also vary across space and time, and exploring areas where information is missing is a necessary part of understanding where and when risks can be reduced. Thus, resource allocation must also give credence to the objective of gathering data about places and times not recently explored.

With unlimited resources, enough agents and sensors could be deployed to simultaneously satisfy the objectives of both exploitative and exploratory strategies. Given current constraints, decisionmakers must make trade-offs, since places and times with historically high levels of risk may be very different from those where future risks will be. A purely exploitative allocation strategy—for example, one that weds decisions closely and exclusively with historical trends—may be vulnerable to intelligent adversaries who adjust to target places or times that receive little attention. Reflecting this point, many border agents noted that low apprehension rates could be explained by either a low level of threat activity or low border patrol presence. However, positioning resources for the sole purpose of exploring risks—for example, distributing resources in a purely random way—is unlikely to satisfy the interdiction mission. Thus, resource constraints give rise to an exploitation-exploration trade-off.

In other words, OBP has some control over the representativeness of historical interdiction data, somewhat ironically via the same decisions supported by pattern and trend analyses. Consider, as a thought experiment, that rather than following historical trends, OBP chooses to position its patrols randomly across the border. Some of the randomly allocated patrols would interdict smugglers, and some would not. But over a period of weeks or months, the resulting interdiction would yield a perfectly unbiased sampling of where, when, and how illegal flows are crossing. Furthermore, it would be immune to an adaptive threat because OBP decisions would be systematically unpredictable.

Of course, a random approach to positioning OBP resources is unlikely to yield satisfactory interdiction rates. In practice, smugglers are subject to operational constraints that can be exploited by OBP through more strategic (i.e., non-random) decisions about how to position resources. Nonetheless, this thought experiment clearly suggests the value of distinguishing two objectives that OBP must consider when allocating resources: *exploiting* and *exploring* risk estimates.

On one hand, OBP may allocate some tactical resources to exploring regions of the border that have not recently been patrolled (or surveilled) but that may, in fact, be used by smugglers. On the other hand, it must ultimately interdict illegal border crossing by exploiting best estimates of where and when risks are greatest. The limitation of using historical data demonstrates the problem with allocating all resources in a manner that exploits without ever exploring. As illustrated by the thought experiment, positioning resources for the sole purpose of exploring risks will not allow OPB to achieve its interdiction mission.

Exploitation-exploration trade-offs do and should depend on operational factors that vary by sector and station. For example, for a given level of detection and interdiction capability, a longer border may have more areas where there is a poor understanding of threats and vulnerabilities. Thus, all else being equal, more exploration may intuitively be needed to ensure success in stations responsible for longer borders relative to those with shorter borders. For a border of fixed length, this may mean that greater capacity and potentially more resources can be tasked for exploration. For example, persistent surveillance—even without an interdiction capability—may alleviate the need to explore altogether. Finally, exploration may be more important for highly adaptive adversaries than for less adaptive ones. Highly adaptive adversaries may motivate more exploration for OBP to track their frequent adjustments; less adaptive adversaries may motivate more exploitative strategies that capitalize on smugglers' limited ability to change. Thus, the length of the border, the extent of interdiction and surveillance, and smuggler adaptability may rightly affect how exploitation-exploration trade-offs are made.

Figure 2.2 illustrates the conceptual relationship between OBP decisionmaking and historical interdiction data. To summarize, historical interdiction data may inform OBP decision-making by identifying where, when, and how OBP can most productively position resources. However, the same decisions can affect the degree to which historical data are representative of future illegal activity.

In practice, there are myriad decisions that OBP might randomize and countless ways to strike a trade-off between exploitation and exploration. For example, OBP could explore different trade-offs for decisions, including, among others,

- the position of patrols, ground sensors, and cameras
- the timing of shift changes and surges in presence
- the configuration of sensors (e.g., directionality, sensitivity).

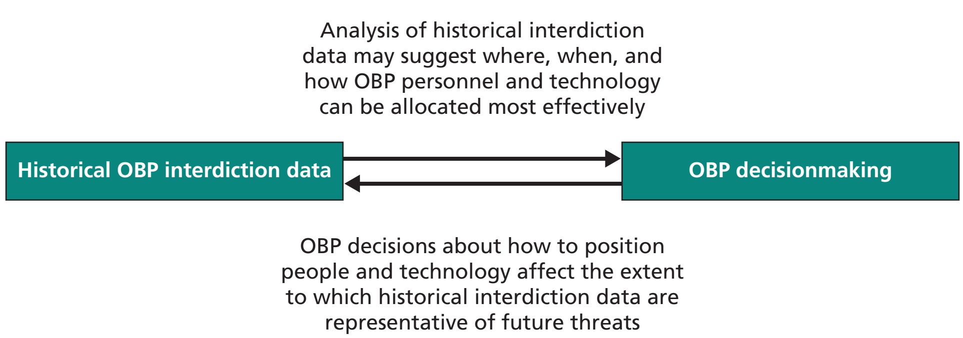
It might strike a trade-off between exploitation and exploration in one of the following ways, among others:

- Select days at random. On randomly selected days, position patrols uniformly at random; on the remaining days, allocate patrols according to whatever other approach is state of the art.
- Each day, allocate a specified fraction of resources to zones selected at random with a uniform distribution across zones; allocate the remaining resources according to whatever other approach is state of the art.
- Each day, perturb historical interdiction data by random amounts, and use the perturbed data to decide how to position or allocate resources.

Four Basic Approaches to Using Pattern and Trend Analysis and Systematic Randomness

Conceptually, there are four distinct classes of approaches to using pattern and trend analysis to allocate border resources. We describe them as classes of approaches—rather than simply "approaches"—because they represent broad categories of approaches among many possi-

Figure 2.2
Two Relationships Between Historical Interdiction Data and OBP Decisionmaking



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ble ways of allocating resources. Each approach amounts to a different way of making the exploitation-exploration trade-off.

Approaches in the first class ignore historical data altogether and allocate *randomly*. This approach would be reasonable given an objective to develop an unbiased estimate of cross-border flows, since random sampling is a statistically principled way of sampling the border for threats. However, as discussed earlier, assuming that the threat is subject to operational constraints that can be exploited by OBP, a purely random approach is unlikely to yield the greatest or even satisfactory interdiction rates in practice. These approaches favor exploration without any exploitation.

Approaches in the second class allocate based on *pattern analysis of historical interdictions.* These approaches arguably represent the state of the art and assume that historical interdictions are representative of current illegal flows. However, as discussed, these approaches may be inappropriate when the assumption is invalid—for example, when interdictions are representative of OBP presence or when smugglers adopt evasive tactics. These approaches favor exploitation without any exploration.

Approaches in the third class allocate based on *pattern analysis of historical crossings* (i.e., assuming perfect hindsight of all crossings, both successful and unsuccessful). These approaches are arguably the ideal, since historical crossings are, by definition, the most representative sample of illegal flow. Such awareness is at least theoretically possible and could be approximated through expensive investments in robust persistent surveillance (e.g., deployment of high endurance unmanned aerial vehicles, dense deployment of unattended ground sensors with a fusion cell). However, these approaches are also the most expensive, as they require persistent surveillance.[3] These approaches circumvent the need to trade off exploitation and exploration; they assume that the resources available for exploration are separate from the resources needed for exploitation and that those resources are sufficient to gain a comprehensive view of historical flows.

Approaches in the fourth class combine the principles of the other classes and allocate based on a *hybrid approach*, blending pattern analysis of historical interdictions and systematic randomness. These approaches represent a combination of approaches in the other classes, since they attempt to sample randomly with sufficient frequency (or with sufficient numbers of resources) to ensure that interdiction data are generally representative of total cross-border flows. But, in general, these approaches follow interdiction trends in an attempt to maximize the interdiction rate. Thus, they represent a balance between exploitation and exploration.

Summary

In this chapter, we introduced a conceptual model of how OBP approaches resource allocation at the headquarters, sector, and station levels. We also discussed the roles of pattern and trend analysis and systematic randomness in resource allocation, as well as the relationship between the two tools in terms of fundamental exploitation versus exploration trade-offs. The following chapters are devoted to a quantitative evaluation of these trade-offs in the border security context.

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[3] Note that allocating resources based on historical crossings assumes that OBP has access to data on historical crossings in hindsight—not that OBP is aware of all crossings *as they happen*.

CHAPTER THREE

Simulation Model of OBP Patrol-Smuggler Interaction

In this chapter, we describe an agent-based simulation model developed at RAND to explore how different approaches to using pattern and trend analysis and systematic randomness affect interdiction rates.

Model Specification and Assumptions

Our model is a multi-agent-based simulation based on S+P agents, with S representing smugglers and P representing patrol agents. The interaction between agents and smugglers is determined largely by the strategies that they use to position themselves along the border each day over the course of a simulated year.

The border is modeled as a set of Z crossing sites (or "zones"). Each day, OBP chooses the crossing sites at which to position P patrols, assigning each patrol to exactly one site. Simultaneously, S smugglers choose the site at which they will cross.

Border Patrol Positioning Strategies

OBP's choice of where to position patrols on a given day is made without information about where smugglers will choose to cross on that day, but it can depend on historical data in one of four ways:

1. *Random allocation:* Allocate randomly, ignoring historical data. OBP positions P patrols at crossing sites sampled from P independent draws from a uniform distribution across zones.
2. *Pattern analysis:* Allocate in accordance with pattern and trend analysis of historical interdictions. OBP computes the distribution over zones in historical interdictions during the preceding 30 days. Then, it positions P patrols at zones sampled from P independent draws from this distribution.
3. *Perfect hindsight:* Allocate in accordance with pattern and trend analysis of historical crossings. OBP computes the distribution across zones in historical crossings during the preceding 30 days. It then positions P patrols at zones sampled from P independent draws from this distribution.
4. *Hybrid:* Allocate in accordance with pattern and trend analysis of historical interdictions with some systematic randomness. OBP computes the distribution across zones in historical interdictions during the preceding 30 days. With probability specified by a parameter, Beta, OBP then positions P patrols at zones sampled from P independent

draws from this distribution; with probability (1-Beta), OBP positions patrols at *P* zones sampled independently from a uniform distribution across zones.

Note that each strategy leverages a form of randomness in the sense that OBP positions patrols according to independent draws from some probability distribution. The probability distribution represents OBP's assessment of historical patterns and trends that it can use as the basis for positioning decisions. Strategies differ according to the way that the probability distribution is formed in accordance with different assumptions about how much information OBP has and how the strategy trades off exploitation and exploration. Table 3.1 summarizes how strategies differ by the focal objective.

Also note that the positioning of patrols is managed centrally by a single decisionmaker representing an OBP station headquarters.

Smuggler Crossing Strategies

The smugglers' choice of where to cross on a given day is made independently, without prior knowledge of where OBP will choose to position patrols, but it depends on historical data. Smugglers determine a particular zone to be "hot" if more than 30 percent of crossings in that zone have been interdicted over the previous 30 days. A smuggler will cross the same zone as the preceding day if the zone is not "hot." If the chosen zone is hot, smugglers will choose a zone at random among zones that are not hot. If all accessible zones are determined to be hot (a rare but technically feasible condition), then smugglers position themselves at sites chosen randomly across all zones.

Note that the choice of crossing site is made separately by each smuggler, but we assume that smugglers share information about which zones are hot.

Our assumption that smugglers will adapt, when risks warrant, by changing the zones at which they cross is supported qualitatively by three sources. First, in interviews we conducted in the San Diego and Rio Grande Valley sectors, officials relayed numerous anecdotes of smugglers attempting to cross specific border sites despite patrol presence—until extra measures were taken to "lock down" the border at the site. Interviewees suggested that in many of these cases, smugglers would cross at other sites where OBP presence was reduced rather than be deterred from crossing altogether. The shift in smuggler behavior before and after a "lockdown" corresponds to crossing a threshold probability at which point smugglers are incentivized to adapt.

A second source of support is empirical modeling of deterrence (e.g., Anthony, 2004), which considers the relation between the probability of interdiction and the willingness of smugglers to attempt crossing. Such models include a "deterrence threshold" that represents the non-zero probability of interdiction required for smugglers to reduce their willingness to

Table 3.1
Focal Objectives of Different Strategies

Strategy	Exploitation	Exploration
Random allocation		X
Pattern analysis	X	
Perfect hindsight	X	NA
Hybrid	X	X

attempt crossing. Our model assumes that smugglers change the site where they cross but are not deterred altogether, and the evidence supports this behavior change.

Finally, interviews and surveys of convicted drug smugglers (see, e.g., Decker and Chapman, 2008) indicate a range of adaptations that smugglers make when efforts to interdict them increase.

We cannot support our particular chosen threshold (0.30 probability of interdiction determines that a zone is hot) with precise quantitative evidence. We note, however, that Anthony (2004) derives a deterrence threshold of 0.13, implying that the threshold for simple adaptation (not deterrence) is less than 0.30. Moreover, Decker and Chapman (2008) report that 63 percent of interviewed cocaine smugglers said that they would continue to smuggle if the chance of interdiction was 50 percent; this suggests that the adaptation threshold may be greater than 0.30. So, our chosen value is between the two published extremes.

Finally, although we did not conduct a thorough analysis of the sensitivity of our results to the threshold parameter, we did vary the parameter between 0.50, 0.30, and 0.15 in the early stages of our analysis. We observed emergent behavior that was generally consistent across parameter settings, so we made a decision to hold the variable constant at the median value of 0.30. Future research should more fully explore the dependency between this threshold of adaptation and how to combine pattern analysis and systematic randomness.

Patrol-Smuggler Interaction

On simulated day d, border patrol and smuggler strategies result in the positioning of $P_{i,d}$ patrols and $S_{i,d}$ smugglers at crossing site $i = 1,\ldots, Z$. The model determines that

- $S_{i,d}$ smugglers are interdicted if $P_{i,d} \geq S_{i,d}$; otherwise,
- $P_{i,d}$ smugglers are interdicted.

We model this interdiction process deterministically. However, note that the number of interdictions in this model is equivalent to the expected number of interdictions given the assumption that the probability that a given smuggler is interdicted at site i on day d is the ratio $P_{i,d} / S_{i,d}$ (normalized to 1 when the ratio exceeds 1).

So, the probability of interdiction in a particular zone increases as the number of patrol agents increases, and it decreases as the number of smugglers increases.

Model Inputs and Outputs

Thus, the model has four main inputs:

- P, the number of patrol agents per day
- Z, the number of crossing sites or zones
- S, the number of smugglers per day
- OBP positioning strategy, chosen among the four strategies described earlier.

Several secondary inputs are needed to fully specify the model. We fix these parameters in the analysis that follows because they are secondary to our analytic objectives and because our analysis suggests that our basic conclusions are not sensitive to the way we have fixed them. Secondary inputs include the following:

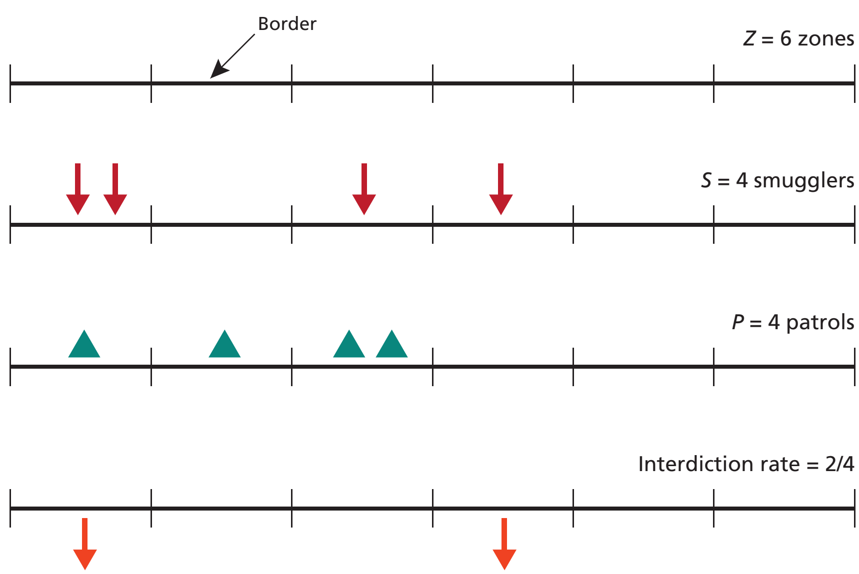
- The number of historical days over which OBP assesses patterns and trends; we set this variable at 30 days in our analysis.
- The interdiction rate that determines whether smugglers view a particular zone as too hot to cross; we set this variable at 30 percent in our analysis.
- Beta, the parameter of the fourth (hybrid) strategy: the probability that OBP positions patrols according to the distribution computed using historical interdictions versus the uniform distribution across zones. We set this parameter at 20 percent in our analysis.

The principal output of the model is the annual interdiction rate—i.e., the percentage of smugglers interdicted over the course of a simulated year.

Figure 3.1 illustrates the basic inputs and outputs of our model in graphical terms. Here, the border is divided into $Z = 6$ zones. $S = 4$ smugglers attempt to cross the border protected by $P = 4$ patrols. Two of the smugglers concentrate on one zone, and the others pursue other approaches; similarly, OBP positions two agents in one zone and two other agents in two other zones. The patrols are aligned with the zones chosen by smugglers such that two smugglers are interdicted.

We explored thousands of configurations of *P*, *S*, and *Z*, which are described in greater detail in Chapter Four. Specifically, we ran the model with a wide range of input parameter settings (shown in Table 4.1 in Chapter Four). We varied the parameters in increments of five, ten, and 15 for *P*, *S*, and *Z*, respectively, and ran the model ten times for each configuration of *P*, *S*, and *Z*. We ultimately simulated more than 1,000 different configurations of *P*, *S*, and *Z*.

Figure 3.1
Illustration of Simulation Model



NOTE: *Z* is the number of zones, *S* is the number of smugglers, and *P* is the number of patrols.
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How the Model Should and Should Not Be Used

This model is obviously a highly simplified approximation of the complex reality along U.S. borders. In actuality, interdiction rates are affected by myriad factors, including illegal drug crop yields, immigration policies, economic conditions, weather, terrain, and sensor performance. Our model does not represent these features.

A more complex model might be more representative, but it would require significantly more time to develop and use, and it would not make commensurate contributions to answering the basic questions under consideration in this study. (Though such a model might answer *other* questions not considered here.)

For example, a more complex model could be designed to represent the physical, technological, and social systems at play along the border and could allow input parameters to be calibrated in ways that represent the alternatives under consideration. To be predictive of actual performance in the cases of interest, the model would need to be validated using data sampled in a way that allows the model to generalize. Developing such a model is an expensive endeavor and was beyond the scope of our project.

An alternative approach to evaluating border security investments and operational concepts is to evaluate them empirically through natural or designed experiments. For example, one might randomly assign border patrol stations to use a given predictive tool (e.g., some stations are assigned to use COMPSTAT to allocate patrols and others are assigned to use their intuition), and then measure the performance of each station over a given period (e.g., through a measure of interdiction rate or some other criterion). Assuming that the assignment strategy allows one to control for confounding factors, one could analyze interstation variations in performance to isolate the effect of different operational concepts on outcomes. We understand that OBP has facilities to conduct these types of experiments, but they too are expensive and allow exploration of only a few alternatives at a given time.

What our model loses in its ability to precisely predict outcomes it gains in its ability to quickly and inexpensively explore high-level trade-offs among many thousands of strategies under a wide range of assumptions. For example, our model can be used to explore

- how different approaches to using pattern and trend analysis affect interdiction rates, in general and relative to one another
- the extent to which the effect of pattern and trend analysis on interdiction rates depends on the number of crossing sites, the daily rate of smugglers, and the number of patrols, as well as other conditions that vary by sector and station.

Such explorations can help decisionmakers focus on the alternatives with the most promise and understand the fundamental trade-offs among them. They can also guide the development of more complex models and facilitate experimental design if further analytic steps are needed to support decisionmaking. In the next chapter, we describe the findings from our analysis. Later, we discuss how these insights may feed further modeling efforts and empirical evaluations.

Thus, this model could be part of a model-test-model approach to planning. In such an approach, the model first provides insights about which strategies to explore; tests are then done on a few strategies to confirm insights from the model, and the model is then used to develop insights about related strategies.

Model Extensions and Variations

There are several extensions to and variations of this simple model that are worth considering. Here, we explore several possibilities and explain why we have chosen not to pursue them.

Imperfect Hindsight of Historical Crossings

OBP agents routinely track "getaways," crossings that are detected but not interdicted. Getaways in principle should be and in practice sometimes are used in OBP pattern and trend analysis.

Our model and analysis does not consider getaways or other mechanisms through which OBP may develop imperfect awareness of historical crossings. Our simplified model of the OBP "kill chain" does not distinguish among detection, identification, and interdiction, as would be necessary to consider alternatives in which OBP does and does not consider patterns associated with smugglers who were detected but not interdicted. A model that makes this distinction would indeed be useful if one wanted to discriminate among investments or strategies that focus on building situational awareness from investments or strategies that build interdiction capacity. (Here, building situational awareness amounts to developing less imperfect hindsight, and building capacity amounts to adding patrols.) Rather, our focus was on the learning trade-off.

Thus, a strategy that combines systematic randomness with imperfect *hindsight* of historical crossings has practical relevance. Future research should consider this effect on interdiction rates and allocation strategies.

Perfect Foresight

Our analysis considers the interdiction rate achieved by perfect *hindsight* as an ideal or benchmark. Perfect hindsight is a practical, if not fundamental, limit on interdiction rates of having a given number of patrols *and* limited situational awareness.[1]

We chose the interdiction rate achieved by perfect hindsight as an ideal because we thought it was a fairer comparison: If we employed perfect *foresight* as the ideal, then OBP strategies would differ in terms of access to foresight and hindsight. By using an ideal of perfect hindsight as a benchmark, the set of OBP strategies differs only with respect to hindsight.

Our model assumes that both smugglers and OBP are without foresight on each other's location on a given day. That is, the smugglers and OBP are aware of each other's historical behavior, but on a given day do not have any further—imperfect or otherwise—intelligence about where the "adversary" is positioned. This is obviously not reflective of reality, since smugglers and OBP go to great lengths to obtain real-time intelligence. However, we would expect the effect of intelligence to have the same influence on interdiction rates regardless of strategy. So, we chose not to model intelligence or real-time situational awareness.

Future research could consider how various mechanisms for developing foresight through intelligence influence resource-allocation strategies.

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[1] Under the assumptions of the model, the interdiction rate achieved by perfect *foresight* can be computed in closed form: $\min(P,S)/S$. This ratio is indeed a fundamental limit on the interdiction rate, imposed by having a given number of patrols in our model.

Terrain and Other Differences Between Zones

In practice, smugglers prefer some zones over others based on features such as terrain, nearness to major routes of ingress/egress, and so on. Our model does not represent these differences, but it could in principle.

Preferences based on terrain features provide something additional for OBP agents to learn through pattern analysis and systematic randomness. But, in fact, there are many factors that influence smuggler preferences and that OBP could derive some advantage from understanding: the weather, labor market conditions, and seasonality, among many others.

Thus, preferences of zone and other characteristics do not amplify or suppress the basic need to trade off exploration and exploitation. As long as resource constraints drive how OBP can apportion resources and smugglers adapt, the fundamental learning trade-off will exist regardless of what exactly needs to be learned. We developed our model and conducted our analysis with a focus on exploring this basic trade-off. Modeling additional features for OBP to learn would add fidelity without providing insight to the basic point.

Future research and modeling should consider how learning and resource allocation strategies should be tuned to the specific requirements that influence smugglers' decisions, including terrain features and other characteristics.

CHAPTER FOUR

Findings from the Analysis of the Simulation Model

In this chapter, we describe how we used our simulation model to explore how interdiction rates are affected by different strategies and by factors such as the number of patrols, the number of crossing sites, and the daily rate of smugglers. Our focus is on two questions:

- What explains the variation in interdiction rates across positioning strategies?
- Which strategies are best, and under what circumstances?

Simulation Model-Run Sampling

We ran the model over a wide range of input parameter settings, described in Table 4.1. Parameters were varied in increments of five, ten, and 15 for *P*, *S*, and *Z*, respectively, and the model was run ten times for each configuration of *P*, *S*, and *Z*. Altogether, we simulated more than 1,000 different configurations of *P*, *S*, and *Z*.

These ranges were chosen for two reasons. The first and primary reason was to develop an understanding of the role of pattern and trend analysis and systematic randomness across the broadest range of conditions—conditions that span but are not limited to cases corresponding to specific OBP stations. Though, in practice, there may not be a station with 500 smugglers, 400 patrols, and 300 zones, exploring this case in the context of thousands of other cases allowed us to understand how the interdiction rate varies with the parameters of interest. Thus, though many cases in our sample may not be representative of actual stations, we believe it includes the cases of interest and that exploring the others will yield generalizable insights.

The broad ranges also serve as a means of abstracting features that we do not have the data to model. In practice, smugglers and border patrol agents make myriad choices, including which site to cross at what time of day; how to configure technologies such as radios, ground sensors, and unmanned aerial assets; and which tactics to employ. We do not have data about

Table 4.1
Simulation Model-Run Sampling

Parameter	Minimum	Maximum
P (patrols per day)	5	405
S (smugglers per day)	5	505
Z (zones)	5	305

the full range of options available to either OBP or the smugglers. However, the number of zones can be interpreted as the total number of options among which smugglers choose when deciding to cross the border; it may be in the hundreds. In this light, the number of border patrol agents and smugglers can be better interpreted as proxies for the overall force structure of OBP and the smugglers, including patrols, technology, and infrastructure. Thus, in an abstract sense, the model allows for a high-level comparison of force structure.

As discussed in Chapter Three, a number of other input parameters were held constant.

What Explains the Variation in the Interdiction Rate?

Looking broadly across model runs and strategies, average interdiction rates vary wildly from very low (less than 5 percent) to very high (100 percent). The variation in interdiction seems to depend largely on ratios: the ratio of *P* to *Z*, the ratio of *P* to *S*, and the ratio of *S* to *Z*. For reasons that we explain later, we refer to the ratio of *P* to *Z* as *coverage*, the ratio of *P* to *S* as *capacity*, and the ratio of *S* to *Z* as *threat density*. Before providing a statistical basis for this statement, we first offer an intuitive explanation for the apparent relevance of these ratios.

Intuitive Explanation

In our model, capacity (i.e., the ratio of *P* to *S*) determines the maximum achievable daily interdiction rate. When the ratio exceeds 0.3, over time, OBP has enough resources to motivate smugglers to adapt (per the assumption in the model). And once smugglers adapt, historical interdiction data cease to represent illegal cross-border flows, and relying on historical interdiction trends to allocate resources would be inappropriate until information is collected to reflect smugglers' new choices. Of course, when the capacity ratio is sufficiently high, smugglers may find it impossible to avoid OBP, regardless of the strategies employed—in which case interdiction rates should be high. Thus, capacity is directly related to the extent to which OBP can induce smuggler adaptation.

In reality, there may not be such a strict threshold at which all smugglers are incentivized to adapt. As discussed earlier, evidence suggests that individual smugglers have such tolerances (see, e.g., Anthony, 2004) so the importance of this "phase change" in behavior is consistent with social science.

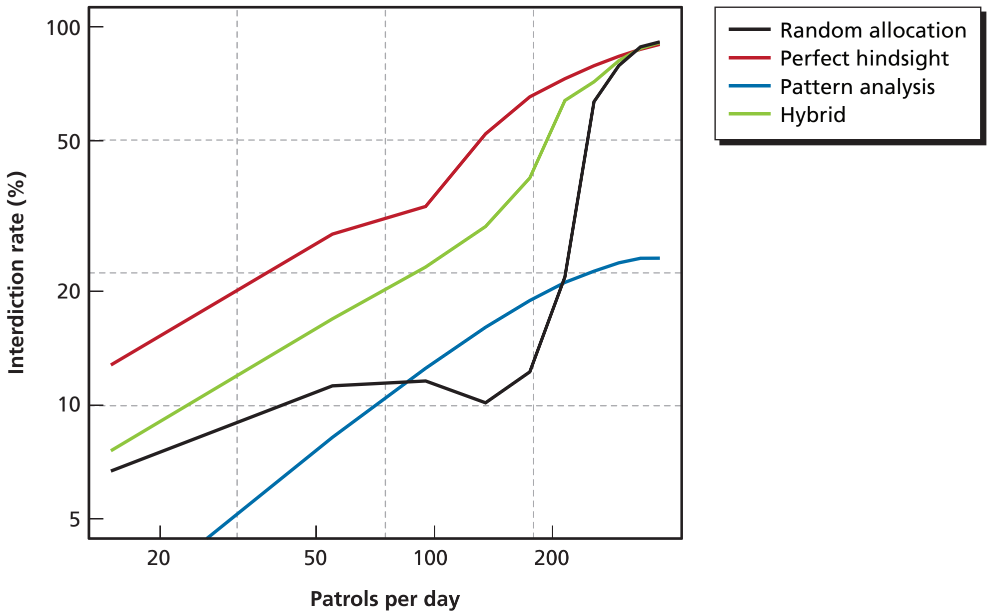
Coverage (i.e., the ratio of *P* to *Z*) determines the percentage of the border that OBP patrols on a given day. For a given distribution of smugglers across the border, a larger ratio of *P* to *Z* means that OBP observes a greater fraction of total flow and thus historical interdiction data will be more representative of illegal flows, notwithstanding adaptations.

Finally, threat density (i.e., the ratio of *S* to *Z*) determines the percentage of the border that smugglers cross on a given day. For a distribution of patrols across zones, smaller ratios of *S* to *Z* mean that there are more alternatives for smugglers to chose from when they are forced to adapt: Smugglers may find it easier to "slip through the cracks."

Results from the Simulations

Figure 4.1 illustrates these assumptions with data from our simulation model. Here, we fix the number smugglers per day (S = 115) and the number of crossing sites (Z = 100) but vary the number of patrols per day (P). As the number of patrols increases, there are more resources to interdict (i.e., capacity increases) and OBP captures a better sampling of illegal activity along

Figure 4.1
Interdiction Rate Versus Patrols per Day, by Strategy (Smugglers = 115, Zones = 100)



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the border (i.e., coverage increases); this explains why interdiction rates increase as a function of P for all strategies. At some point, as P increases, the interdiction rates reach a point at which smugglers are incentivized to adapt, and interdictions begin to plateau or even decrease with marginal increases in P, reflecting smugglers' relative success in avoiding the border patrol. With still additional patrols, interdiction resumes its growth rate, as smugglers are unable to avoid patrols that now saturate the border and OBP has enough resources to track behavior. Note that this basic logic holds true for all strategies.

Even the purely random strategies can motivate smugglers to adapt. The probability that at least one randomly allocated patrol is positioned at a given zone is $1 - 1/Z^P$. When there are few patrols relative to the number of crossing sites, this probability is too low to motivate smugglers to avoid any particular zone. Under these circumstances, smugglers maintain their initial crossing sites and are evenly distributed across these sites. On the other hand, when patrols saturate the border, the probability that at least one randomly allocated patrol is positioned in a given zone approaches 1. Under these circumstances, most zones with relatively few smugglers are considered hot; smugglers are motivated to concentrate in specific zones, since this strategy effectively overwhelms border patrols. Thus, depending on the relative number of resources, random strategies can incentivize smugglers to concentrate or disperse.

These patterns manifest as nonlinearities in the interdiction rate achieved by the random allocation strategy in Figure 4.1. For example, the interdiction rate for the random strategy increases with the number of patrols—up to a point. Then, interdiction actually decreases as smugglers shift from diffuse to concentrated allocations. When patrols again reach another threshold, the interdiction rate stabilizes again. Between these two extremes, there is a transition point at which the interdiction rate achieved in the random allocation strategy decreases with additional patrols and interdiction rates motivate smugglers to cluster. *These behaviors entirely accord with the simple rules in our model.*

Figure 4.2 illustrates how interdiction rates vary with the number of smugglers per day, holding constant the number of patrols (*P* = 205) and the number of crossing sites (*Z* = 215). Capacity drops as we increase the daily rate of smugglers, and the interdiction rate under all strategies drops—more significantly for some than for others. But as the threat density increases, there is a greater chance that border patrol will "stumble upon" crossers, regardless of allocation strategy.

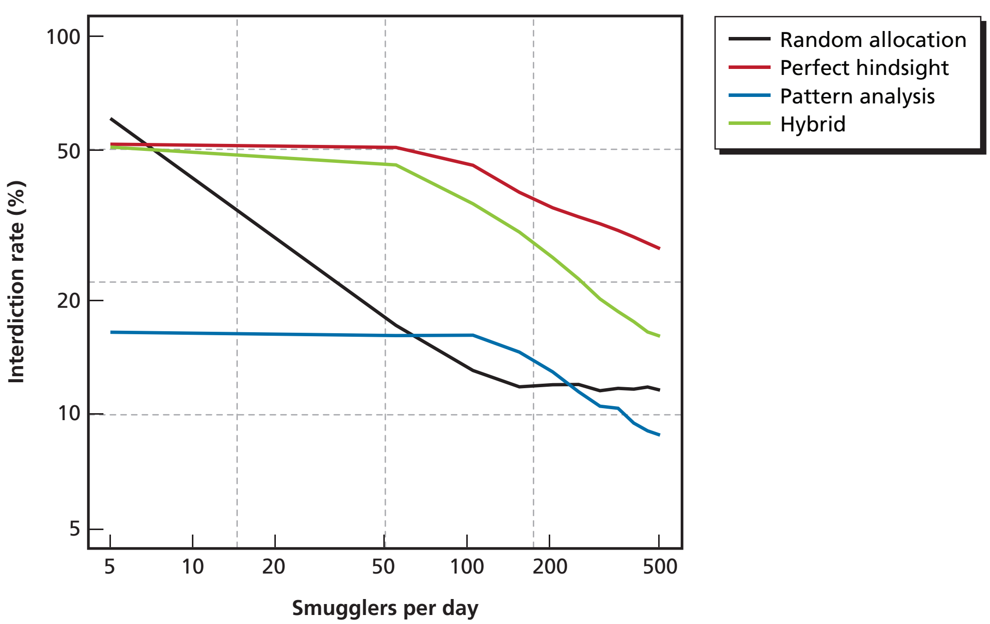
Figure 4.3 illustrates how interdiction rates vary with the number of crossing sites, holding constant the number of patrols (*P* = 55) and smugglers (*S* = 65). As the number crossing sites increases, crossers have more alternatives and it is easier for them to evade border patrol. This explains why interdiction rates under all strategies decrease with increased crossing sites.

The importance of these ratios is further illustrated by Figures 4.4 through 4.6, later in this chapter, which show similar plots with different configurations of *P*, *S*, and *Z* held constant. Figure 4.4, for example, plots the interdiction rate versus the number of patrols per day for nine different configurations of *S* and *Z*. The ratio of *S* to *Z* (i.e., the threat density) is roughly constant along the diagonal of the 3 × 3 array of plots: Plots along this diagonal are essentially shifted versions of one another, underscoring the importance of ratio measures.

Statistical Analysis of Variability in Interdiction Rates

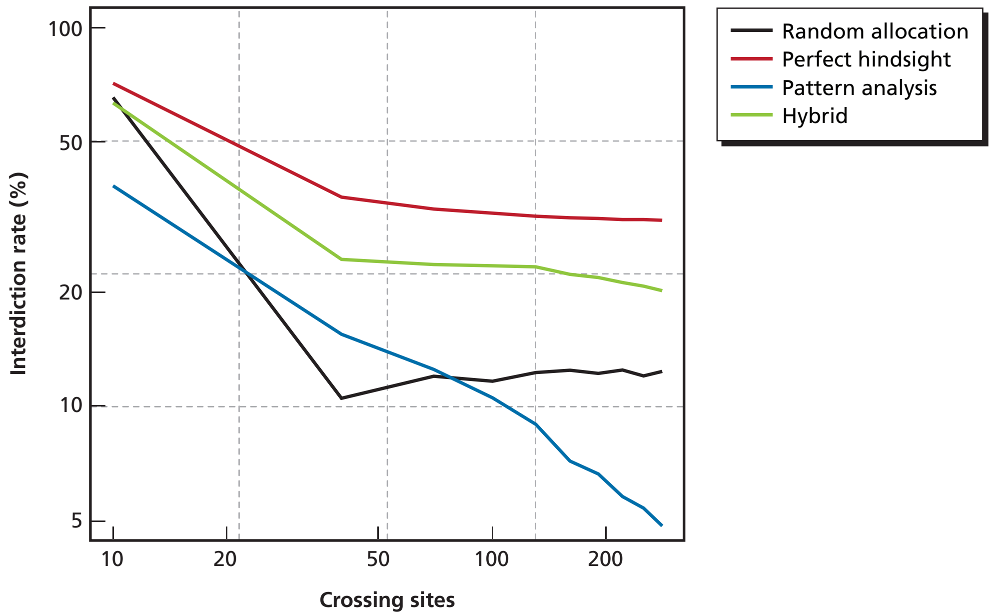
This intuition about the importance of relative measures, such as capacity and coverage, can be validated statistically. We used the interdiction rate as the outcome variable and modeled it as a function of various absolute and ratio-based combinations of the input variables, *P*, *S*, and *Z*. Table 4.2 (page 29) shows the percentage of variability (i.e., R^2) explained by the various configurations for each of the four allocation strategies in our simulation model. Note that each model includes a constant factor. Table 4.3 presents the coefficients for the best fit of the model

Figure 4.2
Interdiction Rate Versus Smugglers per Day, by Strategy (Zone = 215, Patrols = 205)



RAND *TR1211-4.2*

Figure 4.3
Interdiction Rate Versus Number of Crossing Sites, by Strategy (Patrols = 55, Smugglers = 65)



RAND *TR1211-4.3*

log(Cov) + log(Cap) + log(*P*); the interdiction rate variance for this model is shown in the last row of Table 4.2.

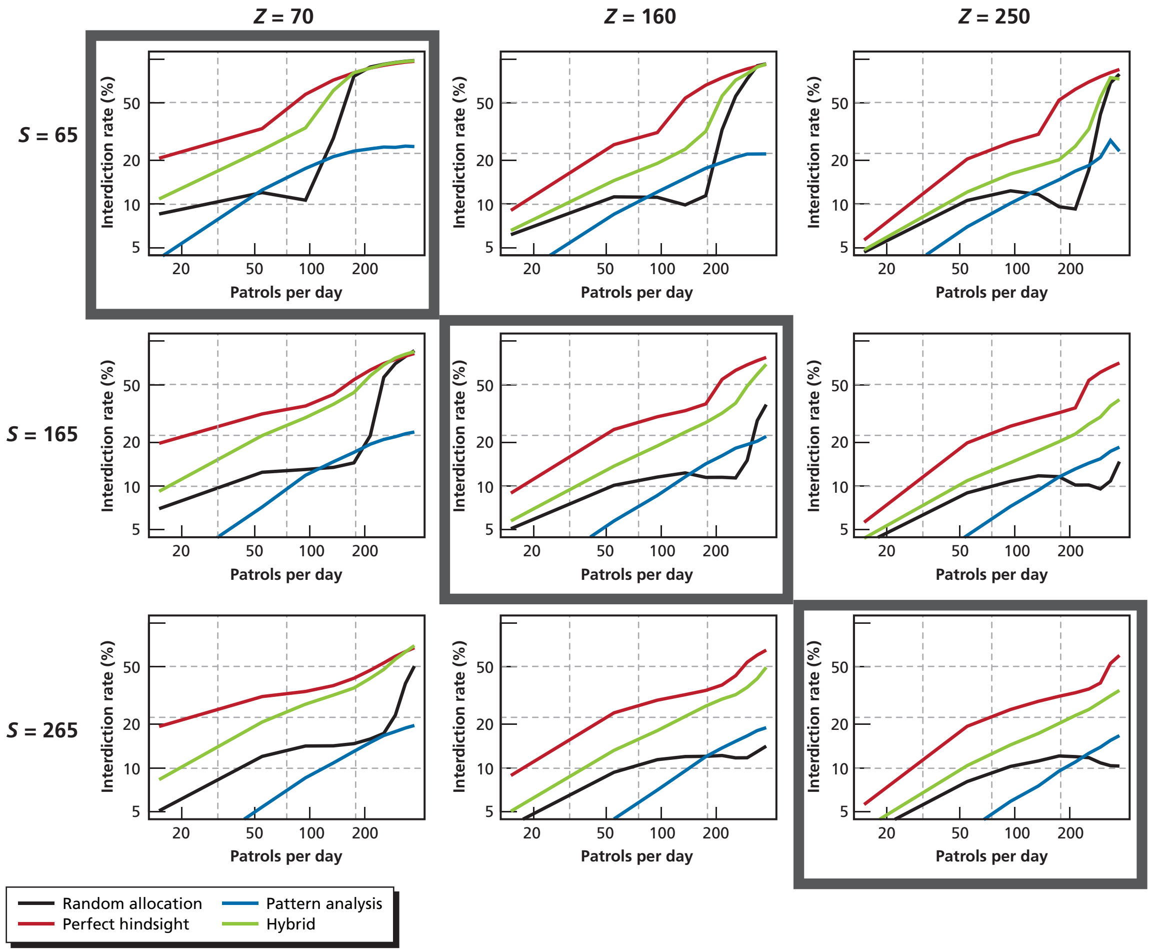
For all strategies, the linear model log(IRate) ~ log(Cov) + log(Cap) + log(*P*) + log(Cov) log(Cap) + c explains the most variability—at least 75 percent—where IRate refers to the interdiction rate, Cov refers to patrol coverage, and Cap refers to patrol capacity. However, a single-variable model, log(IRate) ~ log(Cov × Cap), explains almost as much variability as the full model and explains more variability than any other single-variable model.

Implications

This analysis has two main implications. First, relative measures, such as coverage and capacity, are more predictive of interdiction rate than absolute measures, such as the number of patrols, the size of the border, or the number of smugglers. On the one hand, this appears obvious, but it may lead to counterintuitive conclusions about the extent to which border patrol stations are similar operationally.

In particular, conventional wisdom suggests that a relevant dichotomy divides border patrol stations into northern versus southern stations; the logic appears largely due to differences in the daily cross-border flow and the amount of resources already in place (absolute measures). But stations on the northern and southern borders may be more similar when compared using relative measures. In particular, relative measures may show that stations with few resources and little activity are actually quite similar to stations with high levels of activity and abundant resources. So, conventional wisdom may not be supported when comparing stations by relative measures. We explore this in our empirical examination of border patrol stations in the next chapter.

Figure 4.4
Interdiction Rate Versus Patrols per Day, by Strategy (nine configurations)



NOTE: *S* is the number of smugglers and *Z* is the number of zones. The framed plots share a roughly constant threat density.
RAND *TR1211-4.4*

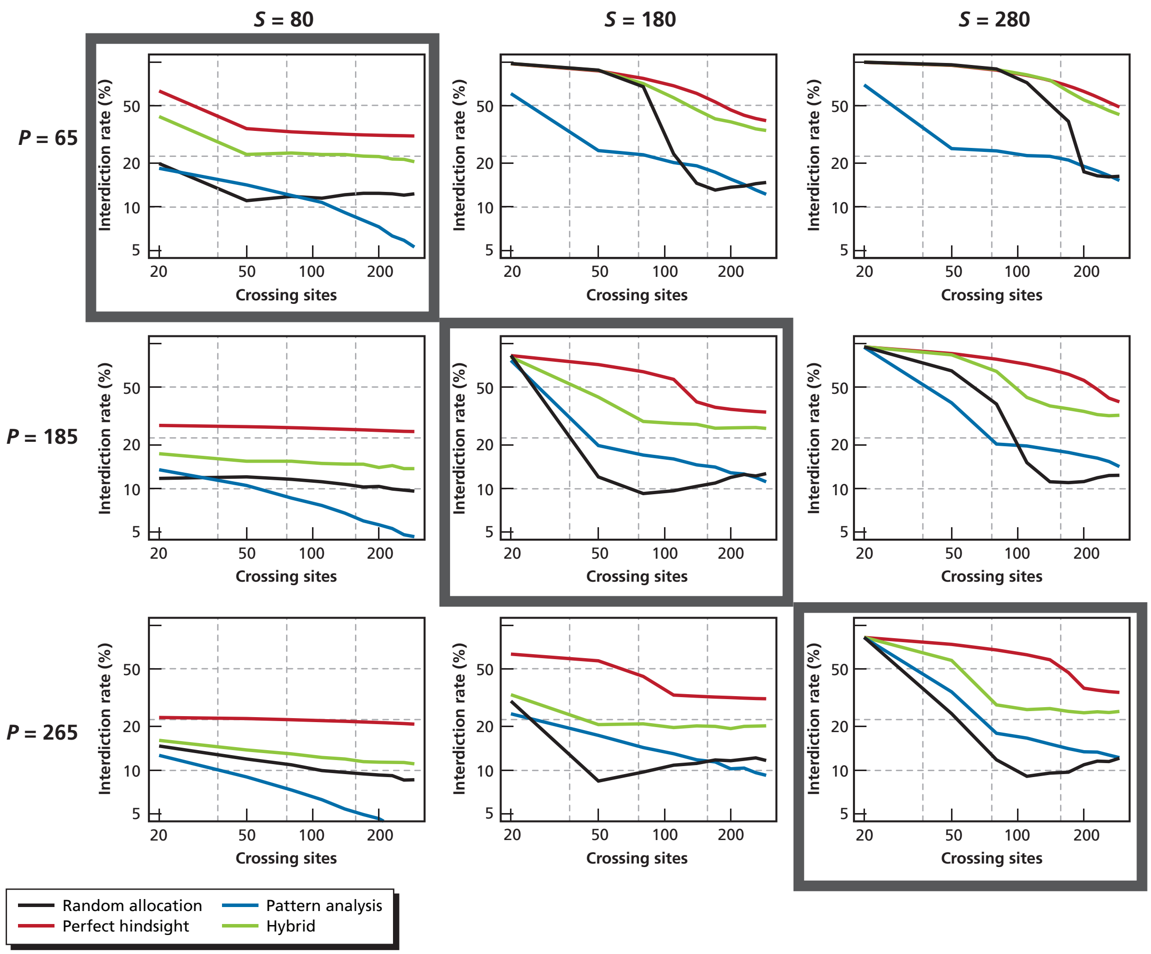
Second, returns on investments in terms of interdiction rates may be logarithmic. So, without changing the allocation strategy, large increases in the number of patrols may be necessary to effect large increases in the interdiction rate. However, as we discuss in the next section, there can be significant benefits to using different allocation strategies.

Which Strategies Are Best, and Under What Circumstances?

Findings

As expected, the strategy that positions patrols based on pattern analysis of perfect hindsight is nearly always best; this approach yielded the highest interdiction rate in 85 percent of all model runs. This can also be observed in Figures 4.4–4.6, which show how perfect hindsight dominates the other approaches in a wide array of configurations. The 15 percent of cases in which the perfect hindsight approach is topped correspond to circumstances under which the

Figure 4.5
Interdiction Rate Versus Crossing Sites, by Strategy (nine configurations)

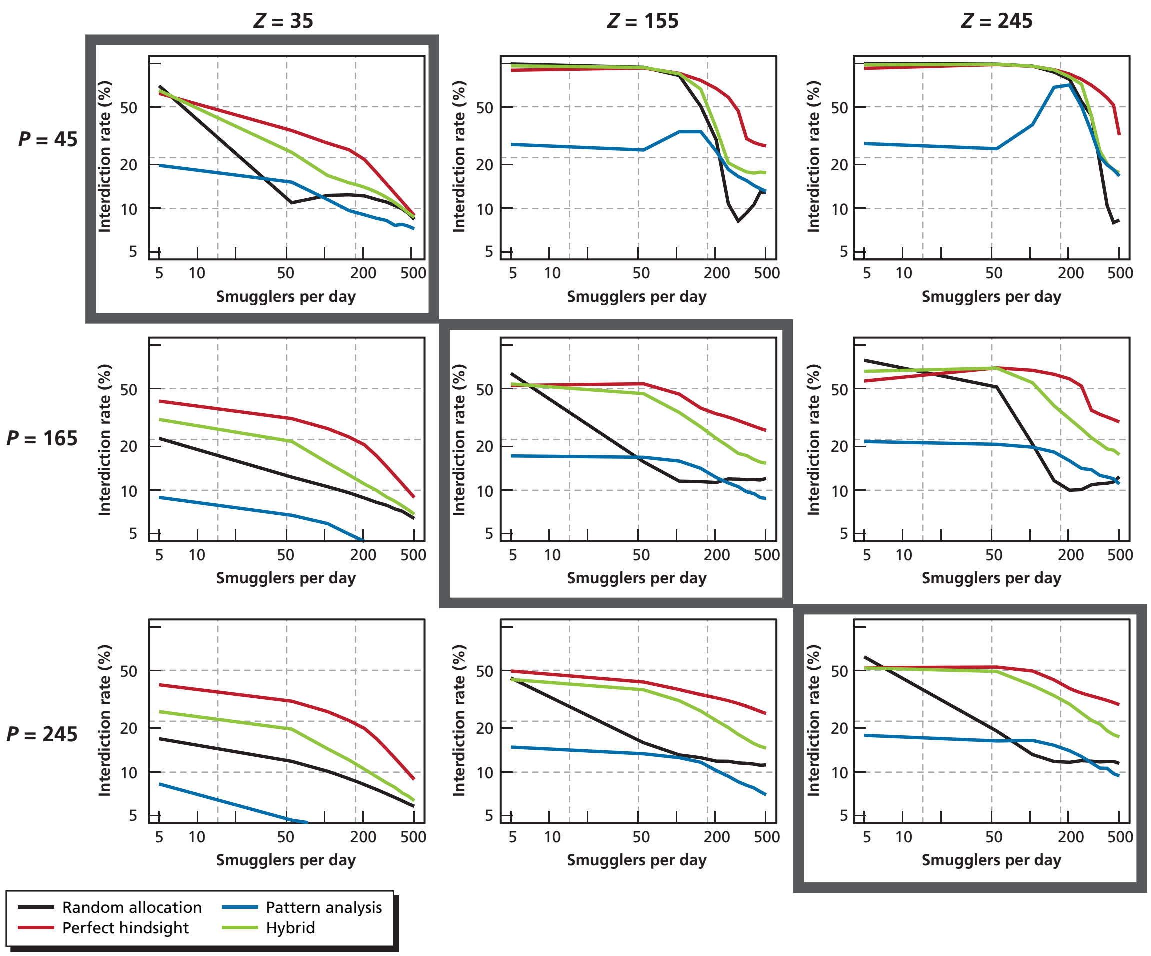


NOTE: *P* is the number of patrols and *S* is the number of smugglers. The framed plots share a roughly constant capacity.
RAND *TR1211-4.5*

number of patrols available is so large (relative to the number of smugglers and the number of crossing sites) that OBP would do well no matter what. Illustrating this point, the median interdiction rate achieved by having perfect hindsight when that strategy is not the best option is 87 percent; this compares to a 36-percent median interdiction rate for the same approach across all model runs.

But the best strategy is not always good, since a positioning strategy cannot make up for having too few patrols. Table 4.4 shows the percentage of model runs in which the interdiction rate exceeds 50 percent, an arbitrary threshold chosen merely for illustrative purposes. Again, we see that allocating resources based on perfect hindsight yielded interdiction rates greater than 50 percent in more conditions than any other strategy (42 percent of the model runs). This means that in almost 60 percent of the circumstances that we modeled, interdiction rates were less than 50 percent. Figures 4.4–4.6 show how interdiction rates can fall to relatively low levels in many circumstances.

Figure 4.6
Interdiction Rate Versus Smugglers per Day, by Strategy (nine configurations)



NOTE: *P* is the number of patrols and *Z* is the number of zones. The framed plots share a roughly constant coverage.
RAND *TR1211-4.6*

The hybrid strategy of combining systematic randomness and pattern and trend analysis is nearly always better than relying on systematic randomness or pattern and trend analysis alone. In 86 percent of cases, the hybrid approach yielded higher interdiction rates than those using either approach alone. Figures 4.4 through 4.6 show how the hybrid approach dominates in a range of conditions. Once again, 14 percent of cases in which the hybrid approach is topped correspond to circumstances under which the number of patrols available is so large (relative to the number of smugglers or the number of crossing sites) that OBP would do well no matter what. Illustrating this point, the median interdiction rate achieved by relying on the hybrid approach when that strategy is not the best option is 88 percent; this compares to a 24-percent median interdiction rate for the same approach across all model runs. The second column of Table 4.5 shows the median interdiction rate achieved by each approach, documenting that, in many circumstances, the hybrid approach yields more than double the interdiction rate of strategies employing either approach alone.

Table 4.2
Percentage of Variance in Interdiction Rate Explained by Different Statistical Models

Model	Percentage Variance in Interdiction Rate Explained by Model (R^2) Random Allocation	Pattern Analysis	Perfect Hindsight	Hybrid
log(IRate) ~ log(*P*)	34.0	64.1	70.9	60.1
log(IRate) ~ log(*S*)	22.6	4.0	10.6	21.0
log(IRate) ~ log(*Z*)	17.3	21.8	4.1	7.0
log(IRate) ~ log(Cov)	51.5	83.0	56.8	56.1
log(IRate) ~ log(Cap)	57.4	50.3	68.9	77.6
log(IRate) ~ log(Cov × Cap)	72.9	87.6	84.0	89.1
log(IRate) ~ log(Cov) + log(Cap)	73.0	91.9	84.4	90.6
log(IRate) ~ log(*P*) + log(*S*) + log(*Z*)	75.8	92.5	87.8	90.7
log(IRate) ~ log(Cov) + log(Cap) + log(*P*)	75.8	92.5	87.8	90.7

NOTE: Shading highlights the single-variable model that explains the most variability—almost as much as the full model and more than any other single-variable model.

Table 4.3
Coefficients for the Best Fit of Model log(Cov) + log(Cap) + log(*P*)

	Coefficients for Model Expressed in Terms of *P*, *S*, and *Z*				Coefficients for Equivalent Model Expressed in Terms of Coverage, Capacity			
Strategy	Intercept	log(*P*)	log(*S*)	log(*Z*)	Intercept	log(Cov)	log(Cap)	log(*P*)
Random allocation	1.79	0.59	−0.45	−0.41	1.79	0.41	0.45	−0.27
Pattern analysis	0.79	0.77	−0.19	−0.46	0.79	0.46	0.19	0.12
Perfect hindsight	1.03	0.69	−0.26	−0.18	1.03	0.18	0.26	0.25
Hybrid	1.29	0.71	−0.41	−0.25	1.29	0.25	0.41	0.06

Table 4.4
Percentage of Modeled Conditions Under Which the Interdiction Rate Exceeds 50 Percent

Strategy	Model Runs in Which Median Interdiction Rate Exceeds 50% (%)
Random allocation	19
Pattern analysis	6
Perfect hindsight	42
Hybrid	24

In many circumstances, the hybrid approach is even competitive with the best approach of relying on perfect hindsight. The third column of Table 4.5 shows the median normalized interdiction rate—the interdiction rate divided by that achieved by the best approach of relying on historical crossing data. The numbers show that in half of modeled circumstances, the hybrid approach achieved at least 66 percent of the interdiction rate achieved by the ideal approach. As a separate statistic, in 90 percent of cases modeled, the hybrid strategy achieved at least half of the interdiction rate achieved by the ideal strategy.

The hybrid approach is competitive with the best approach even under "hard" circumstances, in which adaptive smugglers have mitigated the ideal approach (e.g., because there are too few patrols). Table 4.6 shows median and median normalized interdiction rates for circumstances under which the perfect hindsight approach yielded a rate of less than 50 percent. Again, in more than half of modeled cases, the hybrid approach yielded at least 60 percent of the interdiction rate achieved by the ideal approach. This exceeds the normalized interdiction rate achieved by the rival approaches of pattern analysis or random allocation by at least 23 percent.

The hybrid approach seems to be particularly beneficial in circumstances in which coverage is relatively low but capacity is relatively high. Table 4.7 shows the median normalized interdiction rates for each strategy in four cases corresponding to whether coverage (the ratio

Table 4.5
Interdiction Rates, by Strategy

Strategy	Median Interdiction Rate (%)	Median Normalized Interdiction Rate (%)
Random allocation	12	41
Pattern analysis	14	31
Perfect hindsight	36	100
Hybrid	24	66

NOTE: The normalized interdiction rate for a given model run is the interdiction rate divided by the interdiction rate achieved by the perfect hindsight strategy for the same model inputs.

Table 4.6
Interdiction Rates, by Strategy, for "Hard" Conditions

Strategy	Median Interdiction Rate (%)	Median Normalized Interdiction Rate (%)
Random allocation	11	40
Pattern analysis	9	33
Perfect hindsight	19	100
Hybrid	18	63

NOTE: "Hard" conditions are defined as those under which perfect hindsight yields less than a 50-percent interdiction rate. The normalized interdiction rate for a given model run is the interdiction rate divided by the interdiction rate achieved by the perfect hindsight strategy for the same model inputs.

Table 4.7
Normalized Interdiction Rates, by Strategy, for Different Levels of Coverage and Capacity

		Capacity (*P*/*S*)	
Coverage (*P*/*Z*)	Strategy	Less than 0.5 (%)	Greater than 2.0 (%)
Less than 0.5	Random allocation	50	47
	Pattern analysis	21	24
	Perfect hindsight	100	100
	Hybrid	64	82
Greater than 2.0	Random allocation	48	103
	Pattern analysis	48	28
	Perfect hindsight	100	100
	Hybrid	63	101

NOTE: The normalized interdiction rate for a given model run is the interdiction rate divided by the interdiction rate achieved by the perfect hindsight strategy for the same model inputs.

of *P* to *Z*) or capacity (the ratio of *P* to *S*) is greater than 2 or less than 0.5. The divergence between the hybrid approach and the other strategies is most significant in the scenario corresponding to high capacity and low coverage, in which it yields an 82-percent median normalized interdiction rate. This is nearly 40-percent greater than that under random allocation or pattern analysis.

Implications

This analysis has two main implications. First, there is clearly a significant benefit to perfect hindsight—that is, from having an accurate characterization of historical flows. Perfect hindsight is better in most of the modeled conditions, and often much better. This suggests that OBP may derive advantages from schemes that attempt to track total interdicted and uninterdicted flow. This may be accomplished through surveillance and data collection approaches that record sensor alarms, tips about sightings, or "getaways"—regardless of whether these events lead to an actual interdiction. Such data should be incorporated into pattern and trend analysis.

Second, there is also clearly a large benefit from combining pattern and trend analysis with systematic randomness—more so than when applying either approach separately. These advantages may be particularly strong in cases in which OBP has a large amount of resources relative to illegal flow (i.e., high capacity) but relatively few resources relative to the size of the border (i.e., low coverage). Such circumstances may arise, for example, on the northern border, which has been historically characterized by few resources, relatively low rates of illegal flow, and large, open border areas. But the hybrid approach is never bad, and OBP should consider investments in systematic randomness and pattern analysis simultaneously.

CHAPTER FIVE

Comparison of Border Patrol Stations

Our simulation model suggests measures that may be predictive of interdiction rates and that could be used to compare border patrol stations and determine whether two stations are likely to benefit from similar approaches to using pattern and trend analysis and systematic randomness. The purpose of this chapter is to describe an exploratory data analysis of the similarities and differences between actual border patrol stations using the approximations of the metrics proposed by our model.

Data

OBP supplied RAND with several data sets covering fiscal years (FYs) 2004 through 2009. Included were databases of historical apprehension data, geographic information system (GIS) shapefiles of border patrol zones, and annual reports on the number of zones.

Metrics

We used the shapefiles to compute several metrics for each station:

- *Number of apprehensions (annual):* This number was computed directly from the data, since each apprehension record included a reference to the station where the apprehension was made.
- *Number of patrol agents (estimated):* This number had to be estimated, since the available data specified only the number of agents per sector in FY 2009. We estimated the number of patrol agents per station by apportioning agents to stations proportionally to the number of border zones in each station. OBP determines zones based on operational art; a recent characterization of OBP zones was provided in the GIS shapefile.
- *Number of border miles:* This was computed as the geodesic distance from the easternmost point of the station to the westernmost point of the station.
- *Capacity, or patrol agents per apprehension (estimated):* This metric was computed as the ratio of two earlier metrics. It was motivated by the preceding analysis of our simulation model and is meant to serve as an approximation for the ratio P to S.
- *Coverage, or patrol agents per border mile (estimated):* This metric was computed as the ratio of two earlier metrics. It was motivated by the preceding analysis of our simulation model and is meant to serve as an approximation for the ratio P to Z.

- *Coverage × capacity, or patrol agents per border mile (estimated) × patrol agents per apprehension (estimated):* This metric is the product of the capacity and coverage metrics. It was motivated by the preceding analysis of our simulation model and is intended to serve as an approximation for the coverage-capacity product measure.

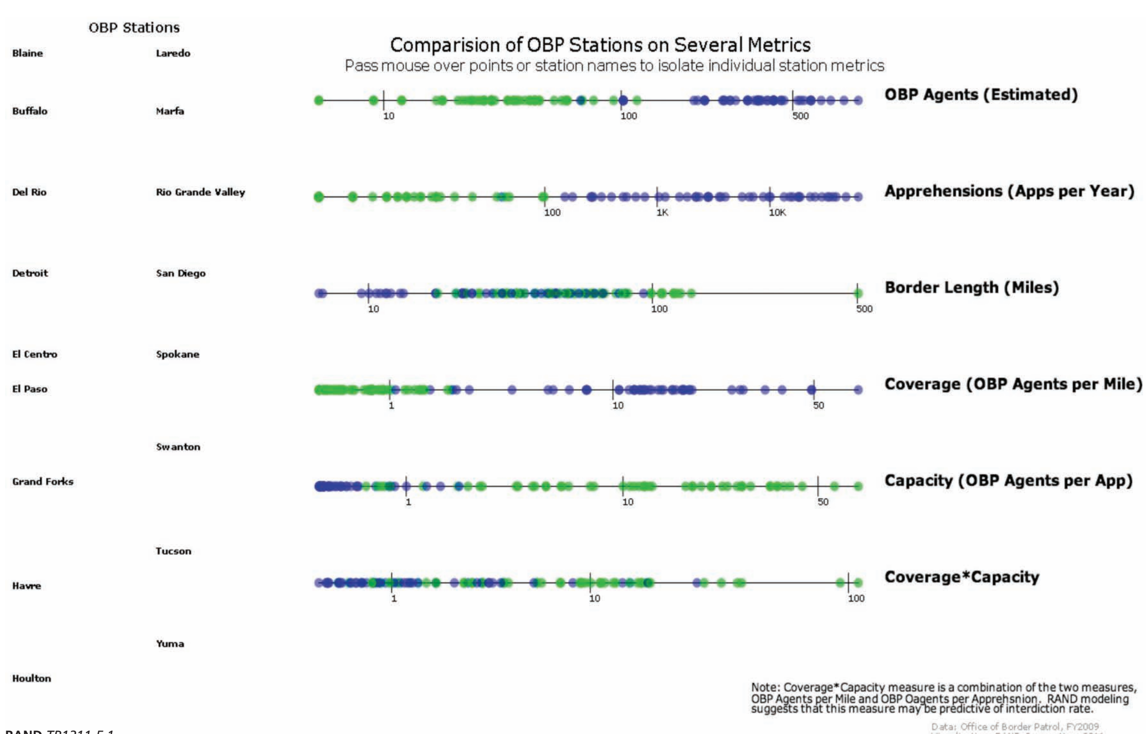
Visualization Tool

We developed a tool to visualize the similarities and differences between OBP stations. Figures 5.1 and 5.2 are screenshots of this tool. The OBP stations are listed in the columns on the left side of the figures and grouped according to sector. In the figures, the data have been redacted to disassociate any particular station with any particular metric value.

The figures show a horizontal axis for each of the six metrics. Each circle represents an OBP station, and its position on the axis corresponds to the value of the metric. The metrics are normalized, so the station with the least value according to a particular metric appears on the left; the station with the greatest value according to a particular metric appears on the right. The stations are positioned on the line according to a nonlinear scale.

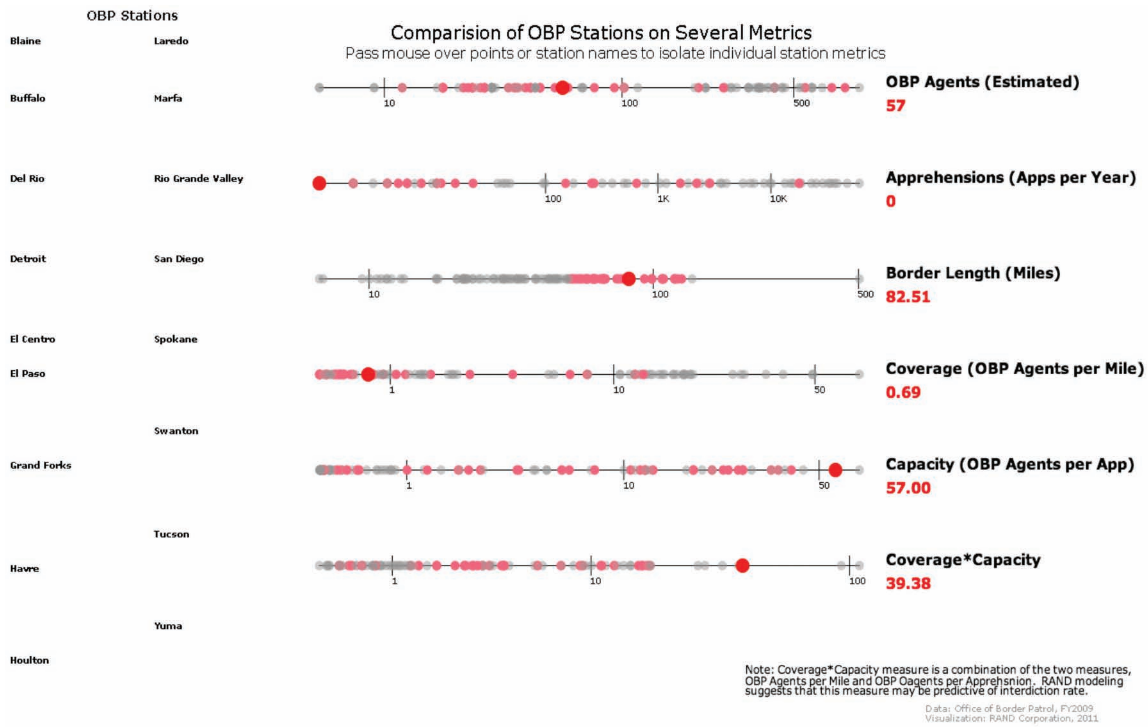
The tool facilitates interaction. When a user passes his or her mouse over a given node (i.e., station), the statistics of that particular station are exposed and stations that are similar with respect to the chosen metric are highlighted. In this way, users of the tool can explore how stations that may be considered similar with respect to one measure (e.g., annual appre-

Figure 5.1
Screenshot of the OBP Station Visualization Tool



RAND *TR1211-5.1*

Figure 5.2
Screenshot of the OBP Station Visualization Tool Showing Interactions



RAND *TR1211-5.2*

hensions) may be dissimilar with respect to other measures (e.g., patrols per apprehension). Figure 5.2 illustrates the product of this kind of interaction.

Findings

We find that what it means to be comparable in this sense does not align with the notions of similarity that OBP tends to use. The large circle in each category in Figure 5.2 corresponds to one particular station, which we'll refer to as Station X. We see that, depending on the metric, Station X may be at the top, bottom, or middle of the ranking of OBP stations. The smaller pink circles correspond to stations that are similar to Station X with respect to border miles. We see that similar stations span a wide variety of conditions corresponding to relative few or relatively many OBP agents, relatively few or relatively many apprehensions, and relatively high or relatively low coverage or capacity.

The broader use of these data and this visualization tool extends beyond any particular finding. It provides a mechanism for comparing and contrasting stations according to the metrics that our model shows are relevant for predicting interdiction rates and the productive role of randomness and pattern analysis.

CHAPTER SIX

Experimental Design for Evaluating the Contributions of Pattern Analysis and Systematic Randomness

The preceding analysis suggests the value of appropriate combinations of pattern and trend analysis and systematic randomness for improving interdiction rates. A natural next step for OBP would be to implement some of these strategies. But in doing so, OBP must choose among countless implementation options and would be wise to proceed with a measured approach that empirically evaluates the contributions that such changes can make to the border security mission. In this chapter, we sketch an experimental design that OBP could use to evaluate the contributions of pattern and analysis and systematic randomness to its mission.

Issues of Experimental Design for Border Security

Suppose OBP settles on a candidate approach to improving the way patrols are positioned through pattern and trend analysis and systematic randomness. How will OBP know whether the approach is productive, compared with the baseline approach or rival approaches? Consider the following design of an experiment to test the contributions:

> Suppose Imperial Beach station (San Diego sector) is given the new tool and is asked to use the new approach for a period of two weeks. Nogales station (Tucson sector) is also given the tool and asked to use it for the same two weeks. Both stations are asked to measure their interdiction rate over the two weeks during which the tool is used. Control conditions would be established over two-week periods prior to the evaluation, wherein stations would position resources without the tool and measure interdiction rates over that control period. The tool will be assessed by comparing intrastation performance with and without the new tool (i.e., by comparing the experimental and control conditions at a given station) or by comparing the interdiction rate achieved at one station using the tool with the interdiction rate achieved at another station without the tool.

There are two basic issues with this experimental design and with empirically evaluating new tools for border security in general.

The first, a widely acknowledged challenge, is how to measure interdiction rates. The trouble is that OBP in general does not know the number of illegal crossers who have been successful and can compute only the number of *apprehensions* with confidence. The interdiction rate—the ratio of apprehensions to total attempted crossings—requires both terms.

Morral, Willis, and Brownell (2011) propose several techniques for measuring interdiction rates, but each requires development and some may be expensive. If we can avoid it, we would rather not validate a measure prior to evaluating new tools. But more importantly, OBP may want to experiment with many options, so, ideally, our measure would be inexpensive. The measures proposed by Morral, Willis, and Brownell may be appropriate for strategic planning at the headquarters level but may not be useful for routine evaluations of options at the station level.

The second challenge is ensuring that the experimental and control conditions are identical except for their use of pattern and trend analysis or systematic randomness. In the example design, we would expect many differences over time, even at the same station. The weather varies over time, as do smuggler tactics and motivations and the supply and demand of drug and labor markets. So, with the experimental design, we may not know whether changes in the interdiction rate (even if it could be measured) were due to the new approach or something else if we only compared interdiction rates achieved with experimental and control conditions. Furthermore, we would expect many differences between the Imperial Beach and Nogales stations, even over the same period. For example, Table 1.1 in Chapter One summarized some of the dimensions that could affect interdiction rates independently of the approach to resource allocation. So, one could not fairly compare experimental and control conditions from different stations.

Of course, one could test the new approach at many stations and attempt to control for the variation in other variables. But this approach would be prohibitively expensive because it would require such extensive participation.

Proposed Experimental Design: Interleaving Strategies

We propose an experimental design that circumvents the challenges described in the previous section and would allow OBP to quickly and inexpensively evaluate the contributions of new approaches to border security.

The experiment is conducted entirely within one station, Station X. We assume that OBP is interested in comparing two approaches to positioning assets: Approach A, nominally the baseline approach, and Approach B, a to-be-specified combination of pattern and trend analysis and systematic randomness.

We partition the time frame into even and odds days. On even days, Station X uses Approach A (the control condition); on odd days, it uses Approach B (the experimental condition). The catch is that Approach A can only use experience or data generated on the even days, when Approach A was used, and Approach B can only use experience and data gathered on the odd days, when Approach B was used. Both conditions run for a given period, say two weeks or a month. OBP can then compare Approach A to Approach B by comparing the number of apprehensions on even versus odd days.

How does this approach address the issues with the earlier design? Since the station is constant and strategies are interleaved over time, we assume that the number of attempted illegal crossings is the same for both the experimental and control conditions. This assumption is reasonable if smugglers cannot detect a difference between even and odd days, so the total number of illegal crossers is the same on even and odd days over the period of evaluation. *Thus, Approach B would yield a greater interdiction rate than Approach A if—and only if—Approach B resulted in a greater number of apprehensions.*

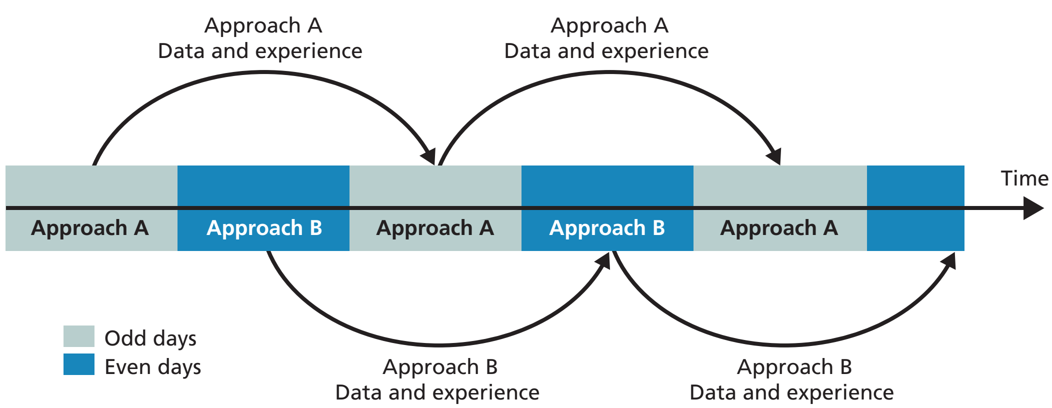
For the same reasons, we assume that all other factors are identical between experimental conditions. Even if smuggler tactics or markets change over the course of the experiment, both the experimental and control approaches will be subject to those effects, since the conditions are interleaved.

The more important issue is that Approach A must only use data and experience gathered on historical days on which that approach was used—that is, on even days. This may be difficult to accomplish in practice; if key trends are observed on odd days, OBP will be tempted to break the condition and leverage that knowledge. This break from experimental protocol would make it impossible to distinguish Approach A from Approach B. One way to isolate the two strategies would be to ensure that different agents are assigned to the two conditions.

Of course, smugglers may behave differently during the period of experimentation than they would otherwise—since they would observe the interleaved strategy and could adjust their behavior accordingly. But these adjustments would affect the two conditions equally, so the comparison would remain fair.

Figure 6.1 illustrates the proposed experimental design. The experiment would support conclusions about whether Approach A yields greater interdiction rates than Approach B at Station X and at stations that are similar to Station X. Further experiments would be needed to assess whether those findings generalize more broadly to other, different stations.

Figure 6.1
Illustration of Experimental Design Based on Interleaving Strategies



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CHAPTER SEVEN

Conclusions and Recommendations

Findings

To summarize, our analysis supports several findings.

Resource allocation approaches that combine pattern analysis and randomness yield greater interdiction rates than approaches that use either strategy alone.

The value of pattern and trend analysis and systematic randomness in border control depends on how representative historical interdiction data are of future illegal flow. In circumstances in which adversaries adapt and OBP coverage is relatively low, there may be multiple explanations for why historical interdictions are higher or lower in a given area and for why smugglers employ certain tactics. OBP can control the representativeness of historical interdiction data by making different exploration versus exploitation trade-offs. In particular, it can choose to position some of its resources for the explicit purpose of exploring unpatrolled regions or identifying new threat patterns, and it can position other resources for the explicit purpose of interdicting threats.

Across a wide range of scenarios that varied by the number of patrols, the number of smugglers, and the number of border zones, hybrid approaches that combine pattern analysis and systematic randomness yielded greater interdiction rates—often double the interdiction rates—than either approach alone. This finding demonstrates the importance of striking a trade-off between exploring for new risks and exploiting existing risk assessments when allocating resources at the tactical level.

Appropriate combinations of pattern and trend analysis and randomness can yield interdiction rates that are competitive with "perfect surveillance."

We find that, in many cases, a combination of pattern and trend analysis and systematic randomness can be competitive with having perfect hindsight of historical crossings, successful and unsuccessful. This is true even in circumstances in which having perfect hindsight is insufficient to achieve high interdiction rates—for example when there are few patrols relative to the rate of smugglers or the number of zones. The hybrid approach may be particularly beneficial when the number of patrols is high relative to the rate of flow but low relative to the size of the border; in these cases, pattern and trend analysis can help avoid dispersing resources too widely and randomness can help track adversary adaptation.

Relative measures, such as coverage and capacity, are more predictive of interdiction rates than absolute measures, such as the number of patrols, the size of the border, or the number of smugglers.

Our analysis clearly demonstrates that, regardless of strategy, interdiction rates are better explained by relative measures, such as coverage and capacity—more so than absolute measures, such as the number of patrols, the number of smugglers, or the number of zones. This implies that stations may be similar operationally, even if they are different in scale. In other words, the performance of strategies for using systematic randomness at stations with few resources but little activity may be similar to the performance of those strategies at stations that have lots of activity and lots of resources.

OBP stations group in counterintuitive ways when compared using relative measures, such as coverage and capacity.

In fact, our analysis of historical patrol and apprehension data suggests that groupings of stations may depart from conventional wisdom. When compared in terms of patrols per apprehension or patrols per border mile, some northern and southern border stations appear more similar than when compared absolutely by the number of patrols, the number of apprehensions, or the length of the border. This means that other categorizations of border crossings may be more useful than the standard dichotomy of northern versus southern border, since this categorization is based largely on conventional wisdom of absolute measures. The operational implications of this finding are worthy of further research.

Recommendations

Our findings support several recommendations. In the event that OBP is in the process of pursuing these or similar approaches, the following recommendations provide reinforcement for those initiatives supported by the analysis presented in this report.

OBP should catalog detections, even those that do not result in interdiction.

Our analysis clearly suggests the value of characterizing the complete set of cross-border illegal flows, whether interdicted or not. An initial step toward increasing the representativeness of the data on which pattern and trend analyses are based is to include in those analyses reports of detections. Detections may include, for example, sightings made by patrol agents, sensor alarms that could not be responded to, or phone tips made by citizens. Reported detections should be characterized by the station or zone where smugglers are expected to cross and measure of the credibility of the report. The credibility measure may provide a measure of confidence that a detected event was, in fact, an illegal crossing; it could range from high confidence, when there is an actual sighting (a "getaway"), to low confidence, when there is an unconfirmed sensor firing or tip. Pattern and trend analyses could be designed to accommodate detection data and appropriately treat information with varying levels of confidence.

OBP should institute a plan to schedule patrols based on daily pattern and trend analysis and systematic randomness. This plan should include a phase of experimentation using randomized control trials.

Our analysis clearly demonstrates the benefit of combining pattern and trend analysis with systematic randomness. We recommend that OBP develop and implement a plan to incorporate pattern and trend analysis and systematic randomness into patrol scheduling. By doing so, OBP will be able to strike a balance between exploiting existing assessments of border risks and exploring for risks that have yet to be characterized.

The first phase of such a plan should include a short period of controlled experimentation to help identify specifically what forms of pattern analysis and randomness may be productive. We outlined one approach to experimentation in Chapter Six of this report. A crucial feature of our experimental design is that it does not require knowledge of successful border crossers.

Obviously but notably, pattern and trend analysis and systematic randomness can mitigate the effects of adversary adaptation but will not stop it. In fact, these approaches will incentivize unique forms of adaptation that OBP may have yet to witness. Fortunately, whatever form these adaptations take, combinations of pattern and trend analysis and systemic randomness will allow OBP to track these changes and position resources accordingly.

OBP should develop a management tool to compare its stations based on relative measures, such as coverage and capacity.

We developed a data visualization tool to facilitate comparing and contrasting OBP stations based on measures that our analysis suggests influence interdiction rates. Such a tool may be useful to OBP as it compares stations on operational grounds and tracks changes over time. Such a tool may also be useful in helping decisionmakers at the station, sector, and headquarters levels explore variation across the border.

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