DISSERTATION

THREE ESSAYS ON INVASIVE SPECIES MANAGEMENT AND RISK

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ABSTRACT

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Invasive alien species (IAS) threaten global biodiversity, ecological services, and economic welfare. Over the past several decades, these growing consequences have seen broader analysis of the determinants and consequences of, as well as responses to, this environmental hazard. This dissertation employs theoretical and empirical tools, demonstrating the role of economics in the management of invasive species. The first and second chapters analyze the effect of research investment as a component of management strategy for IAS population reduction using a continuous time dynamic optimization model. Chapter 3 exploits the historical occurrence of World War I and its impact on international trade to study invasive species risk as a global externality of military conflict and geopolitical institutional shift.

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Chapter 1

R&D Effects in the Management of an Established Invasive Species

1.1 Introduction

Harmful invasive alien species (IAS) pose immediate danger to the global environment, threatening international biodiversity, ecological services, and economic welfare (Chew 2015). IAS are capable of imposing significant economic damages through predation of agricultural commodities, productivity losses due to equipment damage, and disease transmission (Pimentel et al. 2005, Shwiff et al. 2017). Further, the growth of international trade and human movement has been identified as a primary vector for IAS dispersal (Perrings et al. 2002). In the broad economic literature studying invasive species, researchers typically assume convex control costs, but do not account for the possibility that R&D investment in new and better control methods may lower future costs of population reduction. Therefore, the existing economic literature on IAS control misses an important dimension of cost effective management strategies. In this paper, we develop a model of IAS management that incorporates R&D in control methods to illustrate the potential impact of technological change on invasive species management.

A species is considered to be invasive along three general criteria: the species must be non-native to the affected region or ecosystem, the species must be able to survive and establish a population in the new environment, and finally, invasives are responsible for some form of negative impact. Invasive species have long attracted the attention of ecologists for their startling ability to disrupt ecosystems and displace, or even extirpate, native species (Elton et al. 1958, Vitousek et al. 1996, Didham et al. 2005). Pimentel et al. 2005 provides several drastic examples of IAS in the United States: zebra mussels (*Dreissena polymorpha*) have wreaked havoc in the Great Lakes of the United States, causing productivity losses to local businesses by clogging water pipes and damaging property; feral swine (*Sus scrofa*) are capable of substantial property damage to agricultural and recreational areas and are suspected transmission vectors for human disease and pathogens; yellow starthistle (*Centaurea solstitialis*) are an invasive plant species that has made large tracts of California grassland unusable. IAS management demonstrates the defining characteristics of a public good, and in 1999 the United States acknowledged the role of government agencies to "...prevent the introduction of invasive species and provide for their control and to minimize the economic, ecological, and human health impacts that invasive species cause..." (Clinton 1999, p. 1). Accepting the responsibility for this public good provision highlights the importance of this environmental issue for maintaining environmental and economic health.

When specifying a management strategy, the planner must consider the reduced cost of population reduction in the future from research conducted in the present. The addition of a dynamic R&D decision emphasizes the important role of research investment in IAS management that has yet to be studied rigorously in the economic literature on invasive species. In order to focus on the role of technological development, we first apply the model to the management of a specific invasive species, the brown tree snake (*Boiga irregularis*, BTS). Labeled a "catastrophic" invasive species (Burnett et al. 2012), the brown tree snake is a historically damaging invader on the island of Guam that has imposed both ecological and economic harm, and threatens a similar invasion to Hawai'i (Savidge 1987, Burnett et al. 2008, Shwiff et al. 2010). The United States government has targeted this species for eradication from the island (Congress 2004), and has pursued this goal with both population control and active research investment (USGS Brown Tree Snake Lab, USDA National Wildlife Research Center, USDA Wildlife Services). Following analysis of this particular species, we consider different categories of IAS to study how biological and economic characteristics of the managed population impact the benefits from technological development. We find that when R&D is a known management option, significant population reduction can be achieved for much lower cost than in the absence of research. Further, the cost-savings of a comprehensive management program typically far exceed the cost of the research, itself.

The remainder of the paper is constructed as follows: Section 2 reviews the two main bodies of literature that will be used to inform the present study. First, a review of the economic literature on invasive species will establish a foundational understanding of the way that invasive species are an economic problem and the current state of research in the area. Second, the environmental economics literature on technical change will inform the research and innovation component of the model. Section 3 outlines the bioeconomic model and analytical foundations of the model and its solution. Section 4 provides solutions concerning the BTS specification as well as the categorical analysis of species characteristics on the benefits of R&D. Section 5 discusses the model solutions and their implications for policy and future work.

1.2 Literature Review

Bioeconomic models introduce biological processes into models of economic decision-making. While this type of model has been used in a variety of environmental economic studies, they have taken a prominent role in the literature regarding invasive species (Epanchin-Niell 2017). The contribution of this paper is the introduction of additional management options in the form of R&D investment, which influences the cost of population reduction over the management horizon. The practice of modeling R&D and its economic impacts is common in macroeconomic growth models (Romer 1990, Grossman and Helpman 1993), microeconomic study of patents (Griliches 1990, Hall et al. 2001), and environmental protection (Jaffe et al. 2003, Acemoglu et al. 2012). Despite the growing role of technological change in environmental economics, this practice has not extended to economic study of invasive species. The present research fills this gap by adopting the methods of R&D modeling used in the broader environmental economics literature and applying them to a bioeconomic model of invasive species management.

1.2.1 Economics of Invasive Species

Economic study of IAS has experienced a period of substantial growth in the past few decades. There are several comprehensive reviews of the literature overall (Lovell et al. 2006, Olson et al. 2006, Marbuah et al. 2014, Lodge et al. 2016, Epanchin-Niell 2017), but the main branches of research have focused on damage estimation (OTA 1993, Pimentel et al. 2005, Shwiff 2010), the use of dynamic optimization to assist in management strategy (Eiswerth and Johnson 2002, Olson and Roy 2002, Leung et al. 2005, Mehta et al. 2007, Burnett et al. 2008, Epanchin-Niell et al. 2012, Jardine and Sanchirico 2018), and economic analysis of invasive species policy (Margolis et al. 2005, McAusland and Costello 2004, Atkers et al. 2015, Bartkowski et al. 2015). These branches demonstrate an intuitive approach to the issue where steps are taken to identify the problem, develop a solution, and thoroughly study the consequences of policy and management.

The present study is most relevant to the second branch of the literature, relating to the use of dynamic optimization for invasive species management. Due to the natural growth and decay of a species, dynamic models have proven to be a very useful tool in bioeconomics. Existing research has demonstrated the use of continuous time optimal control (Eiswerth and Johnson 2002, Burnett et a. 2008, Haight and Polasky 2010) and discrete dynamic programming (Olson and Roy 2002, Mehta et al. 2007, Hyytiainen et al. 2013). Epanchin-Niell (2017) suggest that the main contributions of this literature to policy design are enhancement of prevention efforts, cost-effective surveillance and monitoring, optimal management of established invasions, private control of spread, and accounting for uncertainty. However, across the literature there are few studies that consider the impacts of changes in control cost apart from sensitivity analyses where this parameter has been shown to have significant impacts on model outcomes (Hyytiainen et al. 2013). In this paper we build on this by examining the introduction of research investment, knowledge accumulation, and control cost reductions within the dynamic model. This is an apt extension as economically valuable knowledge is often structured as a dynamic stock that changes over time with additional research and possible knowledge decay.

1.2.2 R&D Modeling in Environmental Economics

Technological change has become an important topic of study within environmental economics. Jaffe et al. (2003) present a general overview of how considerations of technological change have received growing attention within the literature. Like economic study of IAS, this body of literature has made great use of dynamic optimization modeling (Parry et al. 2000, Goulder and Mathai 2000, Popp 2004, Vogt-Schilb et al. 2018). Most commonly, research has focused on carbon dioxide reduction, and technological change or investment is motivated by private firms avoiding fines or other penalties for their emissions. In these studies the CO_2 imposes damages and exhibits natural decay, while economic activity adds to the stock. When studying invasive species there is also a harmful stock pollutant, but it exhibits the opposite dynamics; growing naturally and being reduced by management activity. A common outcome in these models is that optimal investment occurs early in the planning stage (Goulder and Mathai 2000, Popp 2004, Vogt-Schilb et al. 2018). This result is intuitive as these investments lower the cost of future abatement, and this early action will have the greatest long-run impact.

Despite the methodological similarity between studying invasive species and other environmental stock pollutants, the IAS literature has done little to introduce dynamic R&D decisions into the bioeconomic models. Kim et al. (2010, 2012) appear to be the only examples of scholarly work focusing on technological development in the context of IAS management. This pair of papers studies the effect that technological development has on IAS management, but their model does not include any research cost or research decision as part of the model. The current analysis differs in a variety of ways: the economic decision-making process behind the research investment is of chief importance to this analysis, the model is used to study the optimal behavior to meet the public good target for the minimum cost, and the paper provides a case study of a specific species to demonstrate the applicability of the analysis and its value.

By introducing R&D to the management model we depart from the typical invasive species literature by relaxing the control cost function. As discussed in Jardine and Sanchirico (2018) the convention within the IAS literature is to specify a convex control cost that reflects the diminishing returns of control as effort is scaled up. This convexity reflects that at higher levels of control, it becomes more challenging to capture the reduced number of species. However, such an approach does not account for the efficiency improvements that can be achieved with R&D, which would lower marginal costs. In light of this, we opt for a cost function more similar to that of Goulder and Mathai (2000) that may be convex in the level of control effort, but is decreasing in the level of economically valuable knowledge. This represents a synthesis of the two research categories while also providing a more accurate portrayal of invasive species management.

1.3 Model

1.3.1 Problem Statement and Pontryagin Conditions

The bioeconomic model presents a manager whose goal is to minimize the present discounted value of total IAS costs, which include population control costs, research investment, and the cost of IAS damage. In each period $s \in [t, T]$ the manager chooses levels of population control x_s and research investment I_s, anticipating the impact these decisions have on future costs. Choosing to lower the IAS population n_s reduces the damage from the species, but also makes management less productive (fewer animals are more difficult to capture). This stock effect on IAS capture demands additional effort and higher costs of population control as the stock becomes smaller. Choosing to invest incurs immediate research costs, but the accumulation of knowledge K_s makes future population control cheaper. In the present context we assume that the species has an established population in the ecosystem, but there are no additional introductions or migrations. We have chosen this approach in order to focus the analysis on the relationship between population reduction and research investment.

Total IAS costs are given as the sum of population control costs $C(x_s, K_s)$, the damages caused by invasive species, $D(n_s)$, and the cost of R&D investment, $R(I_s)$.

$$TC(x_s, n_s, I_s, K_s) = C(x_s, K_s) + D(n_s) + R(I_s) \tag{1.1}$$

Control costs are a function of the control effort and knowledge stock; higher levels of population control increase costs at an increasing rate ($C_x > 0, C_{xx} > 0$), while the stock of economically valuable knowledge lowers total and marginal control costs ($C_K < 0, C_{xK} < 0$). The convex costs of population control reflect that in a given time period, increasing control effort is accompanied by higher expenses such as overtime pay, additional resources, etc., although developing new knowledge and lower-cost control methods can mitigate this effect. We acknowledge increasing costs of IAS damage and research investment, but do not make further assumptions as these will be specific to the management context ($D_n > 0, R_I > 0$).

Population growth is composed of a biological growth function, $g(n_s)$ net of population control harvest $h(n_s, x_s)$:

$$\dot{n} = g(n_s) - h(n_s, x_s) \tag{1.2}$$

Biological growth is strictly a function of the IAS population in time s while the harvest is a function of the population as well as control effort. Marginal growth of the species may be increasing or decreasing, given the population ($g_n \gtrless 0$). It is assumed that harvest is a generally increasing function of the population and effort ($h_x > 0, h_n > 0$). Additional information about the exact shape of these functions will depend on the species being managed. An important characteristic of this formulation is that the harvest rate is a function of the IAS population, and as populations decrease so does the marginal success of harvesting. Effectively, this means that at low population levels there must be additional effort expended in order to continue harvesting IAS. Pairing this with the convex control costs featured in $C(x_s, K_s)$ creates a circumstance of stock-dependent costs in line with theory established by Olson and Roy (2008).

The state equation for knowledge is referred to as the knowledge production function (KPF):

$$\dot{K} = \eta(K_s, I_s) \tag{1.3}$$

In this representation knowledge production is dependent on research investment as well as the current knowledge stock. Depending on the relevant research characteristics, a wealth of prior knowledge may contribute to the growth of knowledge as researchers "stand on the shoulders of giants", alternatively if there appears to be some finite quantity of valuable knowledge the research can experience diminishing returns with respect to the stock, or there could be no impact on future innovation at all. This representation permits any of these scenarios, based on model parameterization. In contrast to this, $\eta_I \geq 0$ in all parameterizations.

Combining the model components above, the IAS manager's generic dynamic optimization problem is:

$$\max_{x_s, I_s} \int_t^T [-e^{-rs}[C(x_s, K_s) + D(n_s) + R(I_s)]]ds \tag{1.4}$$

$$s.t. \quad \dot{n} = g(n_s) - h(n_s, x_s) \tag{1.5}$$

$$\dot{K} = \eta(I_s, K_s) \tag{1.6}$$

$$n(0) = n_0 > 0, given \tag{1.7}$$

$$K_0 = K_0 > 0 \tag{1.8}$$

At $s = 0$ there is a positive IAS population stock since we are considering an established invasive species and ecosystem closed to additional introduction. Recall that the social planner's main concern is minimizing the social costs of IAS, shown here as a maximization of the negative of social costs. The problem's current-value Hamiltonian is:

$$H = -[C(x_s, K_s) + D(n_s) + R(I_s)] - \lambda_s[g(n_s) - h(n_s, x_s)] + \mu_s \eta(I_s, K_s) \tag{1.9}$$

Invasive species impose harm upon society and the environment and are recognized as a social "bad", implying that their shadow value be, $-\lambda$. Consequently, $\lambda > 0$ is the marginal social value of reducing the IAS stock. μ_s is the marginal social value of the stock of knowledge.The Pontryagin (necessary) conditions for optimality state:

$$\frac{\partial H}{\partial x_s} = -C_x + \lambda_s h_x = 0 \tag{1.10}$$

$$\frac{\partial H}{\partial I_s} = R_I - \mu_s \eta_I = 0 \tag{1.11}$$

$$\frac{\partial H}{\partial n_s} = -D_n - \lambda_s[g_n - h_n] = \dot{\lambda} - r\lambda_s \tag{1.12}$$

$$\frac{\partial H}{\partial K_s} = -C_K + \mu_s \eta_K = r\mu_s - \dot{\mu} \tag{1.13}$$

$$\dot{n} = g(n_s) - h(n_s, x_s)$$

$$\dot{K} = \eta(I_s, K_s)$$

Solving the model also requires transversality conditions that describe the state and co-state values in the final management period, but these will depend on unique management goals and are left for later discussion.

1.3.2 Optimal Flow Conditions

Using (1.10)-(1.13), we characterize the optimal solution paths analytically. These flow conditions describe the economic decision-making process of the IAS manager when choosing levels of population control and research investment.

IAS Stock Management

Condition (1.10) describes the manager's decision for population control, and can be rearranged to find the following:

$$\lambda_s = \frac{C_x(x_s, K_s)}{h_x(n_s, x_s)} \tag{1.14}$$

$\lambda_s > 0$ is the marginal social benefit of reducing the IAS stock in any period $s \in [t, T]$. (1.14) shows that the optimal level of population control corresponds to the per-unit marginal cost of

IAS removal being equal to the marginal benefit of removal. It can be seen that marginal costs of population reduction are doubly affected by the population control choice. First, $C_x > 0$, so any additional control effort will increase costs, but increased effort further impacts costs via the stock effect of control efficacy. We have stated $h_x > 0$, but if the harvest function exhibits constant or diminishing returns, the marginal cost per-unit of IAS removal will see costs driven upward by the convexity of the control cost function. The basic outcome of marginal benefits equal to marginal costs is to be expected, but can be explored further by examining λ_s more closely.

Co-state equation (1.12) can be manipulated to give the following first-order ordinary linear differential equation:

$$\dot{\lambda} + \lambda_s[g_n - h_n - r] = -D_n \tag{1.15}$$

Integrating (1.15) presents a more detailed description of the marginal social benefit that λ_s represents (detailed steps of the analytical process can be found in the mathematical appendix).

$$\lambda_s = \int_s^T [e^{\int_s^u [g_n - h_n] d\tau} e^{-r(u-s)} D_n] du + \lambda_T e^{\int_s^T [g_n - h_n] d\tau} e^{-r(T-s)} \tag{1.16}$$

(1.16) shows that in any period, s, the marginal benefit of reducing IAS is equivalent to the discounted sum of marginal damages over time, accounting for changes in the growth rate of the population, and the marginal social value of IAS in the final management period. Considering both (1.14) and (1.16), we see that control efforts should be pursued to the point where the marginal cost per snake captured is equivalent to the present value of future IAS damages and the terminal value of the IAS stock.

The first term in (1.16) summarizes the discounted benefit of population control via its impacts on marginal damage from the IAS stock. There are two distinct effects being shown, one reflecting the impact of current population on future marginal growth and the other showing the role of discounting over time. $e^{\int_s^u [g_n - h_n] d\tau}$ shows that because population control at time s impacts IAS stock, it will also have an impact on the marginal rate of IAS growth in future periods. We see that if population control in s leads to IAS populations growing quickly in some future period u ($g_n > h_n$), this leads to greater marginal damages in the future. On the other hand, if population control causes the rate of growth to diminish in u ($g_n < h_n$), then marginal damages will be smaller in the future. The marginal growth rate for any given stock level, n_s, will vary based on the functional forms selected for $g(n_s)$ and $h(n_s, x_s)$. The effect of time on the marginal value of control is determined by $e^{-r(u-s)}$, which is the typical discounting factor using the discount rate r multiplied by the passage of time $(u-s)$. The presence of marginal IAS growth illustrates the additional complexity in the manager's population control choice. By lowering IAS stock they will lower the cost of damage from the species, but depending on how this affects the growth of the species such action may lead to even higher damage in the future.

The presence of λ_T in (1.16) provides insight into how different management goals impact the optimal behavior of the manager. If $n(T)$ is chosen optimally, then management will be suspended when $\lambda_T = 0$. If, instead, the manager has a specific population target such as, but not limited to, eradication then λ_T is solved endogenously within the model.

$$\lambda_T = \frac{\mu_T \eta(I_T, K_T) - [C(x_T, K_T) + D(n_T) + R(I_T)]}{g(n_T) - h(n_T, x_T)} \tag{1.17}$$

Research Investment

The manager's investment decision can be studied in the same way as population control. (1.18) describes the optimal investment behavior, and shows that optimal R&D spending equates the marginal social benefit of knowledge creation with the marginal cost:

$$\mu_s = \frac{R_I(I_s)}{\eta_I(I_s, K_s)} \tag{1.18}$$

Reworking (1.18) as an ordinary first-order differential equation then integrating allows us to describe the marginal benefit of knowledge accumulation (details found in mathematical appendix):

$$\mu_s = -\int_s^T [e^{\int_s^u [\eta_K] d\tau} e^{-r(u-s)} C_{K_u}] du + \mu_T e^{\int_s^T [\eta_K] d\tau} e^{-r(T-s)} \tag{1.19}$$

Keeping in mind our assumption that knowledge corresponds to lower control costs ($C_K < 0$), (1.19) shows that the social value of knowledge for IAS management is equal to the discounted sum of its future cost-savings, adjusted for the impact of investment on marginal knowledge accumulation, plus a discounted terminal value. Together, (1.18) and (1.19) show that optimizing research investment rests on equating the present value of future cost-savings, adjusted for the management goal, with the marginal costs of knowledge production.

The first term in (1.19) shows that marginal benefits of research investment have a direct impact in terms of reducing control costs, but also have an indirect impact since investment can affect future knowledge production. Depending on the KPF, it is possible that a wealth of knowledge contributes to more rapid technological development $\eta_K > 0$, which would make the marginal benefits of investment even greater. On the other hand, if this growth effect diminished, or if there is some limit to the ability for research to lower costs, it might put a cap on the potential benefits of R&D.

The relationship between stock-dependent knowledge growth η_K and the discount rate r, plays an important role in determining the magnitude of the marginal social benefit of R&D spending. In the special case that discounting is exactly offset by the growth of knowledge, the marginal benefit is simplified to the sum of all future cost-savings (plus the terminal value determined by the transversality condition). When this equality does not hold, it drives a wedge between the marginal benefit of R&D spending and future costs savings. The comparison of η_K and r amounts to whether the potential returns of building up a stock of knowledge outweigh the effect of discounting those future benefits. When $\eta_K < r$ the potential savings overstate the marginal benefit since they are not experienced immediately. Alternatively, if $\eta_K > r$ R&D is even more valuable since it builds a stock of knowledge that yields high returns in the future that are positive even in the presence of discounting. We return to this relationship when examining the steady state condition for knowledge below.

1.3.3 Optimal Steady State

The previous section described the behavioral rules that determined the manager's population control and research choices at any point in the planning horizon. We turn our attention to identifying the optimal steady state solutions of the model.

The solution of a dynamic bioeconomic model is characterized by a series of differential equations that dictate how the state and co-state values change over time. The equations of motion for the stock variables (IAS population and knowledge) are given in the problem set up, (1.10) and (1.11), while the co-state equations can be found from (1.12) and (1.13). As a final step, we apply the optimality conditions (1.14) and (1.18) to the co-state equations to find the optimized dynamic system:

$$\dot{n} = g(n_s) - h(n_s, x_s) \tag{1.20}$$

$$\dot{\lambda} = (\frac{C_x}{h_x})[r - (g_n - h_n)] - D_n \tag{1.21}$$

$$\dot{K} = \eta(I_s, K_s) \tag{1.22}$$

$$\dot{\mu} = (\frac{R_I}{\eta_I})[r - \eta_K] + C_K \tag{1.23}$$

When this system of equations all equal zero, there is no incentive to increase or decrease the stock of IAS or knowledge and the system is at rest. It is clear that IAS populations are constant ($\dot{n} = 0$) whenever natural growth is exactly equal to the rate of IAS removal, while the steady state condition for knowledge production ($\dot{K} = 0$) will depend on the form of the KPF. Analysis of the steady state conditions can provide valuable insight into the determinants of the steady state levels for IAS and knowledge.

$$g_n = r + h_n - \frac{h_x D_n}{C_x} \tag{1.24}$$

The steady state condition in (1.24) mirrors a familiar outcome in the management of biological resources such as fisheries (Anderson and Seijo 2011), with the notable exception that the biological stock in this case is harmful rather than beneficial. g_n shows the marginal impact that the IAS stock has on population growth. A higher discount rate corresponds to a higher marginal growth rate, implying a lower steady state IAS stock. The interpretation of this result in a fisheries context is that when future benefits of the resource are discounted, then managers harvest more in the present leading to a smaller steady state population. In the present case where the biological stock is actually harmful, the discounted benefits are the damages avoided in the future as seen in (1.16). A larger discount rate diminishes the value of future harm relative to the current damage of IAS, which may prompt more aggressive population reduction and a lower steady state population. h_n reflects the marginal effect that the IAS population has on the productivity of control efforts. Sensibly, when IAS control is more effective (larger h_n) there is a lower steady state population.

The final term represents the marginal damages avoided per dollar spent on population control. The fraction is positive, and thus its negative will lower the marginal growth rate, implying higher steady state stock. Again, this term is common to extraction problems concerning biological stocks and effectively this shows that as marginal costs of effort increase it puts upward pressure on the steady state IAS population. However, this term is particularly important to the present study as the marginal cost is a function of the endogenously determined knowledge stock. Recall that $C_{xK} < 0$, implying that a larger steady state value of knowledge actually increases the optimal IAS population. At first blush this may seem counterintuitive, but the same result was found in a study examining the impact of endogenous technological change on CO_2 abatement (Goulder and Mathai 2000). In what was termed the "shadow cost effect", we are seeing that the ability of R&D to reduce the marginal cost of control actually makes the damage from IAS less worrisome and allows for a larger stock of IAS at the steady state.

Similarly, at a steady state (1.23) yields the following condition:

$$\eta_K - \frac{C_K \eta_I}{R_I} = r \tag{1.25}$$

The steady state condition presented in (1.25) shows that a steady state knowledge stock is achieved when the economic gains of investment are equal to the social discount rate. The terms on the left-hand-side of (1.25) represent the marginal economic benefits of R&D spending. The first term is simply the marginal productivity of the knowledge stock in producing new information, while the second term represents the marginal impact of research investment on control costs (recall that $C_K < 0$, by assumption). We see that at an optimal interior steady state, investment is suspended when the net marginal economic yield is equally met by the social discount rate. This is an intuitive result as knowledge stock exhibits the positive characteristics of a conventional form of capital, unlike the invasive species stock that imposes social harm.

1.4 Numerical Model

In this section we apply our model to different scenarios of invasive species management to study the dynamic behavior of a resource manager who uses research investment to reduce IAS control costs. We begin with a specific examination of brown tree snake management on Guam to measure the impact of technological advancement for a given species, followed by a more general examination of the research effects on IAS management under varying biological and economic conditions. Invasive species, by definition, impose harm upon society and management ideally seeks to eliminate them from non-native ranges. However, the impact of stock-dependence on control costs can make this outcome particularly challenging to model. Rather, we present a management goal with an ambitious population target, that is still distinct from zero. The prospect of eradication is returned to in the discussion found in section 5.

1.4.1 Brown Tree Snake Management

The brown tree snake has been a persistent nuisance on Guam since they were introduced to the island following World War II by returning military vessels (Rodda et al. 1992). Since that time they have become a prime example of a catastrophic invasive species; causing the extirpation or extinction of 11 of the 13 native bird species on the island (Savidge 1987) while also representing a significant economic threat to the island. The snakes are capable of creating large-scale power outages by inadvertently climbing along electrical equipment, which has led to millions of dollars in lost economic productivity (Fritts 2007). In addition, research has shown that a snake invasion like that on Guam can have startling impacts on the tourism economy of an affected region (Swhiff 2010).

Congress's Brown Tree Snake Eradication Act of 2004 formally targeted the elimination of the species on Guam (U.S. Congress, 2004), an issue made more pressing by an ongoing U.S. military buildup on the island. To support this goal, several branches of the U.S. government are currently engaged in BTS research, namely USDA - Wildlife Services and the US Geological Survey. The research agenda for BTS management currently focuses on reducing the cost of removing snakes from the island. Previous developments in this area identified acetaminophen as a highly-effective, and low-cost toxicant (Savarie et al. 2001), improvements in efficacy of canine detection of BTS (Engeman et al. 2002), and others. Current research projects prioritize the development of a cost-effective process of large-scale dispersal of acetaminophen baits and production of a chemical attractant for BTS traps (Engeman et al. 2018).

The specific eradication target, the island's geographic isolation, and the research emphasis create a precise management scenario that is aligned with the bioeconomic model we have constructed.

1.4.2 Functional Forms and Parameters

We briefly present functional forms for each model component, describe model parameters, and relevant parameter restrictions. Following exposition of the functional forms and generic parameters, we provide a summary of the parameter values and sources.

Total costs reflect the sum of population control costs, BTS damage, and research investment costs. The population control cost function is influenced by both the effort devoted to reducing BTS population (in hours) and the knowledge stock.

$$C(x_s, K_s) = \overline{w}\frac{x_s^{\delta_x}}{K_s^{\delta_K}}$$

In this function $\overline{w}$ is the baseline hourly cost of population control effort (captures all labor and capital costs) while δ_x and δ_K represent the elasticity of control costs to control effort and knowledge stock, respectively. To be consistent with the assumptions made in the analytical section the elasticity parameters must satisfy certain conditions. To have convex costs with respect to control effort, we must specify $\delta_x \geq 2$. To satisfy the assumption that both marginal and total population control costs are decreasing in the stock of knowledge, we must have $\delta_K > 0$.

We employ a simple IAS damage function that is both flexible and common in the literature.

$$D(n_s) = dn_s^{\delta_n}$$

Damages are determined by a damage coefficient d, and an elasticity δ_n that determines the degree of non-linearity in damage as a function of the species stock. The only restriction on the characteristics of the damage function is $\delta_n \geq 1$, allowing for a high degree of flexibility in the damage function while remaining consistent with the assumption that damages are increasing in the stock of the species.

The research investment function employs a likewise simple and flexible form.

$$R(I_s) = \rho I_s^{\delta_I}$$

The cost of investment depends on a generic research cost coefficient ρ and the investment elasticity δ_I. Investment costs are assumed to increase in the level of research effort, and we do not expect the marginal costs to diminish $\delta_I \geq 1$.

Biological IAS growth follows a logistic pattern with Allee effects (Sun 2016) and the harvest function is represented by a Gordon-Schaefer production function (Gordon 1953, Schaefer 1958).

$$g(n_s) = \phi(n_s - n_{min})(1 - \frac{n_s - n_{min}}{M})$$
$$h(n_s, x_s) = \alpha n_s x_s$$

In the biological growth function, ϕ is the instantaneous rate of growth in the IAS stock, while M reflects the natural carrying capacity of the species. Allee effects describe the notion that a population's growth may be dependent on a minimum stock. For instance, it may not be possible for growth to occur when there is only one animal and no available mate. Within the harvest function α is the familiar Gordon-Schaefer catchability coefficient that describes the proportion of the species captured by one unit of effort. Both of these functions are common within bioeconomic models and, together, appropriately model the dynamics of the BTS population.

The KPF builds on work from Goulder and Mathai (2000), but is a common function in growth literature.

$$\eta(K_s, I_s) = \beta K_s + A I_s^{\theta} K_S^{\gamma}$$

Respectively, β and A represent the presence of autonomous knowledge growth and the ability of investment and knowledge to spur new technological development. β is left unrestricted to allow for knowledge to naturally grow, decay, or remain constant. $A \geq 0$ allows for the possibility of a constant knowledge stock, despite investment. The parameters θ and γ describe the returns to research investment, and existing knowledge, respectively. The only restriction on these parameters is that $\theta \geq 0$ to remain consistent with the assumption that $\eta_I \geq 0$. As discussed in the construction of the analytical model, returns to knowledge stock are left to be highly flexible to allow for nuances of stock-dependent knowledge growth. The KPF plays a prominent role in the analysis, and ideally we could rely on empirical foundations for these parameters, but as yet these do not exist for research on IAS species. Specification of an empirically grounded KPF is an important goal for future research.

1.4.3 Solution Overview

We can use these functional forms to present the dynamic system that will determine the optimal BTS management behavior. Upon applying the functional forms to the generic dynamic system given in (1.20)-(1.23), we then use conditions (1.10) and (1.11) to give the system strictly in terms of the state and co-state variables.

$$\dot{n} = \phi(n_s - n_{min})(1 - \frac{n_s - n_{min}}{M}) - \alpha n_s(\frac{\alpha}{\overline{w}\delta_x}\lambda_s n_s K_s^{\delta_K})^{(\frac{1}{\delta_x - 1})} \tag{1.26}$$

$$\dot{\lambda} = \lambda_s[r + \alpha(\frac{\alpha}{\overline{w}\delta_x}\lambda_s n_s K_s^{\delta_K})^{(\frac{1}{\delta_x-1})} - \phi(1 - \frac{2(n_s - n_{min})}{M})] - d\delta_n n_s^{(\delta_n - 1)} \tag{1.27}$$

$$\dot{K} = \beta K_s + A(\frac{A\theta}{\delta_I \rho}\mu_s K_s^{\gamma})^{\frac{\theta}{(\delta_I - \theta)}} K_s^{\gamma} \tag{1.28}$$

$$\dot{\mu} = \mu_s[r - A\gamma(\frac{A\theta}{\delta_I \rho}\mu_s K_s^{\gamma})^{\frac{\theta}{(\delta_I - \theta)}} K_s^{\gamma - 1}] - \frac{\overline{w}\delta_K}{K_s^{\delta_K + 1}}(\frac{\alpha}{\overline{w}\delta_x}\lambda_s n_s K_s^{\delta_K})^{\frac{\delta_x}{\delta_x - 1}} \tag{1.29}$$

Solution of the dynamic system, subject to a transversality condition, yields solution paths for IAS population, knowledge stock, and the co-state variables. Transversality conditions determine the value of state, co-state, and time variables within the model and are subject to the specific circumstances of management. The model is solved for a terminal population that represents 1% of total carrying capacity of the IAS population. The implied transversality condition is that the marginal social value of population reduction in the final planning period, $\lambda(T)$, is endogenously determined within the model. The optimal stock of knowledge, $K(T)$, may not be known prior to management, and is solved endogenously as part of the optimization problem. The transversality condition is thus $\mu(T) = 0$, implying that investment is suspended at the point where there is no longer any social benefit to devote resources to R&D.

1.4.4 Brown Tree Snake Management

Parameters for the model were selected from literature studying the biological characteristics and economic impacts of BTS, as well as studies in the effects of R&D on the provision of environmental public goods.

Table 1.1: Parameter Values

Parameter	Value	Description
A	Range 0-0.02	KPF Productivity (discussed below)
α	0.0049	Catchability coefficient (Schaefer 1957, Calculated with BTS data)
β	0	Ruling out possibility of intrinsic knowledge growth
d	1.73	BTS damage per million snakes in millions of $US (Shwiff 2010)
γ	0.5	Returns to knowledge stock in KPF (Goulder and Mathai 2000)
M	2.6	BTS carrying capacity in millions of snakes (Rodda et al. 1997)
ϕ	0.6	Annual intrinsic growth of BTS population (Burnett et al. 2008)
r	0.05	Discount rate (Epanchin-Niell and Liebhold 2015)
ρ	$117e^{-6}$	Per-unit cost of investment in millions of $US (discussed below)
θ	0.5	Returns to R&D investment (Goulder and Mathai 2000)
$\overline{w}$	$117e^{-6}$	Base per-unit cost of control in millions of $US (Unpublished USDA data)
δ_x	2	Cost elasticity of Pop. Control (Eiswerth and Johnson 2002)
δ_I	2	Cost elasticity of Investment
δ_n	1	Cost elasticity of IAS damage
δ_K	1	Cost elasticity of Knowledge

The majority of the parameters are selected from literature on BTS management, or R&D modeling in environmental economics. However, second order conditions and numerical tractability informed some choices. As our analysis focuses on the affect of research on management, the KPF productivity given by A is the primary parameter of interest. We choose to employ a range of research productivities in order to comment on how the model responds to changes in technological development. The lower bound describes research as completely ineffective, while the upper bound was selected based on productivity estimates in Goulder and Mathai (2000), as well as numerical tractability. Each control variable is measured in hours of effort, and we treat the baseline research and control cost coefficients as being equal. This approach is taken for numerical simplicity, but highlights a demand for better research cost information. The time horizon used is informed by the scheduled military build up on Guam, which the Brown Tree Snake Eradication Act of 2004 was motivated by, at least in part. This buildup is ongoing, and will likely continue into the early 2020s (personal communication, Stephanie Shwiff 2018). Using the legislation from congress as an approximate beginning point for management and the anticipated end of the buildup as the deadline, we solve the model over a 20-year time horizon with a time step of 1-year.

1.4.5 R&D and IAS Management

Using the BTS parameterization, we look at the effect of R&D on management primarily based on varying levels of research productivity. This section presents several measures of how R&D affects IAS management and its costs. We consider the effectiveness of R&D to lower management costs overall, followed by discussions of the detailed cost paths and decision paths, and finally a brief assessment of the responsiveness in management costs to research investment.

Table 1.2 provides model results showing that the present value, discounted at 5% annually, of reaching the target population falls with greater levels of research productivity. While the present value of these management costs is strictly decreasing, the reductions at each level of productivity become smaller, suggesting diminishing returns to research efficiency. We will return to this notion throughout the following discussion.

Table 1.2: Management Costs by Research Productivity

Research Productivity A	Present Value of Management Costs ($US Million)
0	29.50
0.005	16.38
0.01	13.80
0.015	12.63
0.02	11.86

From table 1.2, it is clear that research investment reduces management costs for a given population target. Examining how the productivity parameter A affects the cost-paths of meeting the population target provides additional detail on the effects of research investment on management choices and its benefits. Figure 1.1 depicts the proportional change in management costs relative to the scenario without any research investment ($A = 0$) for varying levels of research productivity over time. A horizontal reference line is included to illustrate the threshold at which the proportional change is equal to zero. Points above this line indicate that accounting for R&D led to management costs being lower in period t, compared to the case without any R&D. Likewise, points below this line represent costs being greater in the presence of research investments.

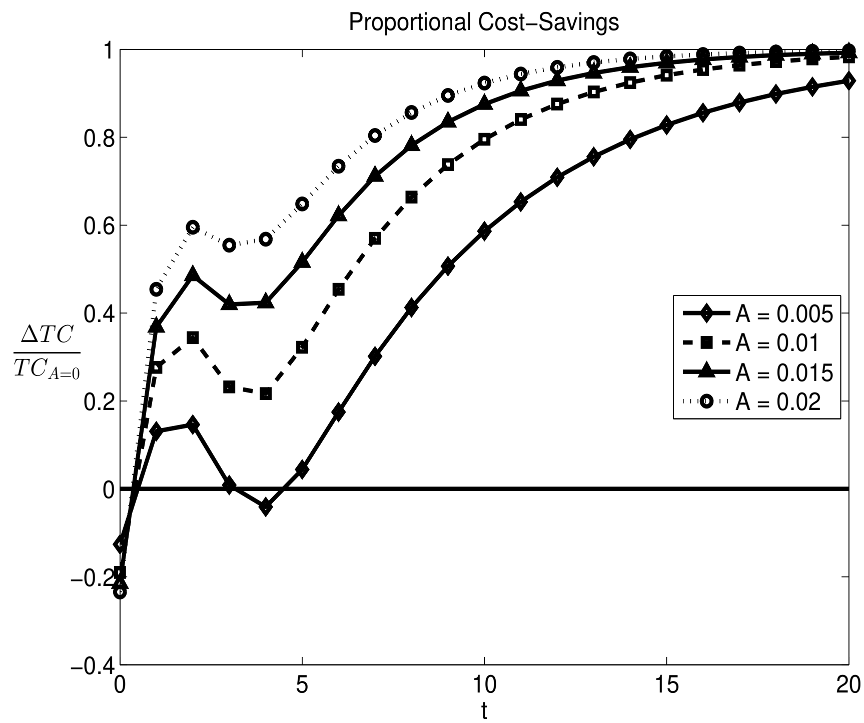

Figure 1.1: Proportional change in management cost

The findings are eye-catching, with R&D reducing costs in the final period by over 90% in all specifications. The efficiency of research investment corresponds to strict improvements in terms of cost-savings in all time periods. Cost-paths are highly non-linear, and while R&D-based management ultimately leads to large cost-savings there are also periods in which it is more costly than simply using conventional removal methods. Cost-dynamics for all levels of research productivity are characterized by an initial period of pronounced cost-savings, followed by a brief regression toward the conventional scenario, and then a more gradual and persistent pattern of cost reduction.

A notable characteristic of the results presented above are that R&D may not lower spending in all management periods. In fact for any level of A, research investment actually has the effect of increasing management costs in early periods. This characteristic is largely a consequence of ambitious R&D spending at the onset of an IAS removal program. Figure 1.2 shows the patterns of R&D spending that characterize the eradication solution. For all cases, investment is shifted toward the earliest management periods, then falls over time. Such a result is intuitive, as it allows for lower control costs over a greater proportion of the management horizon. These investment paths are almost identical by year 5, with the exception of $A = 0$ where there is never any investment. For this reason, and to highlight the differences in initial research behavior, we present figure 1.2 through only for the first five years of management.

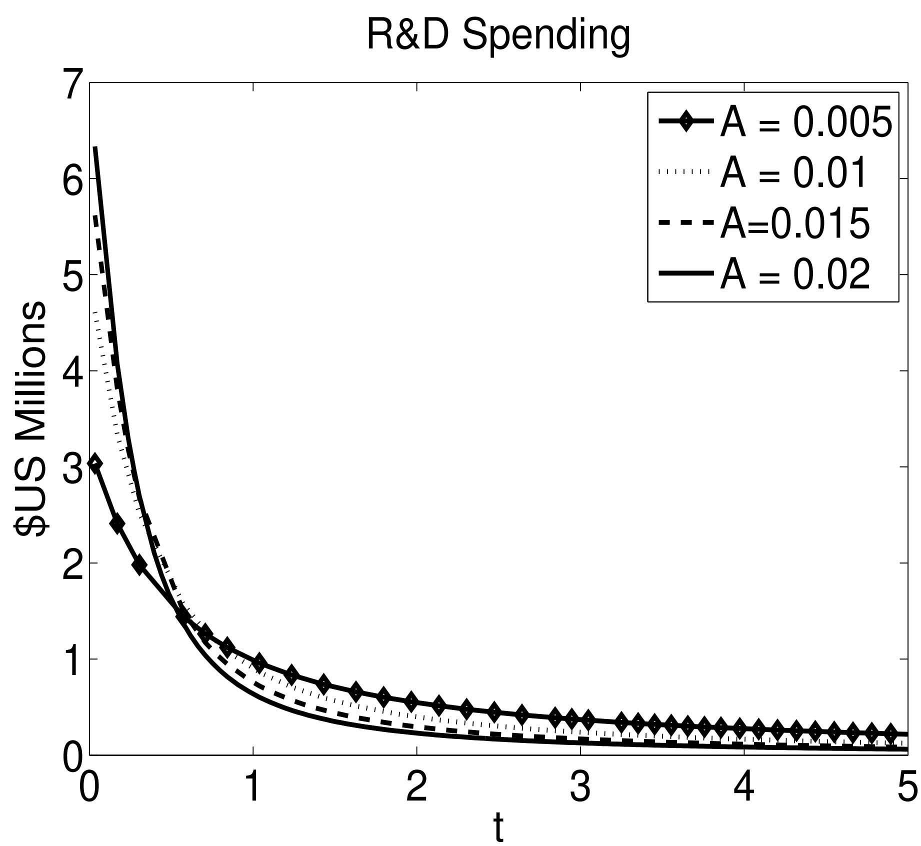

Figure 1.2: Research investment for different levels of A

Whenever research is more productive, it prompts managers to invest more at the onset of management, but with each increase in A the shift in initial investment decreases. Further, as research productivity improves the cost-minimizing investment paths do not shift in a parallel manner, but rather investment decreases over time at faster rate. These outcomes echo the result seen in Table 1.2, which implied that research productivity exhibits diminishing returns in terms of cost-savings.

The regression in cost-savings is also of interest, as one might expect that research should lead to strictly decreasing management costs. However, this brief disruption in cost-reductions is emblematic of the intertemporal trade-off that occurs between the social planner's choice of R&D and IAS removal. A thorough discussion of this effect is relegated to section 5.

Finally, the model can be used to derive a pseudo-elasticity for the management cost's response to changes in knowledge productivity, which are given in Table 1.3.

Table 1.3: Ratio of Cost-Savings to Research Productivity

A	$\frac{\Delta TC}{\Delta A}$
0.005	0.29
0.01	0.25
0.015	0.221
0.02	0.220

The responsiveness of management costs are sizable at each level of A considered, ranging between 22 and 30% cost-savings per marginal increase in research productivity. As before, the results suggest a diminishing marginal benefit of research investment with higher levels of research productivity.

The results above show several key points regarding the role of R&D in invasive species management. It is clear that, in the case of Brown Tree Snakes on Guam, there are real benefits to investing in removal methods in order to reduce the cost of targeted population reduction. The expense of this research may lead to program costs being more costly in the earliest periods of management, but contribute to drastic cost-savings in the future. Finally, the productivity of knowledge creation exhibits diminishing returns as far as these cost-savings.

1.4.6 Effect of Research for Varied Species Type

Results from the preceding analysis demonstrate the role of research investment in the eradication of one particular species, the brown tree snake. In order to demonstrate the flexibility of the model, as well as develop insight about the broader benefits of research in IAS management, four broad categories of IAS are defined on salient biological and economic characteristics. The categories are framed in terms of the overall impact that a candidate species may impose on the invaded ecosystem and economy, as measured by the interaction of economic damage and biological growth rates. A simple matrix of impact categories is given in Table 1.4, including representative species of each category.

Table 1.4: Impact category matrix

	High Damage	Low Damage
Rapid Growth	Feral Swine (*Sus scrofa*)	Brown Tree Snake
Slow Growth	Mongoose (*Herpestus auropunctatus*)	Wild horses (*Equus caballus*)

Representative species for each impact category were determined based on the comprehensive review of invasive species provided by Pimentel et al. (2005). In table 1.3 the Brown Tree Snake's impact is based on the present management context being faced in Guam. As mentioned above, it is possible for the BTS to impose much higher damages, which would change its classification. To apply the model to these additional species, the Pimentel review is supplemented with species specific studies (Garrott and Taylor 1990, Harper and Bunbury 2015, Fukasawa et al. 2013, Johnson et al. 2016). Table 1.5 summarizes the parameterizations for the species that typify each category.

Table 1.5: Parameter Values for Impact Categories

Species	d ($US per animal)	ϕ
Feral Swine	200	0.8
Mongoose	100	0.49
Wild Horse	20	0.05

Using the information from Table 1.5, the model is solved at a constant research productivity $A = 0.01$. Table 1.6 shows the present value of total management costs for each species.

Table 1.6: Management costs for varied species

Species	Present Value of Management Costs ($US Million)
Feral pig	4,904
Mongoose	26.45
Feral Horse	0.59

The values in Table 1.6 show the wide range of impacts that can be imposed by invasive species. The management costs of high impact species, such as feral swine, can be extraordinary, reaching the billions of dollars. Given that current estimates of annual damage are approximately $800 million, we believe that this is a reasonable measure of potential costs for an ambitious population reduction program like the one we have modeled. The cost of addressing moderately harmful species are in the same range as that seen for our analysis of the Brown Tree Snake, and the least harmful species have fairly low management costs.

The cost-minimizing investment behavior varies widely for each species, as can be seen in figure 1.3. For the high- and medium-impact species, we truncate the x-axis due to most investment behavior occurring in the earliest stages of management, much like in the BTS specification.

For the low-impact species, however, we see much different research behavior across the entire management period.

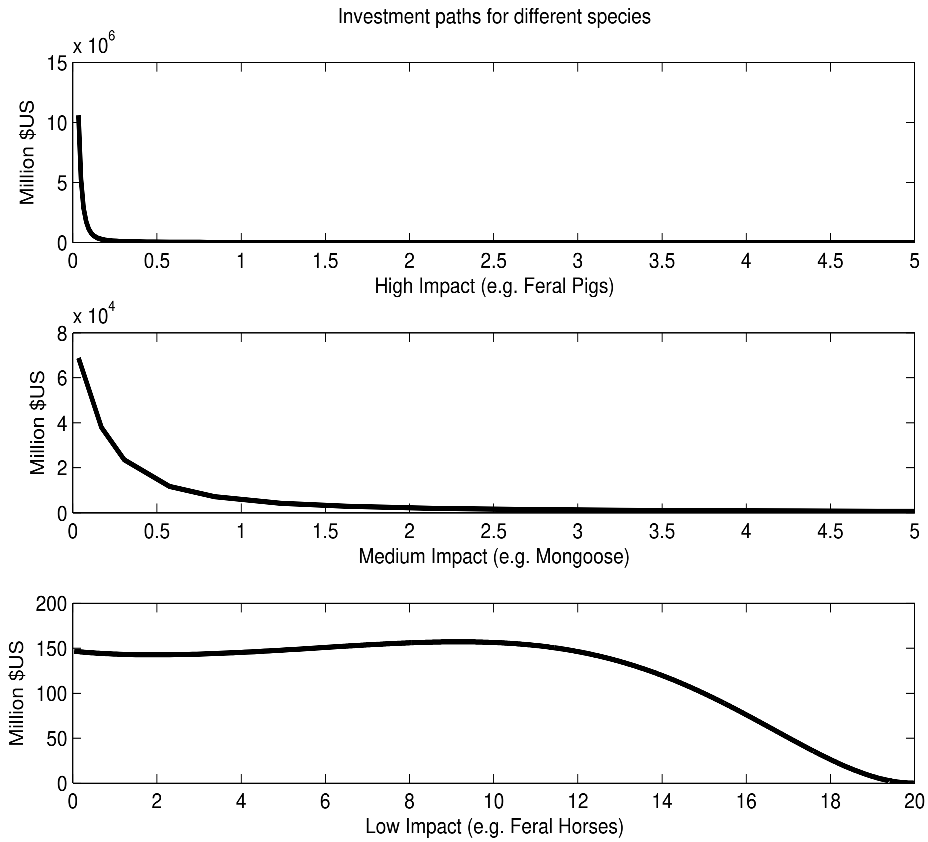

Figure 1.3: Research investment for different species

We see that investment follows a similar pattern as that demonstrated in the BTS model for high- and medium-impact species, with high levels of investment in the earliest periods followed by rapid declines, although this pattern is much more pronounced for the high-impact species. Low-impact species buck this trend demonstrating more consistent R&D investments over the course of the management period.

1.5 Discussion and Conclusion

The fundamental economic concept this paper considers is the effect of R&D investment on IAS management. Despite the growth in study of optimal management strategies, there has been little to no examination of the role that research investment plays in managing an established population in the literature. Using a dynamic optimization model we show that research is capable of reducing overall IAS costs considerably, and should be a deliberate component of management strategies.

By studying the effect of R&D under different levels of productivity, we identified that the overall cost-savings are generally persistent, but diminish as research becomes more productive. This is due to the fact that, even though research makes meeting the target population cheaper, it is accompanied by its own costs. When research is more productive, it prompts greater levels of investment, and a larger R&D expense. This is consistent with the analytical foundations we established in the third section of the paper, specifically the investment flow rule 1.18. When optimal investment is determined by the sum of all future marginal cost-savings (strictly from population control), then as research productivity improves, managers will invest more.

A corresponding effect of this research activity is that it impacts the timing of population reduction, which is delayed in favor of early-stage R&D. Figure 1.4 demonstrates this effect, however we present the results of only three levels of research productivity for clarity of exposition. The general pattern is consistent across all models, though.

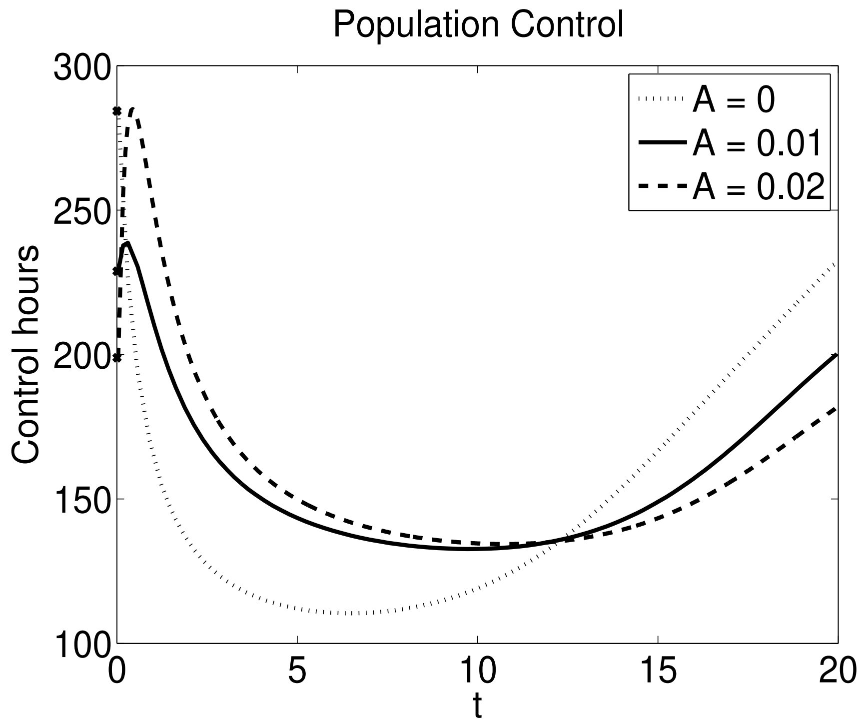

Figure 1.4: Optimal population control

The results shown in figure 1.4 highlight several notable consequences of conducting research on IAS control methods. Higher research productivity corresponds to a lower level of population control initially, which is ultimately followed by a much higher level of effort. When research is more efficient in producing knowledge, this peak is pushed higher, but is also delayed longer. A key takeaway from the above figure is that the control effort needed to reach the given target population decreases with greater technological productivity. This is especially interesting as it relates to the goal of eradication. The nature of stock-dependent harvest (and thus stock-dependent costs) demands higher removal effort at lower populations, but these results suggest that research is able to lower the effort needed to achieve a given population target.

It is this combination of delayed BTS removal and ambitious early-stage R&D that creates the temporary regression in cost-savings seen in figure 1.1. The consequence of this trade-off is mitigated at higher levels of research productivity. In the case with the least efficient research production ($A = 0.005$), the cost of revamping control efforts after the initial delay has a sizable effect on cost-savings, and even becomes more costly than if no research was done at all.

The timing of cost-effective research reflects an intuitive preference for investment at the earliest stages of management, as this corresponds to the greatest cost-savings over the management horizon. For a given species, this effect was seen at all positive levels of research productivity, but may not be the case for low-impact invasives. Referring to the investment rule (1.19), this is likely due to the fact that the benefit of R&D is notably lower when the cost of control is relatively inexpensive.

The model developed in this study represents a synthesis of several bodies of research within economics, applying models of technological change common in climate change literature to invasive species issues. The key similarity between these two environmental issues is the management of a harmful environmental pollutant; the key difference is that in the case of IAS the stock exhibits biological growth as opposed to natural deterioration. The introduction of research-driven knowledge accumulation to the cost function is the primary contribution of this research. Knowledge reduces the costliness of population control, which can offset the convex costs of IAS management.

This research demonstrates the impacts that research investment and knowledge creation can have on IAS management. However, there are a number of important areas where the model could be improved. Results presented above suggest that research investment could possibly address some of the challenges associated with targeting eradication in the presence of stock-dependent costs. This is an important topic within the literature that demands additional exploration. In addition, the prominent role of knowledge creation in the model makes it important to improve the foundations of the KPF and its relevant parameters. Estimating an empirical KPF to inform the parameters for returns to investment and previous knowledge is the next intuitive step in this analysis. Finally, several simplifying assumptions were made to assist in the composition of a tractable model. In future work, we would like to relax these assumptions by introducing more complex biological dynamics such as: allowing for secondary invasions that contribute to the established population, incorporating density-dependent damage function (Yokomizo et al. 2009), and considering the role of knowledge spillovers from R&D.

Chapter 2

Business-As-Usual Cost Assessment of Brown Tree Snake Management on Guam

2.1 Introduction

Chapter 1 showed that for a given IAS management goal of reducing the population of an established species, R&D investment is able to significantly reduce the optimized program costs. This chapter estimates the business-as-usual (BAU) expense of current BTS management on Guam to act as a baseline for comparison against the R&D-based findings from Chapter 1. Using a detailed and novel data set provided by USDA Animal and Plant Health Inspection Service (APHIS), BTS interdictions costs are calculated as a function of shipping traffic. The cost function is then applied to forecasts of shipping traffic in order to provide BAU cost estimates.

Invasive alien species (IAS) management is a costly endeavor, and economists have generally established that prevention is more cost-effective than managing an invasive population (Leung et al. 2005, Epanchin-Niell and Liebhold 2015). As important as prevention is, reducing the spread of invasive species also requires keeping them from escaping areas where they have become established. While the economic literature on invasive species has largely focused on prevention and population reduction, quarantine of high-risk species is a major priority to reducing the global impact of IAS (Margarey et al. 2009). Focusing on BTS management on Guam, this paper treats interdiction as the BAU policy following a successful invasion and estimates annual quarantine costs as a function of shipping traffic, the primary vector of IAS dispersal (Westphal. 2008, Paini et al. 2016).

Drawing from the practice in climate economics, BAU estimates reflect the anticipated cost of a persistent environmental hazard (Heal 2008, Schmittner 2008, Stern 2016). In the case of BTS, the environmental damage has largely been done already (Shwiff et al. 2010), and prior to a concerted eradication effort the main management goal (and associated cost) is to prevent any snake from escaping the island. These estimates are necessary for measuring the benefit of management strategies, and in the present context will be used to measure the relative cost-savings of R&D programs for BTS removal.

Evidence from chapter 1 suggests that R&D is an important component of a social planner's strategy for addressing the brown tree snake, but was structured around a precise population reduction target. This chapter presents an alternative management program that does not impose a target BTS population, but instead focuses on the interdiction of the species to the island without any deliberate effort to reduce the population. Such a departure from the principal management goal explored in the previous chapter provides an additional layer to the management question: is it cost-effective to reduce IAS population versus preventing expansion of the species? Further, emphasis on R&D in the first chapter extends this question to: can research investment make population reduction the economically preferable choice between the two management goals?

The remainder of the paper is as follows: Section 2 provides a very brief review of literature specific to BTS management, and current methodologies, Section 3 presents the cost model and reviews the USDA data on BTS management accessed via the Management Information Systems database, Section 4 presents BAU cost estimates for varied trade forecasts on Guam, Section 5 connects the BAU estimates with the optimal R&D model solutions derived in chapter 1, and Section 6 offers some discussion and analysis.

2.2 Literature Review

Invasive species represent a serious threat not only for ecological and environmental reasons, but also for their ability to inflict significant economic damage (OTA 1993, Pimentel et al. 2005, Shwiff et al. 2010). Pimentel et al. (2005) estimated that terrestrial invasives in the United States alone had an economic impact upward of $100 billion per year. Since their introduction, BTS have been identified as an example par excellence of the potential for invasive species to have devastating consequences. BTS impact is a result of issues characteristic to island ecosystems with no history of snake presence: few predators or competitors, a large prey-base, and prey that lack defensive instincts that would otherwise limit the snakes' high rate of predation. These characteristics of Guam's environment contributed to the rapid growth in the population of brown tree snakes that led to a number of ecological and economic consequences, including the extirpation or extinction of the majority (10 of 13 species native to Guam) of the island's avifauna (Savidge 1987, Wiles

1987, Rodda et al. 1997, Fritts and Chiszar 1997, Fritts and Rodda 1998). One study estimated that extensive power outages caused by BTS cost Guam's economy $4.5 million in lost productivity over a seven year period (Fritts 2002). These facts are especially concerning for other island economies that may be at risk if the snake were to escape Guam (Perry and Vice 2009). Hawai'i is of notable concern due to its large, tourism-based economy and the fact that currently no snakes exist on the island, much like Guam prior to the introduction of the brown tree snake (Kraus and Cravalho 2001, Burnett et al. 2008). Estimates of economic loss resulting from a similar invasion on Hawai'i range between $593 million and $2.14 billion (Shwiff et al. 2010).

Island economies are more dependent on shipping and trade than continental economies, and are particularly important to the transshipment industry (Andriamananjara et al. 2004, Tovar et al. 2015). As a cargo and transportation hub in the central Pacific region, Guam's large brown tree snake population presents a high risk of snake dispersal to other islands. To avoid the spread of brown tree snakes, the U.S. Department of the Interior has committed to the interdiction of the species in Guam, largely through the funding of snake control and research by USDA Wildlife Services (USDA-WS) (Colvin et al. 2005). Snake control methods have been developed to lure and trap snakes before reaching outbound cargo (Engeman and Linnell 1998, Engeman et al. 1998, Avery et al. 2004, Clark et al. 2017) , create a secure perimeter around sensitive cargo areas (Perry et al. 1998, Siers et al. 2016), and to detect and capture snakes that have stowed themselves in outbound cargo and vehicles (Engeman et al. 1998, Vice and Engeman 2000, Engeman et al. 2002, Vice et al. 2002). Research into effective measures for reducing the overall snake population on Guam is ongoing (Linnell et al. 1998, Savarie et al. 2001, Shivik et al. 2002, Dorr et al. 2016, Engeman et al. 2018). While the ultimate goal of management is eradication of the snake from Guam (Congress 2004), interdiction of the snake is of immediate concern until this target is achieved. In this way, quarantine of BTS and its associated costs can be used to develop a "business-as-usual" forecast of management costs.

This study uses data on the cost and frequency of each snake control method as well as cargo traffic information to develop a range of interdiction costs based on three scenarios of trade activity. The control methods analyzed were bait station control, fence-line trapping, hand capture, and canine inspection. We do not consider the costs of aerial dispersal, as this method is still in development stages and is considered to be more a component of R&D. The current control methods create a multi-tiered defensive boundary around areas sensitive to snake escape, such as outbound cargo storage areas. In addition to these direct methods, the USDA-WS also uses educational materials and outreach to increase brown tree snake awareness among cargo handlers (Vice and Clark 2014, personal communication).

The shipping industry is a main component of Guam's economy, as its geographic location has established it as a shipping hub in the North Pacific. Moreover, the military presence on the island leads to even greater traffic. As a primary vector for IAS dispersal, this shipping activity represents the main concern for BTS interdiction on Guam, and is used as the basis for the interdiction cost estimates. This study examines three scenarios of expected future export and transshipment flows commissioned by the Port Authority of Guam (PAG) for several different levels of an ongoing military buildup (Parsons Brinckerhoff 2013, Port Authority of Guam 2013). Using multiple forecasts contributes to a more flexible assessment of interdiction costs.

2.3 Cost Model and BTS Data

2.3.1 Interdiction Network and Cost Model

Total interdiction costs are composed of fixed costs and variable costs, which comprehensively account for all methods of quarantine used on Guam. All data was collected for the fiscal year of 2015.

Fixed costs are dependent on the geographic area being managed, while variable costs are a function of the shipping volume exiting the island. Fixed cost interdiction methods include bait stations (BS), fence-line traps (FT), hand capture (HC) and additional expenses (AE). Additional expenses represent administrative and overhead costs of the interdiction program (E.g. fuel and transportation costs, field supplies and equipment, etc.). Referring to figure 2.1, the fixed costs represent the network of barriers in place to prevent BTS from accessing cargo.

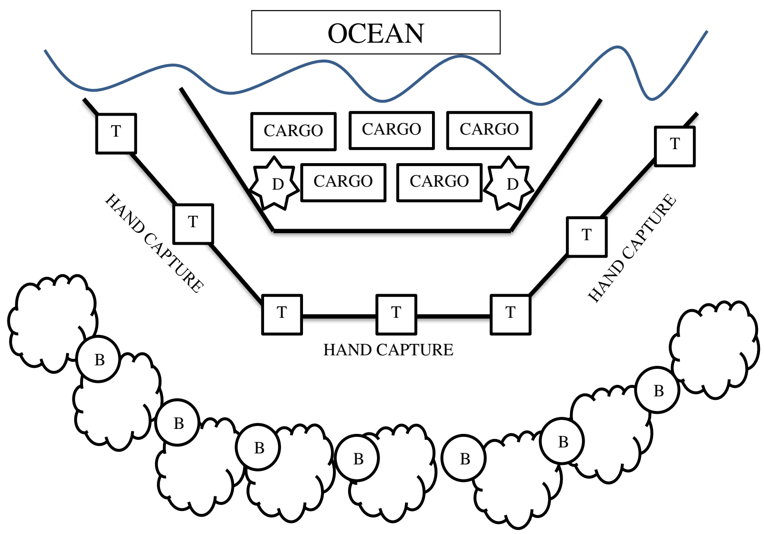

Figure 2.1: Diagram of Brown Tree Snake Control on Guam. BS - bait stations in forested area, FT - Traps along the fenceline, D - Dog inspection teams

Bait stations make up the first stage of defense surrounding ports of exit. Bait stations are PVC pipes placed in forest vegetation, containing a dead neonatal mouse treated with an oral toxicant (acetaminophen). This toxicant is lethal to brown trees snakes, cost-effective, and exhibits very low non-target risk (Savarie et al. 2001, Avery et al. 2004, Smith et al. 2016). Bait stations are typically checked twice a week by USDA-WS specialists, who replace any bait that has been taken (by animals) or decayed. At the time of this study, there were approximately 635 bait stations in use on Guam. Specially designed brown tree snake traps with a live-mouse lure are attached to perimeter chain-link fences on which snakes often travel and/or forage at night. Each trap is visited on a weekly basis by a USDA-WS specialist who checks for captured snakes, cleans the trap, and replaces the food and water for the lure mouse. At the time of this study, 3,439 traps were in use for BTS interdiction on Guam. Hand capture involves nighttime spotlight patrols of perimeter fencing and the collection of snakes found climbing the fences. Patrols are conducted by USDA WS specialists who use trucks with spotlights for the inspections and are conducted weekly or bi-weekly depending on how active brown tree snakes are in the area. Finally, canine detection represents the last stage of BTS quarantine. Detector dog teams are used to target snakes in the process of leaving the island via cargo. Canine inspection involves a dog handler and a detector dog that has been specifically trained to find snakes hiding in cargo and vehicles set to depart from Guam. At the time of this research, there were eighteen canine inspection teams in operation on Guam (Clark 2014, personal communication).

Variable costs are represented entirely by canine inspection (D) of outbound cargo traffic (CT). Every unit of cargo that leaves the island is subject to inspection by the canine teams, making the costs very sensitive to trade fluctuation. Unlike the other elements of the defense network, canine detection has little to no fixed costs with the exception of initial training and veterinary costs, which represent less than 5% of the total canine detection costs for the relevant study period and are incurred at the beginning of a team's tenure. Day-to-day costs associated with kenneling are provided as an in-kind service by Anderson Air Force Base (Colvin et al. 2005).

$$TC_t = BS_t + FT_t + HC_t + AE_t + D(CT_t) \tag{2.1}$$

Individual costs of each method are a function of the necessary labor, capital, and scale at the time of study. These are summarized in Table 2.1.

Table 2.1: Summary of individual fixed cost functions

	Abbreviation	Description
Bait stations	BS	$BS_t * (FAB_{BS} * R_{BS} + M_{BS} + W_{BS} * L_{BS})$
Fence-line traps	FT	$FT_t * (FAB_{FT} * R_{FT} + M_{FT} + W_{FT} * L_{FT})$
Hand capture	HC	$W_{HC} * L_{HC}$
Additional expenses	AE	$V_t + F_t + S_t + E_t + O_t$
Fabrication	FAB	Cost of building or purchasing capital
Replacement rate	R	How often capital must be replaced
Maintenance	M	Cost of regular maintenance of capital
Wage rate	W	Hourly wage rate of workers
Labor	L	Hours of labor used
Vehicles	V	Cost of vehicles and maintenance
Fuel	F	Cost of fuel for vehicles
Supplies	S	Cost of supplies
Equipment	E	Cost of equipment
Overhead	O	Cost of fixed overhead
Canine inspection	D	$(Tr_t + VET_t) * D_t + W_D * L_D * D_t$
Cargo traffic	CT	Twenty foot equivalent units of cargo (TEU)
Canine training	Tr	Cost of canine purchase and training
Canine medical	VET	Cost of canine veterinary services

Variable costs associated with canine detection require understanding of the functional relationship between canine inspection effort and cargo flows, that is, how much time it takes for a canine team to inspect a unit of cargo. This relationship was determined using data on cargo and inspection frequency. This data revealed a linear relationship indicating that, on average, for every hour committed to canine inspection 2.065 twenty foot equivalent units (TEUs) of cargo could be inspected. In addition to inspecting cargo units, canine teams also inspect household goods. To account for this, we add a scalar term H_t to reflect the inspection of households.

$$D(CT_t) = (T_t + VET_t) * D_t + w_{D,t}[\frac{TEU_t}{2.065} + H_t] \tag{2.2}$$

2.3.2 Data

Frequency data on these control methods were obtained from the USDA Management Information Service (MIS) database. The data was presented in a Microsoft Excel file and provided a daily record of all USDA WS interdiction activities for fiscal years 2006-2013. Each entry was categorized by control method and included information on effort (hours), the quantity of components used (e.g. number of traps used, etc.), the number of animals captured, and the species name. The annual record of entries ranged from 31,705 in 2010 to 35,937 in 2008, offering a thorough record of management activity over the eight year period. Data was used to identify the scale and frequency of control methods in terms of effort, the number of traps and bait stations used, how frequently traps were replaced, etc.

Cost data was obtained from USDA-WS personnel overseeing the interdiction efforts on Guam. The data provided an itemized summary of costs for the 2014 fiscal year as well as itemized estimates of costs for the 2015 fiscal year. This data was used to determine per unit costs (including hourly wage) and the number of traps, bait stations, vehicles, etc. All costs are expressed in 2015 dollars. In addition, labor estimates for 2015 provided the total labor hours spent on BTS interdiction, but do not specify how many hours are attributed to each interdiction method. The 2015 distribution of labor was imputed using MIS data to determine the average annual labor share attributed to each interdiction method from 2006 to 2013, and applying these values to the 2015 estimated labor total. Data suggest that the bait station share of labor is 6%, fence-line trap maintenance takes up 42%, hand capture is 4%, and canine detection occupies 48% of hours attributed to interdiction. These estimates are consistent with personal communication with wildlife technicians on Guam (Brown Tree Snake Annual Meeting 2016).

PAG published several forecasts of anticipated cargo flow in terms of containers transported for years 2013-2033. These projected rates of traffic were given in the 2013 Port Authority of Guam Master Plan Update (Parsons Brinckerhoff 2013). Traffic projections were used to estimate potential changes in canine inspection costs in response to cargo traffic. Seaport or surface cargo represents the majority (90%) of all exported goods and materials that move through the Port of Guam (USMC 2010). Therefore, shipping estimates reflect solely seaport activity, excluding air cargo.

2.4 Results

2.4.1 Fixed Costs of Interdiction

Table 2.2 presents fixed cost information for each interdiction method.

Table 2.2: Annual fixed cost breakdown by interdiction method

Method	Annual cost ($US 2015)	% of Total
Bait station	171,823	6%
Fence-line traps	1,369,592	49%
Hand capture	91,536	3%
Canine inspection	51,199	2%
Additional expenses	1,103,184	40%
Total fixed costs	2,787,336	100%

The large costs associated with additional expenses reflect costs that are shared among all interdiction methods. The proportion of fixed costs attributed to fence-line trapping is likely a result of the trap network on Guam that is both widespread and labor intensive. The three other methods combined contribute just over one-tenth of fixed costs. Bait stations are checked more frequently than traps, but require less maintenance and are much fewer in number. Hand capture practices are more similar in frequency to checking traps, but are less time intensive. The contribution of canine inspection is low because most of this method's costs are realized as variable costs via increased cargo inspection, which is discussed below.

2.4.2 Variable Interdiction Costs

Variable costs are calculated over three different scenarios of shipping traffic based on forecasts motivated by an ongoing military buildup on Guam. This buildup is part of the motivation that prompted targeting BTS for eradication in 2004, implying that these forecasts reflect appropriate circumstances to compare the results of the optimal control model against. Originally, the plan included relocation of Marine Corps forces from Okinawa, Japan to Guam, the construction of a new wharf in an existing harbor, and the placement of a missile defense task force on the island. However, in 2012 a revised buildup plan was released that called for approximately 60% of the original number of personnel to be relocated. The Port of Guam is the only commercial port on the island and has been designated a strategic port by the U.S. military, and as such, the buildup will necessarily lead to increased shipping traffic as construction equipment, materials, personnel, and supplies are brought into the island (USMC 2010). Furthermore, there is likely to be a transient increase in population and shipping during the construction of new buildings and infrastructure.

The PAG's Master Plan published in 2013 included cargo forecasts based on the military buildup (Parsons Brinckerhoff 2013). The report presents estimates of annual traffic in TEUs for the years 2013-2033 and features forecasts based on both proposed buildup plans, and a baseline model reflecting natural shipping growth without any buildup. Each of these scenarios reported future cargo flows that incorporated imports, exports, and transshipment. However, in the case of brown tree snake interdiction, export and transshipment traffic are the only categories of concern since imported cargo is not checked by dog teams. To address this issue aggregate shipping data for each scenario was used to calculate annual growth rates of shipping traffic over 2016-2033. These growth rates were then applied to export and transshipment data collected for 2015 to provide a forecast less imports for the remainder of the study period.

The baseline scenario used the current trends in cargo traffic and population growth to calculate a 1.1% growth rate up to 2019 and a 0.9% growth rate onward. The additional scenarios look at the varying levels of buildup and associated expected traffic. Each scenario is identified by the term used in the Port Authority's Master Plan: the baseline scenario is called "ORGANIC" and used as a base of comparison for the impact of the other scenarios, the scenario for the current buildup plan is termed "MID", and the original plan is termed "FULL" (Parsons Brinckerhoff 2013). Examining these scenarios allows the economic calculations in this study to provide a range of costs in an attempt to recognize uncertainty in predicting total interdiction costs. Figure 2.2 presents the variable costs from 2015-2033.

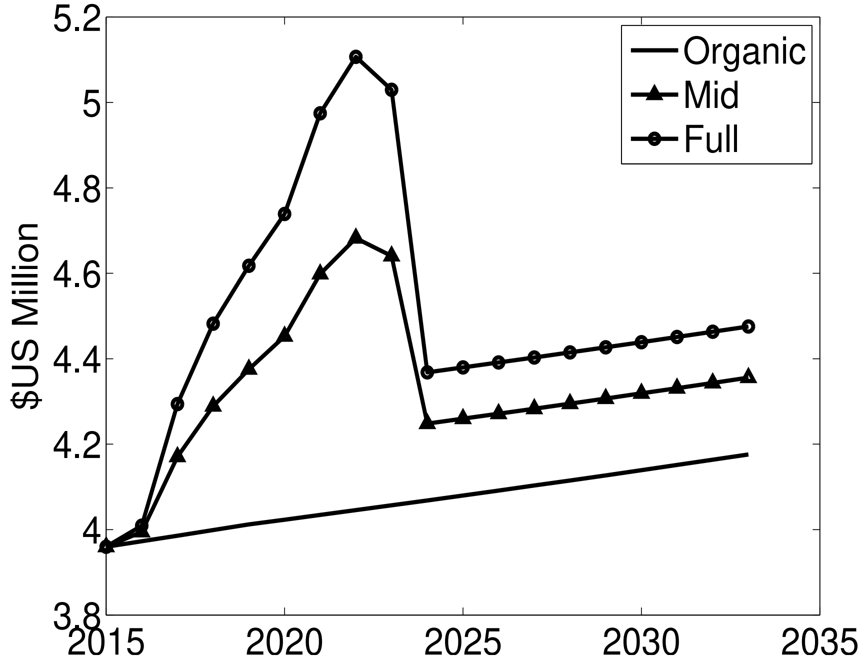

Figure 2.2: Variable cost paths

In both models of military buildup, costs peak in 2022, before returning to organic growth rates in 2025. At this peak, annual variable costs of ORGANIC, MID, and FULL were \$1.3 million, \$1.9 million, and \$2.3 million, respectively. Combining these variable costs with the fixed costs presented in Table 2.2 provide the peak BAU interdiction cost paths. Table 2.3 provides the cost of interdiction at the build-up peak and the present value of interdiction over the entire period, using a 5% discount rate.

Table 2.3: BAU Interdiction Costs 2015-2033 in \$US Million

	Organic	Medium Build-Up	Full Build-Up
Peak	4.05	4.68	5.11
Discounted Sum	29.90	31.78	33.037

2.5 Cost comparisons with R&D Optimal Control Model

This section brings together the results of the optimal control model with those presented in this chapter.

Table 2.4: Cost-Savings of Population Reduction over BAU Interdiction ($ US Millions)

Research Productivity A	BAU-Organic	BAU-Medium	BAU-Full
0	0.4	2.28	3.53
0.005	13.52	15.40	16.66
0.01	16.10	17.98	19.24
0.015	17.27	19.15	20.41
0.02	18.04	19.92	21.18

Under natural trade conditions, the discounted costs of interdiction are approximately the same as population reduction without any R&D. When research is productive at any level, R&D investment is a viable component of a management strategy and there are real cost-savings to lowering the population relative to maintaining interdiction. As we saw in the first chapter, the productivity of research leads to greater savings, although this effect diminishes. As seen in figure 2.2, maintaining interdiction in the face of increased trade, even if it is temporary, sees overall costs increase substantially. Under both cases of increased cargo traffic, we see that it is actually cheaper to lower the BTS population even in the case where there is no R&D and conventional methods have to be used. However, these cost-savings are much greater when research investment is undertaken.

Comparing the BAU interdiction costs with the R&D model results weighs the costs of reducing the BTS population against the cost of maintaining quarantine without any effort to lower the population. The cost-savings attributed to research investment drives a wedge between the expenses of these two approaches. Each cell of Table 2.4, provides the cost-differential between interdiction and population reduction, for a given technology productivity and trade scenario. By normalizing around the difference in costs during a baseline scenario of $A = 0$, we are able to comment on the effect research has on the magnitude of this wedge, and therefore additional cost-savings of R&D-based population reduction over BAU.

Table 2.5: Impact of R&D on Cost-Differential Relative to A = 0

Research Productivity A	BAU-Organic	BAU-Medium	BAU-Full
0.005	34.07	6.75	4.71
0.01	40.57	7.88	5.44
0.015	43.52	8.40	5.77
0.02	45.46	8.73	5.99

In the absence of any trade disruption, we see that R&D dramatically increases the cost-savings of population reduction relative to interdiction. At $A = 0.005$, the difference in costs between interdiction and population reduction is 34 times greater than in the absence of research, and this effect only becomes greater. When accounting for trade disruptions owing to military build-up, the ability of R&D to increase cost-savings is smaller in magnitude only because the population reduction was so much less expensive than interdiction even when $A = 0$. However, there is still a strong positive correlation between research productivity and cost-savings of population reduction.

2.6 Discussion and Analysis

This chapter estimates BAU cost for brown tree snake management on Guam based on interdiction costs to provide a baseline for comparison of the R&D-founded model developed in chapter 1. Using snake interdiction as the BAU setting, costs are estimated using a thorough data set for management effort and trade forecasts reflecting anticipated growth in shipping traffic. The comparisons provide compelling evidence that R&D investment corresponds to large economic benefits in the cost-effective management of a high-risk invasive species, such as the brown tree snake.

Findings show that under typical trade conditions on Guam, there is little added benefit to reducing the population compared to preventing its spread, which is consistent with the history of BTS management on the island. Managers that incorporate research as part of their decision-making process are able to reduce costs substantially by opting for ambitious population reduction rather than interdiction of a large BTS population on the island. Anticipating growth in cargo flows through the island sees population reduction becoming the cost-effective option regardless of whether the manager considers R&D. This supports the decision made by Congress to target the brown tree snake for eradication in relation to the announcement of the buildup on Guam, and the associated growth in shipping. The benefit of R&D is greater in the scenarios with higher shipping traffic, as more cargo translates to additional inspection activity and higher BAU costs.

The results of this BAU estimation demonstrate the substantial costs that exist, even when the goal of management is simply to prevent IAS spread. While this study did not consider prevention efforts or costs, the findings show that quarantine is an expensive process and supports the findings of previous research that prevention of invasive species introductions is a management priority. In the event that prevention fails (or is not pursued), this study shows that R&D can be an important factor in choosing whether cost-effective management is identified by quarantine or taking steps to reduce the population. In the present context, benefits of reducing the BTS population have only been discussed in terms of cost-savings relative to interdiction. However, there are substantial ecological and environmental benefits on the island in terms of ecosystem recovery, and potential for re-introduction of native wildlife extirpated by the snake. The challenging nature of estimating the value of these non-market benefits prevents them from entering the analysis explicitly, but it can be assumed that they would greatly increase the positive outcomes of population reduction.

Chapter 3

Neutral Invaders: The impact of WWI on Invasive Species Dispersal

3.1 Introduction

Studies of economic history and political science have examined the external trade impacts of militarized conflict to provide more comprehensive estimates of the costs of war (Barbieri and Levy 1999, Anderton and Carter 2001, Broadberry and Harrison 2005). In a pair of recent papers (Glick and Taylor 2010, Gowa and Hicks 2017) researchers have called specific attention to these effects as they relate to World War I (WWI), which marked the end of a pronounced period of globalization caused by the technological advancement of the industrial revolution. The aforementioned studies find compelling evidence that the economic costs of the conflict, resulting from changes in international trade, were both persistent and widespread. International trade can be accompanied by its own externalities, notably the introduction and dispersal of invasive species (McNeely 2006, Costello et al. 2007, Hulme 2009, Epanchin-Niell 2017). In this paper we explore the consequence of World War I on invasive species introductions as an extension of the trade externality, and whether the potential environmental impacts mitigate or enhance the overall cost of conflict.

The modern world is characterized by a vast and complex network of global connections, characterized by economics, travel, politics, and often all three. Economic historians have studied this globalization and when it began (O'Rourke and Williamson 2001, O'Rourke and Williamson 2002), but regardless of these details the implication is that actions occurring in one part of the world probably have consequences somewhere else entirely. In many cases, this is most easily seen by the unfortunate event of military conflicts and the costs paid by not only the warring nations, but neutral ones as well. The most obvious costs of war are those represented by the loss of life and the capital and equipment used in the waging of wars. These costs are jarring on their own, but academics in a variety of fields have sought to develop estimates of the indirect costs of war as well (Mansfield and Pollins 2009, Bonfetti and O'Rourke 2017). Indirect costs are exemplified by foregone economic growth, lost trade opportunity, and other standard economic metrics, but there are myriad additional externalities, many of which carry heavy environmental impacts. The present study will focus on just one of these impacts that is closely tied to international trade: invasive species.

Invasive alien species (IAS) are an important environmental and economic concern, with estimates of damage in the United States surpassing $100 billion annually (Pimentel et al. 2005), and once they have been introduced, it is very challenging to eradicate them (Jardine and Sanchirico 2018). These factors have contributed to invasive species being labelled as the second-greatest threat to biodiversity, following habitat loss to human development (Perrings et al. 2000). The study of IAS has begun to focus on human activity and institutions as determinants of species dispersal and impact on ecosystems, economies, and human communities (McNeely 2006, Hulme 2009). In particular, international trade has been shown to be a primary factor in the likelihood of IAS spread (Levine and D'Antonio 2003, Westphal et al. 2008, Epanchin-Niell 2017). Given the ability of invasive species to impose significant environmental damage and economic harm, studies that estimate indirect costs of war attributable to changes in international trade may be over/underestimating the overall costs when they do not account for these species introductions.

Guam's experience with the Brown Tree Snake may be the most prominent example of a biological invasion facilitated by international military conflict. Further, the importance of Guam as a strategically valuable military asset creates additional opportunity for spread as vessels enter and exit the ports and military bases. Looking beyond IAS strictly related to military activities, classic examples of trade-borne invasive species are the Quagga Mussel (*Dreissena rostriformis bugensis*) and the Zebra Mussel, briefly mentioned in chapter 1. Native to Eurasia, these mussels were introduced to U.S. waterways in the late 1980s from ballast water entering the Great Lakes regions of the United States from abroad. It is believed that a single ship traveling from the Black Sea is responsible for the introduction of the zebra mussel to the great lakes, while quagga were introduced from the same region although later (NAS Database 2018). In three decades, these mussels have become established in all of the Great Lakes and all large, navigable rivers in the eastern United States. These species are known for their rapid growth, displacing native species, disrupting food webs via water filtration, and have had a drastic impact from clogging the water pipes of utilities that operate along the coasts of the great lakes, such as power plants, public water supplies, and industrial facilities (Leung et al. 2005, NAS Database 2018). The economic impact caused by the zebra mussel alone is estimated to be $1 billion dollars annually, and the challenge of eradicating the species suggests that these costs may persist for many years (Pimentel et al. 2005).

The global and economic conditions that were present in the years before World War I saw nearly a century of increasing international trade, capital mobility, and increased market access. The technological changes brought by the industrial revolution saw long-distance transportation costs fall to levels never seen before, and thus more travel and international exchange. However, Broadberry and Harrison (2005) state that competition from foreign nations laid the foundations for the eventual conflict that occurred. The protectionist policies that were seen following the war, coupled with the Great Depression, saw a sharp collapse in international trade (O'Rourke 2017). The contrast in trade policies between the pre- and post-war periods, relatively short duration of conflict, and geographic concentration of battles make World War I a convenient natural experiment to measure external impacts of war.

The intuitive basis behind the idea that conflict depresses trade is that warring nations impose embargoes upon their foes, which is highlighted in the case of WWI (and II) by the fact that almost all of the major independent nations participated. Following the arrangement of peace, one might expect trade to then return to its pre-war level, or alternatively that some level of distrust or animosity persists, further dampening trade relations after the war. In some of the most thorough examinations of war's effect on trade, Glick and Taylor (2010) and Gowa and Hicks (2017) use historically-founded gravity models to demonstrate that the negative trade impact of WWI took about 10 years to subside for nations officially participating in the global conflict. However, these studies depart upon the nature of spillover trade effects to neutral countries. Where Glick and Taylor identify a broad, but consistent, negative impact on trade regardless of whether the country was part of the war, Gowa and Hicks argue that warring nations substituted embargoed trade lines with neutral countries, creating a positive spillover effect. Extending these competing hypotheses to include an examination of how WWI affected invasive species risk via trade externalities is the main contribution of the present research.

Due to the role that trade flows embody as a transportation vector for invasive species, a reduction in international trade would correspond to lower invasive species risk. In this way, the temporary trade losses experienced during and after World War I may actually be somewhat offset by fewer IAS species that are able to impose lingering economic damage. However, Costello et al. (2007) show that invasive species risk may be higher between partners with a weaker trade history, as there is a larger pool of candidate species remaining. During World War I, neutral countries were relatively small (with the exception of the United States, which eventually entered) as were their trade flows. If the hypothesis proposed by Gowa and Hicks is valid that war pushed trade to these neutral countries, there may actually have been a greater risk of IAS introduction and even larger indirect costs.

A two-step empirical model is proposed to assess the impact of World War I on invasive species dispersal risk in the United States. The first stage develops empirical estimates of IAS risk in trade, and the second stage tests the impact of WWI on that risk. Applying a trade-based model developed in Costello et al. (2007), maximum likelihood estimation is used to estimate marginal introduction risk (MIR) along trade pathways between two individual port districts in the United States: San Francisco Bay and Chesapeake Bay. These districts were chosen to exploit the fact that most military activity during World War I was concentrated in western Europe, and North Atlantic trade was more heavily impacted than other trade pathways (Miller 2012). Based on this fact we expect greater trade effects in Chesapeake Bay than in the Pacific port of San Francisco. To test this we estimate a difference-in-difference model, where the first difference is MIR disparity between ports, and the second difference is between pre-and post-war MIR.

The remainder of this chapter is structured as follows: Section 2 discusses the motivation and context that informs our study, based on research in economic history, international trade, and economics of invasive species; Section 3 introduces the models of invasion risk and our difference-in-difference, as well as reviews our data and its sources; Section 4 presents preliminary results of the maximum likelihood estimation, and discusses some implications for the second stage model; Section 5 offers analysis of the preliminary results and implications for future research.

3.2 Motivation, Empirical Niche, and Hypotheses

This chapter brings together three bodies of literature that span a variety of disciplines. First, academic study of the comprehensive costs that accompany militarized conflict is a topic that has occupied the attention of not only economic history, but political science, international relations, and many others. International trade and commerce has become such an integral part of modern society that study of its consequences, both intended and incidental, are studied broadly. Finally, the primary externality of interest in this analysis is the economic and environmental harm created by IAS, an issue that has seen marked growth within environmental economics over the past several decades. We conclude the section by establishing the hypotheses to be tested by the empirical model in the paper.

3.2.1 Estimating the Cost of Militarized Conflict

One of the main tasks confronted by the field of economics is measuring costs, and a major cost across the arc of human history is that imposed by violent conflict between nations. By no means is this a new question, with debates surrounding appropriate estimation of war cost (and consequently payment) appearing in some of the earliest volumes of economic journals (Davenport 1919, Viner 1920), and were often fielded by classical economists such as Thomas Malthus and David Ricardo. Overall costs of war can be broken down into direct costs, such as casualties and capital lost to the war effort, and indirect costs, which can include trade losses, sluggish growth, etc. Thoughtful study of these direct costs is important, but the present research focuses on invasive species risk is more in line with indirect costs, thus the literature discussed in this section focuses on that category of research. For a thorough review of direct economic costs of war, readers are directed to Bozzoli, Bruck, and Sottsas (2010).

Indirect costs of conflict have been approached in a variety of ways, one of the most common being to study the trade effects. Relegating that discussion to the following section on international trade economics, economists have also looked at indirect costs from institutional shifts, long-term economic welfare effects, and diversion of foreign investments.

The role of war as a catalyst for institutional change and subsequent economic consequences have seen growing research interest in recent years (Acemoglu et al. 2011, Calomiris and Pritchett 2016). Results of such study support the notion that institutional change is an important factor in economic growth. While research in this vein seems to be more focused on the development of institutional factors, they lend themselves to a broad understanding of the comprehensive costs of war.

The long-term growth effects of conflict may also be considered indirect consequence, as the effect can be delayed well beyond the formal resolution of conflict (Blomberg, Hess, Orphanides

2005). Kubi (2005) estimate the impact of wars on GDP growth rates, and actually finds that nations who have had a war experience improved long term growth rates. Studying the growth effects of conflict is of particular importance to economists concerned with development in low-income parts of the world (Collier 2007, Gates et al. 2011). Gates et al. (2011) find that while most indicators of development suffer from conflict, such as infant mortality or access to potable water, they find evidence of faster growth rates in the reconstruction period after a war, consistent with findings by Kubi (2005). Despite the findings that growth rebounds following conflict, it is unlikely that the gains in growth will match the projected growth of an economy without substantial lag. Abadie and Gardeazabal (2003) study the impact of terrorist activities in the Basque region of Europe on GDP per capita and capital returns, finding that regional violence had substantial negative impacts on both. More importantly, they simulate the economic growth of the region in the absence of conflict and find the economic losses to be severe, even when accounting for "catch-up" effects during the ensuing peace.

The loss, or redirection, of international capital flows have also been studied as an indirect cost of military conflict (Blomberg et al. 2005, Jensen 2006, Jensen and Young 2008, Lee 2016). The inherent risk that accompanies war discourages investment, and carries considerable economic consequence. While many studies look at this by inspecting events that have already occurred, Jensen and Young (2008) look at the perceptions of future risk that would undermine investment even before conflict has taken place. They estimate the factors contributing to perception of risk based on insurance premiums, and find that democratic stability is a significant indicator. Lee (2016) provides counter evidence regarding the standard theory that investment falls due to conflict by focusing on commodity prices, and how they may be affected by conflict. In particular, the study focuses on how military conflicts impact the price of oil and petroleum, and whether that impacts investment. Foreign investment, much like long-run growth effects, plays a large role in development following conflict in poor areas of the world. The rapid growth during reconstruction identified by studies such as Kubi (2005) and Gates et al. (2011) may represent an attractive environment for foreign investors. Garriga and Phillips (2014) look at this concept, specifically in regards to whether or not private foreign investment follows development aid from global institutions. Their results suggest that aid acts as a signal to investors that reconstruction is in progress, and there is relatively little risk of additional violence.

The literature on long run growth and foreign investments provide mixed results regarding the indirect economic costs of war. In both cases, there is evidence that the external consequences of war can have significant negative impacts on economic growth and investments; however there is generally resurgence in both areas following conflict. In the next section discussing the impact war has on trade we will return to this in the context of lagged effects of conflict.

3.2.2 Militarized Conflict and International Trade

Simply stated, militarized conflicts impose external costs on international trade flows by creating barriers to trade, whether those are physical (such as blockades) or political (embargoes). Despite the apparently straightforward reasoning behind this idea, the conclusions of studies on this topic varied widely (Li and Sacko 2002). Several studies examining trade effects provide evidence that wars had the anticipated effect of reducing trade volumes (Anderton and Carter 2001, Blomberg and Hess 2004, Martin et al. 2008b, Glick and Taylor 2010). On the other hand, there is evidence that trade has little impact, or even increases it (Barbieri and Levy 1999, Barbieri and Levy 2001, Gowa and Hicks 2017). Barbieri and Levy (1999) provide an interesting account of circumstances where warring nations actually continue trade with each other, even in open conflict. A growing body of literature actually looks at the relation in the opposite direction, considering how trade impacts likelihood of conflict (Barbieri 2002, Hegre et al. 2010, Schultz 2015). In contrast to this position, Martin et al. (2008a) actually argue that globalization reduces the opportunity cost of military conflict, since it reduces bilateral dependency. This contradicts the position that trade contributes to a liberal peace argument.

There have been multiple attempts to disentangle these conflicting results. Li and Sacko (2002) use rational expectations theory to make the argument that the relationship is not between trade and conflict, itself, as much as it is between trade and the degree to which the conflict was unexpected. Mansfield and Pevehouse (2001) point to the failure to account for institutions, such as preferential trade agreements as an important misstep. Many more explanations have been proposed, but an exhaustive account of this debate is beyond the scope of this paper. Rather, attention is focused upon two papers representing each side of the debate that both analyze World War I. Almost all of the studies previously mentioned focus on conflicts that occurred after the conclusion of the second world war, the exceptions being Glick and Taylor (2010) and Gowa and Hicks (2017). In each of these articles, the authors argue that the world wars are distinct from the following series of conflicts due to the international nature, high participation, and that since the vast majority of great powers participated, most had been trade partners prior to conflict, especially for WWI. Glick and Taylor (2010) use a gravity model and large panel data set to estimate the trade costs of World War I and World War II, with special attention to the lagged and spillover trade effects. Their results show that the lagged effects are substantial, and can take almost a decade to subside, and the spillover effects to neutral countries was also negative as well as significant. Gowa and Hicks (2017) also use a gravity model and panel data set to examine the effects of World War I on trade. They find supporting evidence that the lagged impact of the war imposed substantial economic losses, but argue that the spillover effects were largely positive for neutral countries. This positive effect being caused by trade shifting from belligerent pathways to the neutral countries. The authors cite the difference between their results and Glick and Taylor's as a consequence of inappropriate model specification in the earlier paper. In particular, Gowa and Hicks find the assumption made in the 2010 paper that war affected imports and exports equally to be untenable.

Rather than disprove or support either side of this ongoing debate, the present analysis is related but distinct and seeks to assess how war impacts the risk of invasive species introductions. If conflict has a negative effect on trade, this may actually be accompanied by reduced invasion risk and lower long-run environmental and economic damage. Alternatively, if trade with new partners increases it may increase the chance of novel IAS reaching the host country and the consequent damages.

3.2.3 International Trade and Invasive Species

Economic study of IAS has grown in recent decades, demonstrating the necessity of interdisciplinary cooperation for managing an environmental hazard capable of significant economic harm, and highly connected to economic activity such as trade and development (Epanchin-Niell et al. 2017). Trade is an important vector for unintentional IAS introductions, with a long history of animals stowing away upon boats, planes, and in shipping containers (Hulme 2009). Economic papers on IAS trade range from theoretical analyses of managing introductions (Margolis et al. 2004, Batabyal and Nikamp 2017) , empirical studies of invasion risk (Costello et al. 2007, Westphal et al. 2008, Epanchin-Niell and Liebhold 2015, Brenton-Rule et al. 2016), and policy analysis

(Barbier et al. 2013, Lodge et al. 2016). In this section we focus on the empirical models of risk, mainly those relating to international trade. Marbuah et al. (2014) and Epanchin-Niell (2017) provide more exhaustive discussion of the current state of the economic literature on invasive species.

Most empirical studies aim to identify specific risk parameters that contribute to an invasion of IAS in order to better inform policies targeting IAS prevention. Westphal et al. (2008) represents one of the first comprehensive analyses of global invasion risk, making use of regression tree analysis to study economic, ecological, and biological determinants of risk at the country level. This study established empirical evidence of merchandise import trade as a leading factor in IAS introductions worldwide. Brenton-Rule et al. (2016) study how corruption and governance of trade partners impact IAS introductions to New Zealand over a ten-year period. They find that socioeconomic factors expected to influence governance and quarantine efficacy, such as regulatory quality and the rule of law, had significant bearing on the likelihood of IAS dispersal. Based on their empirical estimates, they state that if New Zealand structured trade policy to account for these governance factors that introductions could be reduced ninefold.

The risk analysis in this paper makes use of the empirical models developed in Solow and Costello (2004) and Costello et al. (2007). In each of these papers, IAS introduction is treated as a Poisson process that is dependent upon shipping. Maximum likelihood methods are used to assess the contribution that shipping traffic has on mean introduction of a harmful species to a new environment. A strength of these models is that they create a statistical relationship between discoveries and introductions, which are distinct, but often treated as the same. Further, the methodology is flexible enough to be used at a global, regional, or even local scale depending on data availability.

3.2.4 Hypotheses

This chapter brings together the discussed literature in order to assess the external consequence of WWI in terms of invasive species introductions. The basic hypothesis of the paper is that the external effect of the conflict on the structural and institutional foundations of global trade influenced the risk of invasive species dispersal, and thus the indirect costs of WWI. We approach this foundational hypothesis along both temporal and spatial lines in order to isolate the effect of WWI on IAS risk. First, if this hypothesis is correct, we would expect to see the marginal invasion risk following WWI to change relative to its pre-war levels. However, there could be several other factors that lead to this change. Geographic concentration of military activities to Western Europe and the North Atlantic Ocean, suggest that changes in IAS introduction risk caused by WWI are probably greater for regions near Europe and the Atlantic. The coincidence of these two hypotheses represents the foundation for the proposal that WWI's effect can be estimated via difference-in-difference. Table 3.1 summarizes the hypotheses of interest in this chapter.

In order to test these hypotheses, we apply a model of IAS introduction and discovery to two geographically distinct U.S. ports, Chesapeake Bay and San Francisco Bay, and estimate the MIR based on model results. The change in MIR is the criteria upon which we test our hypotheses, and the model is detailed in the following section

Table 3.1: Null Hypotheses

Hypothesis	H_0
WWI affected IAS spread	$MIR_{PreWWI} - MIR_{PostWWI} = 0$
IAS externality greater in Atlantic	$\Delta MIR_{CB} - \Delta MIR_{SF} = 0$

As an initial examination of these hypotheses, tables 3.2-3.5 break down the import distribution for each port both before and after the war.

Table 3.2: PreWar CB Composition summary stats; Import share by individual region

	Mean	Min.	Max.	Std. Dev	n
N. America	0.02	0.002	0.05	0.009	42
C. America	0.19	0.04	0.49	0.11	42
S. America	0.06	0.02	0.22	0.03	42
Europe	0.68	0.38	0.91	0.13	42
Eurasia	0.007	0	0.03	0.008	42
Asia	0.002	0	0.01	0.003	42
Africa	0.03	0	0.11	0.03	42
Pacific Oceania	0.0008	0	0.01	0.002	42
South Asia	0.006	0	0.03	0.01	42

Table 3.3: PostWar CB Composition summary stats; Import share by individual region

	Mean	Min.	Max.	Std. Dev	n
N. America	0.11	0.02	0.30	0.09	27
C. America	0.23	0.02	0.40	0.10	27
S. America	0.20	0.07	0.37	0.09	27
Europe	0.32	0.19	0.65	0.13	27
Eurasia	0.04	0	0.10	0.03	27
Asia	0.002	0	0.01	0.003	27
Africa	0.06	0.003	0.32	0.08	27
Pacific Oceania	0.02	0	0.05	0.01	27
South Asia	0.016	0	0.12	0.03	27

Comparing the pre- and post-war import composition in Chesapeake Bay depicts a notable shift in where shipping originated following WWI. The trade from western Europe fell dramatically, and was offset by additional trade along western Atlantic routes from North America (Mexico and Canada), as well as Central and South America. This compositional effect may have contributed to additional invasion risk following the war, as these countries had much less trade with the region prior to the war and consequently less opportunity to introduce non-native species.

Table 3.4: PreWar SF Composition summary stats; Import share by individual region

	Mean	Min.	Max.	Std. Dev	n
N. America	0.28	0.08	0.5	0.10	42
C. America	0.03	0	0.23	0.06	42
S. America	0.11	0.01	0.30	0.06	42
Europe	0.20	0.09	0.38	0.07	42
Eurasia	0.001	0	0.009	0.002	42
Asia	0.13	0.02	0.32	0.05	42
Africa	0.001	0	0.009	0.002	42
Pacific Oceania	0.22	0.07	0.32	0.07	42
South Asia	0.01	0	0.06	0.01	42

Table 3.5: PostWar SF Composition summary stats; Import share by individual region

	Mean	Min.	Max.	Std. Dev	n
N. America	0.25	0.02	0.44	0.12	27
C. America	0.03	0.005	0.09	0.02	27
S. America	0.05	0.001	0.10	0.03	27
Europe	0.06	0	0.10	0.03	27
Eurasia	0.02	0	0.09	0.03	27
Asia	0.33	0	0.59	0.15	27
Africa	0.01	0	0.30	0.06	27
Pacific Oceania	0.23	0.03	0.82	0.20	27
South Asia	0.03	0	0.12	0.03	27

Turning attention to the compositional adjustments in San Francisco, there is a similar reduction in European trade following the war. Most of the import share is taken up by trade with Asia, where the average import share increased by twenty percentage points. Generally speaking, trade with the Pacific region began to occupy more of the import total as a whole. The average trade with Pacific Oceania did not change much, but became highly variable and in one period made up over 80 percent of total import tonnage entering the port of San Francisco. Costello et al. (2007) showed that the western pacific region became a high-risk trade region during the latter half of the twentieth century, which is consistent with this shift in trade composition.

3.3 Methods and Data

The analysis is built on two models to first estimate the marginal invasion risk of trade, then to test for the impact of World War I on the IAS risk. An overview of the data is presented following the brief description of the modeling procedures.

3.3.1 Invasive Risk Model

We model invasive species introduction, as well as discovery, using maximum likelihood estimation. The first-stage applies the introduction model developed in Solow and Costello (2004), and Costello et al. (2007) to estimate risk in the two port districts of study, San Francisco or Chesapeake Bay.

The model uses historical IAS discovery data y_{jt} and bilateral shipping data s_{jt} where j refers to the trade pathway and time is given as t. Introductions are modeled as a Poisson process, with mean λ_{jt}. Although country-level data on the shipping pathways exists, species origin data are not provided at a highly disaggregate level, thus pathways are defined along a vessels region of origin to match. Below, we will discuss how this affects our model estimates.

$$\lambda_{jt} = \beta_j s_{jt} exp(\gamma_j \sum_{i=1}^{t} s_{ji} + \omega_j t) \tag{3.1}$$

β_j is the main parameter of interest, and reflects the intrinsic risk for a given pathway. Because pathways are defined at the regional level β represents the risk of the region's composition as a whole, which may include nations with varying environments, trade histories, and institutional quality. Therefore, if there is a change in the composition overall, or shifts in the institutional or environmental characteristics of the nations that make up that region, we would expect β to change as well.

In the Costello model, $\gamma_j < 0$ is the attenuation of IAS risk as shipping increases. This is based on the expectation that with greater trade activity, more IAS introductions occur along a given pathway. If there is a finite pool candidate species that can be introduced, then this risk should diminish at higher cumulative levels of shipping, as the pool becomes smaller. However, the interpretation of the parameter depends on the level of aggregation in the trade pathway. For instance, at the highest level of aggregation one pathway would represent the entire world and all import tonnage entering a port in a year. The cumulative shipping in this case is more representative of the strain placed on an ecosystem from trade activity over the study period, and could be expected to actually increase introduction risk over time $\gamma_j > 0$. Even disaggregating to regional pathways, the composition effect would make the sign ambiguous as the pool of candidate species would depend on what nations were included.

ω_j captures the time trend, and measures the effect of technological development over time that shortens travel time and increases vessel size, both of which are expected to increase invasion risk.

The IAS discovery process is modeled as following a geometric distribution with constant discovery probability, π, and the Poisson mean for discovery is d_{js}. In the current analysis, the nuisance parameter is taken from Costello et al. (2007), and is $\pi = 0.048$. This corresponds to an approximate discovery lag of 13 years. Note that discoveries must follow introduction, so the mean discovery is a function of the invasion risk during the period which it entered the ecosystem, t, and the geometric discovery process.

$$d_{js} = \sum \pi(1-\pi)^{t-s-1}\lambda_{jt} \tag{3.2}$$

The log-likelihood of IAS discovery is used in order to estimate the risk parameters $\hat{\beta}$, $\hat{\gamma}$, and $\hat{\omega}$.

$$LL(\beta_j, \gamma_j, \omega_j | s_{jt}, y_{jt}) = \sum_{j=1}^{J}\sum_{t=1}^{T}[y_{jt}exp(d_{jt}) - d_{jt}] \tag{3.3}$$

All calculations were conducted using the optimization toolbox in *Matlab 2014a*.

3.3.2 Testing impact of World War I

Chesapeake Bay and San Francisco Bay are both major ports of entry to the United States, but serve different oceanic ranges. *A priori*, we expect that geographical and historical circumstances drive a wedge between invasion risk for our two ports of interest. Further, we believe that this geographic disparity can be used to illustrate the effect that World War I, and its trade consequences had on invasion risk within the United States. We measure these trade-based effects on IAS risk by comparing the change in MIR before and after the war. MLE parameters are used to estimate the marginal invasion risk for each pathway across t, or the additional species introduction expected from an additional unit of shipping.

$$M\hat{I}R_{jt} = \hat{\beta}_j exp(\hat{\gamma}_j \sum_{i=1}^{t} + \hat{\omega}_j t) \tag{3.4}$$

These MIR values are used in the difference-in-difference estimation to test for the external impact of WWI on invasive risk. To test this hypothesis, we will estimate a fixed effect difference-in-difference model shown below, including time trends.

$$(MIR_{jt}|CB - MIR_{jt}|SF) = \phi_1 + \phi_2 WWI + \phi_3\, t + \phi_4\, t * WWI + \epsilon_{jt}$$

3.3.3 Data Collection

This study uses historical data on IAS discoveries in the two ports of study, as well as bilateral trade data at the port-level.

IAS discovery data sets were taken from Cohen and Carlton (1995) for San Francisco, and the Chesapeake Bay data is taken from the National Exotic Marine and Estuarine Species Information System (NEMESIS) database managed by the Smithsonian Institute (Fofonoff et al. 2003). These data include date of discovery, native region, and method of introduction. Table 3.6 provides summary statistics on the number of IAS discoveries for each port.

Table 3.6: Summary Statistics for IAS Discovery

Port	Average	Minimum	Maximum	Std. Dev	n
$SF|PreWWI$	0.79	0	5	1.075	42
$CB|PreWWI$	1.19	0	4	1.215	42
$SF|PostWWI$	1.22	0	5	1.281	27
$CB|PostWWI$	1.07	0	4	1.17	27

Historical import data was collected from the Annual Report on Navigation and Commerce produced by the Census Bureau for the years 1871-1912 and 1919-1945. These data include the import tonnage entering the port district by country of origin, but as discussed above data describing IAS native ranges are not defined at the country level, so the trade data was scaled to regions Table 3.7 provides summary statistics for the annual import tonnage entering each port from all sources.

Table 3.7: Summary Statistics for Import Tonnage (in millions of tons)

Port	Average	Minimum	Maximum	Std. Dev	n
$SF \vert PreWWI$	0.90	0.35	1.36	0.23	42
$CB \vert PreWWI$	1.03	0.31	1.67	0.41	42
$SF \vert PostWWI$	2.01	1.02	8.00	1.36	27
$CB \vert PostWWI$	2.13	1.00	4.13	0.744	27

3.4 Results

Models for IAS risk are estimated for total world trade, as well as regional pathways. In each case estimates are provided alongside likelihood ratio statistics for individual significance. Prior to estimation, figures 3.1 and 3.2 present several basic data plots to illustrate some trends in the discovery and import data.

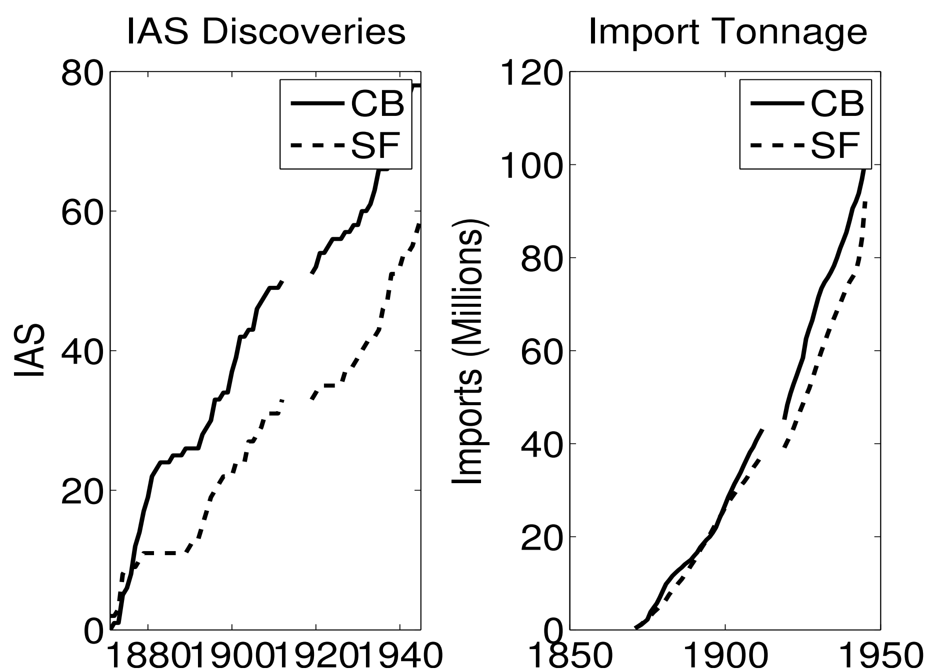

Figure 3.1: Data trends

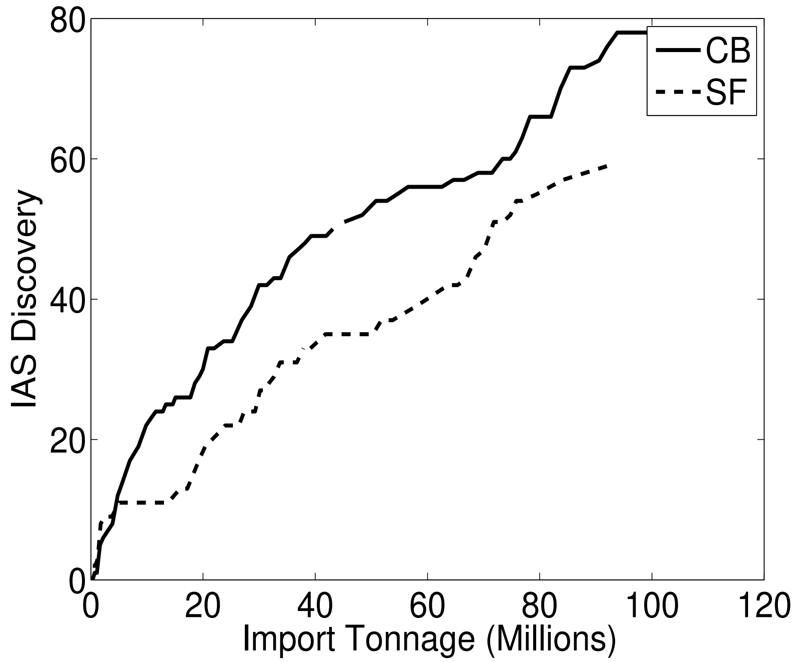

Figure 3.2: Discoveries against imports

The data show that across the pre-war and post-war periods, discoveries and trade are increasing, and there appears to be a positive relationship between import tonnage and the discovery of invasive species. These patterns are all consistent with expectations.

3.4.1 World Trade Risk

The analysis begins at the highest level of aggregation, studying the risk of introduction from imports entering a port from any source region. This decision was made because it provides the most thorough record of introductions and imports while still providing insight to the research question of how WWI affected IAS risk. In particular, the discussion of β in section 3 illustrates that changes in this parameter may reflect compositional changes in trade partners (as might be expected due to evidence from Gowa and Hicks (2016) or institutional shifts that may affect the risk of species introduction. Observations from North America are excluded, as there may be additional entry vectors other than shipping for such species.

Table 3.8 presents MLE estimates across the full data set (1871-1945), but ignoring the years of World War I. Likelihood ratio statistics appear below each parameter estimate in parentheses.

Table 3.8: MLE results for full data set

Parameter	Chesapeake Bay	San Francisco
β_W	10.71***	4.76***
	(63.92)	(244.22)
γ_W	0.24***	0.21***
	(21.75)	(12.82)
ω	-0.34***	-0.22***
	(12.79)	(8.36)

The results of the long-term estimation are individually significant at a high level, and suggest that over the 70-year period, trade entering Chesapeake Bay had a greater overall introduction risk. γ is positive for both ports suggesting that as imports from all regions in the world increased, so did introduction risk. As mentioned in section 3, at this level of aggregation γ can be viewed as the effect of cumulative shipping as an ecosystem disturbance, and the positive estimate fits with expectations. ω shows that introduction risk falls over time, counter to expectations that technological advancement in shipping would cause this factor to increase. This time trend would be expected to capture other factors than technology, which may explain the decline in introduction risk such as institutional or structural shifts. It is worth noting that the attenuation rate observed for San Francisco Bay is substantialy lower than that in Chesapeake Bay, which may reflect such a structural shift towards greater trade in the west coast of the United States. We will examine this prospect more closely in the refined analyses below.

In order to illustrate the effectiveness of the model, figures 3.3 and 3.4 plot the recorded discovery in each port, as well as fitted results for discovery (dashed line) and introduction (dotted line). The vertical line represents the break in data that coincided with the occurrence of WWI.

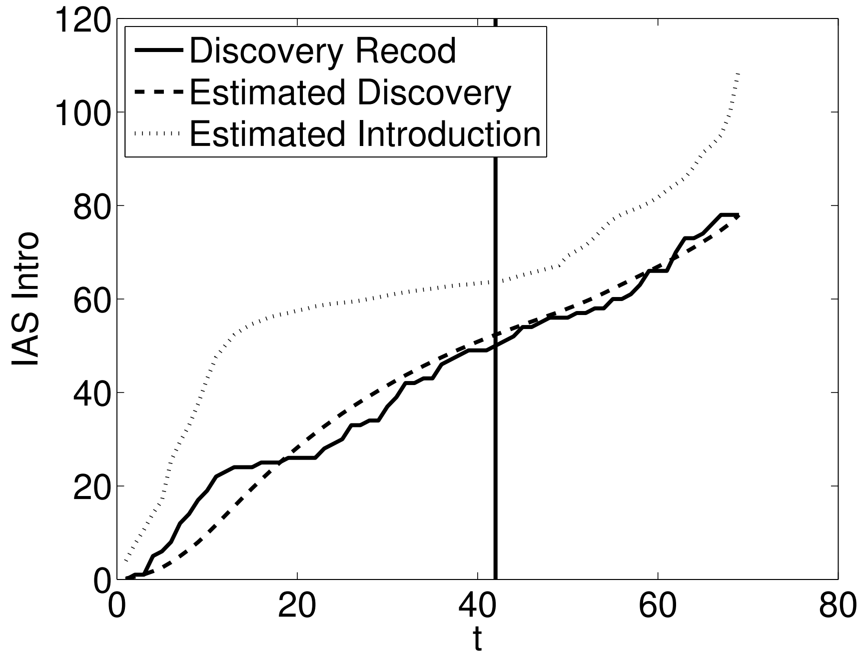

Figure 3.3: Results of full Chesapeake Bay estimation

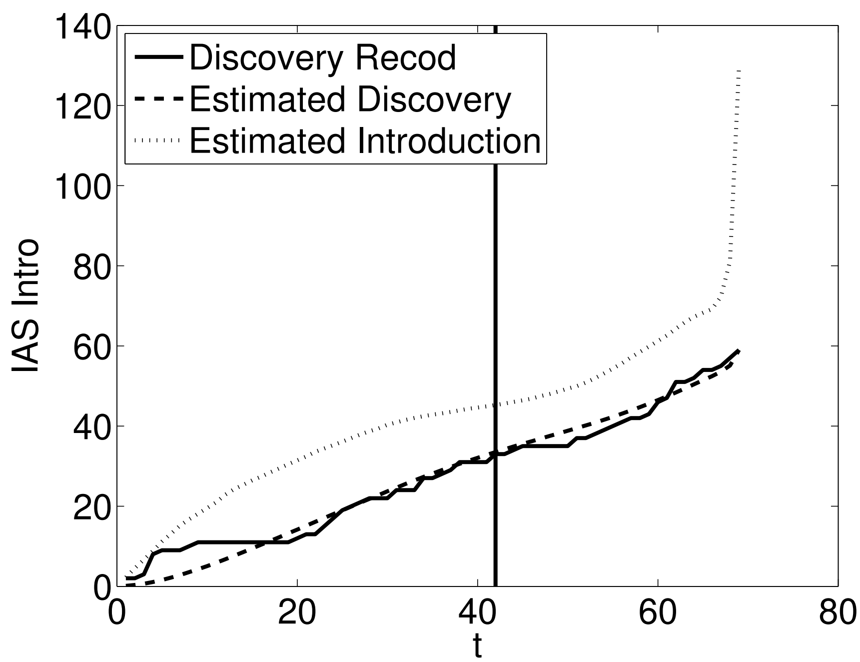

Figure 3.4: Results of full San Francisco Bay estimation

The estimated discoveries fit reasonably well with the historical record, which reinforces confidence in the statistical strength of the results. Findings for Chesapeake Bay appear to show a slight inflection point coinciding with WWI, providing some evidence that the risk relationship changed in response to the global conflict. In both cases introductions appear to jump suddenly at the conclusion of the study period, especially for San Francisco. However, this likely reflects the sharp introduction in shipping seen in San Francisco following the war (seen in 3.1).

In order to assess the impact WWI had on invasive risk, we estimate MLE parameters before and after WWI.

Table 3.9: World trade risk for pre- and post-war

Parameter	CB	SF
β_{Pre}	2.98***	934.60***
	(64.06)	(5.59)
β_{Post}	3.34***	0.76***
	(293.65)	(459.5662)
γ_{Pre}	-9.56	9.34***
	(1.61)	(5.59)
γ_{Post}	-0.70	0.09
	(0.13)	(0.09)
ω_{Pre}	4.20	-6.05***
	(0.87)	(5.59)
ω_{Post}	1.13	-0.01
	(0.11)	(0.08)

The β values all have the expected sign and are individually significant based on likelihood-ratio tests. The only model in which the other parameters are statistically different from zero is for San Francisco prior to the war. In this case, we see that cumulative shipping has a sizable positive impact on introduction risk, which may be attributable to ecosystem degradation. The sign of the time trend ω is negative, which is unexpected, but may reflect advances in monitoring sophistication at the port. The relative change in the risk parameters is of special importance to our analysis, as this is the proposed measure of the impact from World War I.

We first consider the change in pre- and post-war risk in Chesapeake Bay, noting that the β parameter increases moderately. As one of the prominent American shipping ports serving the North Atlantic, this heightened risk can be attributed to additional traffic during and after the war. This increase in risk may also be an outcome of changes in the composition of trade. The summary statistics presented above showed that following WWI, imports entering Chesapeake Bay became more evenly distributed across areas like South and Central America.

San Francisco experienced an enormous change in IAS risk following the war. Referring again to the pre- and post-war import distribution, it is clear that the composition of trade partners entering San Francisco changed, but it is not immediately apparent how this shift corresponds to the dramatic adjustment in invasion risk following WWI. In the analyses below, several different explanations are examined.

3.4.2 Individual Pathway Risk

The trade paths are disaggregated to European and Pacific imports, as these pathways capture the most information regarding both imports and introductions. Table 3.10 presents the MLE results for the Chesapeake Bay pathways before and after WWI.

Table 3.10: Chesapeake Bay regional pathway analysis

Parameter	Europe	Pacific Ocean
β_{Pre}	4.58***	5227.33***
	(269.95	(188.37)
β_{Post}	4.94***	74.64***
	(99.81)	(286.85)
γ_{Pre}	-15.18	646.92
	(1.02)	(0.36)
γ_{Post}	-0.62	-5.51
	(0.62)	(0.21)
ω_{Pre}	3.47	0.05
	(0.37)	(0.06)
ω_{Post}	0.43	0.02
	(0.48)	(0.0007)

Again, we see that the β risk parameter finds the most consistent statistical support. The risk along the European pathway increases following World War I. Although the additional risk is relatively minor, it mirrors the effect seen in the world trade model. The decrease in risk from the Pacific Region is drastic, but remains a high-risk trade pathway. This persistent risk is an important factor in explaining the jump in introduction risk from world trade seen in Table 3.9, as following WWI trade with the Pacific region increases dramatically (seen in appendix).

Table 3.11 presents the results of the regional pathway analysis for San Francisco.

Table 3.11: San Francisco Bay regional pathway analysis

Parameter	Europe	Pacific Ocean
β_{Pre}	2e+04	0.70***
	(7e-06)	(39.58905)
β_{Post}	1.59e+6***	25.73***
	(78.22)	(47.9817)
γ_{Pre}	-251.50	1.88
	(2e-07)	(0.84)
γ_{Post}	263.82	3.21*
	(2.52)	(3.6147)
ω_{Pre}	8.20	-0.62
	(8e-07)	(0.70)
ω_{Post}	-37.07	-4.01*
	(2.53)	(3.63)

Risk along the Pacific trade pathway is significant in both periods, although following WWI risk from the Pacific jumps substantially. European risk is peculiar, exhibiting immense risk with very little statistical evidence prior to the war. Following the war, the intrinsic risk falls but remains high, and the log-likelihood stat rebounds prominently.

Due to the coarse nature of the data, the results shown here obfuscate much of the compositional effects that we expect are responsible for the shifts in IAS risk before and after the war. In order to derive more information regarding the individual pathway risk, data collection and clarification is a priority for future research.

3.4.3 Panama Canal Effect

The Panama Canal may also have had an impact on the introduction risk for either port, as it became an important connection between the Pacific and Atlantic Oceans during this time. Although the canal completed its construction in 1914, it was not open to civilian traffic until 1921 (Maurer and Yu 2008). This places the introduction of a new transcontinental shipping route squarely within the post-war treatment period of our data set.

Maurer and Yu (2008) provide a thorough analysis of the economic benefits afforded by the establishment of this new trade route. The trade opportunities provided by the canal were substantial, and ranged from 27-147 million (1925 $US) in net cost-savings relative to shipping via transcontinental railway. Within intercontinental shipping trade, the majority of these savings were realized along trade routes between the U.S. East Coast to Asia and U.S. West Coast to Europe (Maurer and Yu Table 6). We would expect these cost-savings to increase along these bilateral pathways, along with invasion risk as shipping distance fell dramatically for both.

However, we observed in Table 3.2 - Table 3.5 the exact opposite trend: imports along these routes either fell or were unaffected in our post-war data set. Maurer and Yu point out that most of the traffic along the Panama canal was actually intra-U.S. traffic. In fact, U.S. trade was responsible for 80% of the annual savings from canal shipping on average during the years 1921-1937. Based on these findings, we conclude that the Panama canal did not contribute seriously to imports from outside the U.S. during the relevant study period. Statistical assessment of a relationship between the cost-savings of the trade route on non-U.S. import volumes do not produce evidence of any meaningful connection between the two, further suggesting that the effect of the canal is negligible in the current data set.

Several explanations may exist for why less trade is observed along the relevant shipping paths than the cost-savings estimates might suggest. One factor may be the difference in scope of the present study and that by Maurer and Yu. Maurer and Yu's calculations of social cost-savings along the trade route between the west coast and Europe included shipping to Canada, which benefited enormously due to the substantial lumber trade (although even this was dwarfed by lumber shipments to the Atlantic Coast of the United States). Rockwell (1971) estimated annual cost-savings from the canal to this one industry for years 1921-1940. Comparing Maurer and Yu's estimate for total cost-savings and Rockwell's estimate for lumber-specific savings, benefits to the lumber industry made up over 66% of the total canal savings in the first year of operation. After this initial period, lumber-specific savings increased rapidly, and for the period 1921-1940 averaged over $22 million annually (1926 $US). While there is no similar industry-specific analysis for east coast-Asia trade, it is still possible that different study scopes explain some of the divergent findings.

In addition, issues like transshipment may be hidden in the data. That is to say, it is possible that imports from Europe enter an east coast port temporarily before being shipped via Panama Canal to the west coast and would not be picked up in the data set. Fully addressing this counterintuitive result from the operation of the Panama Canal demands additional research. To examine either of the cases above, the historical import data must be revisited in order to clarify source region and import content.

3.4.4 IAS Externality of World War I

A slight inflection in the long-term species invasion paths in Figure 3.3 and 3.4 provided informal evidence that WWI may have had an external impact on IAS spread. Segmenting the data into pre- and post-war samples for individual period risk assessment saw an increase in intrinsic risk for Chesapeake Bay, but a drastic reduction in risk for San Francisco Bay. Regional analysis provided some explanation for these shifts in world risk, but do not offer formal evidence of a structural change caused by the war.

The difference-in-difference model outlined in section 3 suggests that the relative change between MIR in San Francisco and Chesapeake Bay before and after the war can be used as a formal test for the presence of a trade-based IAS externality. Using the MLE estimates from the regional risk analysis, MIR is calculated for each trade pathway in all study years before and after the war. Table 3.12 presents the summary statistics for each port over the study period. Compared to Chesapeake Bay, the introduction risk for San Francisco is lower and less variable, despite the drastic increase seen in the figures above.

Table 3.12: Summary Statistics for Annual MIR

Port	Average	Minimum	Maximum	Std. Dev	n
$MIR_{World\|CB}$	1.52	0.13	12.6	2.32	69
$MIR_{World\|SF}$	0.46	0	6.36	1.20	69

The lack of strong statistical evidence for the γ_j and ω_j Suggests that these values should be assessed with caution. When these parameters fall out of the MIR equation, the invasion risk is simply equal to the intrinsic risk parameter β which is constant across time. In light of this admitted shortcoming of the model, structural change is assessed against the hypothesis that if World War I had no effect, then the MLE coefficients for each period should be the same. Based on this hypothesis, all models reject the null hypothesis of zero structural change (i.e. $H_0 : \beta_{j|pre} = \beta_{j|post}$) with a high level of confidence $p < 0.001$.

Table 3.13: Difference-in-Difference

	Dependent variable:		
	$MIR_{CB\|W}$	$MIR_{SF\|W}$	ΔMIR_W
	(1)	(2)	(3)
WWI	-8.212^{***}	-2.597^{**}	-5.617^{***}
	(1.944)	(1.177)	(0.871)
LongTrend	-0.187^{***}	-0.085^{***}	-0.101^{***}
	(0.017)	(0.010)	(0.008)
PostWarTrend	0.239^{***}	0.085^{***}	0.154^{***}
	(0.038)	(0.023)	(0.017)
Constant	6.029^{***}	2.597^{***}	3.434^{***}
	(0.427)	(0.258)	(0.191)
Observations	69	69	69
R^2	0.673	0.554	0.750
Adjusted R^2	0.658	0.533	0.739
Residual Std. Error (df = 65)	1.358	0.822	0.608
F Statistic (df = 3; 65)	44.555^{***}	26.890^{***}	65.059^{***}

Note: *p<0.1; **p<0.05; ***p<0.01

3.5 Discussion and Implications

This dissertation chapter presents a novel empirical question inspired by research in the fields of historical and political economy, international trade, and environmental economics. Based on the fact that international shipping act as a vector for invasive species dispersal, trade externalities from World War I are extended to include the consequence of changes in IAS invasion risk. Using historical data on IAS introductions and port-level trade data, risk is assessed at the world and regional levels.

Results show that trade composition was influenced by the institutional shifts accompanying the first World War, but the overall impact on indirect costs remains ambiguous. In Chesapeake Bay, overall risk of introduction was increased due to additional risk and traffic along the Pacific trade pathway. San Francisco, in contrast, experienced a reduction in risk along the same pathway. This difference may be attributed to the trade histories each port had with the Pacific region prior to World War I, San Francisco having maintained greater import volumes both before and after. However, there is little statistical evidence supporting this concept (we would expect to see this attenuation effect in γ).

The results of this analysis demonstrate preliminary evidence that a structural shift in international trade influence the likelihood of IAS introduction. The compositional effects discussed above support the hypothesis that conflict can push trade to new regions, but additional work is needed in order to effectively answer the question of whether or not this environmental externality enhance or mitigate the economic costs of militarized conflict. The Costello model lends itself to individual pathway assessment, but the current state of many IAS databases does not match that of trade flows, which can limit the analysis to coarse levels of aggregation. Beyond the shortcomings of the available data, the empirical model can be refined to focus more specifically on additional risk factors identified within the literature such as specific commodity networks (Chapman et al. 2017), institutions and quarantine efficiency (Brenton-rule et al. 2016), and spatial dependencies (Epanchin-Niell 2017).

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Appendix A

Mathematical appendix for Chapter 1

A.1 Solving for λ_t

We solve equation 1.15 using an integrating factor methodology typical for these types of problems (Simon & Blume p. 639-640). The first step is to identify the integrating factor, a term that I will call ψ_s. The selection of this term will become apparent momentarily, but for now it is given as:

$$\psi_s = e^{\int_t^s [g_{n_\tau} - h_{n_\tau} - r]d\tau} \tag{A.1}$$

As before, the parameter s represents some time period within the interval $[t, T]$ while τ is a constant of integration. Both functions g_{n_τ} and h_{n_τ} are defined for all $s \in [t, T]$. We will pre-multiply 1.15 by ψ_s:

$$e^{\int_t^s [g_{n_\tau} - h_{n_\tau} - r]d\tau}\dot{\lambda} + e^{\int_t^s [g_{n_\tau} - h_{n_\tau} - r]d\tau}\lambda_s[g_{n_s} - h_{n_s} - r] = e^{\int_t^s [g_{n_\tau} - h_{n_\tau} - r]d\tau} D_{n_s} \tag{A.2}$$

At this point, it is helpful to briefly examine the way we chose the form of ψ_s. Simply put, the integrating factor is constructed such that $\frac{d\psi_s\lambda_s}{ds}$ will generate the left-hand-side of A.2. This is demonstrated below:

$$\frac{d\psi_s\lambda_s}{ds} = \frac{de^{\int_t^s [g_{n_\tau} - h_{n_\tau} - r]d\tau}\lambda_s}{ds}$$

$$\frac{de^{\int_t^s [g_{n_\tau} - h_{n_\tau} - r]d\tau}\lambda_s}{ds} = e^{\int_t^s [g_{n_\tau} - h_{n_\tau} - r]d\tau}\dot{\lambda} + e^{\int_t^s [g_{n_\tau} - h_{n_\tau} - r]d\tau}\lambda_s\left(\frac{d\int_t^s [g_{n_\tau} - h_{n_\tau} - r]d\tau}{ds}\right)$$

Focusing for a moment on the red term in parentheses, we can see a direct application of the first fundamental theorem of calculus which states that in the case $F(x) = \int_a^x [f(t)]dt$, then $\frac{d}{dx}F(x) = \frac{d}{dx}\int_a^x [f(t)]dt = f(x)$. Applying this to the present example:

$$\frac{d}{ds}\int_t^s [g_{n_\tau} - h_{n_\tau} - r]d\tau = g_{n_s} - h_{n_s} - r$$

End step-by-step explanation

We can see that the LHS of A.2 is clearly just a time derivative of $\lambda_s \psi_s$.

$$\frac{de^{\int_t^s [g_{n_\tau} - h_{n_\tau} - r]d\tau}\lambda_s}{ds} = \dot{\lambda} e^{\int_t^s [g_{n_\tau} - h_{n_\tau} - r]d\tau} + \lambda_s e^{\int_t^s [g_{n_\tau} - h_{n_\tau} - r]d\tau}[g_{n_s} - h_{n_s} - r]$$

Applying this to A.2:

$$\frac{d\lambda_s e^{\int_t^s [g_{n_\tau} - h_{n_\tau} - r]d\tau}}{ds} = e^{\int_t^s [g_{n_\tau} - h_{n_\tau} - r]d\tau} D_{n_s} \tag{A.3}$$

Moving forward, it will be convenient to separate the constant r from $e^{\int_t^s [g_{n_\tau} - h_{n_\tau} - r]d\tau}$. So A.3 becomes:

$$\frac{d\lambda_s e^{\int_t^s [g_{n_\tau} - h_{n_\tau}]d\tau} e^{-r(s-t)}}{ds} = e^{\int_t^s [g_{n_\tau} - h_{n_\tau}]d\tau} e^{-r(s-t)} D_{n_s} \tag{A.4}$$

Integrating both sides of A.4 from t to T:

$$\int_t^T [\frac{d\lambda_s e^{\int_t^s [g_{n_\tau} - h_{n_\tau} - r]d\tau} e^{-r(s-t)}}{ds}]ds = \int_t^T [e^{\int_t^s [g_{n_\tau} - h_{n_\tau}]d\tau} e^{-r(s-t)} D_{n_s}]ds \tag{A.5}$$

Through familiar application of the second fundamental theorem of calculus, the LHS becomes:

$$\lambda_T e^{\int_t^T [g_{n_\tau} - h_{n_\tau} - r]d\tau} e^{-r(T-t)} - \lambda_t e^{\int_t^t [g_{n_\tau} - h_{n_\tau} - r]d\tau} e^{-r(t-t)}$$

The exponential functions on the second term of the LHS collapse to $e^0 = 1$, so that we are left with

$$\lambda_T e^{\int_t^T [g_{n_\tau} - h_{n_\tau} - r]d\tau} e^{-r(T-t)} - \lambda_t = \int_t^T [e^{\int_t^s [g_{n_\tau} - h_{n_\tau}]d\tau} e^{-r(s-t)} D_{n_s}]ds \tag{A.6}$$

With some quick algebra we can now offer a qualitative statement for the co-state variable λ_t:

$$\lambda_t = \lambda_T e^{\int_t^T [g_{n_\tau} - h_{n_\tau} - r] d\tau} e^{-r(T-t)} - \int_t^T [e^{\int_t^s [g_{n_\tau} - h_{n_\tau}] d\tau} e^{-r(s-t)} D_{n_s}] ds \tag{A.7}$$

A.2 Solving for μ_t

$$\theta_s = e^{\int_t^s [\eta_{K_u} - r] du} \tag{A.8}$$

The function η_{K_u} is defined for all $s \in [t, T]$ and u is an integrating variable. Following the same process as above:

$$e^{\int_t^s [\eta_{K_u} - r] du} \dot{\mu} + e^{\int_t^s [\eta_{K_u} - r] du} \mu_s [\eta_{K_s} - r] = e^{\int_t^s [\eta_{K_u} - r] du} C_{K_s} \tag{A.9}$$

$$\frac{d\mu_s e^{\int_t^s [\eta_{K_u} - r] du}}{ds} = e^{\int_t^s [\eta_{K_u} - r] du} C_{K_s} \tag{A.10}$$

Integrating each side over the time horizon $[t, T]$ and applying the second fundamental theorem of calculus:

$$\int_t^T [\frac{d\mu_s e^{\int_t^s [\eta_{K_u} - r] du}}{ds}] ds = \int_t^T [e^{\int_t^s [\eta_{K_u} - r] du} C_{K_s}] ds$$

$$\mu_T e^{\int_t^T [\eta_{K_u}] du} e^{-r(T-t)} - \mu_t e^{\int_t^t [\eta_{K_u}] du} e^{-r(t-t)} = \int_t^T [e^{\int_t^s [\eta_{K_u}] du} e^{-r(s-t)} C_{K_s}] ds \tag{A.11}$$

Again, we see the exponential functions on μ_t collapse to 1, then rearrange to find:

$$\mu_t = \mu_T e^{\int_t^T [\eta_{K_u}] du} e^{-r(T-t)} - \int_t^T [e^{\int_t^s [\eta_{K_u}] du} e^{-r(s-t)} C_{K_s}] ds \tag{A.12}$$

Appendix B

Additional trade figures for Chapter 3

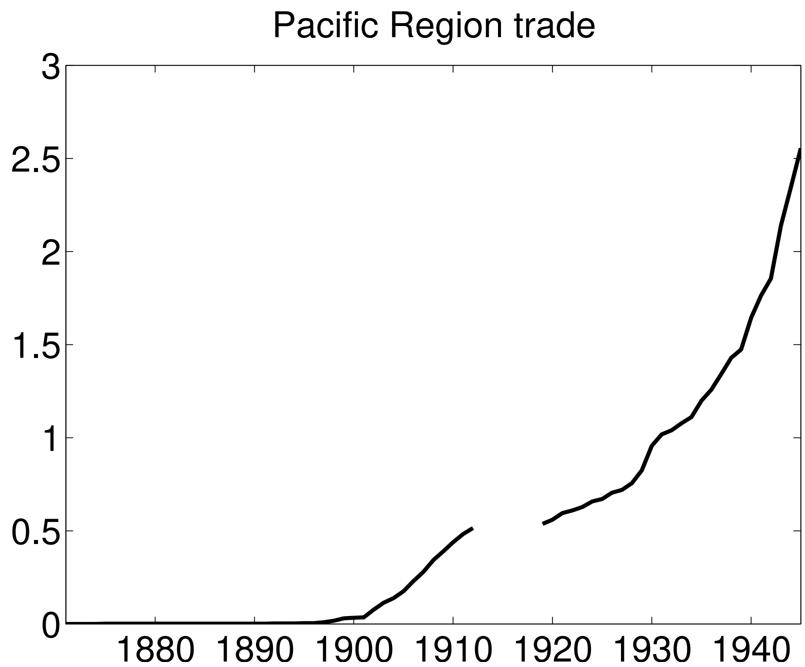

Figure B.1: Chesapeake Bay trade with Pacific

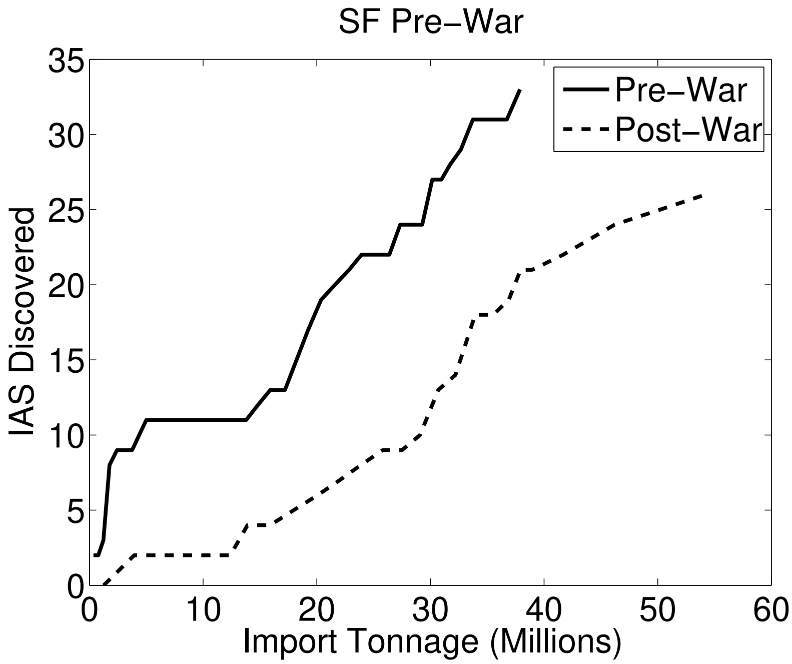

Figure B.2: Comparison of discovery-import relationship in San Francisco