Unintended biological invasions: Does risk vary by trading partner?

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June 1, 2007

Running Title: "Trade and species introductions"

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Abstract

International trade is the primary conduit for unintentional and damaging species introductions. But biogeographic heterogeneity, and differences in historical trade exposure across trade partners suggest that not all imports are equally risky. We develop an analytical model linking exotic species introductions and discoveries to trade volumes. The model is estimated using a novel historical data set on global trade and species introductions by region. Our estimates support theoretical predictions that trade from different regions poses different risks and that the cumulative number of introductions from a region is a concave function of imports. For each trade region we then calculate the marginal and cumulative invasion risk from additional trade. Simple volume restrictions on imports to reduce NIS introductions are not advisable based on coarse cost-benefit calculations.

Keywords: Integrated Likelihood, Introduction, Discovery, Invasive Species, Exotic Species, Trade

1 Introduction

The accidental introduction of non-indigenous species (NIS) is a serious environmental problem. Estimates of the annual economic cost due to NIS range from $4.7 billion (Office of Technology Assessment 1993) to $136 billion (Pimentel et al. 2000).[1] Economic activity is a clear driver of NIS introductions–the leading introduction vector of NIS into the aquatic environment is commercial shipping, with ballast water exchange and hull fouling as the principal modes of introduction (Cohen and Carlton (1995); Ray (2005)). To manage the ship-borne introductions of NIS at a given destination, it is necessary to understand the rate of introductions from different source regions of the world, but deficiencies in modeling and data have prevented such empirical analysis. The introduction rate is expected to vary for at least two reasons.

First, the number of organisms that can potentially be introduced will vary with source region. In part, this simply reflects differences between source regions in the size of the species pool. However, it also reflects differences in the probability that a species introduction will be successful, this latter probability depending in part on the environmental similarity between the source region and the destination. Second, as cumulative shipping traffic from a given source increases over time, introductions will occur, the remaining pool of introducible species will be depleted, and the rate of new introductions will decline. In short, invasion risk will likely decrease in cumulative import volume and vary according

[1] The figure cited by Pimentel et al. (2000) should be viewed carefully. On one hand, it does not include the difficult-to-quantify costs of species loss arising when NIS displace native species. Williamson (1999) argues that competition from NIS is the second most important cause of species loss worldwide; the leading cause is habitat loss. On the other hand, the figure does include the costs of dealing with harmful NIS that have been present in the United States for centuries such as rats and feral pigs.

to the region from which imported goods originate. The latter theoretical prediction may suggest a role for discriminatory policy based on a region's invasion risk, but has not been empirically tested.

In this paper, we use the discovery record of NIS in the San Francisco Bay in conjunction with newly compiled shipping data to estimate the marginal introduction rates for different source regions. To do so we build a structural model which takes into consideration the role played by cumulative import volumes and biogeography of an importer's trade partners. Before taking this model to the data, however, we must also take into account the fundamental difference between NIS introductions and *discoveries* of those introductions. As Costello and Solow (2003) argue, the discovery record is a poor proxy for actual introductions because it reflects a combination of both the introduction and discovery process. While the former depends on trade patterns, the latter depends on a variety of endogenous factors, not least of which is effort allocated to detecting established NIS in the host region.

We therefore employ a model of NIS discoveries which allows for a baseline marginal arrival rate (per unit of imports) to attenuate as a function of cumulative imports while including a delay between arrival and discovery of a species. The baseline arrival rate and speed of attenuation over cumulative imports are estimated using data on NIS discoveries and a novel data set we have collected for foreign trade volume, by country of origin, into the San Francisco Bay area from 1853-1994. The resulting dynamic model includes parameters relating to the introduction and discovery processes. Parameters are estimated via a maximum integrated likelihood approach (Berger et al. 1999). Since our measures of imports and NIS include region of origin, we are able to calculate region-specific estimates. Combining those estimates with others' estimates of future import volumes allows us to make region-specific predictions of the future marginal invasion risk of imports, the key statistic on which discriminatory policy would be based.

2 Species introduction dynamics

Although initial empirical characterizations of species invasion dynamics by Ruiz et al. (2000) and Solow and Costello (2004) acknowledge imports as a key vector, lack of trade data lead both to model the number of cumulative invasions as a function of time. Each assumes that cumulative invasions are an exponential function of time and thus are able to provide a close fit to their respective data sets, which generally reflect a convex relationship between aggregated invasions and time.

Levine and D'Antonio (2003) were the first to estimate a dynamic link between NIS accumulation and trade. The authors also explicitly allow for attenuation in the trade-introductions relationship: "Each new container ship does not bring with it a whole new set of species; instead, each ship brings samples from regions already sampled by previous ships. Thus, as import volume increases, the per-ship probability of transporting a new introduction declines" (p. 323). Cumulative invasions into the United States are modeled as an increasing, concave function of national imports. Costello et al. (2006) also use discovery and trade data aggregated across exporters. They examine the efficacy of ballast water exchange in reducing the number of NIS introductions to the North American Great

Lakes. They find that the discovery lag could be responsible for continued discoveries, even if ballast water exchange was completely effective.

An important limitation of these studies arises from the aggregation of NIS and trade data over source and host regions (i.e., the region of NIS origin and the region invaded). An ideal empirical approach would estimate the trade-introduction relationship between an ecologically distinct source and host. Ruiz et al. (2000) and Solow and Costello (2004) distinguish between host regions but not source regions. Levine and D'Antonio (2003) acknowledge that their "relationships would ideally be derived for the different biogeographic sources of exotic species" (p. 325), but do not use disaggregated trade data simply because "the requisite data were unavailable" (p. 325).

Drake and Lodge (2004) take a unique approach which allows disaggregation of source and host regions down to the port level. Attempting to identify global hotspots of marine invasions, they estimate introduction rates using data on the number of ships visiting 243 ports worldwide in 2000. They first use a gravity model to estimate the number of vessel trips between each of the port pairs, then, assuming a constant per-ship-call probability of initiating invasion, identify the ports that contribute most to inter-region exchange of NIS. Admirable in scope, the assumption of one global constant marginal rate of invasion is nonetheless an important limitation for reasons discussed above.

Solow and Costello (2004) develop a method for estimating the delay between discovery and introduction (though in that model NIS introductions are not directly linked to trade). Here an important nuance is made explicit—the observed discovery record is a combination of both an unobserved introduction record and a discovery process.

The present paper builds all of these important features into a single framework – attenuation of the trade-introductions relationship, region-specific risk and discoveries versus actual introductions – providing the first estimates of current risk from trade related invasions on a region-by-region basis. We focus on unintentional introductions of NIS, as these are more likely to be harmful than are intentionally introduced exotic species.[2] Specifically targeting contaminated shipping traffic enables our empirical application; the invasion effect is localized in a particular bay allowing the pairing of specific sets of trade and NIS discoveries.

3 An empirical model and estimation procedure

3.1 A model of introduction and discovery

In this section, we describe the basic model of NIS introductions and discoveries. The introduction model generalizes that of Solow and Costello (2004) by (1) simultaneously estimating region-specific invasions, (2) including contemporaneous shipping by region and (3) allowing introductions to attenuate as a function of both cumulative volume (by region) and time. Attenuation by shipping volume captures the possibility that a given host region contains a limited species pool; as introductions take place, the pool's size is diminished. Attenuation by time captures the possibility that temporal changes in shipping technology,

[2]According to the OTA (1993) report, this is only true for a subset of phyla: "Far more unintentional introductions of insects and plant pathogens have had harmful effects than have intentional introductions. For terrestrial vertebrates, fish, and mollusks, however, intentional introductions have caused harm approximately as often as have unintentional ones, suggesting a history of poor species choices and complacency regarding their potential harm." (OTA 1993 p.6)

shipping time, or ecological conditions of the host region might effect the rate of introductions. For example, over time hull materials have changed while ship size and speed has increased (Ruiz et al. 2000); ceteris paribus these effects are expected to increase invasions over time. The discovery model captures the probabilistic nature of species discoveries, conditional upon introduction; the longer the time since introduction, the larger is the probability that it will have been detected. Model parameters relating to shipping volume will therefore be region-specific, while parameters based on time will be shared across all host regions.

To begin, consider introductions from a single source region j to a single destination. Let the random variable N_{jt} be the unobservable number of introductions from that region in year t. We will assume that N_{jt} has a Poisson distribution with mean

$$\lambda_{jt} = \beta_j s_{jt} \exp(\gamma_j S_{jt} + \omega t), \tag{1}$$

($\beta_j > 0$, $\gamma_j \leq 0$, and $\omega \lesseqgtr 0$) where s_{jt} is shipping volume in year t and S_{jt} is cumulative shipping volume through year t. In Equation 1, β_j reflects the intrinsic infectiousness of the source region to the destination—infectiousness depends on the biogeographic similarity between the two regions. The parameter γ_j measures the rate at which introductions attenuate (provided $\gamma_j < 0$) with cumulative import volume and ω measures the rate at which introductions increase with time; a result of temporal changes in shipping speed and technology. Let the observable random variable Y_{jt} be the number of NIS from source j discovered in year t. It is straightforward to show that Y_{jt} also has a Poisson distribution with mean

$$d_{jt} = \sum_{u=0}^{t} \lambda_{ju} p_{ut}, \tag{2}$$

where p_{ut} is the probability that an NIS introduced in year u is discovered in year t. Finally, in the absence of a reliable measure of discovery effort, we will assume that the post-introduction waiting time to discovery is geometrically distributed such that

$$p_{ut} = \pi(1-\pi)^{t-u-1}, \tag{3}$$

where π is the annual discovery probability.

In considering multiple source regions $j = 1, ..., J$, we will assume that the parameters β_j and γ_j of the introduction process may vary between regions, but the time-only parameters ω (from the introductions process) and π (from the discovery process) are shared by all source regions. Let the observation period be $t = 0, 1, ..., T$, β=(β_1, β_2... β_J), and γ=(γ_1, γ_2... γ_J). Apart from irrelevant factors, the likelihood of the observed discovery record conditional on parameters β, γ, ω, and π is given by

$$L(\beta, \gamma, \omega, \pi) = \prod_{j=1}^{J} \prod_{t=1}^{T} \exp(-d_{jt}) d_{jt}^{y_{jt}}. \tag{4}$$

The introduction parameters β, γ, and ω and the scalar nuisance parameter π can be jointly estimated by maximizing (4) directly. However, maximum likelihood estimation is known to perform poorly in these kinds of models so we instead estimate β, γ, and ω by maximizing the integrated likelihood:

$$IL(\beta, \gamma, \omega) = \int_0^1 L(\beta, \gamma, \omega, \pi) d\pi, \tag{5}$$

(Berger et al. (1999); Osborne and Severini (2000)).[3] Let $\hat{\beta}$, $\hat{\gamma}$, and $\hat{\omega}$ be the estimates of β, γ, and ω found by maximizing $IL(\beta, \gamma, \omega)$. An estimate of the nuisance parameter π can then be found by maximizing over $L(\hat{\beta}, \hat{\gamma}, \hat{\omega}, \pi)$.

4 An example from San Francisco Bay

Here we implement the integrated likelihood approach to estimate the parameters of the introduction process using data on shipping and species discoveries in San Francisco Bay. The San Francisco Bay lies in central California at the confluence of the Sacramento and San Joaquin Rivers, draining 40% of the state's land surface area (Nichols et al. 1986). An important economic center and trade hub, the area had received over 436 million short tons of imported goods by the year 1994 (the final year for which the NIS discovery data are available).

The Bay is one of only a small number of estuaries whose NIS populations have been thoroughly studied (Ray 2005). A particular advantage of focusing on this estuary is that early biological studies began at roughly the same time as the advent of major vectors of NIS introductions, reducing the possibility that early arrivals are mistaken for indigenous

[3]We adopt the common convention of a uniform distribution over the nuisance parameter π (Berger et al. (1999); Osborne and Severini (2000)).

species (Ruiz et al. 2000). Recognized as perhaps the most invaded aquatic ecosystem in North America, the Bay has been profoundly altered by NIS introductions. For example, no shallow water habitat in the Bay remains uninvaded, and in some areas 100% of common species are NIS. Moreover, NIS species are the dominate force in ship and hull fouling, and introduced species are thought to have accelerated intertidal-region erosion (Cohen and Carlton 1995).

4.1 Historical data

Our trade data set includes yearly import tonnage via ocean vessel through the San Francisco Customs District (SFCD) for years 1856 through 1994, disaggregated by foreign country of origin. Figure 1 shows aggregate imports over the period of study.[4] We assembled the series from four different published sources, each of which is based on U.S. Department of Commerce (USDOC), Bureau of the Census records (see detailed data source description in Appendix A).[5]

NIS discovery data for years 1853 through 1994 are taken from the Cohen and Carlton (1995) case study of the biological invasions of the San Francisco Bay and Delta, an

[4] Import spikes in the years 1973 - 1977 were driven by oil imports – over three quarters of 1977 tonnage was crude or shale oil. As a result of domestic price controls from the Emergency Petroleum Allocation Act (1973) U.S. imports of crude oil rose by more than 100 percent by 1977 (Energy Information Administration 2002). Additionally, a fatal oil tanker explosion and fire in Los Angeles Harbor in December of 1976 may have led some diversion of shipments to the SFCD(Moreau et al. 1977).

[5] Data for war years of 1866, 1867 and 1913 through 1918 could not be located and were estimated using a linear step function between the pre- and post-gap four-year averages. Aggregate tonnage for years covered by digital data sources was checked against figures published by the U.S. Army Corps of Engineers (USACE 1986). Figures from both sources agree to within a few percent for each year except 1976 and 1977, when USDOC tonnage is 43% lower and 87% higher, respectively. USDOC data for both years was scaled to be consistent with the USACE figures because the USACE aggregate data trend was considered more plausible than the large yearly swing from 1976 to 1977 observed in the USDOC data.

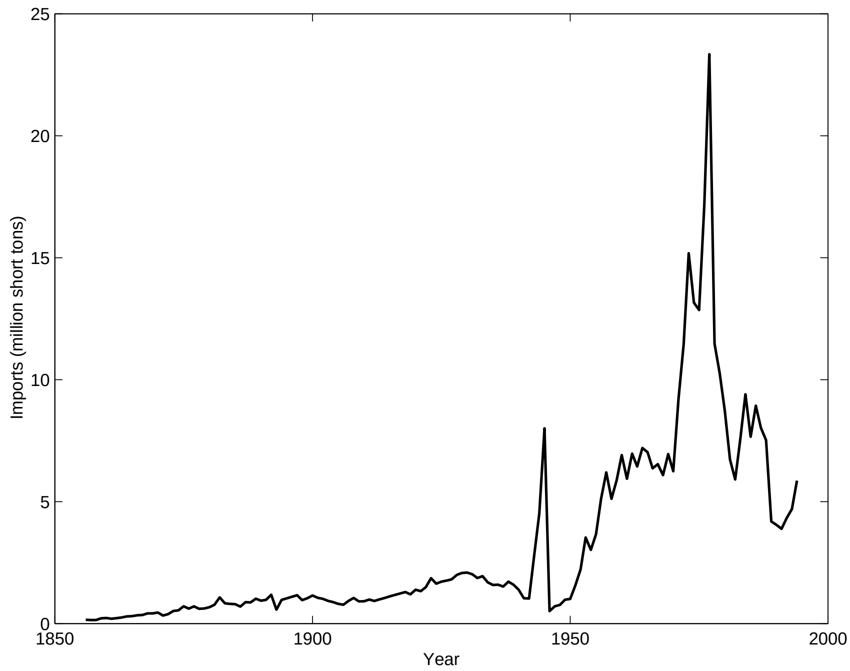

Figure 1: Yearly imports by vessel, San Francisco Customs District, 1856-1994

exhaustive compilation of all known NIS introductions in the region as reported by academic literature, periodicals, government agencies (e.g. California Department of Fish and Wildlife) and by the authors themselves. A minor update received directly from the authors was also appended. The data set includes (where known) the earliest discovery date, likely vectors of introduction and native region for every NIS discovery.

Over the 142-year period of study, 232 NIS were discovered in San Francisco harbor, for an average of 1.6 discoveries per year. Of these 232 species, 78 are thought to have arrived by some vector other than ocean vessel—this includes intentional or accidental release by individuals and government agencies. The remaining NIS are characterized as having arrived "possibly by ocean vessel" (in ballast water or in a ship's seawater system, in solid ballast, in ship fouling or boring, and unknown). We exclude the 78 non-vessel

NIS species in our analysis. Thus, when we speak of NIS discoveries without qualifying the regions from which those NIS originally hail, we will be refering to a pool of 154 discovered NIS.

However in much of the analysis to follow we will instead prefer to focus on the NIS hailing from one region or another. For this analysis, we have divided up all possible source regions into seven groups, and assigned discovered NIS to these groups according to the native regions from which these NIS originally come. Unfortunately, we will lose some additional observations in this process. Of the 154 species believed to have entered San Francisco Bay via shipping traffic, 27 have native regions that are unknown, and 5 lack a description of origin of appropriate precision to assign to a single region. Thus, in our disaggregated pool, we exclude these 32 additional species, leaving 122 species upon which to conduct our region-by-region analysis.[6]

The number of NIS discoveries and cumulative shipping trade by region of origin through 1994 is presented in Table 1. There is large variation in both NIS invasions and volume of trade over regions and it is readily apparent that invasions do not scale uniformly with trade. Differences may also stem from difficulty in classifying species as nonindigenous when their apparent ranges may be nearby. Mexico and Canada, for example, are part of the Northeastern Pacific region which has not been a certain source for any ship-borne invasions in our data set. For further discussion of San Francisco Bay NIS native origins, see Cohen and Carlton (1995).

[6]A breakdown to the country level is not currently possible because species origins are not typically assessed with that level of precision.

Region		NIS	Cumulative Imports (to 1994) (million tons)
Atlantic/Mediterranean	(ATM)	74	62
West Pacific	(WPC)	43	202
Indian Ocean	(ION)	3	75
Southeast Atlantic	(SEA)	1	2
Southeast Pacific	(SEP)	1	10
Northeast Pacific	(NEP)	0	77
Southwest Atlantic	(SWA)	0	5
Unknown	(UNK)	32	2

Table 1: NIS discoveries and cumulative imports by region.

In Figure 2 we plot cumulative discoveries against time; discovered NIS that were not introduced by vessel are included for comparison. Diagrams such as Figure 2 have led many researchers to conclude that NIS *introductions* are increasing at an increasing rate.

However, if we instead plot discoveries versus cumulative imports—see Figure 3—we see that the relationship between shipping volume and new discoveries instead appears to be non-increasing, or possibly even declining. Teasing apart introductions (unobserved) from discoveries (observed) may further increase the concavity (Costello and Solow 2003). Indeed, in the following section our empirical estimates will confirm the concavity between actual introductions and cumulative shipping.

5 Results

In this section we will apply the species discovery data and trade volume data described in Section 4 to the likelihood-based model we developed in Section 3. Following that proce-

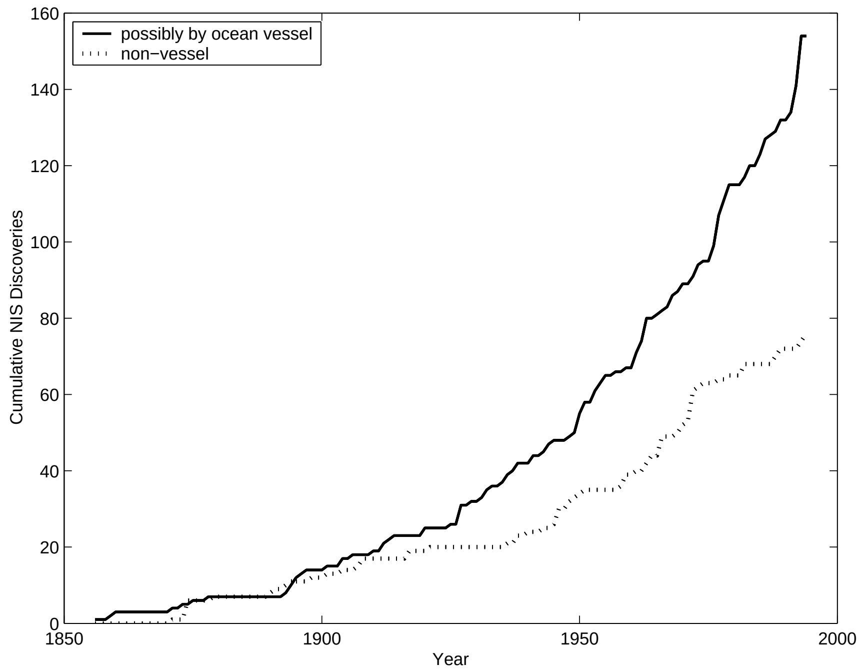

Figure 2: Cumulative NIS discoveries in San Francisco Bay over time and by vector: ocean vessel and other

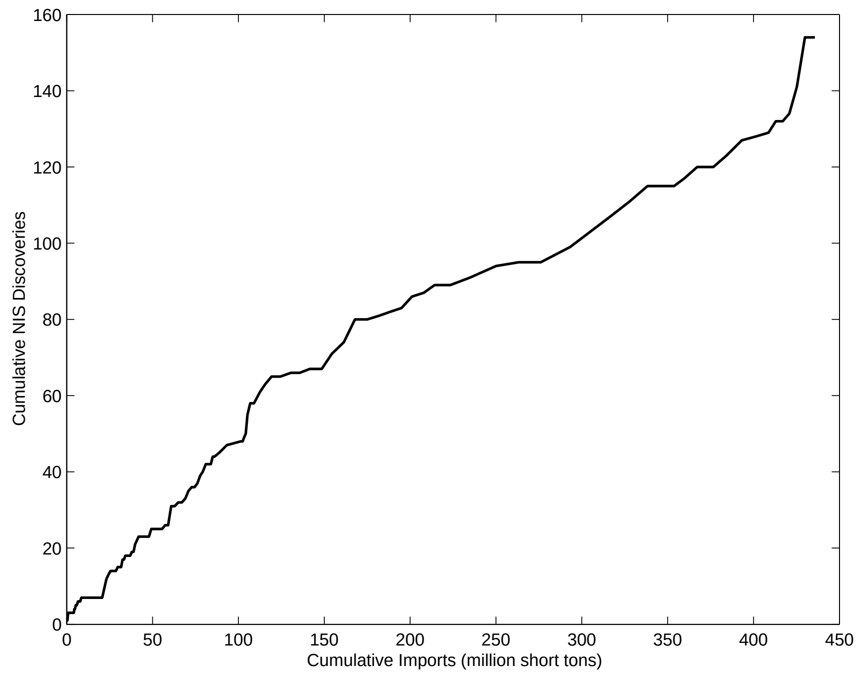

Figure 3: Cumulative NIS discoveries versus cumulative imports

Region		$\hat{\beta}$	$\hat{\gamma}$	$\hat{\omega}$
Atlantic/Mediterranean	(ATM)	2.3	-0.08	
		(1.3, 4.0)	(-0.15,-0.04)	
West Pacific	(WPC)	0.07	-0.002	0.015
		(0.02, 0.21)	(-0.01,0.006)	(0.001,0.03)
Indian Ocean	(ION)	1.3	-1.06	
		(0.1, 7.5)	(-3.45,-0.18)	

Table 2: Unrestricted estimates of the base rate of introduction (β) and attenuation (γ and ω) parameters. Likelihood ratio 90% confidence intervals are in parentheses.

dure, we estimate the parameters γ_i, β_i, and ω for the three regions for which we have more than one NIS discovery between 1856-1994. Those regions are Atlantic/Mediterranean (ATM), West Pacific (WPC), and Indian Ocean (ION). The unrestricted parameter estimates are given in Table 2. Using these estimates, the ML estimate of the nuisance parameter is $\hat{\pi} = .048$ implying a median introduction-to-discovery lag of about 13 years and that 90% of species are discovered between 1 and 60 years after introduction. Accompanying the introduction model parameter estimates are 90% confidence intervals, which are calculated using a likelihood ratio approach.

From the perspective of NIS introductions, an important characteristic of a trade partner is its inherent capacity to supply NIS to San Francisco. At the beginning of a trade relationship, how infectious are the different partners? The infectiousness of a trade partner is based, as was previously discussed, on both the number of introducible species and on biogeographic similarities between regions. We can estimate the base rate of introductions by evaluating Equation 1 at $S_{it} = 0$, $t = 0$, $s_{it} = 1$ and $\omega = 0$, which simply yields β_i. The parameter β_i can then be interpreted as the number of NIS introductions that would be expected to arrive with the first million short tons of imports. Using the likelihood ratio test we reject the hypothesis that $\beta_{ATM} = \beta_{WPC}$ but fail to reject that β_{ION} is equal to either at the 10% level.

Considering only estimates of β it is tempting to think that ATM is the most risky trade partner, followed closely by ION, and that WPC is a nearly riskless trade partner. That intuition would only be correct in the absence of attenuation of NIS introductions. A central feature of our story about NIS introductions is the attenuation of introductions with respect to trade volume and time itself. In Equation 1 we represent this attenuation via the parameters γ and ω. Intuitively, we would expect that the more trade "experience" a country has with its partner, the less likely it is that new species will be introduced (and so $\gamma < 0$). The estimated attenuation rate from shipping alone in ATM is about 8% per million short tons of trade (see Table 2), and is statistically significant ($p < .01$). In WPC it is .2%, though not statistically significant ($p = .70$). Consistent with the small number of discoveries found only early on in the shipping record from ION, the attenuation rate from shipping in ION is much larger (106%, $p < .01$)—it is very unlikely that new species will be introduced from ION to San Francisco. Despite the wide confidence interval over $\hat{\gamma}_{ION}$, using the likelihood ratio test we reject the hypothesis that the attenuation rates are equal between any pair of our regions.

Likelihood ratio-based confidence intervals for ATM and WPC parameters are satisfyingly tight, while those for ION are much wider. This is because ION is associated with only three discoveries which come relatively early in the shipping record. The estimated discovery rate is therefore initially moderate and curtails sharply. This pattern can be generated with similar likelihood by relatively high baseline rates which attenuate quickly or just a relatively low baseline rate, leading to a wide confidence interval. Despite the width of the confidence intervals for the ION parameters, we will show below in Section 6.1 that this does not translate into large uncertainty in the risk posed by future imports from the region.

The increase in shipping speed over the data period is expected to affect attenuation in the opposite direction. Shorter transoceanic travel time increases species survival in transit which increases invasion rates. Thus we expect $\omega > 0$. Our point estimate is $\hat{\omega} = 0.015$ ($p = .09$) which corresponds to a time rate of increase in invasions of 1.5%, ceteris paribus. This finding suggests that a single unit of shipping could deliver eight times more introductions in 1994 (the end of the data record) than in 1855 (the beginning of the data record).

While these results confirm our theoretical predictions, a number of alternative theories exist regarding the effects of globalization on the attenuation of species introductions. In particular, it could be the case that cumulative global shipping, regardless of source, alters the overall invadability of a host region. There is no clear consensus on whether we should expect additional global shipping to suppress invasion rates, for instance by filling ecological niches, or inversely to increase susceptibility as invasions disturb the ecosystem (Ruiz et al. 2000). To capture this possibility, we generalize Equation 1 still further to allow for an attenuation from cumulative global shipping to the destination port, as follows:

$$\lambda_{jt} = \beta_j s_{jt} \exp(\gamma_j S_{jt} + \omega t + \eta S_t) \tag{6}$$

where $S_t = \sum_{j=1}^{I} S_{jt}$. Under this model estimates for the original parameters β, γ, ω, and π are nearly identical to those in Table 2, and our estimate for the newly added parameter $\hat{\eta} = 0.0011$ is not statistically significant ($p = .62$). We thus adopt the introduction model in Equation 1 for the remainder of this paper.

Under introduction model (1), we derive both the fitted cumulative discovery record (from Equation 2) and the cumulative introduction record (from Equation 1) over the period 1856-1994 for the three source regions of interest. Figure 4 is organized as follows. The three rows correspond to regions ATM, WPC, and ION respectively. The first panel in each row plots the cumulative number of NIS against trade volume, and the second panel in each row does so with time on the horizontal axis. Each row provides the cumulative discoveries (dots) and fitted discoveries (solid lines).

Figure 4 also plots *estimated introductions* (dashed lines) over the period 1856-1994. Recall from our earlier discussion that there is usually a lag between actual introduction of a new NIS species and the date when that new species is first sighted, and so the discovery record does not accurately reflect the true introduction process. Our model in Section 3 accounts for this fact; the number of *undiscovered* species from source j at any point in time can be estimated by

$$\sum_{t=0}^{\tau} (\lambda_{jt} - d_{jt}) \tag{7}$$

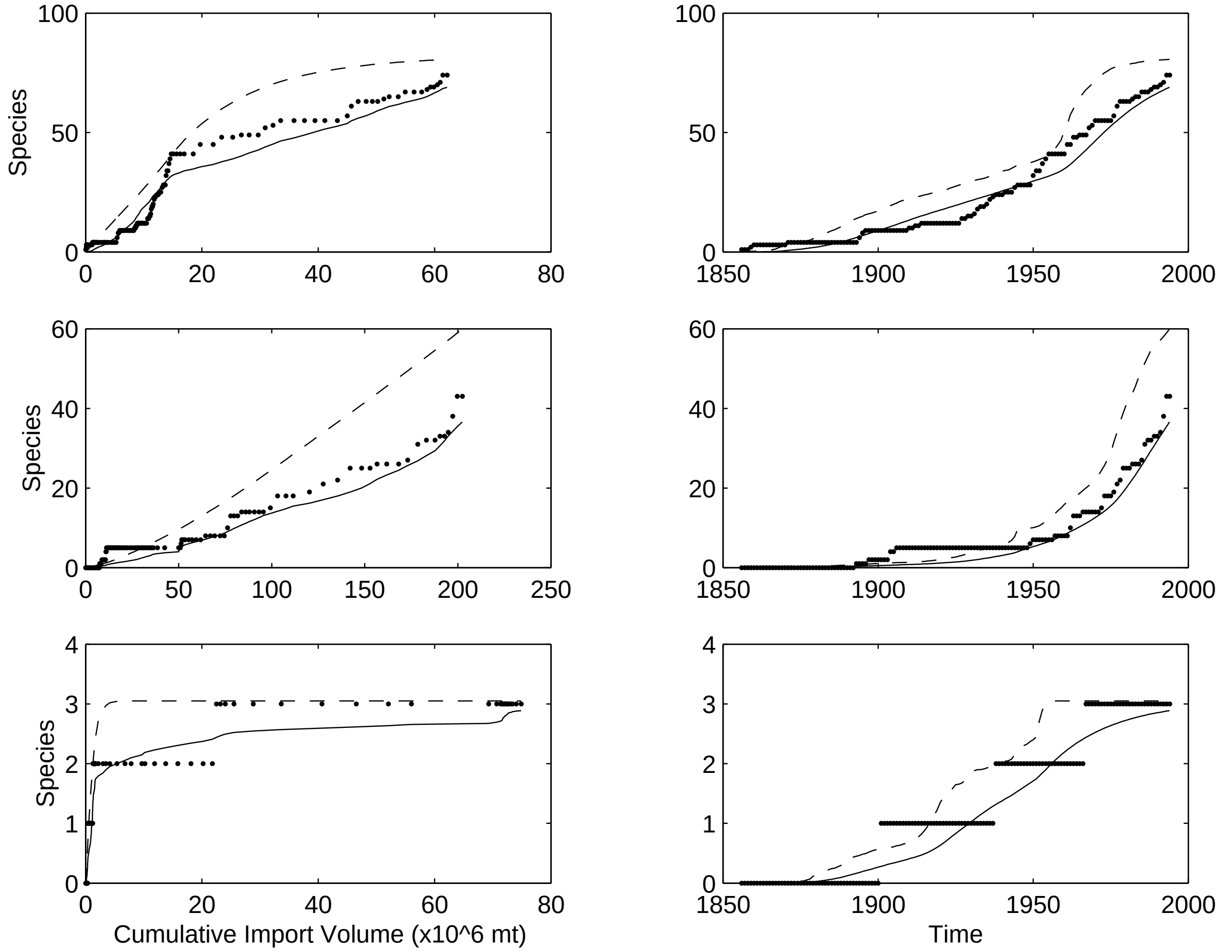

Figure 4: Cumulative discoveries (dots), fitted discoveries (solid), and fitted introductions (dashed) over the period 1856-1994. Top row is for ATM, middle row is for WPC, and bottom row is for ION.

Trade Region	# Discovered Species	# Introductions	# Undiscovered Species (1994)
ATM	74	80.6	6.6
WPC	43	60.0	17.0
ION	3	3.1	0.1

Table 3: Regional NIS discoveries and estimated introductions to 1994

which is visually observed as the vertical distance between the dashed and solid lines in Figure 4. Maintaining the assumptions above, we estimate the number of undiscovered species in 1994 attributable to each trade region.

These results are presented in Table 3. According to the estimates above, about seven yet undiscovered species from the ATM region were present in San Francisco Bay as of 1994. About 17 such species exist from WPC, and none from ION.

6 Predictions

A central objective is to predict current and future invasion risk posed by each trade region. To do so we will first estimate the predicted number of new NIS, by region of origin, that will arrive in the next unit of trade after 1994. We will interpret this statistic as the "marginal invasion risk" of a trade partner. To accommodate changes in future trade patterns and volume we then attempt to predict the number of new NIS over the period 1995-2020 by incorporating partner-specific trade volume forecasts over the same period. We will conclude this section with a thought experiment designed to put the costs of additional NIS in a policy context. This paper estimates the relationship between gross import tonnage and NIS; by the same logic, our results suggest trade restrictions can serve as a blunt instrument for preventing future NIS introductions. We use estimates from the literature to calculate the deadweight loss from restricted imports and compare this to the benefits from reduced NIS. Results suggest that the marginal invasion risk from each region is too small to justify crude volume restrictions as instruments for mitigating future NIS damages.

6.1 Marginal Invasion Risk

On the margin, predicting new NIS introductions amounts to estimating the expected number of new NIS arriving in one more unit of trade from each region. Marginal invasion risk from region j in 1994 (year $t = 138$) is driven by three factors: (1) intrinsic infectiousness (β_j), (2) attenuation over own shipping history ($\gamma_j S_{jt}$), and technology-related increases in species success in transit (ωt), as follows:

$$MIR_{i1994} = \beta_j \exp(\gamma_j S_{j138} + \omega 138) \tag{8}$$

Applying our parameter estimates from Table 2 yields MIR estimates of 0.11 (ATM), 0.38 (WPC), and 0 (ION), indicating that, ceteris paribus, we would expect increased imports from ION to be relatively innocuous while we would expect about one new species introduction with every 9 million short tons of imports from ATM and every 3 million short tons from WPC (see Table 5). Using the likelihood ratio test we reject the hypothesis that MIR$_{ION}$ is equal to MIR$_{ATM}$ or MIR$_{WPC}$ ($p < .01$), though the latter two are not significantly different from each other ($p = .13$).

While the ATM region has the largest inherent ability to infect the San Francisco Bay ($\hat{\beta}_{ATM} = 2.3$), by 1994 its marginal invasion rate had reduced substantially (to 0.11). Two opposing effects generate this result. The positive estimate of ω suggests increasing risk over time. But in ATM, this effect is overshadowed by the strong attenuation in invasion risk with cumulative trade ($\hat{\gamma}_{ATM} = -0.08$). The opposite case holds for WPC. Its small inherent infectiousness ($\hat{\beta}_{WPC} = 0.07$) transforms into a large marginal invasion risk by 1994. This result is driven by its nearly non-existent attenuation from trade experience ($\hat{\gamma}_{WPC} = -0.002$) which, by 1994, was significantly overshadowed by the time effect of technology changes in shipping. Of final note is our point estimate of zero and extremely narrow confidence interval over MIR_{ION}. This result makes sense when considering the discovery record (pictured in the bottom left graph of Figure 4). All three discoveries of NIS from ION occurred relatively early in the import history, leading to a flat discovery curve over the last 50 million short tons. The fitted introductions curve is of similar shape. Although the data may be generated with similar likelihood from a wide range of β_{ION} and γ_{ION} parameter values which trade off against each other, each combination still leads to a relatively small contemporary MIR.

6.2 Forecasting Introductions

To predict future shipborne NIS introductions into San Francisco Bay by region of origin we use forecasts of future imports into the San Francisco district of lading (district 28) from Haveman and Hummels (2004). Forecasted values are drawn from the Global Trade

Region	2002 (actual)	2020 (forecasted)	Annual growth rate
Atlantic/Mediterranean (ATM)	1,888	2,638	1.9
West Pacific (WPC)	14,115	23,964	3.0
Indian Ocean (ION)	1,162	5,220	8.7
Rest of world	1,303	3,772	6.1
Overall	18,468	35,593	3.4

Table 4: Forecasted import volume growth rates based on forecasted trade values (millions of dollars)

Analysis Project (GTAP)[7] using an extension of the basic GTAP model from Walmsley et al. (2000).[8]

From the Haveman and Hummels data set we aggregated 2002 imports (actual values) and 2020 imports (forecasted values) by region. We then calculated the (constant) rate of annual import growth that would account for this predicted change. Table 4 presents imports, by region, into the San Francisco district of lading for 2002 and 2020 (predicted), as well as the implied annual growth rates for imports.

Although average (weighted by 2002 import values) import growth is predicted to be only 3.4% per year, region specific growth rates vary widely, running as low as 1.9% for San Francisco imports from the Atlantic/Mediterranean region, and as high as 9.9% and 8.7%

[7]We are tremendously grateful to the authors for supplying us with the disaggregated projections. For more information on GTAP, see Hertel (1997), Dimaranan and McDougall (2002) or visit http://www.gtap.agecon.purdue.edu.

[8]According to Haveman and Hummels (2004), this extension "draws on World Bank forecasts of growth rates in gross domestic product, gross domestic investment, capital stocks, population, skilled labor and unskilled labor for each country. The model further assumes a set of trade policy changes, including the full implementation of Uruguay Round commitments, the implementation of China's accession to the World Trade Organization, and the implementation of the agreement on textiles and clothing. It further assumes that, after the full implementation of the Uruguay Round commitments, there will be gradual tariff reductions commensurate with the rate of liberalization that has occurred in recent decades." (p.76)

Region	Marginal Invasion Risk	Projected Imports	# New NIS
ATM	0.11	30.4	1.4
	(0.01, 0.36)		(0.1, 6.3)
WPC	0.38	125.7	52.4
	(0.18, 0.62)		(17, 108)
ION	0	182.6	0
	(0, 0)		(0, 0)

Table 5: Marginal invasion risk (as of 1994), projected import volumes (millions of tons, 1995-2020) and predictions of new NIS invasions (1995-2020). Likelihood ratio 90% confidence intervals are in parentheses.

from the Southeast Atlantic and Indian Ocean regions respectively. We use the forecasted annual growth rates in import value (dollars) as a proxy for growth rates in import volume (tonnage).

Combining these trade forecasts with the introductions model from Equation 1, we are in a position to predict the number of new introductions from 1995-2020. Table 4 provides the estimates of the projected trade volume from 1995-2020, and the estimated number of new NIS introductions from each trade partner over the same period. Focusing attention on the MIRs of the three regions, it is clear that WPC and ATM are the most risky (though statistically indistinguishable) and ION is no risk at all. But if we are interested primarily in predicting the number of new NIS before 2020, we must account for the projected trade volume, which is substantially higher in WPC than in ATM. Once trade volumes are factored in, the predicted number of new NIS is much larger from WPC (52 new species) than from either of the other two regions (1.4 from ATM, 0 from ION). Importantly, trade with ION is projected to be the highest of the three regions (182 million short tons), but

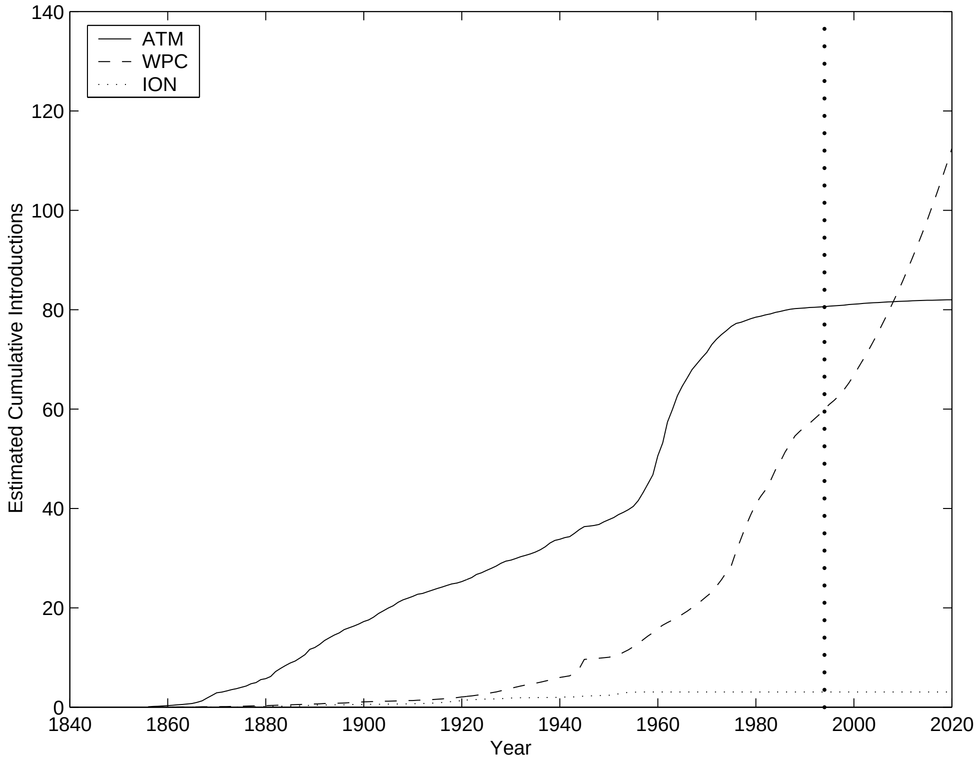

Figure 5: Estimated NIS introductions. Data record (1856-1994) separated from forecast time period (1995-2020) by vertical dotted line.

because the marginal risk is so low, our results suggest no new introductions from this substantial trade volume.

Accompanying Table 5 which presents the predicted number of new NIS introductions by 2020 is Figure 5 which shows the estimated cumulative number of introductions over both the data record (1856-1994) and the forecast time period (1995-2020). Consistent with the forecast estimates in Table 4, the slope of the NIS introduction process is flat for ION, relatively flat for ATM, and relatively steep for WPC.

6.3 Economic costs and benefits from avoiding NIS

To understand MIR in economic terms, we need to weigh the costs of additional shipborne NIS against the benefits of trade. We offer the following thought experiment: suppose the U.S. used trade restrictions to reduce by one the expected number of NIS in 2020 originating from each region. By how much would the U.S. have to reduce imports? What would be the associated deadweight loss, and how would damages from the foregone NIS compare? Admittedly, curtailing imports is one of the crudest possible methods for stemming NIS introductions; we have no intention of promoting coarse trade restrictions as a solution. Rather, we offer this thought experiment simply so as to put the risks from future NIS into an economic context.

Manipulating the familiar formula for the excess burden from a trade restriction—see, for example, equation 7.7' in Feenstra (2004, p. 217)—suggests the Deadweight Loss (DWL) in year t can be approximated as

$$DWL_t \approx \frac{1}{2}\frac{\hat{M}_t^2}{\epsilon} P_t M_t,$$

where $\hat{M}$ is the percentage reduction in imports, ϵ is the elasticity of import demand, and PM is the value of imports. Expected benefit B_t in year t of the import/NIS reduction program is

$$B_t = D \sum_{s=1995}^{t} [\lambda_s^u - \lambda_s^r] \tag{9}$$

where D is annual damage from an average NIS and λ_s^u and λ_s^r measure mean introductions in year s when trade is unrestricted and restricted, respectively.

We consider an import/NIS reduction program in which import volumes are reduced by a constant percentage each year. We perform this exercise for ATM and WPC only, since we expect no new NIS from ION. Using the estimated introduction curve (i.e., Equation 1 evaluated at the parameter estimates reported in Section 5), reducing expected NIS in 2020 from each region by one would require reducing ATM imports by 90% and WPC imports by 2%.

We assume ϵ is constant over time and across regions; we use $\epsilon = -1.23$, which Hooper and Marquez (1995, p. 133) report as a typical estimate for the U.S. import demand elasticity for merchandise (i.e., non-oil) imports. For M_t we use unrestricted import volumes; for 1995-2000 we use actual imports, while for 2001-2020 we use projected import volumes based on the constant growth rates reported in Table 4. We assume the real dollar/ton ratio is also constant over the 1995-2020 period, and so choose P such that PM_{2002} using M_{2002} from our forecasts exactly equals actual 2002 import values as reported by Haveman and Hummels (2004); this yields P_{ATM} =\$1769 and P_{WPC} =\$3399.

Discounting annual DWL using a 5% discount rate and 1995 as the base year, our calculations indicate that the total discounted DWLs from using import restrictions to reduce expected 2020 NIS from ATM and WPC are \$9,520 million and \$44 million respectively. In order for the costs and benefits of restrictions on ATM imports to balance, annual damages from the (prevented) introduction would have to be about \$1,063 million per year; for WPC, annual damages per NIS would have to equal around \$8.33 million.

How do these figures compare to costs from current NIS present in the United States?

Three of the most expensive aquatic NIS to have invaded the United States to date are Asian clams, zebra mussels and *Teredo navalis*, a shipworm. Respectively, the annual costs from these NIS have been estimated at \$1 billion (Pimentel et al. 2005), \$700 million (U.S. Army Corps of Engineers 2002) and \$205 million (Cohen and Carlton 1995, p. 193).

If policy makers *knew* the NIS prevented via trade restrictions was to have damages of the same magnitude as either of these three aquatic invaders then import restrictions on WPC imports would indeed pass the cost-benefit test; for ATM, the deadweight loss of restricting imports is slightly higher than the benefits of avoiding an invasive as damaging as the most costly to date (Asian clams). However, these examples are drawn from the most costly end of the NIS spectrum. The damages avoided by preventing an *unspecified* future NIS are likely much smaller. One very rough estimate of the cost of a *typical* NIS is total annual US damages from invasives averaged over all NIS in the United States. Pimentel et al. (2005, p. 282) report that there are over $50,000$ NIS present in the United States, imposing a total of \$120 billion in damages and control costs per year. Thus a rough estimate of D is \$2.4 million, which falls far short of the \$1,063 million figure for ATM; this rough estimate is also less than a third of the \$8.33 million in damages necessary to justify restrictions on imports from WPC, however it is of the same order of magnitude.

We close this section with two observations. Firstly, *if* policy makers want to use broad import restrictions to reduce total expected NIS in 2020, it will be cheaper to do so by targeting trade with WPC rather than ATM. Intuitively, this is because MIR_{WPC} shows no signs of attenuating. Secondly, broad import restrictions do not appear to be a cost-effective tool for stemming NIS invasions into San Francisco Bay: regardless of trade partner, costs appears to outweigh benefits.

7 Concluding remarks

We developed a structural model of the trade-introduction-discovery process for non-indigenous species. We used the model to estimate the inherent infectiousness of trade with a variety of trade partners (aggregated into regional groupings) and estimated the rate at which infectiousness changes over time, both with cumulative exposure from each region (which decreases the introduction rate over time) and with shipping technology changes that increase species survival in transit (which increases the introduction rate over time). Employing forecasts of future trade volumes and patterns, we then used our estimates to identify trade regions that are likely to be sources of substantial NIS introductions in the near future.

Our parameter estimates provide some support for the theoretical hypothesis that cumulative introductions are a concave function of cumulative imports, though the shipping technology effect tends to dampen, even reverse (in the WPC region) this effect. While the attenuation effect from cumulative shipping in WPC was statistically indistinguishable from zero, both the ION and ATM regions showed a significant rate of decline in the baseline rate of introduction as functions of cumulative shipping.

We found that a trade region's baseline infectiousness (β_i) is a poor predictor of the marginal invasion risk, a measure of the regions current infectiousness; β_{WPC} is 20 times smaller than β_{ION} and 30 times smaller than β_{ATM}, yet the WPC region poses the largest current marginal risk. This result obtains because of the near-zero attenuation rate over shipping volume in WPC. When combined with forecasts of large trade volumes from WPC, this result suggests that many new species are expected to arrive from that region (about 52 new species 1995-2020). Thus, biologists should expect to encounter new species from WPC in far greater numbers than for any other region. Simple volume restrictions on imports to reduce NIS introductions are not advisable based on coarse cost-benefit calculations.

Before concluding, we note some limitations. The spatial resolution of our empirical approach was hampered by uncertainty about the native range of many NIS. In estimation, we faced a tradeoff between geographic precision and bias introduced from exclusion of observations with broad native range designations. Perhaps the allocation of additional resources for such NIS forensics will be fostered by demonstrations of the value of detailed source information such as in this paper. A limitation of our theoretical model stems from our assumption of regional independence, that is, the infectedness of one region does not affect that of another. It is likely that some number of NIS discovered in the Bay are secondary invaders, having used some port between their native range and the Bay as a "stepping-stone". We partially captured this globalization effect in our generalized specification (Equation 6), though we found this effect to be statistically insignificant. Better data resolution and perhaps modeling innovations beyond those expressed here will be required to accurately tease out this effect.

Caveats notwithstanding, this paper represents a first attempt to quantify the risk of species invasion by region of trade origin, which is the key parameter on which discriminatory policy could be based.

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