

31 **1.0 Introduction**

32 Non-native insect species outnumber all other alien animal species, with nearly 500 non-native
33 insect species established in Japan, over 1,500 in Europe and nearly 4,000 in North America
34 (Yamanaka et al. 2015). Insects also include some of the most notorious damaging invaders,
35 with ant species noted among the most widespread and costly non-native insects (Angulo et
36 al., 2022; Holway et al., 2002; Rabitsch, 2011). Five ant species are ranked among the 100 of
37 the world's worst invaders by the International Union for Conservation of Nature (IUCN),
38 including the Argentine ant, *Linepithema humile*, and the Red Imported Fire Ant, *Solenopsis*
39 *invicta* (Global Invasive Species Database, 2020). Within introduced regions, non-native ants
40 can cause declines in native biodiversity, alter ecosystem processes and trigger declines in
41 ecosystem services such as agricultural production and human health. Non-native ants can lead
42 to substantial economic costs (Angulo et al., 2022). In the United States of America (USA)
43 alone, the total costs associated with *S. invicta* have been estimated at \$6.7 billion per year
44 (Lard et al. 2006). In Australia, the total losses incurred from *S. invicta* in rural industries is
45 estimated to be \$5.1 billion over 30 years (ISSG, 2014).

46

47 Most invasions of insects are unintended consequences of globalization manifested in trade
48 and travel. Many types of insects are inadvertently transported in cargo or accidentally
49 introduced directly with people and their belongings via tourism, migration and during wars
50 (Brockerhoff et al. 2006; Liebhold et al., 2006; Liebhold et al., 2012). While individual
51 countries and international conventions have made considerable progress implementing
52 quarantine measures to limit the movement of insects (MacLeod et al., 2010), increases in trade
53 and travel continue to drive insect movement worldwide (Liebhold et al. 2016). Garnas et al.
54 (2016) and Roques et al. (2016) provide evidence to show that invasive insect species are
55 spreading much faster now than in the past likely due to rapid changes in the pathways. To
56 develop more effective strategies for minimizing future invasions and their impacts, it is
57 necessary to understand both the biogeographic and the socioeconomic drivers of invasions as
58 well as their interactions. Even though there has been good progress in identifying specific
59 invasion pathways that are responsible for transporting insects in trade (Meurisse et al. 2019,
60 Gippet et al. 2019), the connection between imports and insect invasions remains murky.

61

62 To address these issues, we analyse historical patterns of ant invasions globally and over many
63 decades to elucidate the individual roles of—and interplay between—biogeographic and
64 socioeconomic drivers. Biological drivers in the form of species attributes have been

65 emphasized in the ecological literature as key drivers of invasion patterns for insects and other
66 taxa (Lester 2005; Jeschke and Strayer, 2006; Sol et al., 2012; Capellini et al., 2015; Hill et al.,
67 2016; Allen et al., 2017). Specifically for ants, several studies have identified ecological traits
68 often associated with invasive species (Lester, 2005; Lloret et al., 2005; Wittenborn and
69 Jeschke, 2011; Fournier et al., 2019). While these studies make clear the important role of
70 biology, they have typically done so in isolation from socioeconomic drivers. Two exceptions
71 within the ecological literature highlight the important role of trade as a key driver, including
72 Westphal et al. (2008) who found it was the most important explanatory variable in a global
73 study of invasions across all taxa and Liebhold et al. (2016) who showed it was more strongly
74 linked to global insect invasions than was the life history of the species involved.

75

76 The economics and environmental management literature has focused on imports as a key
77 driver, highlighting that this risk varies among trading partners (Costello et al. 2007;
78 Dalmazzone and Giaccaria, 2014; Hlasny and Livingstone, 2008, Hume, 2021). Using
79 historical trade data, both Costello et al. (2007) and Essl (2011) showed the importance of prior
80 economic variables (trade and GDP) on current discoveries of biological invasions (in San
81 Francisco, USA and European countries, respectively). Overall, these studies found that
82 imports contribute significantly to biological invasions, however, they mostly focussed on
83 trade and ignored biological drivers such as species characteristics and climatic similarity.
84 However, as we show, these drivers do not operate independently but rather interact with one
85 other.

86

87 An important feature of global invasions that was, until recently, absent from economic and
88 ecological analyses of historical invasions is the so-called “bridgehead effect”, where
89 previously invaded regions serve as the source of additional invasions elsewhere through
90 secondary introductions (Lombaert et al. 2010, Bertelsmeier and Keller 2018). Bridgeheads are
91 a form of “spatial” spillover in trade-facilitated invasions, where invasion of a new region
92 creates a spillover risk for their trading partners (Barbier and Shogren, 2004; Zipp et al., 2021).
93 Yet, most analyses ignore the extent of these spatial spillover effects (e.g. Perrings et al., 2000).
94 In the context of marine invasions, Keller et al. (2010) was an early example of research
95 highlighting the role of stepping-stone invasion processes. More recently, Bertelsmeier et al.
96 (2018) showed that bridgehead effects play a major role in ant invasions in the USA and New
97 Zealand. While these studies illustrate the pivotal role of bridgeheads in shaping insect
98 invasions globally, the relative importance of bridgehead effects within the broader set of

99 biogeographic and socioeconomic drivers still remain uncertain and thus important for study
100 (Ricciardi et al., 2021).

101

102 A final key environmental driver—and one that modulates the role of imports and the network
103 of potential bridgeheads—is the habitat suitability of the receiving environment. A proxy for
104 this suitability is the climatic similarity (CS) between a species’ native range and a new
105 environment, which has been found to be a major determinant of the probability of species
106 establishment (Pauchard et al. 2004, Roura-Pascual et al., 2011; Thuiller et al. 2004; Duncan,
107 2016). Three economic studies have either implicitly or explicitly accounted for this factor.
108 Costello et al. (2007) allow for the “infectiousness” of imports to vary by exporting partner,
109 but only at the aggregated scale of seven global regions. The regional distinctions thus coarsely
110 account for a host of factors (CS and others like shipping technology and policy) specific to
111 each region, which are not disentangled. While Springborn et al. (2011) is the first paper from
112 the economics literature that explicitly introduces a metric for climate similarity in a study
113 examining the risk of introductions of invasive species with trade, they ignore import volumes.
114 Dalmazzone and Giaccaria (2014) incorporate CS between trading partners within a model that
115 links establishment of invasive species to import volumes disaggregated by the country and
116 region of origin. They showed that accounting for the geographic structure of trade flows and
117 CS between origin and destination countries significantly improves our understanding of the
118 drivers of biological invasions. A limitation of this study is that they model aggregate numbers
119 of invasive species, and do not account for individual species traits.

120

121 With a few exceptions (e.g. Costello et al. 2008; Hlasny and Livingston, 2008), the studies
122 summarized above equated species discoveries with species introductions and restricted
123 analyses to short periods. This is problematic because there are typically long lags on the order
124 of decades between introduction and discovery. Many previous studies also suffer from the
125 difficulty of using a flow variable such as imports measured for a specific year to explain the
126 variation in a stock variable, such as the cumulative number of invasive species up to a certain
127 date (Perrings et al, 2000; Perrings, 2007; Dalmazzone and Giaccaria, 2014). We address these
128 issues by using a long-run multi-decadal data set for both imports and non-native ant discovery
129 records and account for lags between species establishment and discovery by relating historical
130 species discoveries to historical trade-flows and dates during periods that well precede the time
131 of discovery.

132

133 Just as multi-decadal invasion dynamics require a long run temporal scale, the global nature of
134 trade and the complexities of bridgeheads motivate a global scale of analysis. Prior studies of
135 invasion drivers have been conducted at various scales, from national (Areal et al., 2008;
136 Levine and D'Antonio, 2003; Lin et al., 2007; Liebhold et al. 2013; Ward et al., 2020) to
137 regional (Hume, 2007; Pysek et al., 2010; Vila and Pujadas, 2001) and global (Bellard et al.,
138 2016; Dalmazzone and Giaccaria, 2014; Lin et al., 2011; Liebhold et al. 2016, 2018; Westphal
139 et al., 2008). Despite the broad spatial coverage of some of these analyses, several are confined
140 to a few species and countries (except Bellard et al., 2016; Dalmazzone and Giaccaria, 2014;
141 Fournier et al., 2019; Liebhold et al. 2018) and examine pathways and species traits in isolation
142 (except Liebhold et al., 2016). To date, most of these drivers are considered separately, with
143 little examination of the interactions between the level of imports and other variables that can
144 also influence biological invasions (Hume, 2021).

145

146 We address limitations surveyed above by estimating a model of ant invasions that incorporates
147 both species traits and trade as well as modulating factors of CS and bridgeheads in a multi-
148 decadal and global analysis. We use a Cox proportional hazards model (Cleves et al., 2016), to
149 estimate the relative role of these drivers in contributing to the “hazard” or likelihood of a non-
150 native species establishing. We model the accumulation of non-native ant species as a hazard
151 function of historical trade-flows while accounting for biogeographic factors such as source
152 native regions, climatic similarity (CS), and species-specific attributes. The model incorporates
153 imports from both native regions and invaded (or bridgehead) countries over a period spanning
154 185 years. Our study addresses the following questions: (1) How much do imports increase the
155 risk of the introduction of non-native ant species globally? (2) How does invasion risk change
156 over time and vary by different trading regions? (3) How significant are imports, species
157 attributes and CS as drivers of ant species invasions? (4) Is the bridgehead effect important in
158 explaining historical ant invasions?

159

160 Our study offers four contributions relative to the existing literature. First, it unifies two strands
161 of models which are more narrowly focused on establishment risk from either: (A) species
162 attributes and CS, or (B) trade. Our approach integrates these static and dynamic factors and
163 allows assessment of the significance of each to forecast invasion risk. Second, it expands the
164 scope and scale of analysis by utilizing global bilateral imports data spanning 185 years (1827-
165 2012) and using individual species-level establishment records (rather than simple cumulative
166 counts). Third, the model accounts for invasions from both the native range and from

167 previously invaded regions (i.e., bridgehead regions). Fourth, we incorporate CS between
168 source country and recipient country. No previous studies of species invasions have integrated
169 data on species attributes, CS and dynamic propagule pressure (trade) at a global scale. We
170 show that CS interacted with cumulative imports during the 20 years prior to a species
171 discovery in any given year is an important predictor of establishment, consistent with a delay
172 between initial species establishment and discovery. Ultimately, our results can be used to
173 target biosecurity efforts to prevent new ant establishments, while the methods are easily
174 generalizable to other taxa that hitchhike through international trade pathways.

175

176 **2.0 Methods**

177 *2.1 Econometric model*

178 We used a Cox proportional hazards model (Cox, 1972), which includes time-dependent and
179 time-independent predictors (Cleves et al., 2016), to estimate the relative drivers of invasion
180 risk. We combined two groups of predictors. First, we considered the intensity of the import
181 pathway, specifically the value of region-specific imports recently received (leading up to any
182 given year), as potentially modulated by the CS between source and receiving region. Second,
183 we considered a set of species attributes, i.e., morphological and life-history traits potentially
184 associated with invasiveness (Bertelsmeier et al., 2017). Given the panel structure of the data
185 and to control for spatial variation between regions that is constant over time, we included fixed
186 effects for (1) species native regions and (2) importer regions. While survival analyses have
187 been used to estimate invasion risk as a hazard function for individual invasive insect species
188 such as the emerald ash borer in the USA (Ward et al., 2020), these studies do not fully integrate
189 invasion risk from pathway volumes with species attributes.

190

191 The invasion status for each species in each receiving country in the dataset is a binary variable
192 set to “uninvaded” annually until the discovery of invasion occurs, triggering a status of
193 “invaded” thereafter. In our Cox proportional hazards model framework, the probability of
194 discovering species k , in receiving country i , in year t is given by:

195

$$196 \quad d_{tik} = h_0(t) \exp(f(\tilde{M}_{tik}, \overline{CS}_{ik}|\alpha) + \beta Z_k + \varphi_l + \varphi_j), \quad (1)$$

197

198 where $h_0(t)$ is the baseline hazard, Z_k is a vector of species attributes, l is region in which
199 receiving country i is located, j is the source region of the imports, and φ_l and φ_j are importing

200 region and exporting region fixed effects, respectively. In this case, the effects of all regions
 201 are treated as fixed and we can account for them by including indicator variables identifying
 202 regions in the model. The function $f(\tilde{M}_{tik}, \overline{CS}_{ik}|\alpha)$ specifies the way in which imports (\tilde{M}_{tik})
 203 and climate similarity (\overline{CS}_{ik}) enter the model. In addition to fixed effects, the coefficients to be
 204 estimated include the vectors α and β . Next, we describe our approach to characterizing relevant
 205 imports and CS before specifying possible forms for their combination in the imports-CS
 206 function, f .

207 The import summary variables were constructed as a vector of aggregate lags, $M_{ijk}^{u,v} \equiv \sum_{s=u}^v m_{sijk}$
 208 , where m is annual imports from year u through v . Specifically, we considered imports from j
 209 to i over the most recent decade ($M_{ijk}^{t-9,t}$), the decade before that ($M_{ijk}^{t-19,t-10}$) and, alternatively,
 210 over the most recent 20 years ($M_{ijk}^{t-19,t}$). Thus, the import measure may either be a scalar, e.g.
 211 $M_{tijk}^{t-9,t}$, or a vector, $M_{tijk} = [M_{tijk}^{t-9,t}, M_{tijk}^{t-19,t-10}]$. We included these aggregate (over time) lags since
 212 we expect that the likelihood of discovering a species in year t depends on the likelihood it was
 213 introduced via imports in a year leading up to t . These import summary variables are the time-
 214 varying measures of interest in the model, which are the main potential drivers of dynamic
 215 estimates of invasion risk (along with the expansion of newly invaded bridgehead regions).²
 216

217 We define J_{tk} as the set of countries in which species k is present by year t . Recall that M_{tijk}
 218 summarizes cumulative imports to country i from country j which has species k over a fixed
 219 number of years leading up to year t . We aggregated over the n_{tk} relevant countries in J_{tk} for
 220 species k and take the natural log: $\tilde{M}_{tik} = \log(\sum_{j \in J_{tk}} M_{tijk})$. CS_{ij} is an index of climatic
 221 similarity between source and receiving countries. The average CS across the n_{tk} relevant
 222 countries is given by $\overline{CS}_{tik} = (1/n_{tk}) \sum_{j \in J_{tk}} CS_{ij}$.³ Our “full” specification is given by direct and
 223 interacted import and climate similarity terms in the imports-CS function:

224

$$225 \quad f(\tilde{M}_{tik}, \overline{CS}_i|\alpha) = \alpha_0 \tilde{M}_{tik} + \alpha_1 \overline{CS}_{ik} + \alpha_2 \overline{CS}_{ik} \tilde{M}_{tik}. \quad (2)$$

² We also estimated models including the three import summary variables separately and jointly in the same model. However, there were strong collinearity problems in the latter model, which was subsequently dropped. The current analysis estimated separate models for the three import summary variables.

³ Instead of a simple average of CS values, another logical way to specify CS is by computing a trade-weighted CS index. We compared results from such a model to the specification in the main text and found that results were very similar. We do not report these additional results for brevity purpose.

226 We considered models with each term in this function on its own as well as all three together
227 (as indicated in Equation (2)) in order to identify a preferred specification. While these
228 specifications allow us to test for whether CS is a significant contributing variable in general,
229 they constrain the impact of CS to a linear form.

230

231 To assess whether the effect of varying CS depends on the level of CS, we also considered a
232 heterogenous CS effects model using a dummy variable for each block of CS values I in the
233 set of blocks, L , where I denotes CS percentiles. In this case, the imports-CS function is given by:

234

$$235 f(\tilde{M}_{tik}, \overline{CS}_{ik} | \alpha) = \sum_{I \in L} \alpha_I \cdot 1(\overline{CS}_{ik} \in \overline{CS}_I) \cdot \tilde{M}_{tik}. \quad (3)$$

236

237 We evaluated two approaches to specifying J_{tk} . In the first, $J_{tk} = J_k$ does not vary over time
238 and is limited to countries in which species k is *native*. In the second “bridgehead”
239 specification, newly invaded regions may themselves become source regions for further
240 invasion, thus we allowed for J_{tk} to grow over time, adding countries in which species k is
241 newly discovered. We used robust standard errors clustered at the importing country-species
242 level and Cox-Snell residuals to evaluate model fit (Cox and Snell, 1968).

243

244 We estimated multiple versions of the Cox model, which differ in three ways. First, we
245 considered two approaches to the scope of imports to include: imports from countries within
246 the native range of each species only versus combined imports from native range *plus*
247 bridgehead (previously invaded) countries. Second, we allowed for CS to enter as a standalone
248 variable and/or interacting with imports, or not included at all.⁴ Third, we allowed for the length
249 of recent import history driving discovery likelihood each year to be either the past 10 years or
250 20 years (including the current year). We included a set of dummy variables for each native
251 region and each importing biogeographic region in the model. The omitted reference region
252 (for both native and importing region) was selected to be Asia. These fixed effects capture non-
253 time varying factors such as the underlying invasibility of the destination region, and properties
254 associated with the invasiveness of species from different source regions. This would include
255 the persistent effect of export or import commodity mix, shipping technology, and policy-

⁴ As a robustness check we considered additional specifications for CS, which are discussed in the online appendix.

256 related variables including implementation of sanitary and phytosanitary standards (SPS) that
257 are specific to either native or destination regions (Lichtenberg and Olson, 2018).

258

259 2.2 Data

260 For estimation, we merged economic and ecological data listed in Table 1. Information on the
261 year that each established non-native ant species was first discovered in each country represents
262 the core outcome data. These were compiled by Bertelsmeier et al. (2017) from different
263 sources including public online databases, scientific publications, books and personal
264 collections. The dataset contains historical first records for the 36 most widespread alien ant
265 species across the world (1793-2012) for which dates of first observation at the country level
266 were available from the literature (Bertelsmeier et al., 2017). For each ant species included, the
267 dataset specifies native regions as well as each country outside of its native region where it has
268 been discovered and the year it was first reported there. We also compiled two key life-history
269 traits for each species that have previously been associated with invasiveness (Bertelsmeier et
270 al., 2017): (i) Gyny, indicating whether the species typically has single or multiple queens (0,1;
271 0=monogynous, 1= polygynous), and (ii) Habitat generalism, indicating the number of
272 different habitat types in which the species occurs (integers, 1:8).⁵ This dataset was compiled
273 by Bertelsmeier et al. (2013) using the Antprofiler database, which leveraged expert opinion
274 from professional ecologists. We combined ecological data with global bilateral import value
275 data obtained from the TRADHIST database (Fouquin and Hugot, 2017).⁶ The data set
276 contains nominal trade flows for 197 countries from 1827 to 2014, converted to real values
277 (2019 US\$).

278

279 Many studies have shown that CS between a species' native range and a new environment is a
280 major determinant of the probability of species establishment (Pauchard et al. 2004, Roura-
281 Pascual et al., 2011; Thuiller et al. 2004). We calculated CS for each country pair as follows.
282 First, we quantified the land area of each of the 32 Köppen-Geiger Climatic subgroups in each
283 country (Kottek et al., 2006). Then, we specified a distance measure between each Köppen-
284 Geiger climate using 19 bioclimatic variables sourced from the WorldClim Global Climate
285 Database at a resolution of 5 arc-minutes globally (Hijmans *et al.*, 2005). Finally, we took the
286 proportion of land area falling in each Köppen-Geiger subgroup land area for each country pair

⁵ Habitats include: tropical rain forest, tropical dry forest, temperate forest, boreal forest (taiga), tundra, grasslands, scrubland, riparian zones, desert, coastland, urban areas and agricultural areas.

⁶ Available at: <http://www.cepii.fr/CEPII/en/welcome.asp>

287 and weighted it by the distance measure between each subgroup category. After normalizing
288 values to the unit interval and subtracting from 1 we arrived at a CS index spanning from 0 (no
289 similarity) and 1 (identical) (see Appendix). In the online appendix Figure A1, we show the
290 distribution of CS index levels for the full set of country pairs. The CS index is relatively low
291 for country pairs that are distant in terms of climatic conditions (for example Canada-Brazil,
292 $CS_{ij} = 0.36$) and relatively high for climatically similar countries (for example Canada-USA,
293 $CS_{ij} = 0.78$).

294

295 **3.0 Results and discussion**

296 *3.1 Descriptive statistics*

297 Figure 1 shows the temporal distribution of the year a species was discovered in each country,
298 pooled across importing countries. From 1793-2012, a total of 1,485 discoveries were reported
299 across all countries, giving an average of approximately seven discoveries per year. Recorded
300 invasions increased in the second half of the 19th-century corresponding to the first wave of
301 globalisation (Baldwin and Martin 1999) while the second increase in invasions corresponds
302 to the post World War II second globalisation (Bertelsmeier et al. 2017). Thus, ant invasions
303 have been increasing over time, although with fluctuations due to changes in trade. This is
304 consistent with a more general finding from Bonnamour et al. (2021) that insect and plant
305 invasion rates surged following the two globalization waves. The average number of countries
306 invaded by each of the 36 species is approximately 53. Online appendix A2 shows an example
307 of the geographical distribution of the year of discovery for one selected species, the red
308 imported fire ant, *Solenopsis invicta*.

309

310 In Table 2 we present descriptive statistics of key variables used in the final regressions. The
311 overall dataset spans 197 countries, 36 ant species and about two centuries. In Appendix Figure
312 A3, we show annual imports for seven regions over the last several decades, during which time
313 imports to North America, Asia and Europe have sharply increased. To bridge the slight
314 mismatch between the spans of datasets covering ant discovery (1793-2012) and imports
315 (1827-2014) we truncate to 1827-2012. At the start of the dataset, this means that the two
316 species discovered before 1827 (both in 1793) are treated as being discovered in 1827. We also
317 tested the effect of dropping the two earlier discoveries and found that it had no impact on the
318 model estimates. Figure 1 illustrates that the vast majority of species discoveries occur from
319 1850 onward.

320 *3.2 Cox hazard regression model results*

321 We now turn to the results of the hazard model estimation. The full estimation results are shown
322 in Tables A4-A7 in the online appendix. Our preferred model (3B in appendix Table A1, based
323 on Akaike and Bayesian information criteria) features a cumulative imports over the last 20
324 years (versus 10) and imports interacted with CS (versus uninteracted). In Table 3, we present
325 the full set of hazard ratio estimates for this preferred model (3B). For any country in any year,
326 we estimate that an increase in CS-interacted cumulative imports from the previous 20 years
327 leads to a significant increase in the likelihood of discovering a new species invasion in that
328 year. With respect to the combined impact of CS and imports, these results align with those of
329 Hlasny and Livingstone (2008), Costello et al. (2007), and Westphal et al. (2008) and
330 Dalmazzone and Giaccaria (2014) showing imports to be the major determinant of invasions.

331

332 We also confirmed findings in the literature that species attributes are significant predictors of
333 invasion risk for individual ant species (Table 3, first column). Our results show that species
334 that have a wide habitat range (habitat generalism) present a higher relative risk of invasion.
335 Thus, a unit increase in the habitat range is associated with an 11% increase in the hazard rate.
336 This can be explained by the fact that habitat generalists can exploit many different habitats
337 spanning many countries (Bertelsmeier et al., 2017). The effect of multiple queens per colony
338 (polygyny) was also statistically significant. Polygynous ant species present a 20% higher
339 hazard compared to monogynous species. Our results for these attributes agree with those of
340 Bertelsmeier et al. (2017) who showed that species traits are important for ant establishment.
341 We advance the analysis of Bertelsmeier et al. by considering multiple variables in the
342 regressions simultaneously in a probabilistic fashion. More generally, these results are
343 consistent with existing findings that such species traits are significant predictors of invasion
344 risk for many taxa (Sol et al., 2012, Allen et al., 2017).

345

346 As anticipated, the relative risk of invasion varies across native/source regions as well as across
347 importing/receiving regions (Table 3). The omitted region in both groups is Asia, which thus
348 carries an implicit hazard ratio of 1. Compared to Asia, we found that ant species from Africa,
349 Central and South America, and Indo-Pacific regions have decreased risk. For example, ant
350 species from Africa present a 20% lower hazard than species from Asia. Similarly, ant species
351 from Central and South America and Indo-Pacific convey a 36% and 22% lower hazard
352 respectively, compared to species from Asia. This finding is consistent with several studies
353 which suggest that invasion risks from certain regions are higher – although these studies are

354 not for individual species and part of the elevated invasion risk identified in these studies may
355 arise because there may simply be more species, i.e., a larger species pool (Hui et al., 2016;
356 Liebhold et al., 2017). Bellard et al. (2016) reported that most of the invasion of invertebrates
357 and plants into Europe and Central America originated from species native to Asia, especially
358 India, China, and Indonesian islands. Dalmazzone and Giaccaria (2014) reported that countries
359 in Asia are the riskiest trading partners for invasive species. The higher invasion risk that we
360 identified for individual species native to Asia may reflect the inherent greater invasiveness of
361 these species, though it remains unclear what species characteristics may drive such a
362 difference. This result suggests that exports from Asia—and from countries in which Asian
363 species have established bridgehead populations—present a higher-risk source region for ants
364 and should be considered for biosecurity focus.

365

366 Turning to importing regions, our results indicate that Europe faces a significantly lower hazard
367 compared to Asia (Table 3). Countries in Europe face only 68% of the risk of invasion faced
368 by Asia. North America and Oceania have hazard ratios greater than one but are not significant.
369 No other regions were significant at a 5% level compared to Asia. This may reflect differences
370 in the inherent invasibility of these regions but the reasons for these differences also are not
371 disentangled here. One possible hypothesis is that policy variables such as the investment in
372 invasive species prevention and control could also play a role. It has been shown that inspection
373 efforts can reduce invasibility (Surkov et al., 2008; Hill et al., 2016). Another explanation is
374 the fact that low income countries tend to have less effective regulations thereby increasing the
375 risk of invasions (Perrings, 2007). A related factor is the heterogeneity in the level of
376 biosecurity expenditures globally, with Australia, New Zealand, USA and UK as the countries
377 with the largest investment in prevention policies (0.076%-0.001% of GDP) (CBD, 2012).

378

379 Our preferred model in Table 3 integrates two strands of existing models, which are more
380 narrowly either (1) a “trade-focused” model without species attributes (e.g., Costello et al.,
381 2007; Hlasny and Livingstone, 2008; Dalmazzone and Giaccaria, 2014), or (2) a “species-
382 focused” model with only species attributes and CS as an independent variable but without an
383 indicator of propagule pressure like imports (e.g., Sol et al., 2012; Allen et al., 2017). In Table
384 3 we show estimates from implementing both of these typical, more narrow approaches. In the
385 trade-focused model, we use total imports from all countries instead of imports from only
386 native and bridgehead countries (for each species) to be more comprehensively naïve on the
387 species dimension. One caveat here is that the species-focused model presented here indirectly

388 and partially accounts for imports via the region dummy variables, which will loosely account
389 for regional differences in average imports.

390

391 Surprisingly, we do not find that either narrower model leads to substantial bias in hazard ratio
392 estimates for terms shared with the comprehensive (preferred) model. In addition, for the trade-
393 focused model, cumulative imports have the expected positive impact on species discoveries.
394 In the species-focused model, the hazard ratios on species attributes remain statistically
395 significant and in the expected direction of impact as in the previous models. Thus, while both
396 “incomplete” models miss important drivers, in our case the estimates they do provide are not
397 misleading. As before, we evaluated the overall fit of the alternative models using Cox-Snell
398 residuals. In Figure A6 (online appendix) we observe a lack of fit for both of the limited models
399 (trade-focused and species-focused). Note that the first subplot is the same as the first subplot
400 in Figure A4 (i.e. the preferred model). The comprehensive model shows the best overall fit,
401 indicating that both the biological and economic factors should be incorporated for accurate
402 prediction of invasions.

403

404 We further explore the role of climate similarity (CS) using the full specification of the imports-
405 CS function (model 4B) in Equation (2). Online appendix 4 provides the detailed analysis and
406 results of varying the level of CS on establishment risk. These results have several important
407 implications. First, they demonstrate that accurate estimates of the impacts of trade on
408 establishments require information on both trade and CS. Models that include only trade
409 provide a good estimate of the hazard of trade for countries with average CS. But trade-only
410 models will overestimate the hazard for countries that are climatically dissimilar and under-
411 estimate the hazard for more similar country pairs. Second, these results imply that it may be
412 desirable to vary the intensity of biosecurity effort focused on imports from different countries.
413 Trade between countries that have more similar climates presents a higher hazard. The results
414 indicate that risk of ant invasions is lowest between country pairs with the lowest 15% of CS
415 values and that above this threshold CS has a strong impact on risk.

416

417 Finally, we estimated the fitted hazard function, which shows that the hazard rate is increasing
418 over time and varies across exporter regions (Figure A7). We also conducted several robustness
419 checks to test and evaluate the model fit (online appendix 6-8). Overall, we fail to find evidence
420 of problems with the assumption of proportional hazards (See online appendix 6).

421

422 **4. Conclusions**

423 In this study, we assessed the socioeconomic and ecological drivers of ant invasions globally
424 by fitting a Cox proportional hazard model. Our key results highlight the importance of
425 bridgehead imports in explaining invasion risk. This indicates that such spatial spillover effects
426 are important temporal and dynamic drivers of biological invasions. We also find that
427 expanding the historical horizon over which cumulative imports are considered from one
428 decade to two decades improves explanatory power. Our preferred model incorporates CS as
429 an interaction of imports (the likely pathway of species introduction) rather than as a standalone
430 factor. We find that a model including only trade (and excluding species-specific factors) can
431 still provide a reasonable estimate of the hazard of trade for countries with average CS. But
432 trade-only models will over-estimate the hazard for countries that are climatically dissimilar
433 and vice versa.

434

435 When we compare estimates of individual effects of key variables from our comprehensive
436 model to those obtained from a less-complete (trade-focused or species-focused model)
437 surprisingly we find little bias in these less-complete model effect estimates. However, when
438 we turn our attention from individual drivers to prediction of risk, the comprehensive model
439 shows a much better fit overall. As expected, we found that the relative risk of establishment
440 also varies by species attributes, native regions of a species and by importing region.

441

442 There are also limitations to this study. As previously stated, the data on trade flows is highly
443 aggregated and does not allow us to identify how establishment risk may differ by product type
444 or time of year. A limitation to our study of the role of CS is that this measure was calculated
445 at the country scale in order to match the scale of the establishment and import data. We would
446 expect CS to show even greater explanatory power should future resolution of data make it
447 possible to pinpoint the sub-national location of species establishment, allowing for tighter
448 connections between that localized climate and the source region climate. While we accounted
449 for regional fixed effects as well as establishments, trade and CS at the country level, there may
450 be other important sources of within-region heterogeneity that are not represented. Finally,
451 while international trade is likely responsible for the increased spread of ant invasions, it is not
452 the only factor here at stake and knowledge on ant taxonomy and biogeography, ease of
453 identifications, and increased sampling efforts in particular habitats and regions are important
454 co-factors. While this approach in this paper is novel in its integration of both trade flows over
455 time and species attributes, additional integration in further research would be fruitful.

456 Specifically, recent studies have identified climate change, and land-use change as important
457 factors in biological invasions (Epanchin-Niel et al., 2021; Robinson et al., 2020; Roura-
458 Pascual et al., 2021).

459

460 These results provide useful information for informing biosecurity policies that facilitate
461 international trade while minimizing future invasions. Our results provide support to allocating
462 substantial resources for mitigating invasive species at the introduction stage through policy
463 instruments such as trade inspections. Several economic studies have shown that allocating
464 resources for the prevention of introductions of invasive species can be more cost-effective
465 than control and eradication (Born et al., 2005; Leung et al., 2002, 2005). Our results show that
466 global ant invasions are driven by international trade and suggest that essentially all countries
467 should be implementing one or more of the trade policy instruments available to address
468 invasive species—targeted inspections (Surkov et al., 2008), tariffs (Margolis et al., 2005;
469 Lichtenberg and Olson, 2020; Perrings et al., 2005) and tradable risk permits (Horan and Lupi,
470 2005)—to address this market failure. There is also potential to use insights from our analysis
471 to improve surveillance and early warning systems for the management of biological invasions.
472 Our findings on the importance of bridgeheads emphasizes the importance of countries with
473 deep experience and expertise in preventing trade-driven invasion risk working to disseminate
474 that knowledge to other countries. In addition, our model can be applied to other taxa for which
475 accidental transport through trade is the primary pathway and where there is data on the year
476 individual non-native species were discovered to have invaded individual countries or regions,
477 for example, bark beetles, termites and other insects.

478

479 **References**

480 Allen, W. L., Street, S. E., & Capellini, I. (2017). Fast life history traits promote invasion
481 success in amphibians and reptiles. *Ecology Letters*, *20*(2), 222-230.

482 doi:10.1111/ele.12728.

483 Angulo, E., Hoffmann, B. D., Ballesteros-Mejia, L., Taheri, A., Balzani, P., Bang, A.,
484 Renault, D., Cordonnier, M., Bellard, C., Diagne, C., Ahmed, D. A., Watari, Y., &
485 Courchamp, F. (2022). Economic costs of invasive alien ants worldwide. *Biological*
486 *Invasions*, *24*(7), 2041–2060. <https://doi.org/10.1007/s10530-022-02791-w>

487 Areal, F. J., Touza, J., MacLeod, A., Dehnen-Schmutz, K., Perrings, C., Palmieri, M. G., &
488 Spence, N. J. (2008). Integrating drivers influencing the detection of plant pests carried in

489 the international cut flower trade. *Journal of Environmental Management*, 89(4), 300–307.
490 <https://doi.org/10.1016/j.jenvman.2007.06.017>

491 Baldwin, R. & Martin, P. Two Waves of Globalisation: Superficial Similarities, Fundamental
492 Differences (National Bureau of Economic Research, 1999).

493 Barbier, E. B., & Shogren, J. F. (2004). Growth with Endogenous Risk of Biological
494 Invasion. *Economic Inquiry*, 42(4), 587–601. <https://doi.org/10.1093/ei/cbh083>

495 Bellard, C., Leroy, B., Thuiller, W., Rysman, J.-F., & Courchamp, F. (2016). Major drivers of
496 invasion risks throughout the world. *Ecosphere*, 7(3), e01241. doi:10.1002/ecs2.1241

497 Bertelsmeier, C., & Keller, L. (2018). Bridgehead effects and role of adaptive evolution in
498 invasive populations. *Trends in ecology & evolution*, 33(7), 527-534.

499 Bertelsmeier, C., Ollier, S., Liebhold, A. M., Brockerhoff, E. G., Ward, D., & Keller, L.
500 (2018). Recurrent bridgehead effects accelerate global alien ant spread. *Proceedings of the*
501 *National Academy of Sciences of the United States of America*, 115(21), 5486-5491.
502 doi:10.1073/pnas.1801990115

503 Bertelsmeier, C., Ollier, S., Liebhold, A., & Keller, L. (2017). Recent human history governs
504 global ant invasion dynamics. *Nature Ecology & Evolution*, 1(7), 0184.
505 doi:10.1038/s41559-017-0184

506 Bertelsmeier, Cleo & Luque, Gloria & Amandine, Confais & Courchamp, Franck. (2013).
507 Ant Profiler - A database of ecological characteristics of ants (Hymenoptera: Formicidae).
508 Myrmecological News. 18. 73-76.

509 Bonnamour, A., Gippet, J. M. W., & Bertelsmeier, C. (2021). Insect and plant invasions
510 follow two waves of globalisation. *Ecology Letters*, 24(11), 2418–2426.
511 <https://doi.org/10.1111/ele.13863>.

512 Born, W., Rauschmayer, F., & Bräuer, I. (2005). Economic evaluation of biological
513 invasions—a survey. *Ecological Economics*, 55(3), 321–336.
514 <https://doi.org/10.1016/j.ecolecon.2005.08.014>

515 Brockerhoff, E. G., Bain, J., Kimberley, M., & Knížek, M. (2006). Interception frequency of
516 exotic bark and ambrosia beetles (Coleoptera: Scolytinae) and relationship with
517 establishment in New Zealand and worldwide. *Canadian Journal of Forest Research*,
518 36(2), 289-298. doi:10.1139/x05-250

519 Capellini, I., Baker, J., Allen, W. L., Street, S. E., & Venditti, C. (2015). The role of life
520 history traits in mammalian invasion success. *Ecology Letters*, 18(10), 1099–1107.
521 <https://doi.org/10.1111/ele.12493>.

522 Cleves, M., Gould, W., Gutierrez, R., & Marchenko, Y. (2016). *An Introduction to Survival*
523 *Analysis Using Stata*: Stata Press.

524 Convention on Biological Diversity (CBD) (2012). Costs of meeting Aichi Targets for 2020:
525 Target 9 –Invasive Alien Species. Draft report by J. Turpie and C. Jurk, 31 July 2012.
526 [https://www.cbd.int/doc/meetings/fin/hlpgar-sp-01/information/hlpgar-sp-01-aichitargets-](https://www.cbd.int/doc/meetings/fin/hlpgar-sp-01/information/hlpgar-sp-01-aichitargets-05-en.pdf)
527 [05-en.pdf](https://www.cbd.int/doc/meetings/fin/hlpgar-sp-01/information/hlpgar-sp-01-aichitargets-05-en.pdf)

528 Costello, C., Springborn, M., McAusland, C., & Solow, A. (2007). Unintended biological
529 invasions: Does risk vary by trading partner? *Journal of Environmental Economics and*
530 *Management*, 54(3), 262-276. doi:<https://doi.org/10.1016/j.jeem.2007.06.001>.

531 Cox, D. R. (1972). Regression Models and Life-Tables. *Journal of the Royal Statistical*
532 *Society. Series B (Methodological)*, 34(2), 187-220. Retrieved from
533 www.jstor.org/stable/2985181

534 Cox, D. R., & Snell, E. J. (1968). A General Definition of Residuals. *Journal of the Royal*
535 *Statistical Society. Series B (Methodological)*, 30(2), 248-275. Retrieved from
536 www.jstor.org/stable/2984505

537 Dalmazzone, S., & Giaccaria, S. (2014). Economic drivers of biological invasions: A
538 worldwide, bio-geographic analysis. *Ecological Economics*, 105, 154-165.
539 doi:<https://doi.org/10.1016/j.ecolecon.2014.05.008>

540 Duncan, R. P. (2016). How propagule size and environmental suitability jointly determine
541 establishment success: a test using dung beetle introductions. *Biological Invasions*, 18(4),
542 985–996. <https://doi.org/10.1007/s10530-016-1083-8>

543 Epanchin-Niell, R., McAusland, C., Liebhold, A., Mwebaze, P., & Springborn, M. R. (2021).
544 Biological Invasions and International Trade: Managing a Moving Target. *Review of*
545 *Environmental Economics and Policy*, 15(1), 180-190. doi:10.1086/713025

546 Fouquin, M., Hugot, J. (2017). Two Centuries of Bilateral Trade and Gravity Data: 1827-
547 2014. CEPII Working Paper, No 2016-14, February 2017

548 Fournier, A., Penone, C., Pennino, M. G., & Courchamp, F. (2019). Predicting future
549 invaders and future invasions. *Proceedings of the National Academy of Sciences*, 116(16),
550 7905–7910. <https://doi.org/10.1073/pnas.1803456116>.

551 Gippet, J. M., Liebhold, A. M., Fenn-Moltu, G., & Bertelsmeier, C. (2019). Human-mediated
552 dispersal in insects. *Current opinion in insect science*, 35, 96-102.

553 Global Invasive Species Database (2020). Downloaded from
554 http://www.iucngisd.org/gisd/100_worst.php on 09-09-2020.

555 Greene, W. H. (2012). *Econometric analysis* (7. ed., international ed., [veränd. Nachdr.]).
556 Pearson.

557 Hijmans, R. J. *et al.* (2005) ‘Very high resolution interpolated climate surfaces for global land
558 areas’, *International Journal of Climatology*, 25(15), pp. 1965–1978. doi:
559 10.1002/joc.1276.

560 Hill, M. P., Clusella-Trullas, S., Terblanche, J. S., & Richardson, D. M. (2016). Drivers,
561 impacts, mechanisms and adaptation in insect invasions. *Biological Invasions*, 18(4), 883–
562 891. <https://doi.org/10.1007/s10530-016-1088-3>.

563 Hlasny, V., & Livingston, M. J. (2008). Economic Determinants of Invasion and Discovery
564 of Nonindigenous Insects. *Journal of Agricultural and Applied Economics*, 40(1), 37-52.
565 doi:10.1017/S1074070800023452

566 Holway, D. A., Lach, L., Suarez, A. V., Tsutsui, N. D., & Case, T. J. (2002). The Causes and
567 Consequences of Ant Invasions. *Annual Review of Ecology and Systematics*, 33(1), 181–
568 233. <https://doi.org/10.1146/annurev.ecolsys.33.010802.150444>

569 Horan, R. D., & Lupi, F. (2005). Tradeable risk permits to prevent future introductions of
570 invasive alien species into the Great Lakes. *Ecological Economics*, 52(3), 289–304.
571 <https://doi.org/10.1016/j.ecolecon.2004.06.018>

572 Hui, C., Richardson, D. M., Landi, P., Minoarivelo, H. O., Garnas, J., & Roy, H. E. (2016).
573 Defining invasiveness and invasibility in ecological networks. *Biological Invasions*, 18(4),
574 971–983. <https://doi.org/10.1007/s10530-016-1076-7>

575 Hulme, P. E. (2007). Biological Invasions in Europe: Drivers, Pressures, States, Impacts and
576 Responses. In R. E. Hester, R. M. Harrison, R. Harrison, & R. Hester (Eds.), *Biodiversity*
577 *Under Threat* (pp. 56–80). The Royal Society of Chemistry.
578 <https://doi.org/10.1039/9781847557650-00056>

579 Hulme, P. E. (2021). Unwelcome exchange: International trade as a direct and indirect driver
580 of biological invasions worldwide. *One Earth*, 4(5), 666–679.
581 <https://doi.org/10.1016/j.oneear.2021.04.015>

582 ISSG, 2014. Global Invasive Species Database (GISD). Invasive Species Specialist Group of
583 the IUCN Species Survival Commission. <http://www.issg.org/database/welcome/>.

584 Jeschke, J. M., & Strayer, D. L. (2006). Determinants of vertebrate invasion success in
585 Europe and North America: Vertebrate Introductions. *Global Change Biology*, 12(9),
586 1608–1619. <https://doi.org/10.1111/j.1365-2486.2006.01213.x>.

587 Keller, R. P., Drake, J. M., Drew, M. B., & Lodge, D. M. (2011). Linking environmental
588 conditions and ship movements to estimate invasive species transport across the global

589 shipping network: Estimating ship-based invasions of global ports. *Diversity and*
590 *Distributions*, 17(1), 93–102. <https://doi.org/10.1111/j.1472-4642.2010.00696.x>

591 Kiritani, K., & Yamamura, K. (2003). Exotic insects and their pathways for invasion.
592 Invasive species: vectors and management strategies. Island Press, Washington, 44-67.

593 Kottek, M., Grieser, J., Beck, C., Rudolf, B., & Rubel, F. (2006). World map of the Köppen-
594 Geiger climate classification updated. *Meteorologische Zeitschrift*, 15(3), 259-263.

595 Lard, F. C., Schmidt, J., Morris, B., Estes, L., Ryan, C., & Bergquist, D. (2006). *An*
596 *Economic Impact of Imported Fire Ants in the United States of America*.

597 Lester, P. J. (2005). Determinants for the successful establishment of exotic ants in New
598 Zealand: Predicting invasive ant species. *Diversity and Distributions*, 11(4), 279–288.
599 <https://doi.org/10.1111/j.1366-9516.2005.00169.x>.

600 Leung, B., Finnoff, D., Shogren, J. F., & Lodge, D. (2005). Managing invasive species: Rules
601 of thumb for rapid assessment. *Ecological Economics*, 55(1), 24–36.
602 <https://doi.org/10.1016/j.ecolecon.2005.04.017>

603 Leung, B., Lodge, D. M., Finnoff, D., Shogren, J. F., Lewis, M. A., & Lamberti, G. (2002).
604 An ounce of prevention or a pound of cure: bioeconomic risk analysis of invasive species.
605 *Proceedings of the Royal Society of London. Series B: Biological Sciences*, 269(1508),
606 2407–2413. <https://doi.org/10.1098/rspb.2002.2179>

607 Levine, J. M., & D'Antonio, C. M. (2003). Forecasting Biological Invasions with Increasing
608 International Trade. *Conservation Biology*, 17(1), 322-326. doi:10.1046/j.1523-
609 1739.2003.02038.x

610 Lichtenberg, E., & Olson, L. J. (2018). The fruit and vegetable import pathway for potential
611 invasive pest arrivals. *PLOS ONE*, 13(2), e0192280. doi:10.1371/journal.pone.0192280.

612 Lichtenberg, E., & Olson, L. J. (2020). Tariffs and the risk of invasive pest introductions in
613 commodity imports: Theory and empirical evidence. *Journal of Environmental Economics*
614 *and Management*, 101, 102321. <https://doi.org/10.1016/j.jeem.2020.102321>

615 Liebhold, A. M., Brockerhoff, E. G., & Kimberley, M. (2017). Depletion of heterogeneous
616 source species pools predicts future invasion rates. *Journal of Applied Ecology*, 54(6),
617 1968–1977. <https://doi.org/10.1111/1365-2664.12895>

618 Liebhold, A. M., Brockerhoff, E. G., Garrett, L. J., Parke, J. L., & Britton, K. O. (2012). Live
619 plant imports: the major pathway for forest insect and pathogen invasions of the US.
620 *Frontiers in Ecology and the Environment*, 10(3), 135-143. doi:10.1890/110198

621 Liebhold, A. M., McCullough, D. G., Blackburn, L. M., Frankel, S. J., Von Holle, B., &
622 Aukema, J. E. (2013). A highly aggregated geographical distribution of forest pest
623 invasions in the USA. *Diversity and Distributions*, 19(9), 1208-1216.

624 Liebhold, A. M., Work, T. T., McCullough, D. G., & Cavey, J. F. (2006). Airline Baggage as
625 a Pathway for Alien Insect Species Invading the United States. *American Entomologist*,
626 52(1), 48-54. doi:10.1093/ae/52.1.48

627 Liebhold, A. M., Yamanaka, T., Roques, A., Augustin, S., Chown, S. L., Brockerhoff, E. G.,
628 & Pyšek, P. (2016). Global compositional variation among native and non-native regional
629 insect assemblages emphasizes the importance of pathways. *Biological Invasions*, 18(4),
630 893-905.

631 Liebhold, A. M., Yamanaka, T., Roques, A., Augustin, S., Chown, S. L., Brockerhoff, E. G.,
632 & Pyšek, P. (2018). Plant diversity drives global patterns of insect invasions. *Scientific*
633 *Reports*, 8(1), 12095. <https://doi.org/10.1038/s41598-018-30605-4>

634 Lin, W., Cheng, X., & Xu, R. (2011). Impact of Different Economic Factors on Biological
635 Invasions on the Global Scale. *PLOS ONE*, 6(4), e18797.
636 doi:10.1371/journal.pone.0018797

637 Lin, W., Zhou, G., Cheng, X., & Xu, R. (2007). Fast Economic Development Accelerates
638 Biological Invasions in China. *PLOS ONE*, 2(11), e1208.
639 doi:10.1371/journal.pone.0001208

640 Lloret, F., Medail, F., Brundu, G., Camarda, I., Moragues, E., Rita, J., Lambdon, P., &
641 Hulme, P. E. (2005). Species attributes and invasion success by alien plants on
642 Mediterranean islands. *Journal of Ecology*, 93(3), 512–520. [https://doi.org/10.1111/j.1365-](https://doi.org/10.1111/j.1365-2745.2005.00979.x)
643 [2745.2005.00979.x](https://doi.org/10.1111/j.1365-2745.2005.00979.x).

644 Lombaert, E., Guillemaud, T., Cornuet, J.-M., Malausa, T., Facon, B., & Estoup, A. (2010).
645 Bridgehead Effect in the Worldwide Invasion of the Biocontrol Harlequin Ladybird. *PLOS*
646 *ONE*, 5(3), e9743. doi:10.1371/journal.pone.0009743

647 MacLeod, A., Pautasso, M., Jeger, M. J., & Haines-Young, R. (2010). Evolution of the
648 international regulation of plant pests and challenges for future plant health. *Food Security*,
649 2(1), 49-70. doi:10.1007/s12571-010-0054-7.

650 Margolis, M., Shogren, J. F., & Fischer, C. (2005). How trade politics affect invasive species
651 control. *Ecological Economics*, 52(3), 305–313.
652 <https://doi.org/10.1016/j.ecolecon.2004.07.017>

653 Meurisse, N., Rassati, D., Hurley, B. P., Brockerhoff, E. G., & Haack, R. A. (2019). Common
654 pathways by which non-native forest insects move internationally and domestically.
655 *Journal of Pest Science*, 92(1), 13-27.

656 Pauchard, A., Cavieres, L. A., & Bustamante, R. O. (2004). Comparing alien plant invasions
657 among regions with similar climates: where to from here?. *Diversity and Distributions*,
658 10(5-6), 371-375.

659 Perrings, C. (2007). Pests, pathogens and poverty: Biological invasions and agricultural
660 dependence. In A. Kontoleon, U. Pascual, & T. Swanson (Eds.), *Biodiversity Economics:
661 Principles, Methods and Applications* (pp. 131-165). Cambridge: Cambridge University
662 Press. doi:10.1017/CBO9780511551079.008

663 Perrings, C., Dehnen-Schmutz, K., Touza, J., & Williamson, M. (2005). How to manage
664 biological invasions under globalization. *Trends in Ecology & Evolution*, 20(5), 212–215.
665 <https://doi.org/10.1016/j.tree.2005.02.011>

666 Perrings, C., Williamson, M. H., & Dalmazzone, S. (Eds.). (2000). *The economics of
667 biological invasions*. Edward Elgar.

668 Pyšek, P., Jarošík, V., Hulme, P. E., Kühn, I., Wild, J., Arianoutsou, M., . . . Winter, M.
669 (2010). Disentangling the role of environmental and human pressures on biological
670 invasions across Europe. *Proceedings of the National Academy of Sciences*, 107(27),
671 12157-12162. doi:10.1073/pnas.1002314107

672 R. Garnas, J., Auger-Rozenberg, M.-A., Roques, A., Bertelsmeier, C., Wingfield, M. J.,
673 Saccaggi, D. L., Roy, H. E., & Slippers, B. (2016). Complex patterns of global spread in
674 invasive insects: eco-evolutionary and management consequences. *Biological Invasions*,
675 18(4), 935–952. <https://doi.org/10.1007/s10530-016-1082-9>

676 Rabitsch, W. (2011). The hitchhiker’s guide to alien ant invasions. *BioControl*, 56(4), 551-
677 572. doi:10.1007/s10526-011-9370-x

678 Ricciardi, A., Iacarella, J. C., Aldridge, D. C., Blackburn, T. M., Carlton, J. T., Catford, J. A.,
679 Dick, J. T. A., Hulme, P. E., Jeschke, J. M., Liebhold, A. M., Lockwood, J. L., MacIsaac,
680 H. J., Meyerson, L. A., Pyšek, P., Richardson, D. M., Ruiz, G. M., Simberloff, D., Vilà,
681 M., & Wardle, D. A. (2021). Four priority areas to advance invasion science in the face of
682 rapid environmental change. *Environmental Reviews*, 29(2), 119–141.
683 <https://doi.org/10.1139/er-2020-0088>

684 Robinson, T. B., Martin, N., Loureiro, T. G., Matikinca, P., & Robertson, M. P. (2020).
685 Double trouble: the implications of climate change for biological invasions. *NeoBiota*, 62,
686 463–487. <https://doi.org/10.3897/neobiota.62.55729>.

687 Roques, A., Auger-Rozenberg, M.-A., Blackburn, T. M., Garnas, J., Pyšek, P., Rabitsch, W.,
688 Richardson, D. M., Wingfield, M. J., Liebhold, A. M., & Duncan, R. P. (2016). Temporal
689 and interspecific variation in rates of spread for insect species invading Europe during the
690 last 200 years. *Biological Invasions*, *18*(4), 907–920. [https://doi.org/10.1007/s10530-016-](https://doi.org/10.1007/s10530-016-1080-y)
691 1080-y

692 Roura-Pascual, N., Hui, C., Ikeda, T., Leday, G., Richardson, D. M., Carpintero, S., . . .
693 Worner, S. P. (2011). Relative roles of climatic suitability and anthropogenic influence in
694 determining the pattern of spread in a global invader. *Proceedings of the National*
695 *Academy of Sciences*, *108*(1), 220-225. doi:10.1073/pnas.1011723108

696 Roura-Pascual, N., Leung, B., Rabitsch, W., Rutting, L., Vervoort, J., Bacher, S., Dullinger,
697 S., Erb, K.-H., Jeschke, J. M., Katsanevakis, S., Kühn, I., Lenzner, B., Liebhold, A. M.,
698 Obersteiner, M., Pauchard, A., Peterson, G. D., Roy, H. E., Seebens, H., Winter, M., ...
699 Essl, F. (2021). Alternative futures for global biological invasions. *Sustainability Science*,
700 *16*(5), 1637–1650. <https://doi.org/10.1007/s11625-021-00963-6>

701 Sol, D., Maspons, J., Vall-llosera, M., Bartomeus, I., García-Peña, G. E., Piñol, J., &
702 Freckleton, R. P. (2012). Unraveling the Life History of Successful Invaders. *Science*,
703 *337*(6094), 580-583. doi:10.1126/science.1221523

704 Springborn, M., Romagosa, C. M., & Keller, R. P. (2011). The value of nonindigenous
705 species risk assessment in international trade. *Ecological Economics*, *70*(11), 2145–2153.
706 <https://doi.org/10.1016/j.ecolecon.2011.06.016>

707 Surkov, I. V., Oude Lansink, A. G. J. M., van Kooten, O., & van der Werf, W. (2008). A
708 model of optimal import phytosanitary inspection under capacity constraint. *Agricultural*
709 *Economics*, *38*(3), 363–373. <https://doi.org/10.1111/j.1574-0862.2008.00306.x>

710 Thuiller, W., Richardson, D. M., Pyšek, P., Midgley, G. F., Hughes, G. O., & Rouget, M.
711 (2005). Niche-based modelling as a tool for predicting the risk of alien plant invasions at a
712 global scale. *Global change biology*, *11*(12), 2234-2250.

713 Vilà, M., & Pujadas, J. (2001). Land-use and socio-economic socioeconomic correlates of
714 plant invasions in European and North African countries. *Biological Conservation*, *100*(3),
715 397-401. doi:[https://doi.org/10.1016/S0006-3207\(01\)00047-7](https://doi.org/10.1016/S0006-3207(01)00047-7)

716 Ward, S. F., Fei, S., & Liebhold, A. M. (2020). Temporal dynamics and drivers of landscape-
717 level spread by emerald ash borer. *Journal of Applied Ecology*, *57*(6), 1020-1030.
718 doi:10.1111/1365-2664.13613

719 Westphal, M. I., Browne, M., MacKinnon, K., & Noble, I. (2008). The link between
720 international trade and the global distribution of invasive alien species. *Biological*
721 *Invasions*, 10(4), 391-398. doi:10.1007/s10530-007-9138-5

722 Wittenborn, D., & Jeschke, J. (2011). Characteristics of exotic ants in North America.
723 *NeoBiota*, 10, 47–64. <https://doi.org/10.3897/neobiota.10.1047>

724 Yamanaka, T., Morimoto, N., Nishida, G. M., Kiritani, K., Moriya, S., & Liebhold, A. M.
725 (2015). Comparison of insect invasions in North America, Japan and their Islands.
726 *Biological Invasions*, 17(10), 3049-3061. doi:10.1007/s10530-015-0935-y.

727 Zipp, K. Y., Lewis, D. J., Provencher, B., & Zanden, M. J. V. (2019). The Spatial Dynamics
728 of the Economic Impacts of an Aquatic Invasive Species: An Empirical Analysis. *Land*
729 *Economics*, 95(1), 1–18. <https://doi.org/10.3368/le.95.1.1>

730
731
732
733
734
735
736
737

738 Table 1: List of variables and data sources

<i>Variable</i>	Description	Years	Source
Discovery years	Year of discovery for each species and invaded country (years)	1793-2012	Bertelsmeier et al. (2017)
Value of imports	Bilateral trade (\$billions/year)	1827-2014	TRADHIST (Fouquin and Hugot, 2017)
Species attributes	Morphological and life history traits	static	Bertelsmeier et al. (2017)
Climatic similarity	Climatic similarity between origin and importing countries	static	Derived from Kottek Koppen-Geiger climate subgroups (Kottek et al., 2006)

739

740 Table 2: Summary statistics for regression variables.

Variable	Obs.	Mean	Std. dev.	Min.	Max.
<i>Dependent variable</i>					
Year of discovery (by species and country)	1,485	-	-	1793	2012
<i>Trade partner variables (bilateral)</i>					
Value of imports (US\$2019, billions)	1,129,259	0.13	2.03	0.00	365.9
Climatic similarity index	17,952	0.63	0.10	0.00	1.00
<i>Species attributes</i>					
Gyny (queen number)	36	1.33	0.48	1.00	2.00
Habitat generalism	36	4.42	2.06	1	8

741

742

743

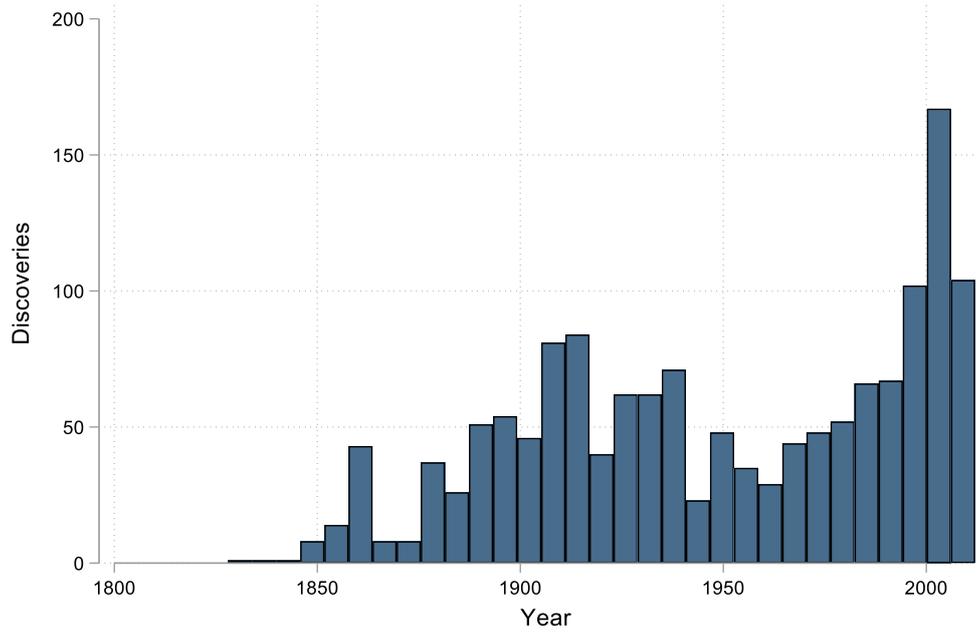
744 Table 3: Full Cox regression model hazard ratio results for the preferred model specification, model
 745 3B, where imports are from native and bridgehead regions over the past 20 years and are CS-weighted.
 746 Alternative limited models (trade- and species-focused) are also presented in the final two columns.
 747

<i>Variable</i>	Preferred model (3B)	Trade-focused model	Species-focused model
Log imports		1.04* (2.50)	-
CS			1.39 (1.05)
CS*Log imports	1.04*** (3.70)		
<i>Species attributes</i>			
Monogynous	0.80** (-2.60)	-	0.81* (-2.44)
Habitat generalism	1.12*** (5.11)	-	1.12*** (5.33)
<i>Native region</i>			
Africa	0.80* (-2.27)	0.71*** (-3.74)	0.84 (-1.85)
Central and South America	0.65*** (-3.71)	0.77* (-2.45)	0.67*** (-3.61)
Indo-Pacific	0.78* (-2.51)	0.75** (-3.02)	0.80* (-2.31)
Other	0.84 (-1.63)	0.84 (-1.65)	0.85 (-1.44)
<i>Importer region</i>			
Central and South America	1.03 (0.25)	1.03 (0.27)	
Europe	0.68*** (-3.44)	0.67*** (-3.68)	
Middle East & North Africa	1.13 (1.02)	1.12 (0.93)	
North America	1.38 (1.74)	1.17 (0.91)	
Oceania	1.15 (1.01)	1.18 (1.20)	
Sub Saharan Africa	0.91 (-0.75)	0.94 (-0.46)	
<i>Model statistics</i>			
Chi-square	80.3	42.6	57.3
LL	-4958.5	-4978.8	-4974.5
AIC	9942.9	9979.6	9963.0
BIC	10063.7	10081.8	10028.0
Obs.	79997	79997	79997

748 Notes: Figures in parentheses are t-values; significance levels: * p<0.05; ** p<0.01; *** p<0.001; omitted
 749 category for native and importer regions is Asia; LL=log pseudolikelihood.
 750

751

752



753

754

Figure 1: Worldwide non-native ant species discoveries (new species-country combinations) during the period 1793-2012

755

756

757

758

759