When you care enough
to send the very best pest

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Abstract

Border inspections are a powerful tool for preventing pest invasions through the pathway of international trade. Inspection resources, however, are highly constrained, meaning only a small subset of incoming shipments is actually inspected. Inspection efficiency can be improved by targeting effort, for example, towards shipments of fresh produce and horticultural products from exporters with a history of sending contaminated products. While such targeting is well-understood and used by many importers, it is not effective for the targeting of novel and/or transient threats. In this study, we combine theory and empirical analysis to investigate how market-based signals such as price spikes can be exploited to fine-tune inspection effort. We build a simple theoretical model to analyse the behaviour within the supply-chain for perishable goods when heterogeneous manufacturers (e.g. hothouses) face capacity constraints and risk-mitigation is endogenous. The theoretical model suggests price fluctuations in the market may provide early warnings of increasing risk in a pathway. The underlying mechanism is that wholesalers may increase purchases from non-traditional sources when prices spike—sources that have no reputational risk from supplying infested products—thereby increasing the contamination rate for shipments received from a given shipper. The primary testable hypothesis is that price spikes correlate with higher infestation rates, especially when the price spikes are unanticipated. We test this hypothesis using data from the UK inspection agency on import inspections from 2010-2019. After controlling for seasonality, commodity and exporter fixed effects, we find a strong, positive link between price increases and pest infestation. Historically, profiling imports for pest risk has been limited to using the outcomes of prior inspection outcomes. Our analysis offers an important new tool for leveraging real-time market data to enhance the cost-effectiveness of scarce border inspections for the mitigation of damaging pests, especially from novel, emerging threats.

1 Introduction

Phytosanitary inspection of incoming shipments at the border is a major means for preventing pest invasions through international trade (Leung et al., 2002; Lichtenberg and Olson, 2018). But in most countries, including the UK, inspection resources are highly constrained, allowing inspection of only a small fraction of incoming shipments (National Research Council, 2002). Better predicting when incoming shipments are likely to contain pests can improve inspection efficiency by informing how to target inspection effort on critical shipments and sources Surkov et al. (2008). However, this task is made difficult by the fact that risk is not constant over time as commodity pathways, products, origins, and environmental factors shift. In this study, we seek to test observable signals which may provide early warnings of increasing risk in a particular pathway.

We developed a theoretical model in which firms are heterogeneous in their phytosanitary risk, and assess how price fluctuations can affect the likelihood that traded goods are infested with pests. One hypothesis we explore is that price movements may serve as a warning, or “leading indicator”, of risk of pest invasions. Price shocks increase trade volumes and diversify supply sources. As prices rise, so too does the motivation for entry of products from fringe firms. Fringe firms are less likely to have established and consistent procedures
for mitigating contamination of their products with non-native organisms. These firms, who face a high likelihood that their shipments will be found to be infested (and thus rejected or destroyed), may be unwilling to export when prices are low but willing to send out shipments when prices are sufficiently high. Thus, demand surges in an importing country, and subsequent price increases, can lead to imports from new regions and suppliers, increasing invasion risk.

Here we investigate whether economic data be used to predict biological invasions? Few studies have examined the link between price changes and biological invasion risk. Surkov et al. (2008) applied a multinomial logistic regression model to data on import inspections of ornamental plant commodities in the Netherlands from 1998 to 2001 to investigate whether it is possible to predict the probability that a shipment will be infested and rejected. They showed that variables that characterize the imported shipment’s region of origin, the shipment’s size, the company that imported the shipment, and season and year of import were significant predictors of the probability of rejection. Lichtenberg and Olson (2018) analysed inspection data on U.S. fruit and vegetable imports from 2005-2014 and estimated a logistic model of the probability of potential invasive species arrival for 2,240 commodity/country of origin combinations. They identified clear patterns in the geographic origin and commodity pathways for potential pests. A similar study by Lichtenberg and Olson (2020) developed a theoretical model of tariffs and the risk of invasive species introductions in commodity imports. They reported that higher tariffs have ambiguous effects on invasive species introductions. While these studies consider general indicators of risk of invasion, they did not include prices.

In our empirical analysis, we estimate a model for predicting when and for what products there exist leading indicators, such as price spikes, that would allow better targeting of border inspections. We estimate the model using imports and border inspections data covering the period 2000-2019 provided by the Plant Health and Seeds Inspectorate (PHSI) in the United Kingdom (UK). To our knowledge, this is the first study to establish a link between pest infestation and prices of horticultural imports. The analysis is important both to understand the effectiveness of inspection efforts and consequently to predict the risk of introduction of non-indigenous species.

2 Theoretical model

There are two types of firms: hothouses and wholesalers. Each hothouse’s product carries an exogenously determined probability $f$ that it is infested at a given point in time; $f$ is the infestation risk. Whether a product is infested is not revealed until it is inspected. Let $g(f)$ be the density of hothouses with infestation risk $f$. Normalize units so the mass of hothouses is 1.

There are two markets for hothouse goods: Destination and Elsewhere, in which unit prices for hothouse goods are $p$ and $p^*$. The price in Elsewhere, $p^*$, is exogenous and fixed while $p$ is a random variable with a known distribution. Assume any infested shipments arriving at Destination are seized and destroyed by border services, while Elsewhere allows infested units to be sold without intervention.

The model has two periods. In the first period, the wholesaler offers contracts to selected
hothouses; the contracts stipulate quantities to be delivered and renumeration to be paid in the second period. Once contracts are offered and signed, hothouses commence production (i.e. plant seeds). In the second period, the price in Destination is revealed and hothouses harvest their crops. Contracts are honoured and, if it wishes, the wholesaler buys additional units from non-contracted hothouses on the spot market. Goods shipped to Destination are inspected and any infestations are revealed. Infested units are destroyed and non-infested units are released for sale in the Destination market. Remaining units are sold in Elsewhere.

Shipping to Elsewhere is costless.

If a hothouse wants to sell units in Destination, it requires the wholesaler to act as an intermediary and there are iceberg transport costs \( \tau \). Specifically, let \( \frac{1}{\tau} \) be the fraction of goods that survive transport to Destination’s port of entry; assume \( \tau \geq 1 \). Thus, a firm wanting to deliver 1 unit of the good to Destination needs to send \( \tau \) units. Destination’s border inspections are costless and detect infestations with perfect accuracy.

We model supply as the result of a two-stage process: in the first stage, individual hothouses sign contracts with the wholesaler (or not) and plant crops. In the second stage, hothouses harvest their crops. Those with contracts deliver their output to the wholesaler; those without contracts sell their goods in the spot market (where the wholesaler might purchase some goods from them) and all goods are shipped to either Destination or Elsewhere. Destination inspects incoming shipments and discards those found to be infested.

2.1 First Stage

2.1.1 Hothouses

Let \( c(q) \) measure a hothouse’s total cost of producing \( q \) units; \( c \) is the same for all hothouses. Each hothouse has the option of selling as much as it wants at price \( p^* \) in Elsewhere. Elsewhere doesn’t have any SPS protections, so every unit shipped to Elsewhere will receive \( p^* \). Define

\[
q^* = \arg\max_q \left[ p^* q - c(q) \right]
\]
as the amount a hothouse would send to Elsewhere if that market was its best option. The variable \( q^* \) solves

\[
p^* = c'(q^*).
\]

Define \( \pi^* \equiv p^* q^* - c(q^*) \) as the profit a hothouse will make if it serves Elsewhere instead of Destination.

2.1.2 Wholesaler

Assume the wholesaler knows each hothouse’s \( f \) as well as the common cost function \( c \). The wholesaler can engage with hothouses two ways: they can sign an advance contract, or the wholesaler can buy units on the spot market. Advance contracts specify the number of units to be provided and total renumeration, \( R \), for those units.

The wholesaler’s expected profit is

\[
\int_0^\infty h(p) \left[ (1 - f) \frac{p}{\tau} q - R \right] dp.
\]
Because \( f, q \) and \( R \) are all independent of \( p \), we can factor out these terms and rewrite expected profits as

\[
\int_0^{\infty} h(p) \left[ (1 - f) \frac{p}{\tau} q - R \right] dp = \frac{1 - f}{\tau} q \int_0^{\infty} h(p)p dp - R = [1 - f] \frac{\mathbb{E}(p)}{\tau} q - R
\]

where \( \mathbb{E}(p) = \int_0^{\infty} h(p)p dp \) is the expected price in Destination.

Because any hothouse can earn \( \pi^* \) by selling in Elsewhere, its participation constraint is \( R \geq \pi^* + c(q) \). To keep things simple, assume there’s only one Wholesaler to whom a given hothouse can sell; this means the Wholesaler reaps any excess profits, i.e. the wholesaler will offer

\[
R(q) = \pi^* + c(q)
\]

in exchange for \( q \) units.

In light of a hothouse’s participation constraint (1), the wholesaler will set the contracted quantity so as to

\[
\max_q \frac{\mathbb{E}(p)}{\tau} [1 - f]q - c(q) - \pi^*.
\]

Denote by \( q(f, \mathbb{E}(p)) \) the quantity solving (2) for a firm with infestation risk \( f \): \( q(f, \mathbb{E}(p)) \) solves

\[
\frac{\mathbb{E}(p)}{\tau} [1 - f] = c'(q(f, \mathbb{E}(p))).
\]

Differentiating (3) shows that low-risk hothouses are asked to supply more:

\[
\frac{dq(f, \mathbb{E}(p))}{df} = -\frac{\mathbb{E}(p)}{\tau c''(q(f, \mathbb{E}(p)))} < 0.
\]

For any \( \mathbb{E}(p) \), there’ll be some hothouses from which the wholesaler’s expected profit from \( R(q(f, \mathbb{E}(p))) \), \( q(f, \mathbb{E}(p)) \) is negative.

Let \( \bar{f} \) denote the infection rate of a marginal hothouse, i.e. a hothouse from which the wholesaler can just break even in expectation: \( \bar{f} \) solves

\[
\frac{\mathbb{E}(p)}{\tau} [1 - \bar{f}] q(\bar{f}, \mathbb{E}(p)) = c(q(\bar{f}, \mathbb{E}(p))) + \pi^* \quad (ZCP)
\]

which, borrowing terminology from the new-new trade literature, is the “zero cutoff profits” (ZCP) rule. The wholesaler will not offer a contract to any hothouse with \( f < \bar{f} \). Those hothouses will instead produce \( q^* \) units each for the Elsewhere market. The zero cutoff profit rule is depicted in Figure 1, where the wholesaler’s expected revenue, \( [1 - f] \frac{\mathbb{E}(p)}{\tau} q \), less a wholesaler’s reservation price \( \pi^* \), is tangent to the common cost function \( c(q) \) at \( q(\bar{f}, \mathbb{E}(p)) \). Notably, firms with \( f > \bar{f} \) are asked to supply more than a firm with cutoff infestation probability \( \bar{f} \), such as for a hothouse with \( f = f^o \) as depicted in Figure 1.
2.2 Second Stage

At the start of the second stage, hothouses harvest their output and Destination’s price is revealed. If \( p \leq \mathbb{E}(p) \) then the wholesaler has no interest in buying additional units in the spot market. The total amount of goods arriving at Destination is

\[
Q_c = \int_0^f g(f)q(f, \mathbb{E}(p))df
\]

while the number of infested units arriving at Destination is

\[
I_c = \int_0^f g(f)fq(f, \mathbb{E}(p))df.
\]

Things are more interesting if \( p > \mathbb{E}(p) \). In this case, there are some inframarginal, non-contracted hothouses from whom the wholesaler is willing to buy units at \( p^* \). These are the hothouses for which \( f \in (\bar{f}, \tilde{f}] \) where \( \tilde{f} \) solves

\[
\frac{p}{\tau}[1 - \tilde{f}] = p^*.
\]

Specifically, these are hothouses that were not worth buying from when the wholesaler expected the price to be \( \mathbb{E}(p) \), but from whom its expected profit is positive when the realized price is high. Note: \( \tilde{f} \) is increasing in \( p \) and \( \lim_{p \to \mathbb{E}(p)} \tilde{f} = \bar{f} \). The wholesaler buys \( q^* \) units from each hothouse with \( f \in (\bar{f}, \tilde{f}] \). Denote the total number of units bought from non-contracted hothouses as

\[
Q_s = \begin{cases} 
0 & \text{for} \ p \leq \mathbb{E}(p) \\
\int_\bar{f}^{\tilde{f}} g(f)q^*df & \text{for} \ p > \mathbb{E}(p)
\end{cases}
\]

while

\[
I_s = \begin{cases} 
0 & \text{for} \ p \leq \mathbb{E}(p) \\
\int_\bar{f}^{\tilde{f}} g(f)f q^*df & \text{for} \ p > \mathbb{E}(p)
\end{cases}
\]

indicates the quantity of goods infested/intercepted that were produced by non-contracted hothouses.

To wrap things up, note that the total quantity supplied to Destination is

\[
Q = Q_c + Q_s
\]

while the total number of infested units shipped to Destination is \( I_c + I_s \). The infestation rate is thus

\[
\frac{I}{Q} = \frac{I_c + I_s}{Q_c + Q_s}
\]
3 Comparative Statics

3.1 Anticipated Price Surges

There are periods each year where prices surge in the Destination market. Sometimes these surges are expected, like Valentine’s Day for roses and Super Bowl Sunday for avocados, and so on. Anticipating prices will be higher on these days, the wholesaler will contract for more output from regular suppliers at these times: differentiating (3) gives

\[
\frac{dq(f, E(p))}{dE(p)} = \frac{1 - f}{\tau c''(q(f, E(p)))} > 0.
\]

Differentiating the ZCP condition and rearranging shows \( \bar{f} \) is also increasing in \( E(p) \):

\[
\frac{d\bar{f}}{dp} = \frac{1 - \bar{f}}{p} > 0.
\]

This is sensible: as expected prices in Destination rise, the wholesaler is willing to pay more for any given firm’s product, which allows marginal hothouses to now serve Destination.

Proposition 3.1 A fully-anticipated increase in expected price \( E(p) \) raises \( Q \) and \( I \) and has an ambiguous effect on the infestation rate \( I/Q \).

Proof: “Fully-anticipated” means the realized price \( p \) equals \( E(p) \) and so \( Q_s = I_s = 0 \) and so \( Q = Q_c \) and \( I = I_c \). A rise in \( E(p) \) drives the following changes in \( Q_c \) and \( I_c \):

\[
\frac{dQ_c}{dE(p)} = g(\bar{f})q(\bar{f}, E(p)) \frac{d\bar{f}}{dE(p)} + \int_0^{\bar{f}} g(f) \frac{1 - f}{\tau c''(q(f, E(p)))} df > 0
\]

and

\[
\frac{dI_c}{dp} = g(\bar{f})\bar{f}q(\bar{f}, E(p)) \frac{d\bar{f}}{dE(p)} + \int_0^{\bar{f}} g(f) f \frac{1 - f}{\tau c''(q(f, E(p)))} df > 0.
\]

Regarding the effect on the infestation rate \( I/Q \). On one hand, the rise in \( \bar{f} \) means that the new contractors are more likely than low-\( f \) firms to be sending infested goods. On the other hand, if the distribution \( g(\cdot) \) is skewed toward low-\( f \) firms, their expanded supply of low-\( f \) units may dominate the effects of entry by high-\( f \) firms, and so the average infestation/interception rate may actually fall.\(^1\)

\(^1\)Suppose costs are quadratic: \( c(q) = \alpha + \frac{\beta}{2} q^2 \). Then \( c' = \beta q \) and so

\[
q(f, E(p)) = \frac{E(p)(1 - f)}{\tau \beta} \quad \text{while} \quad \bar{f} = 1 - \sqrt{\frac{2\alpha}{p/\tau}}.
\]

With this cost function, \( q(f, E(p)) \) is multiplicatively separable in \( E(p) \), and so the \( E(p) \) terms in the numer-
Notably, $Q_c$ and $I_c$ rise with $\mathbb{E}(p)$ because of expansion along both the intensive and extensive margins. For the intensive margin, each contracted hothouse is asked to grow more for high-price periods; along the extensive margin, even firms with a moderately high risk of producing goods that will ultimately be seized can help the wholesaler earn an expected profit if retail prices are expected to be high.

**Proposition 3.2** An unexpected price surge (i.e. an event where $\mathbb{E}(p)$ is unchanged but $p > \mathbb{E}(p)$) raises $Q$ and $I$ and raises the infestation rate $I/Q$ unambiguously.

**Proof**: Holding $\mathbb{E}(p)$ constant, a realization of $p > \mathbb{E}(p)$ has no effect on supply from contracted hothouses. Thus $dQ_c/dp = dQ_s/dp = 0$. Since $\bar{f} > \tilde{f}$ when $p > \mathbb{E}(p)$, when there is an unexpected price surge, the wholesaler will purchase units from non-contracted hothouses and so $dQ/dp = dQ_s/dp = q^* g(\tilde{f}) \frac{df}{dp} > 0$. The associated increase in interceptions is $dI/dp = dI_s/dp = q^* \bar{f} g(\bar{f}) \frac{df}{dp} > 0$. The change in the interception rate is

$$
\frac{dI}{Q} = \frac{d}{dp} \frac{I_c + I_s}{Q_c + Q_s} = \frac{q^* g(\tilde{f})}{Q_c + Q_s} \left[ \bar{f} - \frac{I}{Q} \right] \frac{df}{dp}
$$

which is positive given that the infestation risk from the marginal hothouse necessarily exceeds the average infestation rate of inframarginal hothouses: $\bar{f} > \frac{I}{Q}$.

Intuitively, if the price surge is unanticipated, all of the extra supply must come from the spot market, which will carry higher infestation risk than that from already-contracted hothouses.

Collectively, these propositions suggest the following: an unexpected price surge will raise the interception/infestation rate by more than does an expected price surge.

### 4 Empirical Analysis

#### 4.1 Logistic Model of Infested Consignments

We employ a logistic model to estimate the probability of pest infestation as a function of consignment volume, average prices, commodity type, country of origin, seasonality, and year of import. We use the model to identify “indicators” of increased risk of pest infestation to target phytosanitary inspections. The log odds of the probability (Long and Freeze, 2014)

$$
\frac{I}{Q} = \frac{\int_0^\tilde{f} g(f) f [1 - f] df}{\int_0^\tilde{f} g(f) [1 - f] df}
$$

and so

$$
\frac{d\tilde{f}}{dp} = \frac{g(\tilde{f}) [1 - \tilde{f}]}{\int_0^\tilde{f} g(f) [1 - f] df} \left[ \tilde{f} - \frac{I}{Q} \right] \frac{df}{d\mathbb{E}(p)} > 0;
$$

which is positive so long $\tilde{f} > \frac{I}{Q}$, which holds provided the distribution isn’t degenerate. If the distribution is degenerate then $\frac{dI/Q}{d\mathbb{E}(p)} = 0$. Recap: when cost functions are identical and quadratic, expansion along the extensive margin dominates and so interceptions, quantity, and average interceptions all rise with $\mathbb{E}(p)$. 8
of an infested consignment, \( \phi_{ijmt} \), in commodity \( i \), from exporter \( j \), in month \( m \), and year \( t \) is conditional on the characteristics of the consignment and is given as follows:

\[
\frac{\phi_{ijmt}}{1 - \phi_{ijmt}} = \beta_0 + \beta_1 \ln(\text{Weight}_{ijmt}) + \beta_2 \ln(\text{Price}_{ijmt}) + \sum_i \beta_3 \text{Origin}_i + \sum_k \beta_4 \text{Commodity}_j + \sum_m \beta_5 \text{Month}_m. \tag{4}
\]

The outcome variable, infested consignment, takes on the value 1 for shipments that are infested and a value of 0 otherwise. \( \text{Weight}_{ijt} \) is the weight, in tonnes, of a commodity \( i \) consignment, shipped from country \( j \), during month \( m \), in year \( t \). Likewise, \( \text{Price}_{ijmt} \) represents the average monthly price of commodity consignment \( i \), shipped from country \( j \), during month \( m \), in year \( t \). The \( \beta \) terms are the coefficients to be estimated. We used robust standard errors clustered at the exporting country-commodity level. Variation in the model comes from inspections on multiple monthly level consignment observations, across commodities, exporting source countries (Lichtenberg and Olson, 2018), and years.

### 4.2 Data and descriptive statistics

Our main data set consists of records of 555,672 consignments received in the UK over 10 years (January 1, 2010 to December 31, 2019) including whether each consignment was inspected by the personnel of the Plant Health and Seeds Inspectorate (PHSI). The data includes: (i) a unique reference code for each consignment, (ii) the country of origin, (iii) the genus and species of fruits, vegetables and cut-flower product, (iv) the date of inspection (if any), (v) whether pests were found in the consignment, and if so, (vi) what pests were detected. The data were carefully examined to correct for entry, typographical errors, and missing values. The data set covers 18 types of regulated plant materials (by CN codes) and shipments originate from 110 countries. We focus on the 18 horticultural commodities with the highest volume/value of regulated materials. All 18 types of horticultural materials were inspected, and inspections were made on consignments received from 93 countries. Of these, 153,861 consignments (approximately 28%) were inspected while 401,811 imports were not inspected\(^2\). Of the 153,861 imports inspected, 4,962 (3.3%) of the shipments were found to be infested with one of the 6,412 pests identified. There are 388 combinations of country (93) and commodity (18) inspections. Pests were found on imports from 68 different countries and at least once on every commodity. Of the 388 country-commodity combinations, pests were found on 214 of them.

Table 1 provides summary statistics on inspections and interceptions for all commodities in our data set. The inspection rate is the percentage of consignments of a given commodity that are inspected. Overall in aggregate 27.7% of consignments were inspected, with rates at the commodity level ranging from a low of 6.2% for tomatoes to a high of 61.8% for chillies. The interception rate is the percentage of inspected consignments that are found to have a

\(^2\)Of the 555,672 records of imports, 266,603 consignments were listed as not requiring inspections under the “reduced inspection” policy of the EU. These were subsequently dropped from analysis. Shipments with a “failed physical” attributes were also dropped from the analysis because they were perfectly correlated with infestation.
pest. Celery, chillies, aubergines and limes have the highest interception rates. In aggregate, 3.2% of inspections identified a pest. Substantial differences were also observed among the commodity groups in terms of the inspection rate. The inspection rate was particularly high for plant products—chrysanthemums and orchids—as well as chillies, celery, aubergines, and citrus fruits.

Table 1: Inspection and interception rate by commodity

<table>
<thead>
<tr>
<th>Commodity</th>
<th>Inspection rate (%)</th>
<th>Interception rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Apples</td>
<td>11.9</td>
<td>0.8</td>
</tr>
<tr>
<td>Aubergines</td>
<td>37.5</td>
<td>5.1</td>
</tr>
<tr>
<td>Carnations</td>
<td>10.0</td>
<td>1.0</td>
</tr>
<tr>
<td>Celery</td>
<td>42.6</td>
<td>8.9</td>
</tr>
<tr>
<td>Chillies</td>
<td>61.8</td>
<td>5.8</td>
</tr>
<tr>
<td>Chrysanthemums</td>
<td>58.3</td>
<td>2.3</td>
</tr>
<tr>
<td>Citrus - Clementines</td>
<td>27.1</td>
<td>0.6</td>
</tr>
<tr>
<td>Citrus - Lemons</td>
<td>44.2</td>
<td>0.8</td>
</tr>
<tr>
<td>Citrus - Limes</td>
<td>48.3</td>
<td>4.5</td>
</tr>
<tr>
<td>Citrus - Oranges</td>
<td>37.2</td>
<td>1.1</td>
</tr>
<tr>
<td>Citrus - Satsumas</td>
<td>31.8</td>
<td>1.3</td>
</tr>
<tr>
<td>Nectarines</td>
<td>20.6</td>
<td>1.5</td>
</tr>
<tr>
<td>Orchids</td>
<td>57.0</td>
<td>2.0</td>
</tr>
<tr>
<td>Peaches</td>
<td>32.1</td>
<td>2.8</td>
</tr>
<tr>
<td>Plums</td>
<td>12.1</td>
<td>2.1</td>
</tr>
<tr>
<td>Quinces</td>
<td>22.9</td>
<td>3.7</td>
</tr>
<tr>
<td>Roses</td>
<td>10.2</td>
<td>1.4</td>
</tr>
<tr>
<td>Tomatoes</td>
<td>6.2</td>
<td>3.6</td>
</tr>
<tr>
<td>Aggregate</td>
<td>27.7</td>
<td>3.2</td>
</tr>
</tbody>
</table>

The consignment level data from PHSI does not contain consignment level prices, which is a key variable in testing our theory model. To obtain information on commodity level prices we downloaded monthly trade data of exports of plant products to the UK from the UN Comtrade Database (UN Comtrade, 2021). The data are disaggregated by harmonized system (HS) commodity type (HS code) and country of origin. Aggregate monthly trade volumes (in tonnes) and export values of plant products imported to the UK were collected for the following HS codes: 060311 (Roses), 060312 (Carnations), 060313 (Orchids), 060314 (Chrysanthemums), 070200 (Tomatoes), 070930 (Aubergines/Eggplants), 070940 (Celery), 070960 (Capsicum), 080510 (Oranges), 080521 (Mandarins), 080522 (Clementines), 080550 (Lemons/figures), 080810 (Apples), 080840 (Quinces), 080930 (Peaches) and 080940 (Plums). Average monthly prices were calculated by dividing the aggregate monthly trade values by the weight of monthly trade for every commodity and trade partner. Average monthly prices were then matched to the consignment level data for every given month-commodity-exporter triplet.

One important source of variation in the data that is necessary to identify the effects of price movements on infestation risk is that there must be variation in commodity prices.
across time. Figure 2 shows an example of a plot of monthly prices for one selected commodity (cut flower imports) during the period of study. It shows significant variation in prices across product types and months.

![Roses](#) ![Carnation](#) ![Orchids](#) ![Chrysanthemums](#)

Figure 2: Prices of cut flower imports by types between January 2010 and December 2019 in the UK

Table 2 presents summary statistics for the key variables of number of infested shipments as well as monthly price and weight. As evidenced by the large standard deviations, there is substantial variation in the data in both prices and consignment weights.

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Infested shipment</td>
<td>0.03</td>
<td>0.18</td>
<td>0.00</td>
<td>1.00</td>
<td>153,861.00</td>
</tr>
<tr>
<td>Weight of consignment in tons</td>
<td>9.29</td>
<td>27.38</td>
<td>0.00</td>
<td>6,829.49</td>
<td>153,861.00</td>
</tr>
<tr>
<td>Price per tonne</td>
<td>3,361.93</td>
<td>6,199.22</td>
<td>177.37</td>
<td>895,809.50</td>
<td>139,306.00</td>
</tr>
</tbody>
</table>
5 RESULTS

5.1 Logistic Model Results

Table 3 presents the results of various estimations of the logistic regression model in equation (4). We report the estimates as the odds ratios rather than coefficients to provide a more intuitive interpretation of the results. For example, for a unit change in the predictors (x), the odds are expected to change by a factor of \( \exp(\beta_x) \), holding all other variables constant. For \( \exp(\beta_x) > 1 \), it can be said that the odds are “\( \exp(\beta_x) \) times larger” while for \( \exp(\beta_x) < 1 \), we can say the odds are “\( \exp(\beta_x) \) times smaller” (Long and Freese, 2006). The p-values refer to null hypothesis tests that exponentiated coefficients on Log weight and Log price are each equal to 1.

Our primary variable of interest from the theory model is to test whether positive price movements increase the probability that a consignment is infested. In column (1) we run a simple version of the model where the probability of a shipment being infested is only a function of the natural log of weight and price. The odds ratios on both weight and price are statistically significant but less than 1, indicating that increases in the weight and price of a consignment decrease the probability that an inspected shipment will contain pests. This is contrary to the predictions of our theory model. Two things may be confounding the results.

First, with respect to the price variable, the theory predicts that infestation risk will increase due to unanticipated price increases; the prediction with respect to anticipated price shocks is indeterminate. Second, the result that larger (by weight) shipments decrease the probability of an infested shipment is counter-intuitive, suggesting that there may be unobserved characteristics of shipments that are correlated with weight that may be biasing the results downward.

The panel nature of our dataset allows us to employ several dimensions of fixed effects to help control for these unobserved characteristics. With respect to price, there are many differences amongst the commodities in our sample in terms of the type of product, where they come from and the seasonality (e.g. month) for which we might expect them to be imported to the U.K. Many of these location, month, or product characteristics are predictable to the markets but unobserved by the researchers. Employing a variety of fixed effects along these dimensions allows us to control for the predictable but unobserved characteristics that may be correlated with weight that may be biasing the results downward.

We test these results by adding a variety of dummy variables to our basic regression in columns (2)-(5) of Table 3. In column (2) we include dummy variables for each of the 16 commodity types. In column (3) we include both commodity dummies as well as dummy variables for each of the exporting countries. These dummy variables capture commodity specific factors across exporters, and country of origin specific factors across commodities, which can reflect the implementation of Sanitary and Phytosanitary (SPS) measures, and other country specific characteristics that are correlated with price and weight of a consignment (Dalmazzone and Giaccaria, 2014; Lichtenberg and Olson, 2018). In both columns we see that high prices and consignment weight now have a statistically significant and positive effect on the odds ratio, just as our theory suggests. In column (3), the odds ratio on the price variable suggests that a 1% increase in price increases the probability that a
shipment will be infested by 39% relative to its baseline probability of being infested. A 1% increase in weight increases the probability that a shipment will be infested by 8.7% relative to its baseline probability of being infested. This finding on weight is consistent with several studies which show that an increase in the volume of horticultural imports is correlated with increased risk of invasion (Areal et al., 2008; Mwebaze et al., 2010).

In column (4), we recognize that price changes may not only be common to specific commodities or countries, but that there may be unobserved characteristics that are specific to commodity by exporter pairs. To control for that possibility we employ a full set of commodity by exporter pairwise dummy variables. The odds ratios on weight and price remain statistically significant with similar qualitative results, although the odds ratio on price is cut by about half. In column (5) we run the same regression as in column (4) but also include separate month dummies to capture any seasonality in prices. The results in column (5) are similar to those in column (4). After controlling for monthly and commodity by exporter pairwise unobserved effects the odds ratio on price indicates that a 1% increase in price increases the probability that a shipment will be infested by 15.3% relative to its baseline probability of being infested.

Table 3: Logistic model results (odds ratios)

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log weight</td>
<td>0.859***</td>
<td>1.080***</td>
<td>1.087***</td>
<td>1.124***</td>
<td>1.125***</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.014)</td>
<td>(0.015)</td>
<td>(0.016)</td>
<td>(0.016)</td>
</tr>
<tr>
<td>Log price</td>
<td>0.881***</td>
<td>1.238***</td>
<td>1.392***</td>
<td>1.170**</td>
<td>1.153**</td>
</tr>
<tr>
<td></td>
<td>(0.020)</td>
<td>(0.042)</td>
<td>(0.082)</td>
<td>(0.076)</td>
<td>(0.074)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.083***</td>
<td>0.002***</td>
<td>0.011***</td>
<td>0.003***</td>
<td>0.003***</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.001)</td>
<td>(0.015)</td>
<td>(0.002)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Commodity FE</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Exporter FE</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Comm-Exporter FE</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Month FE</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>139303</td>
<td>139303</td>
<td>139221</td>
<td>137381</td>
<td>137381</td>
</tr>
</tbody>
</table>

Notes: Exponentiated coefficients; Standard errors in parentheses;
* \(p < 0.10\), ** \(p < 0.05\), *** \(p < 0.01\)

As anticipated, the relative risk of pest infestation varies across source regions. Several exporters present significant risk of pest infestation. Figure 3 is a plot of the odds ratios of the countries of origins with the highest likelihood of pest infestation. Countries such as Nigeria, Trinidad and Tobago, United Arab Emirates, St Vincent and the Grenadines, Venezuela, Canada, Albania, Iran, Guatemala, Bangladesh, Senegal and China represent origins with the highest probabilities of pest infestation, with averages across all commodities, seasons, and years of 6-36 times higher than the baseline risk of infestation. At the other end, Chile, Argentina, Mozambique, and South Africa are low risk sources of potential pest infestation.
6 CONCLUSION

Phytosanitary inspection of agricultural products at the border is an effective means of preventing shipments infested with unwanted and potentially costly pests from invading a country’s borders. But only a small fraction of shipments can actually be inspected. We develop a model of exporter behavior and show that the probability that a shipment is infested is positively related to unanticipated price shocks. This is due to wholesalers increasing their use of marginal suppliers when prices rise. Using consignment level data in the UK covering 16 agricultural commodities over 10 years and more than 90 exporting countries we show that the risk of a consignment being infected is in fact positively correlated with unanticipated price increases. The results are important for customs officials who are interested in identifying leading indicators for risk of pest infestation. Our theory and empirical model results suggest that positive price shocks in international agricultural markets are a signal that customs officials should pay attention when allocating their limited inspection resources.
References


Mwebaze, P., Monaghan, J., Spence, N., MacLeod, A., Hare, M., and Revell, B. (2010). Modelling the risks associated with the increased importation of fresh produce from emerging supply sources outside the EU to the UK. *Journal of Agricultural Economics, 61*(1):97–121.
