MODELLING THE RISKS ASSOCIATED WITH INCREASED IMPORTATION OF FRESH PRODUCE FROM EMERGING SUPPLY SOURCES TO THE UK

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Abstract-**The risk of non-indigenous pests entering the UK via international trade in fresh produce is increasing. Suppliers of fresh produce to UK and EU multiple retailers are utilising new procurement areas for fresh produce importation to reduce their costs of production. The objective of this paper is to identify current and future supply sources for UK fresh produce importers and examine the extent to which they provide invasion pathways. The hypothesis that increased importation of fresh produce from new sources outside the EU could increase the risks of non-indigenous pests is tested in a bio-economic model in which the number of species detections per unit of imports is a function of the number of inspections per unit of imports and country of origin, while the volume of imports is itself a function of the gross domestic product, relative import prices, policy and seasonality variables. The study has identified clear trends, which show import volumes and pest species detections increasing from new supply sources. The study found that risk of pest species differs significantly with the country of origin of commodity. If this trend should continue in the future, then UK plant health inspectors should expect to confront pest species in much greater numbers. The results support the case for discriminatory policy to use the limited resources available in a way that will more closely target inspection efforts on the higher risk trade pathways.**

Keywords-*Quarantine pests, pathways, trade*.

I. INTRODUCTION

The unintentional introduction of non-indigenous species (NIS) has become a serious global concern. Estimates of damages caused by NIS globally including control costs exceed $314.7 billion per year [1,2]. Trade is a major driver of introductions of NIS [3-8]. The development of new trade routes is opening up new pathways[1] for introductions and the growth of trade along existing routes is increasing the risk of introductions [11,12]. One pathway under increasing scrutiny is the fast growing trade in fresh horticultural commodities [13,14]. This trade, often transported by air, has introduced several cryptic quarantine plant pests that hide inside fresh produce and packaging, for example, fruit-fly larvae, Thrips and leafminers [15]. Most quarantine plant pests may be regarded as invasive alien species (IAS), according to the Convention on Biological Diversity (CBD), as they are alien to a specified region, and threaten ecosystems, habitats and other species [16].

This paper examines the potential risks associated with the increased importation of fresh produce from emerging supply sources outside the EU to the UK. According to Eurostat [17], fruit and vegetable imports into the UK amounted to €5.0 billion and 5.2 million tonnes in 2005: More than half of the value of the fruit and an increasingly large share (14%) of the vegetables originated from countries outside the EU. Suppliers of fresh produce to UK and EU multiple retailers are utilising new growing areas to reduce their costs of production [18]; for example in countries such as Morocco, Tunisia, Algeria, Turkey, Egypt, Ghana and Senegal. There are major grounds for concern with this approach including issues with production inexperience, naïve supply chain infrastructure, inadequate plant health inspection regimes and reduction in the number of approved chemical pesticides for pest control [15,19,20]. There may be significant risks of introductions of harmful pests and diseases that urgently need to be addressed.

In situations where there is a detrimental risk, the World Trade Organisation (WTO) Agreement on the application of Sanitary and Phytosanitary (SPS)

[1] A pathway is 'any means for pest entry' [9] and is commonly described using the country of origin, country of import and the commodity [10].

measures allows national governments to require appropriate phytosanitary measures in order to protect plant health from introduction, establishment and spread of harmful pests. But for any such measures to be taken on plant health grounds, it is necessary to show first the probability that the pest would become established in the importing country, and second that measures proposed would reduce this probability [21].

Modelling how the growth of trade affects species introductions is complicated by the paucity of time series on species introductions to match the available time series on trade. However, a number of studies have successfully developed empirical models containing a range of economic (e.g. trade flows, GDP), institutional and policy variables (e.g. import duties) for the historical establishment of NIS [22,23]. The modelling approach has been further developed by incorporating basic trade forecasts to predict future rates of biological invasions [24]. More recently, Costello *et al*. [8] developed a model linking exotic species introductions and discoveries to trade volumes and combined the model with estimates of future trade volumes to make region-specific predictions of future invasions by trade partner. Their results suggest that trade from different regions pose different risks and that the cumulative number of introductions is a concave function of the volumes of imports.

This paper incorporates the different modelling approaches drawn from the published studies. The objectives of the study were three fold: (i) to identify current and potential future supply sources for UK fresh produce importers (ii) to examine the extent to which they provide invasion pathways and (iii) to determine the major trade and economic drivers of changes in the volumes of imports of fresh produce. The paper will test the hypothesis that increased importation of fresh produce from countries outside the EU could increase the likelihood of introduction of non-indigenous pests in the UK. The results may be useful to develop future trade policies that will minimise the chances of 'contaminated' commodities arriving in the UK in the first instance.

The rest of the paper is organised as follows. Section II describes the modelling approach, estimation and data sources. Empirical results are reported and discussed in section III. Section IV concludes the paper.

II. METHODOLOGY

A. The model and estimation

We modelled the relationship between changes in the volumes of imports and arrival rate of species. We extended the modelling approach provided by McAusland and Costello [25], and Costello *et al*. [8], making use of the following assumptions. We assumed that a single commodity originates from a single exporting country to a single importing country. 'Arrival' occurs when trade facilitates transport of species from the exporting country to the importing country but the species need not take hold in the new location. It was further assumed that the importing country uses border inspections to reduce species introductions, where by higher inspection levels are costly but facilitate a higher detections rate.

Let the random variable I_t denote the intensity with which each unit of imported commodities is inspected in a given time period t. Also let the random variables N_t and S_t denote the number of species that arrive and the number of species that get intercepted respectively in time t. In contrast to S_t, N_t is unobserved [8,12]. Following Costello *et al*. [8], Dalmazzone [22], Vila and Pujadas [23], Levine and D'Antonio [24], Costello and McAusland [26], the arrival rate of species (N_t) is a function of the volumes of imports (1).

$$N_t = f\left(M_t\right) \tag{1}$$

Where: M_t is the volumes of imports, M>0, $\dfrac{\partial N}{\partial M} > 0$ reflects the potential of imports to transport species. There are no direct observations on the variable N_t. The observed variable is the number of species detections (S_t), which can be expressed in cumulative form [8] as in Equation (2).

$$S_t = \sum_{t=1}^{t} s(t) \tag{2}$$

Where: the variable *s(t)* is the number of species that are detected in time (t), and the cumulative number of species detections (S_t) is obtained by summation (2). But the number of species detections depends on a number of endogenous factors not least of which include the detection effort (I_t) and volumes of imports (M_t) [12,14, 27] as in Equation (3).

$$S_t = f(I_t, M_t) \tag{3}$$

Where: I_t is a non-negative quantity ($I_t \geq 0$), S_t will change due to a change in I_t, even if M_t remains constant. S_t may change due to a change in M_t, even if I_t remains constant. However, if M_t changes, I_t will also likely change, such that an increase in the volumes of imports will likely lead to an increase in the detection effort and vice-versa. The variables M_t and I_t are therefore likely to be highly co-linear in the model. Thus one needs to control for the changes in the volume of imports in the modelling.

Equation (3) needs to be adjusted to allow for a multiple country of origin scenario, in which the variables S_t, I_t and M_t can change with each country of origin. To determine the relative rates of species detections between different countries of origin while at the same time controlling for changes in the volume of imports, one would model the number of detections per unit (tonne) of imports (i.e. detection rate) as a function of the number of inspections per tonne of imports (i.e. intensity of inspections), introducing a dummy variable for each country of origin to allow for the change in the intercept, as in Equation (4).

$$\frac{S_{it}}{M_{it}} = f\left(\frac{I_{it}}{M_{it}}, d(i)\right) \tag{4}$$

Where: $\left(S/M\right)_{it}$ is the rate of species detections and $\left(I/M\right)_{it}$ is the intensity of inspections, and the dummy variable (d_i) is used to represent each country of origin (i = 1, …n countries) included in the model.

But from econometric investigations of import demand, the volume of imports is itself a function of the real incomes of the importing country, measured by the Gross Domestic Product (GDP), import prices, domestic prices, exchange rates, tariffs and a dummy variable is usually introduced to account for unusual periods such as devaluations, policy changes and seasonality [28-31], as in Equation (5).

$$M_t = f\left(Y_t, \left(\frac{P_m}{P_d}\right)_t, T(t)\right) \tag{5}$$

Where: Y_t is the real GDP in time t, P_m is import prices and P_d is domestic prices both measured in the same currency. The exchange rate was introduced indirectly by expressing all prices in common currency units. The relative price ratio adjusted for the exchange rate gives a measure of the real exchange rate [32]. T(t) is a time trend (with values 0-1 for each quarter) to capture the effect of seasonality on import volumes.

Equations (4) and (5) show import volumes of fresh produce affecting arrival and detection rates of species, and itself being affected by the GDP of the importing country, relative import prices, policy and seasonality variables. There are two hypotheses that can be jointly tested. The first hypothesis represents a model of the determination of species detections and the second hypothesis represents a model of the determination of import volumes of fresh produce. The two equations can be brought together to give a bigger model as in Equations (6) and (7) where the log-linear functional form specification is used. The log-linear form is the most widely used functional form in empirical studies of import demand [28,29,30,33]. The estimated coefficients give directly the relevant elasticity coefficients. This specification has the added advantage of reducing the problem of heteroskedasticity in empirical studies [34].

$$\ln M_t = \alpha_0 + \alpha_1 \ln Y_t + \alpha_2 \ln\left(\frac{P_m}{P_d}\right)_t + \alpha_3 t + e_t \tag{6}$$

$$\ln\left(\frac{S}{M}\right)_{it} = \beta_0 + \beta_1 \ln\left(\frac{I}{M}\right)_{it} + \sum_{i=1}^{i=n} \beta_{2i} d_{it} + u_{it} \tag{7}$$

Where: *ln* stands for the natural logarithms of the relevant variables; α_1-α_4 are elasticity coefficients with respect to the relevant variables in Equation (6), α_0 is the intercept term, and e_t is the error term with its classical properties. In Equation (7), β_0 is a constant, β_1 measures the rate at which the number of species detections per tonne of imports increases with the intensity of inspection and u_t is the error term with the usual properties. We assume a single commodity and use the dummy variable (d_i) to represent the country of origin (i =1, …n), β_{2i} effectively are proxy estimates for the detection rate for each country of origin.

The *a priori* sign expectations are as follows. The impact of the first two explanatory variables in Equation (6) is derived from the theory of demand

[28]. Following the standard demand theory, the coefficient of real income (y) is expected to take a positive sign ($\alpha1>0$) and the relative price to have a negative sign ($\alpha2<0$). In Equation (7), the marginal rate of species detections is expected to increase with the intensity of inspections ($\beta_1>0$). The signs of the intercept dummy variables should vary with each country of origin, so no hypothesis is given.

B. The empirical framework

Equation (6) could be estimated using the standard OLS regression if the variables are stationary and the error term (e_t) is uncorrelated and homoskedastic. However, if the variables are non-stationary in their levels, the standard OLS regression method could become inappropriate because the 't' and 'F' tests may give misleading results [35]. More significantly, the estimated coefficients could be 'spurious' [36]. In this case, one would need to apply cointegration techniques to estimate Equation (6). The following two well-known and widely used techniques were used to examine the time series properties of the variables; (a) the Augmented Dickey-Fuller (ADF) test and (b) the Phillips-Perron (PP) test [37,38].

If the variables were found to be non-stationary, one would then proceed to apply cointegration techniques as follows: (i) determining the order of integration of the variables using the ADF and PP unit-root tests, (ii) if the variables are integrated of the same order, the Johansen-Juselius (JJ) [39-41] maximum likelihood method of cointegration is applied to obtain the number of cointegrating vectors (r), and (iii) if the variables are cointegrated, an error correction model (ECM) can be specified and estimated using standard methods and diagnostic tests. Since this technique is widely known in the literature, the methodology is not again repeated due to space limitation. The empirical analyses that follow were performed using two econometric software programs: Econometric Views (EVIEWS) (Quantitative Microfit Software) and STATA (StataCorp LP, College Station, Texas).

Equation (7) could be estimated using the standard OLS regression method but one needs to control for heteroskedasticity and correlations across the panels. We therefore used the feasible generalised least squares (FGLS) estimation with an AR (1) structure, employing STATA. This method allows for robust estimation in the presence of cross-sectional correlation and heteroskedasticity in the data.

C. Data

We used historical dataset that comprised plant health and trade variables. Plant health data comprised phytosanitary inspections and interceptions. Data on phytosanitary inspections were obtained from the Plant Health and Seeds Inspectorate (PHSI), which is the agency responsible for inhibiting the introduction of quarantine plant pests into the UK. PHSI import inspections generally focus on pathways that are likely to transport harmful pests. All major fruit, cut flowers, potatoes and some leafy vegetables are currently listed in the EU Plant Health Directive 2000/29/EC [42] as 'plant health controlled' imports, meaning that they can present some risk but the risk is mitigated if criteria set out in the plant health directive are met, such as being examined before export to ensure freedom from quarantine pests. If the conditions are met, a phytosanitary certificate can be issued by the plant protection service of the exporting country to show that the commodity meets the plant health requirements of the importing country [9].

These commodities that require a phytosanitary certificate are regularly inspected by the PHSI and suspect plant pests that are intercepted are submitted to the Central Science Laboratory (CSL) for identification. Data pertaining to each inspection are held in a PHSI import database. The data consists of about 8 variables including (i) a unique reference code, (ii) date of inspections, (iii) place of inspections, (iv) genus and (v) species of plant product inspected, (vi) country of origin, (vii) pest taxonomic identity and (viii) the plant pest status of organisms detected. Inspections data for the period 1996-2007 were downloaded from the import inspections database. The data were imported into an Excel spreadsheet and intensively examined to correct for entry, typographical errors and missing values.

The historical trade data comprised domestic production, imports and the total market volume of fresh fruit and vegetables in the UK for the period

1988-2007. Volumes and values of imports of fresh fruit and vegetables were obtained from HM Revenue & Customs via Defra statistics. The data were disaggregated by commodity and country of origin. Data on the domestic production and total market volume and value of fresh fruit and vegetables were obtained from Defra statistics online. Data on the UK's GDP were downloaded from the Office of National Statistics online. Data on the price of domestically produced substitutes are simply not available, and researchers have tended to use a more general domestic price index [43]. Consumer Price Index (CPI) data for fresh fruit and vegetables were obtained from the Office of National Statistics.

Finally, only pathways with significant trade volumes and which transport relatively large numbers of species ($Y \geq 40$) were included in the final analysis in order to ensure sufficient variability to allow for statistical analyses. The selected countries were Morocco, Turkey, Egypt, South Africa, Kenya, Ghana, Zimbabwe and Zambia. The full dataset therefore included quarterly observations for 4 major commodities for the 8 countries during the period from the first quarter of 1996 through to the fourth quarter of 2007, giving a total of 1408 observations.

III. RESULTS AND DISCUSSION

A.Descriptive analysis

This section describes the trends in the volumes of imports and the associated economic drivers. Figure 1 suggests an upward trend in the total market volume of fresh fruit and vegetables. Since 1996, the market volume has grown by over 1.2 million tonnes or some 16.8%. This partly reflects increased consumer demand for convenience and 'healthier foods' (e.g. 5 portions a day). A closer look at figure 1 reveals the market still has potential for further expansion in order to meet consumption targets. If the entire UK population were to eat the recommended 5 portions per day, actual consumption should be in the region of 8.8 million tonnes. However, the domestic production is far smaller than consumption and seems to be in a gradual long-term decline. Over the 15 years from 1992-2006, UK production of fruit and vegetables showed an overall downward trend. Conversely, there is a clear upward trend in the volumes of imports of fresh fruit and vegetables in the UK (Fig. 1).

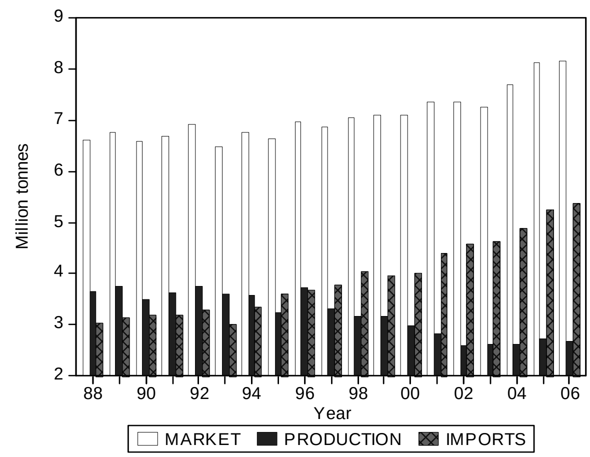

Fig. 1: UK's domestic production, imports and total market volume of fresh fruit and vegetables (1988-2006)

Source: Defra Statistics

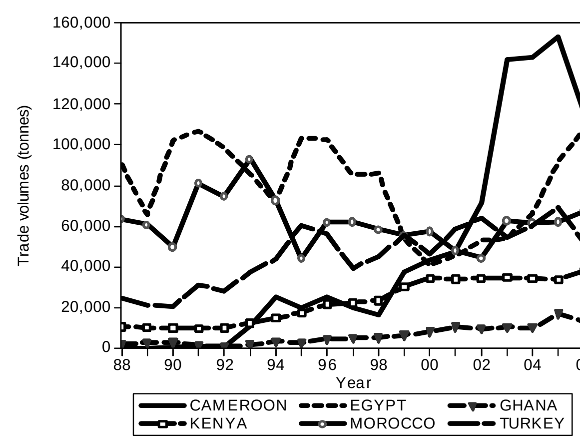

Fig. 2: UK's volumes of imports of fresh produce by selected countries of origins (1988-2006)

Source: Defra statistics

Figure 2 shows the UK's volume of imports of fresh fruit and vegetables disaggregated by selected countries of origin. There is a general trend of increasing volumes of trade from across the selected countries. High growth rates were particularly evident from Cameroon, Egypt, Turkey and Kenya. These high growth rates can be attributed to the combination of global market conditions, international policies and institutions, demand for year-round supply, reduction of tariffs and special preferential access agreements, improvements in production and post-harvest technologies especially availability of international cold chain logistics [44-46]. These trends are generally expected to continue into the future.

The increasing volumes of imports of fresh produce resulted in a large number of pest detections (Table 1). There were a total of 2,253 pest species interceptions, of which 32.0% originated from Kenya, 30.4% from Ghana, 12.5% from Egypt, 10.8% from S. Africa and 14.3% from the remainder of the selected countries. However, the detection effort appears to have been skewed and not evenly distributed among the selected countries. The most inspections occurred on imports from Egypt (33.8%), Kenya (28.2%), S. Africa (11.1%) and Ghana (10.3%). We found a high positive correlation ($R^2>0.80$) between volumes of imports and the number of inspections, and this confirms that inspections tend to increase with the volumes of imports. The highest rate of pest discovery occurred on imports originating from Ghana where a species was detected on average every 3 inspections, while the lowest rate of species discovery occurred on imports originating from Morocco where a species was detected on average every 21 inspections. This suggests that the relative rates of contamination of imports differ with the country of origin.

Table 2 provides the taxonomic details of the most frequently detected pests. Put another way, Table 2 indicates the relative importance of the selected countries of origin as 'pest donors' [12] in terms of the number and taxonomic richness of the intercepted pests. The most frequently intercepted genera were *Liriomyza* and *Thrips*, which together accounted for about 17% of the total detections. Ghana, Kenya and Zimbabwe together accounted for largest diversity of recognised EU quarantine pests.

Table 1: Historical data summarised by selected countries of origin (1996-2006)

Country of origin	Total No. of inspections	Total No. of detections	Rate of detection
Ghana	2,672	684	0.368
Turkey	1,036	91	0.134
S. Africa	2,877	244	0.127
Kenya	7,328	721	0.126
Zambia	553	70	0.126
Zimbabwe	1,583	124	0.119
Egypt	8,785	281	0.076
Morocco	1,166	38	0.048
Total	26,000	2,253	0.087

Notes: Countries of origins are listed in order of the rate of detections.

Table 2: Taxonomic details of the most frequently detected species by country of origin (1996-2006)

Country of origin	Taxonomic details of intercepted pests
Ghana	**Thrips* (77), **Bemisia tabaci* (72), **Liriomyza* (24), **Thrips palmi* (16), Tephritidae (15), **Aleyrodicus dispersus* (13), **Frankliniella occidentalis* (6)
Kenya	**Liriomyza* (142), *Helicoverpa* (79), Thripidae (33), **Thrips* (20), **Frankliniella occidentalis* (9)
Egypt	**Ralstonia solanacearum* (75), *Aonidiella* (28), *Parlatoria* (25), Helicoverpa (7), **Liriomyza* (5)
Zimbabwe	**Liriomyza* (45), *Helicoverpa* (29), *Aonidiella* (4), **Thrips* (3), **Bemisia tabaci* (2)
Morocco	**Liriomyza* (4), **Bemisia tabaci* (2), **Thrips* (2), *Aonidiella* (2),
Zambia	*Helicoverpa* (37), **Liriomyza* (17), **Thrips* (3)
S. Africa	*Aonidiella* (56), **Liriomyza* (6), Helicoverpa (6)
Turkey	*Aonidiella* (19), *Parlatoria* (5), **Liriomyza* (2)

Notes: *Quarantine pests of major economic significance

B. Stationarity and cointegration test results

The ADF test procedure was performed first by examining the optimal lag lengths using Akaike's Information Criterion (AIC) and the Schwarz Information Criterion (SIC), before proceeding to identify the probable order of stationarity. The results of the tests for all the variables and for the two alternative models are summarised in Table 3[2], first for their logarithmic levels and then (in cases where we found a unit root) for their first differences. The results indicate that the null hypothesis of a unit root is accepted for each of the series when the variables are defined in levels. Results show that a number of

[2] Data used in the analysis is aggregated for ease of presentation.

lagged dependent variables were required to ensure a 'white noise' error term. However, first-differencing the series removes the non-stationary components in all cases and the null hypothesis of a unit root is robustly rejected at the 5% level of significance indicating all the variables are integrated of order one.

Table 3: ADF unit root test results

Variable	Level/ First diff.	Constant No trend	Constant Trend	k
Ln (M)	Level	-0.42	-2.04	3
	First diff.	-13.19**	-12.90**	2
Ln (P)	Level	-2.21	-1.49	3
	First diff.	-8. 36**	-9.34**	2
Ln (Y)	Level	-1.06	-2.28	2
	First diff.	-5.06**	-5.19**	-

Notes: ** Denotes significance at the 5% level and the rejection of the Null hypothesis of non-stationarity. Critical values obtained from Fuller [47] are –2.89 and -3.47 for the first and second model respectively.

Because results from the alternative Philips-Perron test are not fundamentally different from the respective ADF results, they are not reported due to space limitations. We concluded that all variables in the model should be treated as I(1), and proceeded to use the Johansen cointegration technique to uncover the appropriate long-run relationships.

Before undertaking the cointegration tests, one must first specify the number of lags to include for the underlying Vector Autoregression (VAR), such that the residuals become uncorrelated and homoskedastic. The Akaike's Information Criterion (AIC) and the Schwarz Information Criterion (SIC) are used to determine the appropriate lag order for the underlying VAR. We used two lags (k=2 quarters) for this model because both the AIC and SIC tests choose two lags. Based on this specification, Table 4 presents the results of the trace test derived from the Johansen maximum likelihood procedure. To implement this test, one would then proceed sequentially by first testing the null hypothesis of zero cointegrating vectors (H_0: $r \leq 0$). If H_0 was rejected, one would test for one or more cointegrating vectors ($r \leq 1$) and so on, until the null hypothesis cannot be rejected. At both 5% and 1% significance levels, the null hypothesis of zero cointegrating vectors is strongly rejected, while the hypothesis of one or more cointegrating vectors is not. According to the trace statistics, there appears to exist at most one cointegrating vector involving the specified variables.

An alternative test that has greater power than the trace test is the maximal eigenvalue test [39]. Table 5 presents results of the sequential testing procedure, which at both the 5% and 1% levels of significance confirms the existence of a unique cointegrating vector. Therefore, based on the results of both tests, it appears there is at most one statistically significant cointegrating vector involving the three variables identified in the model. This unique cointegrating vector is reported in Table 6, which gives coefficient estimates normalised on the volume of imports.

Table 4: Trace test for cointegrating vectors

Hypothesised No. of CE (s)	Trace statistics	5% Critical Value	1% Critical Value
r = 0	44.28	29.68	35.65
$r \leq 1$	7.27**1*5	15.41	20.04
$r \leq 2$	0.03	3.76	6.65

Notes: the trace statistics are asymptotically $\chi 2$ (n) variates under H_0. The LR tests that the number of cointegrating vectors (r) is at most equal to r. The sequential testing stops when H_0 cannot be rejected. **1 and *5 denote rejection of H_0 at the 5% (1%) levels of significance respectively.

Table 5: Cointegration test: maximal eigenvalue test

Hypothesised No. of CE(s)	Max-Eigen statistic	5% Critical Value	1% Critical Value
r = 0	37.0136	20.97	25.52
r = 1	7.2624**1*5	14.07	18.63
r = 2	0.0034	3.76	6.65

Notes: The test statistics are asymptotically χ^2(n) variates under H_0. The sequential testing stops when H_0 cannot be rejected. The **1 and *5 denote rejection of H_0 at the 5% (1%) levels of significance respectively.

Table 6: Estimates of long-run cointegrating vector

Ln (M)	Ln (Y)	Ln (P)	Constant
1.0000	1.1247	-0.3975	2.2687
	(0.0715)	(0.1036)	
	[15.7346]	[-3.7493]	

Notes: (i). The long-run equilibrium relationship is:
$$\ln(M) = 1.12\ln(Y) - 0.38\ln(P) + 2.3$$
(ii). (standard errors); [t-statistics].

Identification of the parameters in the cointegrating equation was achieved by constraining some of them to be fixed, and fixed parameters do not have standard errors. In this case, the coefficient on the volume of imports has been normalised to 1, so its standard error is missing. The constant terms was also backed out from other estimates. The coefficients on real GDP and relative import price in the cointegrating equation are both statistically significant. The analysis suggests that (a) the major long-run determinant of the UK's volumes of imports of fresh produce is the real GDP with estimated income elasticity of 1.1, and (b) changes in the price of imports of fresh produce relative to the price of domestic substitutes appears to have a moderate impact on the UK's volumes of fresh produce imports in the long-run with, with an estimated long-run price elasticity of only –0.39.

The short-run dynamics are reported in Table 7. The real GDP (lagged four quarters or a year), real import prices (lagged one quarter) and the volume of imports (lagged one quarter) have emerged as the major determinants of the import demand function. The estimated coefficient of the error-correction term is statistically significant ($p<0.05$) and with the appropriate sign. This suggests the validity of a long-run equilibrium relationship among the variables in the model. The estimated coefficient value of –0.79 implies rapid adjustment towards equilibrium. Diagnostic tests[3] statistics show no evidence of misspecification of functional form, no serial correlation, nor any problems of heteroskedasticity.

Table 7: Estimated error-correction model

Parameter estimates	Coefficients	t-statistics
Constant	0.024	0.659
Δln M (-1)	0.557	2.793***
ΔlnY(-4)	4.141	3.999***
Δln P(-1)	-0.136	-1.81*
Error correction term	-0.788	-4.283***
Adjusted R^2	0.722	
Log likelihood	66.82	
F-statistics	17.23	
AIC	-2.614	
SIC	-2.293	
Serial correlation: χ^2 (3)	5.61	
Normality: χ^2 (3)	5.17	
Heteroskedasticity: χ^2(1)	0.344	

Notes: The error correction term is the first lag of the residuals from the cointegrating equation.

[3] The diagnostic tests include LM test for autocorrelations, Jargue-Bera (JB) test for non-normality, Goldfeld-Quandt test for heteroskedasticity.

C. The rate of pest species detections

The estimated coefficients from the regressions of the rate of species detections on the intensity of inspections are given in Table 8 and Table 9. The results show pooled regressions by selected fruit and vegetable imports. We used categorical variables to represent each country of origin, and allowed for interaction terms between intensity of inspections and country of origin. Looking at Table 8, both models were statistically significant according to the Likelihood Ratio (LR) χ^2 statistic, and the explanatory variables took the expected positive signs and were statistically significant ($p<0.01$). An increase in the intensity of inspections increases the rate of species detections, assuming other factors are constant. However, it is important to note how the interpretation of the coefficients changes in the presence of interaction terms. The presence of significant interaction terms implies the relationship between the intensity of inspections and rate of species detections depend on the country of origin.

Table 8: Estimations of the rate of pest species detections on vegetable imports (1996-2006)

Parameter estimates	Leguminous vegetables	Other vegetables
Intensity of inspections	0.0181 (0.0078)	0.0584 (0.0185)
Inspections*Kenya	0.1868 (0.0481)***	0.5143 (0.0774)***
Inspections*Zimbabwe	0.2313 (0.0592)***	0.2165 (0.0733)***
Inspections*Zambia	0.4663 (0.0629)***	-
Inspections*Ghana	-	0.6819 (0.0883)***
Constant	0.0257 (0.0149)*	0.1163 (0.0388)***
Wald χ^2 value	135.83***	276.15***
No. of obs	176	176

Notes: Other vegetables include aubergines, peppers, onions etc
Legend: coefficient/ (s.e), * p<0.1, ** p<0.05, *** p<0.01.

Consider the legumes model, where the overall interaction effect is significant (χ^2=135.83, $p<0.01$). This implies that the regression lines for the 4 countries of origin differ significantly. Egypt was specified as the baseline country of origin in the model. Therefore the coefficients of the interaction terms measure the rate of species detections relative to that of Egypt. All the interaction terms were significant ($p<0.01$), indicating that the rate of species detections and consequently the risks were significantly higher from Zambia, Zimbabwe and Kenya relative to Egypt. Consider the other vegetables model, where the overall model and interaction effect were statistically significant (χ^2=276.15, $p<0.01$). Once again, the rate of species detections and possibly risk differed significantly with the country of origin. The significant coefficients of the interactions means the rate of species detections was significantly higher from Ghana, Kenya and Zimbabwe (in that order) relative to Egypt (Table 8). These results suggest that inspection effort can be increased for these countries but also reduced on imports from Egypt without necessarily increasing the risks of pest species.

Table 9: Estimations of the rate of pest species detections on fruit imports (1996-2006)

Parameter estimates	Citrus	Miscellaneous fruits
Intensity of inspections	0.0347 (0.0186)*	0.2724 (0.0478)***
Inspections*Egypt	0.5141 (0.0838)***	-
Inspections*Turkey	0.1207 (0.0586)**	-
Inspections*Ghana	-	0.2363 (0.0911)***
Constant	0.0136 (0.0072)**	-0.0043 (0.0029)
Wald χ^2 value	63.26***	105.22***
No. of obs	132	88

Notes: coefficient/ (s.error), * $p<0.1$, ** $p<0.05$, *** $p<0.01$.
Miscellaneous fruits under EU product classification include mangoes, passion fruit, avocados, figs, kiwi fruit, melons, papaya and pineapples.

For the citrus and miscellaneous fruit, S. Africa was used as the baseline country of origin for comparison (Table 9). Thus, the coefficients of the interaction terms measure the rate of species detections relative to that of S. Africa. Looking at the citrus model, the overall model, explanatory variables and interaction effects were statistically significant (χ^2=63.3, $p<0.01$). An increase in the intensity of inspections increases the rate of species detections, *ceteris paribus*. But the significant coefficients of the interaction terms imply that the rate of species detections and perhaps the risk was significantly higher from Egypt and Turkey relative to S. Africa. However, note that the coefficient of S. Africa (0.0347, $p<0.05$) is statistically different from zero (Table 9). For the miscellaneous fruit, the overall model, explanatory variables and interaction terms were also statistically significant ($p<0.01$), which means the rate of species detections was significantly higher from Ghana (0.236, $p<0.01$) relative to S. Africa (Table 9). But the coefficient for S. Africa is statistically significant compared to zero (0.2724, $p<0.01$). The implications are that inspections effort could be increased to target fruit imports originating from Egypt, Ghana and Turkey but reducing inspection effort on fruit imports from S. Africa would increase the risks of pest species.

These results clearly suggest that the risk from imports is not equal but vary significantly with the country of origin. What explains the differences in risk of pests and diseases between exporting countries? There are a number of factors to consider. Firstly, the number of species that can potentially be transported will vary with each source region, which simply reflects differences in the size of the species pool [8]. Secondly, the differences may be related to the production and supply chain infrastructure at the origin. In this regard, developing countries are likely to face difficulties in implementing high level sanitary and phytosanitary standards [20, 48]. The developing country context is one which is characterised by naïve production systems, which are dominated by smallholder producers, highly fragmented supply chains, lack of technical and human investments and weak communications infrastructure [49]. Most developing countries lag in their capacity for effective export inspections and control [20].

Thirdly, there may be differences in pest pressures which are caused by bio-geographical factors that influence the variations in insect pest activity [12]; for example the wetter and more humid conditions in some tropical countries may make it more difficult to control insect pests at source [11]. Even of more significance are the recent changes in EU pesticide regulations, which have limited the options to control potential pests and diseases at source [19]. Plant health risks from imports are therefore a function of a number of endogenous variables including soil quality, geographical area, agricultural techniques, monitoring procedures and quarantine and pest control measures adopted. A recent study to examine factors that determine the rejection probability of imported cut-flowers in the Netherlands concluded that the geographical position of the exporting country, the characteristics of the importing company, the size of imported shipments, and the intended use of the commodity were significant variables on which shipments were targeted for inspections [50].

But what is the actual risk from importing pests on produce? Historically, the risk was not considered to be serious since there was no clear pathway enabling the pests to get to UK places of crop production. Fresh produce is purchased relatively quickly from retailers and effectively destroyed through consumption. This was considered to severely limit the probability of pests becoming established. However, with the year-round demand for a large variety of fresh produce, suppliers increasingly source produce from overseas to supplement or combine with domestic production. Bringing imported produce carrying pests in close proximity to UK growing crops could provide a clear pathway for new pests to enter and potentially establish [51]. There have been some outbreaks of quarantine pests but it is difficult to link specific cases to contaminated imports because of the time lags between import and detection of the outbreaks.

Given that arrival and entry are merely the first steps in the invasion process, non-indigenous pests could also be challenged by environmental factors, which must be overcome if the species are to become established [7,52]. Estimates of establishment rates of accidentally introduced species are very low ranging from 2% [53] to 10% [52]. But a recent publication predicted that with an establishment rate of only 2%, 42 new species of non-indigenous insects transported to the US in cargo might have become established between 1997 and 2001 [27]. Whether this is true or not remains an open question but it is clear that the true risk of establishment of NIS via different the pathways is highly dynamic and often surrounded by a high degree of uncertainty.

IV. CONCLUSIONS

This study was conducted to assess the potential risks from current and future procurement options of imported fresh produce in the UK. The rates of detections of pest species were estimated for various countries of origin. We also employed advanced cointegration analysis to uncover the major long-run drivers of the volumes of imports of fresh produce. The major findings indicate a general trend of increasing volumes of imports from emerging and existing supply sources. Cointegration results show clearly that demand for fresh produce imports is strongly dominated by the real GDP and relative import price. These results are consistent with both economic theory and the empirical literature. Income elasticity of demand was found to be very high, indicating that the volume of imports of fresh produce will increase more than proportionally with higher incomes. The coefficient of the relative price variable was inelastic. This suggests that fresh produce imports are less sensitive to import price changes. This approach allows prediction of potential inflows of commodities from a number of economic scenarios.

Results further show that the increasing volumes of imports resulted in a large number of pest species. We found that the rate of species detections and possibly the risk vary significantly with the country of origin. This may be attributed to differences in the production and supply chain infrastructures, export inspection regimes and bio-geographical factors at origin. Kenya and Ghana appear to be major sources of recognised EU quarantine pest species, together accounting for approximately 60% of the total pest detections from the selected countries. Volumes of imports have increased significantly over the past 15 years, with new countries entering the supply chain. If this trend should continue in the future, then UK plant health inspectors can expect to confront species from these countries in much greater numbers and cases.

These results have important implications for the conduct of UK plant health policy to protect against introductions of non-indigenous pests. The results highlight the need for increased phytosanitary inspections in the UK but more especially at the country of origin. PHSI should continue to inspect commodities such as citrus, pineapple, melon and other fruits regularly. Aubergine, legumes, peppers and leafy vegetables are also likely to transport serious plant pests to the UK and should be inspected frequently. But future plant-health policies should focus more on actions that minimise the chances of importing contaminated commodities by being more actively involved with exporting countries. Such policies would facilitate trade and reduce inspections costs, as they would help exporting countries to send less of the contaminated material to the UK. The results from this study clearly support the case for discriminatory policy to use the limited resources available in a way that will more closely target inspections on the higher risk trade pathways. Inspection efforts should focus on identifying and targeting pathways carrying large numbers of pests.

We acknowledge some limitations in the data used in the study before concluding. The commodities targeted for inspections and inspection protocols evolve with time, depending on the pest or commodities of concern to the PHSI at a given time. High-risk commodities that are associated with quarantine pests may receive extra inspections, perhaps increasing the proportion of pests intercepted on such commodities compared to a purely random process. Another limitation arises from the fact that pathways with large numbers of species detections may not necessarily present the most risk. For example, a high rate of detections of pest species on citrus imports does not mean a high risk because citrus is not commercially produced in the UK. Nevertheless, the UK has an obligation to other EU countries that have commercial citrus production. Limitations notwithstanding, this paper represents a significant attempt to model changes in supply sources in response to economic factors and quantify the likelihood of arrival and entry of non-indigenous pests via the international trade in fresh produce from new supply sources outside the EU, by the country of origin, the key criterion for discriminatory policy.

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