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ILLICIT TRADE AND INFECTIOUS DISEASES*

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Illicit Trade and Infectious Diseases*

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Abstract

We collect a novel dataset that covers about 130 countries and the six four-digit live animal categories in the Harmonized System (HS) over a sixteen-year period, to study the link between illicit trade in live animals and threat to animal health from infectious diseases. Our results imply that a one percent increase in illicit imports in an HS four-digit live animal category is associated with a 0.3 to 0.4 percent rise in infections amongst related species in the importing country. We explore the mechanisms and find that mis-classifying or under-pricing an imported species are the channels through which illicit trade impacts animal health.

Keywords: Illicit trade; missing imports; disease; live animals

JEL Classification: F14; F18; I18; K42; Q57

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1 Introduction

In 1995 an illegally imported monkey brought a deadly Ebola-like virus into the United States. While that simply is the premise of a popular American medical disaster movie,[1] it encapsulates a real phenomenon. For instance, illicit trade in wildlife is responsible for spreading pathogens like Avian influenza, Newcastle disease or retroviral infections that can jump species barriers to infect wildlife, domestic animals and human beings (Gómez and Aguirre, 2008). The illicit nature of such trade flows implies that we do not have a credible estimate of the impact on local health, and whether measures to restrict imports can limit the spread of infectious diseases.

In this paper we take a new approach to estimate the disease burden from illicit trade in live animals. We measure illicit trade through discrepancies in mirror trade statistics that are reported by trading partner countries, a methodology that has been used to uncover evidence on smuggling of items such as antiques and cultural artifacts, mineral resources and electronics (Fisman and Wei, 2009; Vézina, 2015; Rotunno and Vézina, 2017).[2] We consider the impact of illicit trade on infection cases in animals, using previously unexplored data on animal related diseases. The focus on animal health, instead of human health, is due to the nature of available data rather than an under appreciation of the consequences that illegal live animal trade might have for humans.

We hypothesize that illicit trade in live animals is positively related to the spread of infectious animal diseases. This is likely for three reasons. Legal imports undergo standardized testing and quarantine procedures before entering the domestic market (Rappole and Hubálek, 2006). Illicit imports can circumvent testing or quarantine protocols and are hence more likely to introduce pathogens in the local environment. Moreover, illicit trade is carried out through practices that can enable pathogens to jump between species. For instance, wild-caught animals are bundled in consignments carrying similarly looking captive breds (Wyatt et al., 2018). The close contact between animals can enable the spread of pathogens from wild-caught to captive breds. Finally, while policy

[1] For a synopsis of the movie, entilted "Outbreak", see `https://www.rogerebert.com/reviews/outbreak-1995`.

[2] Morgenstern (1950) and Bhagwati (1974) were the first to suggest that discrepancies in mirror trade statistics could be due to illicit transactions in international trade.

interventions to curtail infections can effectively restrict legal imports of live animals, this is not necessarily the case for illicit trade, which could even be incentivized by such interventions.

We compile a dataset that covers about 130 countries and the six four-digit product categories of live animals in the Harmonized System (HS) classification of traded products, over the period from 2004 to 2019. We capture 'missing imports' as the difference between the value of exports reported by all partner countries to an importing country, and the value of imports reported by the importing country from all its partner countries. Data on missing imports at the importer-product-year level are matched to data on outbreak of diseases in the importing country which are specific to species included within a product category. We carry out the matching by exploiting detailed information on which types of animals were affected by each disease outbreak.

The empirical analysis proceeds in several steps. First, we show that missing imports are a reasonable proxy for illicit trade, using two complementary approaches. We show that missing imports in live animals are positively associated with import tariffs, in line with the tariff evasion literature (Fisman and Wei, 2004; Javorcik and Narciso, 2008; Rotunno and Vézina, 2012). We further document a positive correlation between missing imports and the number of illegally imported live animal specimens that are confiscated by customs agencies.

We next examine the relationship between missing imports of live animals and their disease burden. We find a fairly consistent positive relationship between missing imports and the number of infection cases in regressions controlling for importer, product (HS4) and year fixed effects (or alternatively for importer-product and year fixed effects). A one percent increase in missing imports is associated with a 0.3 to 0.4 percent increase in the number of infections among species that are included in a given HS4 product category.

A potential challenge for causal interpretation is due to reverse causality. We consider two potential channels through which a disease outbreak can simultaneously affect missing imports. First, a disease outbreak can elicit policy response in form of an import ban on the associated live specimen. There is evidence that trade prohibitions can incentive illicit trade in associated products (Vézina, 2015). A disease outbreak can therefore incentivize

illicit trade through imposition of trade bans, which would bias the estimates upwards. We empirically address this concern in estimations that exclude all instances where an import ban was imposed following a disease outbreak. Second, a disease outbreak can reduce the benefit from engaging in illicit trade by lowering import demand. According to economic theory, the benefit from engaging in tariff evasion is positively related the size of imports (Yang, 2008; Javorcik and Narciso, 2017). Due to this reverse causality feedback, the estimated responsiveness of new infection cases to missing imports may underestimate the true effect. This would however imply that our baseline estimate is a lower bound of the true effect, and reverse causality does not drive the positive relationship between infection cases and missing imports.

We perform a battery of tests and show that omitted variables are also unlikely to drive the underlying relationship. We control for country-specific linear time trends to account for potential correlation between trade and smoothly evolving institutional developments such as a shift in political preference, or diffusion of scientific knowledge regarding a disease. In addition, we perform a placebo test where were randomly assign missing imports across product categories within the same importer-year. The estimated coefficients of missing imports that are incorrectly assigned across 100,000 random draws converge to zero. The evidence suggests that time varying country level omitted variables are unlikely to drive the baseline relationship. Next, we control for product specific import tariffs that can simultaneously affect missing imports and new infection cases. The inclusion of import tariffs has little impact on our baseline estimate. Finally, in the spirit of Oster (2012), we also test and rule out that missing imports in future years have an effect on new infections in the current year. This alleviates the possibility that our result is driven by some omitted variable, and justifies our choice of specification.

Naturally, the next question is whether evasionary practices can explain the relationship between missing imports and disease burden in the importing country. Practices such as mis-classifying of species and mis-declaration of consignment value are often identified as some of the methods through which live animal species are trafficked (Wyatt et al., 2018). We find that missing imports are associated with higher disease burden in product categories that are likely to be mis-classified to evade taxes. We also find evidence that

missing imports are associated with a larger disease burden in product categories where evasion can take place through under-reporting of unit prices.

In a final empirical exercise we assess whether illicit trade in live animals can impact human health through spreading zoonotic diseases. We find some evidence for a positive link between missing imports and the probability of infection outbreak among humans. However, these results should be interpreted with caution since we observe very few instances of infections spreading to humans in the sample.

This paper makes a two-fold contribution to the literature. Our first contribution is to the economic literature on trade and health. Early empirical literature had postulated that income gains from globalization and international trade would raise global health standards (Dollar, 2001; Owen and Wu, 2007). On the contrary, human history is replete with examples of international commerce enabling the spread of communicable diseases (Harrison, 2012). Boerner and Severgnini (2014) focus on the case study of Black Death in Europe and find that the disease's transmission time is dependent on geographical, political and cultural factors. Closest to our study, Oster (2012) investigates contemporary trade practices and finds that exports facilitated the incidence of HIV in Africa. She interprets this result as suggesting that higher exports increase the movement of people, which facilitates transmission of disease through sexual activity. In contrast, we provide evidence that the illicit practices used in trading of live animals can be directly responsible for spreading communicable diseases.

There is also a substantial qualitative research outside economics that discusses the role of licit and illicit trade channels in spreading infectious diseases (Karesh et al., 2005; Fèvre et al., 2006; Chomel et al., 2007; Smith et al., 2012; Beltran-Alcrudo et al., 2019). We are only aware of one study that quantifies the introduction of infectious diseases into European Union via channels such as legal trade of animals and meat; illegal trade; pets; human travel; and windborne vectors (Simons et al., 2019). A concern with Simons et al. (2019) is that they use unpublished statistics of seizures from the UK border agency to proxy illegal imports into the European Union. In contrast, our empirical analysis employs a proxy of illicit trade that has been used in the economics literature to capture smuggling across various items, and captures more precisely the link between illicit trade of animals

and diseases outbreak worldwide.

Our second contribution is to develop an intersection between a growing literature on the spread of infectious diseases and the literature on illicit trade. New research in light of the COVID-19 pandemic has highlighted the role of environment, demography and government policies in determining its transmission (Borjas, 2020; Carleton and Meng, 2020; Chinazzi et al., 2020). Instead of focusing on a specific zoonotic disease, we consider a variety of pathogens that are known to afflict animal species, some of which can also cross over to human beings. We can therefore study the spread of infectious diseases over a longer time horizon as well as focus on a specific channel of transmission through international trade, which has important policy implications. Our work is similar in spirit to Chimeli and Soares (2017), who estimate the social cost of illicit trade in the form of escalating violence. Our work highlights the costly effect of illicit trade in the form of harming animal health.

2 Background: contagion risk from illicit trade in live animals

Globalization has enabled greater trans-border movement of live animals (The Guardian, 2020). This has resulted in a higher threat to animal populations from pathogens that can cause virulent animal diseases. Imported infected live animals may lead to disease outbreaks by directly infecting other animals at the destination (Beltran-Alcrudo et al., 2019). Since the mid-1990s, the precipitous outbreak of diseases that afflict livestock are estimated to have cost the global economy over US$ 80 billion (Karesh et al., 2005). Besides, there is an additional risk that diseases can spread to humans, if they come in contact with the infected animals.[3]

While both licit and illicit trade entail a risk of spreading diseases, the threat from illicit animal trade is higher (Beltran-Alcrudo et al., 2019). This is because licit trade is governed

[3]In a list of 1,415 pathogens that can affect humans, about 60 percent are zoonotic, i.e. they are transmitted from animal species to humans (Karesh et al., 2005). A 2012 study by the International Livestock Research Institute (ILRI, 2012) estimated that some 56 zoonoses were together responsible for around 2.5 billion cases of human illness and 2.7 million human deaths a year.

by international protocols that are set to protect animal and consumer health in the importing countries (Beltran-Alcrudo et al., 2019). Conversely, illicit trade in animals can circumvent screening and quarantine protocols. For example, in Saudi Arabia, most cases of Brucellosis – a disease which infects animals like sheep and cattle – are reportedly due to unscreened imports from Africa (Fèvre et al., 2006). Additionally, policy mechanisms that can limit market access to formal trade, through import restrictions, fines and other regulatory barriers, can incentivize illicit trade practices (Beltran-Alcrudo et al., 2019).

Illicit trade in live animals can be classified into three categories: tax evasion in large commercial imports, import of illegal wildlife, and informal import for personal use (Beltran-Alcrudo et al., 2019). The first category involves commercial enterprises that engage in tax avoidance by entering the country through understaffed port locations, or through deliberate falsification of cargo shipments. The falsification can occur through mis-classification of species to a similar variety, or by declaring lower values or lesser volumes to reduce the chance of inspection by customs officials (Wyatt and Cao, 2015).[4]

The second category involves smuggling of illegal wildlife, such as endangered animal species whose trade may be prohibited, but is highly lucrative due to their value as exotic pets or their utility in traditional medicine (Van Uhm, 2016). Common practices that involve smuggling of illegal wildlife include mislabeling illegal wildlife as a legally traded, declaring 'wild caught animals' as 'captive-breds', and obtaining certificates from corrupt officials (Van Uhm, 2016). As in the science fiction movie cited in the introduction, there are also instances where a legal shipment of live animals is mixed with protected illegal species to avoid detection (Wyatt, 2013).

Third, and finally, there are small-scale operations where animals are imported in the country through concealment in passenger luggage (Beltran-Alcrudo et al., 2019). Such methods are particularly risky when it comes to exposure to zoonotic diseases.

The qualitative evidence presented in this section highlights the link between illicit

[4]Even in a country with advanced customs administration like the United States, only 25 percent of wildlife shipments that are declared at the border are inspected (Williams and Grante, 2009). Customs officials are likely to inspect more valuable consignments to ascertain their true value, in order to maximize import tariff revenues. Under-staffing of trained officials is yet another issue. The US Fish and Wildlife Service (FWS) is in charge of monitoring or detecting illicit trade in endangered species, invasive species or regulated wildlife. In 2006 the FWS had posted a mere 112 wildlife officials at 38 ports of entry across country. In that year about 185,000 shipments were declared across US ports (Williams and Grante, 2009).

trade in live animals and spread of infectious diseases. The various methods of illicit imports discussed above can lead to disease outbreaks in destination countries, through eluding monitoring protocols, transmitting pathogens amongst different varieties of animal specimens, as well as through creating a close proximity between infected animals and human beings. In the following sections we investigate whether data are consistent with the qualitative evidence.

3 Data sources and dataset construction

We construct a dataset that covers about 130 countries and the six live animal categories of the Harmonized System (HS) classification: 0101 (horses, asses, mules and hinnies); 0102 (bovine animals); 0103 (swine); 0104 (sheep and goats); 0105 (poultry, fowls of the species Gallus domesticus, ducks, geese, turkeys and guinea fowls); and 0106 (live animals not elsewhere classified). The period under analysis is 2004-2019. This section describes the key variables and their sources.

3.1 Animal diseases

The dependent variable in the main estimations is $\textit{Infections}_{ikt}$ – the number of observed animal infection cases by importing country i, live animal category k and year t. The raw data, sourced from the FAO's EMPRES Global Animal Disease Information System (EMPRES-i), describe outbreaks of thirty-two diseases (e.g. African swine fever, Bovine spongiform encephalopathy, or Avian influenza), including the date and location of occurrence, and their impact in terms of number of animals at risk, number of cases of infected animals, of deaths, of animals destroyed, and of animals slaughtered.[5] EMPRES-i data are available from 2004 till 2019.

Out of thirty-one diseases with confirmed cases from EMPRES-i, the World Organiza-

[5]FAO EMPRES data are available at `http://empres-i.fao.org/eipws3g`. One disease covered in the database, Rinderpest, is only observed in unconfirmed cases. We exclude all unconfirmed cases from the dataset to reduce the scope for measurement error. This leads to the exclusion of Rinderpest from the sample. We only focus on the number of cases because deaths and subsequent actions are likely to be driven by the institutional response. We obtain similar results if we use the number of animals at risk as the dependent variable. These results are not reported here and are available upon request.

tion of Animal Health (OIE) classifies fifteen as affecting a single class of species, fourteen as affecting multiple species and two as 'other diseases' (see Table A-1). While it would be straightforward to match the diseases that affect a single species to an HS4 live animal category, the matching of diseases that affect multiple species is complicated. To overcome this challenge and precisely assign diseases to an animal category k (four digit HS heading), we use detailed information on the species affected by each outbreak that is contained in the raw data.

As reported in Table A-2, out of 94,738 observations in the FAO EMPRES-i database, 1,602 observations across eight different diseases affect HS heading 0101 (horses, asses, mules and hinnies); 13,119 observations across 16 diseases affect HS heading 0102 (bovine animals); 24,281 observations across 13 diseases affect HS heading 0103 (swine); 11,607 observations across 12 diseases affect HS heading 0104 (sheep and goats); 30,806 observations across seven diseases affect HS heading 0105 (poultry, fowls of the species Gallus domesticus, ducks, geese, turkeys and guinea fowls); and 6,983 observations across 17 diseases affect HS heading 0106 (live animals not elsewhere classified). Finally, 6,340 observations across 24 diseases could not be assigned to any HS heading in live animals, and therefore are excluded from the data.[6]

Among the fifteen diseases that the OIE classifies as affecting single species, and which account for over two-thirds of the disease outbreaks in our data, 94 percent of episodes are on average concentrated in only one HS4 heading (which also aligns with the OIE classification of species affected) according to our detailed correspondence of Table A-2. In contrast, less than 70 percent of episodes are concentrated in one HS4 heading in the detailed correspondence of Table A-2, for diseases that are listed as affecting multiple species in the OIE classification of Table A-1. The twin results that the majority of disease outbreaks for 'single species' diseases are concentrated in an HS4 category that aligns with the OIE classification, combined with a significant difference in concentration of disease episodes within an HS4 category across OIE's 'single species' and 'multiple species' diseases, corroborate our matching exercise.

[6]Cases in which it was not possible to assign observations from FAO EMPRES to an HS heading typically involve descriptions that include two or more live animal categories.

All cases affecting live animals in HS heading k during year t are summed across all locations within each country i, yielding a dependent variable, $Infections_{ikt}$, which varies by country, HS heading, and year. Note that this variable takes value zero if no cases were reported in any location of country i in sector k and year t.[7]

3.2 Illicit trade

Illicit trade, the explanatory variable of interest, is not directly observable, and one needs to measure it through proxies. Following the literature on tariff evasion, the proxy used in this paper is 'missing imports', computed as the difference between the log value of exports (augmented by one) reported by all exporting countries to importing country i in live animal category k in year t (X_{ikt}) and the log value of imports (augmented by one) reported by country i from all countries (M_{ikt}):

$$mi_{ikt} \equiv \ln(1 + X_{ikt}) - \ln(1 + M_{ikt}). \tag{1}$$

Trade data used in (1) are from UN COMTRADE.[8]

3.3 Other variables

We create two measures of policy that can be associated with disease outbreak. Our first measure is the Most-Favoured-Nation (MFN) tariff that is imposed by the importing country i on product k in year t. We obtain tariff information from UNCTAD TRAINS and (if data are missing in that database) WTO IDB.[9] The second measure, 'Import ban' is a binary variable equal to one if the importing country i imposed an emergency Sanitary and Phytosanitary (SPS) measure to stop importing product k in year t from any partner country. This dummy is built based on textual analysis of WTO Integrated Trade Intelligence

[7]We present a robustness test in Section 5.2 relaxing the assumption that the dependent variable takes value zero if no cases were reported in any location of country i in sector k and year t, i.e. without replacing missing values with zeros. The results are unaffected.

[8]UN COMTRADE data are sourced from the World Integrated Trade Solution (WITS), available at `https://wits.worldbank.org`.

[9]There are gaps in coverage across countries, sectors and years. We do not attempt to fill these gaps, except in the rare cases in which, within each ik combination, two identical tariffs rates in years $t-1$ and $t+1$ respectively precede and follow a missing value in year t. In such cases, we replace the missing value with the value reported in $t-1$ and $t+1$. UNCTAD TRAINS and WTO IDB data are sourced from WITS.

Portal (I-TIP) data.[10]

Other control variables include missing imports in HS chapter 02 (Meat and edible meat offal) and in HS heading 0504 (Guts, bladders and stomachs of animals other than fish), which are constructed in the same way as mi_{ikt} in (1), and from the same data sources as described in Section 3.2; GDP per capita in current US$ and population (both in logs), sourced from IMF's World Economic Outlook data, October 2019 edition; health expenditure as percentage of GDP, sourced from the World Health Organization's Global Health Expenditure database; the quality of port infrastructure, sourced from the World Economic Forum's Global Competitiveness Report; and the time to import (the time associated with importing a standardized cargo of goods by sea transport, calculated in calendar days), sourced from the World Bank's Doing Business Indicators, 2006-2015 methodology.[11]

Table A-3 presents the in-sample summary statistics of all the variables that are used in the empirical analysis.

4 Empirical Strategy

The effect of missing imports on infections is estimated by Poisson pseudo-maximum-likelihood (PPML) using the following specification:

$$Infections_{ikt} = \beta_1 mi_{ikt} + \gamma \mathbf{Z}_{ikt} + \mathbf{FE}_i + \mathbf{FE}_k + \mathbf{FE}_t + \epsilon_{ikt}, \tag{2}$$

[10]The data are available at `http://i-tip.wto.org/goods`. The WTO SPS Agreement does not require WTO members to notify every SPS measure. The general notification obligations of Annex B of the agreement apply only when an international standard, guideline or recommendation does not exist, or the content of a proposed SPS regulation is not substantially the same as the content of an international standard, guideline or recommendation (in the case of animal health and zoonoses, the standards, guidelines and recommendations of reference are those developed by the OIE), and if the regulation may have a significant effect on trade of other Members. The data on import bans we collect through WTO I-TIP, therefore, do not necessarily cover all emergency SPS measures imposed by WTO members. NTM data available on WITS cannot be used in this study because they are recorded only as of 2012 (2010 for the European Union).

[11]The October 2019 edition of the IMF's World Economic Outlook is available at `https://www.imf.org/en/Publications/WEO/weo-database/2019/October`. The last three variables are sourced from World Bank Open Data, available at `https://data.worldbank.org`. Data on time to import are only available between 2006 and (due to 2016 a change in methodology in the World Bank's Doing Business indicators) until 2015.

where *Infections*$_{ikt}$ and mi_{ikt} (missing imports) were defined in Section 3 above. $\mathbf{Z}_{ikt}$ is a vector of control variables that vary along all the dimensions of the data (MFN tariff) or within country over time (missing imports in HS chapter 02 and in HS heading 0504; log of GDP per capita; log of population; health expenditure as percentage of GDP; quality of port infrastructure; time to import). The model also includes importer fixed effects ($\mathbf{FE}_i$), product fixed effects ($\mathbf{FE}_k$) and year fixed effects ($\mathbf{FE}_t$). In alternative, more conservative specifications we control for importer-product ($\mathbf{FE}_{ik}$) and year fixed effects, and we also add country specific linear time trends. Disease outbreaks can exhibit both serial and spatial auto-correlation. Therefore, we cluster standard errors at country-level and year-level to permit valid inference if errors are auto correlated within country, as well as within years across countries (Cameron et al., 2011).[12] The coefficient of interest in model (2) is β_1, which measures the elasticity of new infection cases to missing imports.

4.1 Threats to identification

Reverse causality The first challenge for identification is potential reverse causality, specifically if higher disease burden raises illicit trade. Reverse causality can drive our results through two plausible channels. First of all, a disease outbreak may elicit policy response in form of a ban on the import of associated species. There is in fact some evidence that trade prohibitions can incentive illicit trade in associated products (Vézina, 2015). In that case, the reverse causality could generate an upward bias in our estimate. To address this concern we perform a robustness check where we exclude all instances where an import ban was imposed following a disease outbreak. We argue that disease outbreaks in these cases are most likely to affect illicit trade and excluding them should minimize the potential upward bias due to reverse causality.

Further, a disease outbreak can reduce demand for the associated imported products. For instance, the demand for imported beef in South Korea fell by 47 percent in value between 2003 and 2004, following the reporting of Bovine spongiform encephalopathy or 'mad cow disease' in December 2003 (Giamalva, 2013). While the import demand recov-

[12] In a robustness exercise, we cluster standard errors at the country level for inference if errors are only auto-correlated within country.

ered in subsequent years it did not reach the 2003 levels even by the end of the decade (Giamalva, 2013). The theory on tariff evasion suggests that the benefit from misrepresenting consignment value is a positive function of the size of imports (Yang, 2008; Javorcik and Narciso, 2017).[13] In results reported in Appendix B, we show a negative correlation between licit imports and disease occurrence, which we interpret as evidence that the latter reduces import demand. A disease outbreak could therefore reduce missing imports in associated animal specimen through its negative impact on import demand. This reverse causality feedback would lead to underestimate the elasticity of new infection cases to missing imports, implying that our estimates are a lower bound of the true effect.

Omitted variables A second challenge stems from omitted variables. The inclusion of importer-product and year fixed effects in a conservative version of model (2) implies that any confounding variable should vary within an importer-product over time. In a robustness exercise, we show that the results are unaffected when employing an even more conservative specification, which includes importer-product and time fixed effects along with country-level linear time trends. These trends should account for any smoothly evolving changes over time, for example, the diffusion of disease related knowledge or changes in government policy that might affect at the same time new infections and illicit trade (Oster, 2012).[14] Another issue is that import tariffs can affect disease outbreaks through curtailing licit trade. The positive relationship between import tariffs and missing imports is also well established in the tariff evasion literature (Fisman and Wei, 2004; Javorcik and Narciso, 2008; Rotunno and Vézina, 2012). Omitting import tariffs could therefore lead to underestimate the true effect of missing imports on new infections.

Measurement issues The final concern is about the measurement of illicit trade. First, missing imports may be estimated with a measurement error. Discrepancy in the values of mirror trade statistics can arise as exports are recorded in free on board (FOB) terms,

[13] According to Yang (2008) the net benefit from evasion (B) is the difference between the value of tariff evaded from smuggling and the cost of evasion. The value of tariff evaded itself is increasing in the smuggling rate (γ), tariff rate (τ) and the size of imports (M).

[14] For example, the government might engage in trade facilitation reforms that reduce trade costs while better managing trade risks. Trade facilitation reforms affect traders' incentives to engage in illicit trade practices, and could be a source of omitted variable bias which is controlled for by country-specific time trends.

while imports are calculated including the cost of insurance and freight (CIF). It is reasonable to think that the systematic components of such discrepancy are absorbed by fixed effects, and therefore are not correlated with the errors. For instance, freight and insurance cost may systematically differ across animal categories, within or across countries. Such systematic differences are accounted for by importer and product (or importer-product) fixed effects.[15]

Second, one may wonder whether missing imports are a good proxy at all for illicit trade in live animals. In defense of our approach, there is evidence that discrepancies in mirror trade statistics capture illicit trade in a diverse set of items, such as antiques, timber and mineral products (Fisman and Wei, 2009; Vézina, 2015). In addition, we conduct empirical tests to assess whether missing imports capture illicit trade in live animal specimen. First, we look at the association between missing imports and import tariffs. The tariff evasion literature suggests that higher tariffs incentivize importers to misrepresent the consignment value to evade taxes (Fisman and Wei, 2004). A positive correlation between missing imports and import tariffs would suggest that missing imports is a suitable proxy for illicit trade in live animals. Second, we collect, from the the CITES Trade Database, country-level data on the number of illegally imported live animal specimens that were confiscated by customs authorities.[16] These specimens are confiscated on account of distorted paperwork or concealing contraband live animals in the shipments (D'Cruze and Macdonald, 2016). Assuming that a proportion of illicit imports are seized by custom authorities, a positive association between missing imports and the number of seizures would give further credence that missing imports capture illicit trade in live animals.

[15]Country-specific time trends, included in some estimations, further account for the systematic variation in missing imports within country over time, for instance due to gradual reforms affecting the logistics sector.

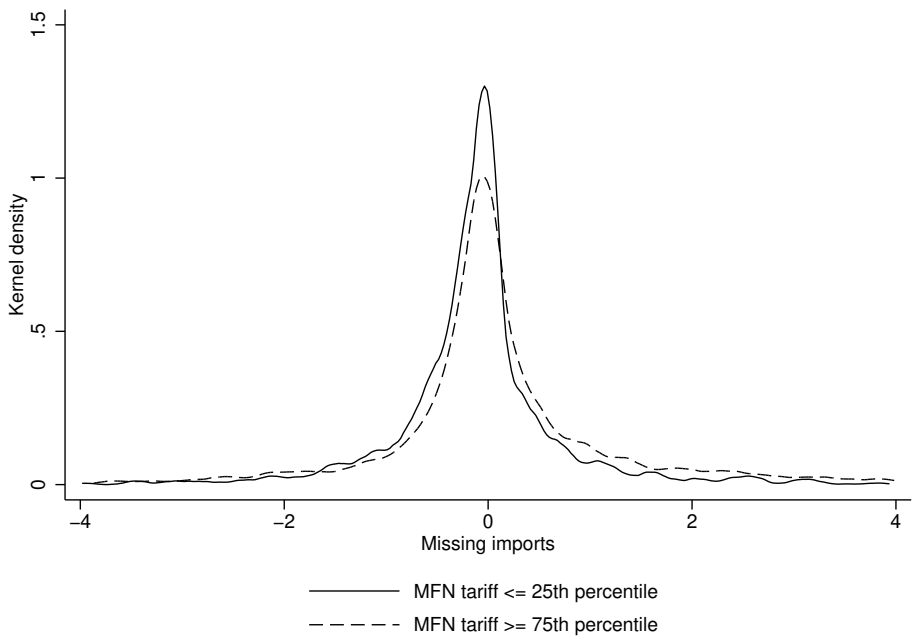
[16]CITES is the Convention on International Trade in Endangered Species of Wild Fauna and Flora. The CITES Trade Database is available at `https://trade.cites.org`.

5 Results

5.1 Missing imports as a proxy for illicit trade in live animals

Before estimating the relationship between missing imports and disease burden, we assess whether missing imports is a suitable proxy for illicit trade in live animals. Figure 1 graphically illustrates the relationship between missing imports and import tariffs. The right-skew in the distribution of missing imports at high tariff rates visible in the figure suggests that imports are systematically under-reported relative to exports when tariffs are high.

Figure 1: Tariff rate and illicit trade in live animals



Notes: For exposition clarity, the Kernel densities of missing imports are shown for values of missing imports between the 1st and the 98th percentile (respectively, -4 and 4). See Section 3 for variables' description.

This relationship is confirmed in column (1) of Table 1, which estimates the effect of MFN tariffs on missing imports by OLS. This specification controls for importer, HS4 product and year fixed effects. The effect is statistically significant at 10 percent level. The point estimate implies that a one percentage-point increase in tariff rate is associated with a 0.12 percent increase in missing imports. The estimated tariff semi-elasticity of missing imports in live animals is comparable to but slightly smaller in magnitude than tariff

semi-elasticities estimated in recent studies covering a large set of countries and an exhaustive list of product categories.[17] In column (2) we estimate the relationship between missing imports and the number of confiscated animal specimens using a PPML specification, where we control for importer and year fixed effects.[18] The coefficient is positive and statistically significant at 5 percent level. The point estimate implies that a one percent increase in missing imports is associated with a 0.78 percent increase in the number of confiscated animal specimens. Overall, the results in Figure 1 and Table 1 suggest that missing imports is a suitable measure for illicit trade in live animals.

<< Table 1 about here >>

5.2 Missing imports and disease burden

Baseline results Table 2 reports the estimates of the effect of missing imports on the number of new infection cases in related species corresponding to model (2), i.e. in a specification with importer, product (HS4) and year fixed effects. The effect is positive and statistically significant at the usual level of significance in all estimations. The point estimate of column (1) implies that a one percent increase in missing imports is associated with a 0.31 percent increase in the number of new infection cases. In columns (2)-(3) we include controls for missing imports in meat products (HS code 02) and meat products that are generally used as animal fodder (HS code 0504). This is to alleviate the concern that communicable diseases such as Bovine spongiform encephalopathy ('mad cow disease') are caused by contaminated animal fodder. The point estimate on missing imports is only slightly smaller in magnitude. In columns (4)-(8) we introduce a number of country-level variables to control for level of economic development (GDP per capita, in logs), size (population, in logs), the quality of health services (health expenditure as percent of GDP), and customs characteristics (quality of port infrastructure and days to

[17] Beverelli and Ticku (2020) estimate a tariff semi-elasticity of 0.2 to 0.3 percent in a sample that includes over 120 countries and around 5000 HS6 product categories during the years 2012, 2015 and 2017. Bussy (2020) estimates a tariff semi-elasticity of 0.16 percent in a sample that spans 197 countries and around 5000 HS6 product categories during the years 1988-2017.

[18] We calculate missing imports in quantities rather than in values as the confiscation variable is measured in number of units instead of consignment value.

import). The effect of missing imports is robust to inclusion of these variables.[19] Table 3 presents the estimates of a more conservative specification with importer-product and year fixed effects. The effect of missing imports on new infection cases is slightly larger compared to Table 2. Overall, we find a fairly consistent effect of missing imports on new infections that is robust to alternative specifications and to the inclusion of additional controls.

<< Tables 2 and 3 about here >>

Robustness checks We perform four robustness check on the main estimations of column (1) of Tables 2 and 3 respectively. The results are presented in Table 4. In columns (1)-(2) we cluster standard errors at the country level for inference if errors are only autocorrelated within country. The standard errors are only slightly smaller than those reported in the baseline specification. This suggests that the assumption that errors are correlated within year-across countries is not critical for inference. In columns (3)-(4) we estimate the effect after excluding years 2004 and 2019 respectively. This is necessitated for two reasons. In 2004 the number of new infections is about six times larger than the sample average. The high number of cases is mainly driven by the outbreak of the 'mad cow disease' in December 2003. Similarly, in 2019 the missing imports data are only available for 39 countries. We exclude 2004 and 2019 to ensure that the results are not driven by these outlier years. Results presented in columns (3)-(4) of Table 4 confirm that our results are robust to excluding these years. In columns (5)-(6) we use a more conservative version of the dependent variable, without any replacement of missing values with zeros. Although the number of observations is greatly reduced, the point estimates are quite similar to the corresponding estimates of column (1) of Tables 2 and 3. Finally, in columns (7)-(8) we use discrepancy in mirror trade statistics that is measured in unit quantities (instead of traded values).[20] The coefficient on the alternative definition of missing imports is smaller in magnitude compared to the baseline estimates, and the effect is statistically not different

[19] In specifications which are not reported here and are available upon request, the effect of missing imports is still statistically significant when all controls (with the exception of time to import, which reduces the sample size by more than a third) are added simultaneously. The point estimate is however larger than in column (1), most likely due to multicollinearity issues.

[20] We calculate missing imports (qty.) replacing J (in values) with J^Q (in quantities), $J = \{M, X\}$ in equation (1).

from zero. This result suggests that evasion of live animals through underreporting of total quantities imported may not be an important channel of spreading infectious diseases (Javorcik and Narciso, 2008).

<< Table 4 about here >>

5.3 Identification issues

In Section 4.1 we argued that our results can be biased upwards due to reverse causality if an import ban is imposed following a disease outbreak. We alleviate this concern in columns (1) and (2) of Table 5 where we exclude all instances where an import ban was imposed following a disease outbreak.[21] Results show that excluding such cases has little effect on the estimated impact of missing imports on new infections.

Yet another challenge for causal interpretation stems from confounding factors that could vary within importer-product over time. We perform four additional exercises to alleviate the concern of omitted variables driving our results. First, we estimate the baseline models along with country-level linear time trends. Such a specification accounts for any smoothly evolving changes, such as improved knowledge regarding a disease or an increase in prevention spending. The results are presented in columns (3)-(4) of Table 5 and suggest that the baseline effect is robust to inclusion of country-specific time trends.

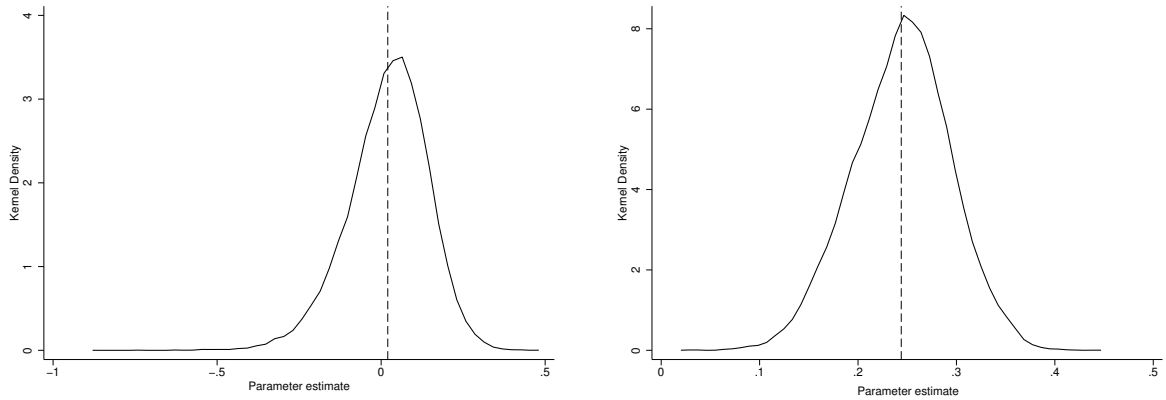
In addition to this evidence, we conduct a placebo test to address the concern that omitted time varying country level variables could be driving the relationship between missing imports and new infections. We randomly assign missing imports across product categories within the same importer-year and estimate a specification that corresponds to column (1) of Table 3, after excluding observations where the random assignment matches the correct assignment. Panel (a) of Figure 2 plots the sampling distribution of the coefficient of interest, obtained from 100,000 estimations incorrectly assigning product categories while holding the country-year constant. The coefficient of interest converges to zero when we incorrectly assign product categories. Panel (b) plots the distribution of the coefficient of interest across the same set of restricted samples, when we correctly assign the product categories. The distribution with correct assignment is starkly different,

[21] In the sample of columns (1) of Table 3, 63 out of 134 countries ever imposed import bans.

and the coefficient converges to 0.25, which is closer to our baseline effect. The close to zero effect of missing imports across incorrectly assigned product categories, even when the importer-year dimension is held constant, suggests that omitted time varying country level variables are unlikely to drive the relationship between missing imports and new infections.

Figure 2: Placebo test

(a) Random assignment (b) Correct assignment



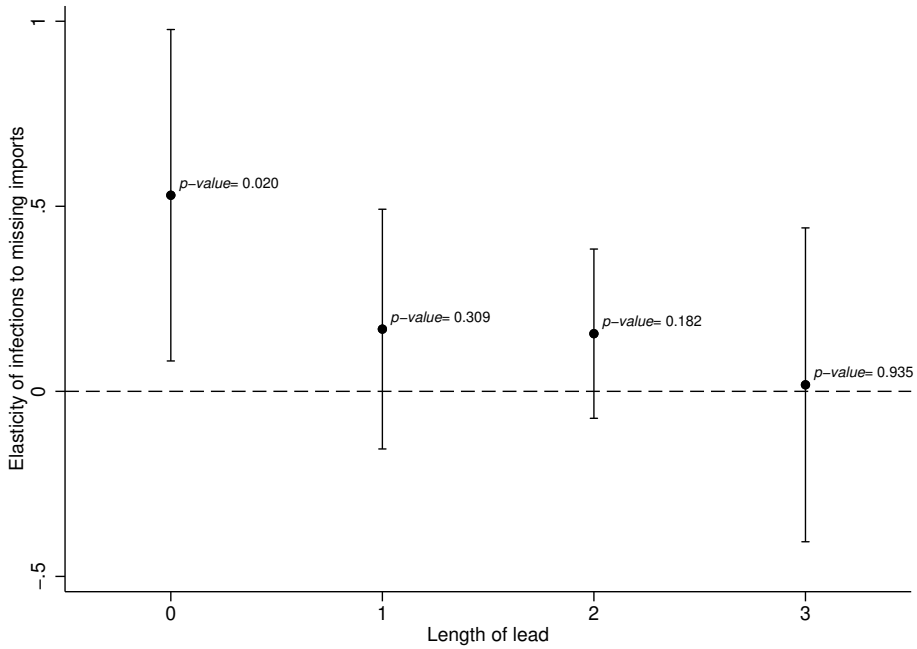
Notes: Panel (a) depicts a sampling distribution of the coefficients of missing imports from 100,000 regressions with the same specification as column (1) of Table 3, after randomly assigning missing imports across product categories k in the same country i and in the same year t. The coefficients are estimated after excluding observations where the random assignment matches the actual assignment. Panel (b) depicts the distribution of the coefficients of missing imports with the same specification and across the same set of restricted samples, when product categories are assigned correctly. Dashed vertical lines represent sample means.

In addition, there could be policy measures that simultaneously affect missing imports as well as the cases of new infections. In columns (5)-(6) we include a control for the MFN tariff rate (see discussion in Section 5.1 on the correlation between tariffs and missing imports). Reassuringly, even after controlling for import tariffs, the coefficients on missing imports remain positive, statistically significant and very similar in size to the corresponding coefficients in column (1) of Tables 2 and 3. We conclude that omitting MFN tariffs has a negligible impact on the results.

<< Table 5 about here >>

In a final check we explore the causality issue broadly to see if future missing imports drive present infection cases. If this was the case, it would indicate some omitted variables or cast reservation on the specification. We consider a specification that regresses the number of new infection cases in year t on missing imports in year t, along with missing

Figure 3: Current and future missing imports and disease burden



Notes: Estimated coefficients from a modified version of the model in column (1) of Table 3, where in addition to missing imports in year t we also include missing imports in year $t+1$ to year $t+3$. Point estimates in circles.

imports in year $t+1$ to year $t+3$. Figure 3 shows the effect of contemporaneous and future missing imports on new infection cases. We find that the effect of missing imports in lead years is statistically not different from zero. The contemporaneous effect of missing imports continues to be statistically significant and it is conspicuously larger in magnitude than the lead effects.

Together, these results support a causal interpretation, i.e. an increase in missing imports in a given HS4 product category leads to a higher number of new infections in the related animal species.

The evidence thus far is silent on the mechanisms through which the impact of missing imports on new infections occurs. In the following section we investigate whether evasionary practices that are highlighted in the tariff evasion literature can explain the relationship between missing imports and new infections.

6 Channels of illicit trade and disease burden

The tariff evasion literature identifies three channels through which evasion can occur. First, tariff evasion can occur through the mis-classification of products, i.e. an importer

could report a higher taxed product as a lower taxed variety (Fisman and Wei, 2004). Second, tariff evasion can occur through the under-reporting of unit prices (Javorcik and Narciso, 2008, 2017). Finally, tariff evasion can occur through the under-declaration of product quantities (Rotunno and Vézina, 2012). In this section, we investigate whether the first two among these mechanisms could drive the positive association between illicit trade and disease spread. We leave aside the third mechanism because, to measure under-declaration of product quantities, different products should be measured in different units (e.g., kilos vs. number of items) – see Beverelli and Ticku (2020). This is not possible with the data at hand, since the quantity of traded live animals, when reported, is only reported in number of items.

To test whether illicit trade increases the spread of infectious diseases through mis-classification, we adopt two complementary approaches. In a first approach, we construct the dummy variable 'High MFN tariff w.r.t. live animals (HS 01)', which equals one if the MFN tariff τ_{ikt} is larger than the average tariff on live animals (HS chapter 01) applied by importer i in year t, computed excluding HS heading k.[22] Intuitively, if this dummy variable is equal to one, a trader interested in minimizing tariff payment could mis-classify live animals across categories, declaring them as belonging to headings that are taxed less at the border. The 'High MFN tariff w.r.t. live animals' dummy variable is then interacted with missing imports. A positive coefficient on the interaction term would indicate that missing imports have a larger impact on the spread of infectious diseases in cases where traders have the incentive to mis-classify across live animal categories to evade import tariffs.

A problem with the 'High MFN tariff w.r.t. live animals' dummy is that misreporting across different HS headings may not be feasible, because the HS headings are quite distinct categories of animals: it may simply not be feasible to declare a horse a cow. We propose a second approach to address this issue, which relies on a comparison between the MFN tariff on HS heading $k \in [0101, 0102, 0103, 0104, 0105]$ and the MFN tariff in HS

[22] For instance, the tariff imposed by the importing country on live swine (HS heading 0103) is compared to the average tariff on other HS headings in chapter 01 (0101, 0102, 0104, 0105, and 0106). If it is larger than this average, the dummy takes value one. Note that such dummy varies along all the three dimensions of the dataset.

heading 0106 (live animals not elsewhere classified). The idea is that it may still be feasible to misreport live animals in 0101, 0102, 0103, 0104, and 0105 as live animals under 0106 if the animals are similar enough. For instance 'Guinea Fowls', which are classified in HS category 0105, could be mis-classified as 'other live birds' in HS category 0106. Similarly, 'wild goats', which are classified in HS category 0104, could be mis-classified as 'antelopes' in HS category 0106. The dummy 'High MFN tariff w.r.t. other animals (HS 0106)' takes value one if the MFN tariff applied on HS heading k, τ_{ikt}, $k \in [0101, 0102, 0103, 0104, 0105]$, is larger than the MFN tariff on HS heading 0106, $\tau_{i\ell t}$, $\ell = 0106$. This dummy is interacted with missing imports. As in the case of the dummy 'High MFN tariff w.r.t. live animals', a positive coefficient on the interaction would indicate that missing imports have a larger impact on infectious diseases in cases where mis-classification is incentivized. The results on the misreporting channel are displayed in columns (1)-(4) of Table 6, and provide empirical support to the hypothesis that evasion through mis-classification is responsible for higher disease burden.

Next we assess whether evasion of live animals through under-pricing results in a higher disease burden. To test the under-reporting of unit prices channel, we exploit the Rauch (1999)'s (conservative) classification. As described in Appendix C, HS headings 0102, 0103, and 0104 are treated as homogeneous, while HS headings 0101, 0105, and 0106 are treated as differentiated.[23] Differentiated products are those whose prices may range widely due to difference in product quality, and hence it may be difficult for customs officials to detect under-pricing of the consignment (Javorcik and Narciso, 2017). Results presented in columns (5)-(6) of Table 6 show that the effect of the interaction term is positive and statistically significant at one percent level. This confirms that evasion through under-reporting of unit prices is responsible for higher disease burden.

<< Table 6 about here >>

Having presented empirical evidence on the relationship between channels of tariff evasion and spread of infectious disease, we turn to qualitative evidence on illicit trade

[23]The Rauch classification, available at `https://econweb.ucsd.edu/~jrauch/rauch_classification.html`, is at the 4-digit level of aggregation of the SITC Rev. 2 classification. Standard crosswalks, available at `http://wits.worldbank.org/product_concordance.html`, are used to concord the classification to the HS 2007 classification.

and diseases to highlight the potential reasons for transmission. Mis-classification across product categories can result in circumventing testing and quarantine protocols which are put in place in anticipation of a particular infectious disease. For instance, a consignment of 'domestic chicken' that is mis-labeled as 'other live birds' may escape additional scrutiny at customs which is put in place in anticipation of a disease that specifically affects poultry. Significant variation in tariff rates across similarly looking live animals could also incentivize bundling of different species that can enable the spread of pathogens (Wyatt et al., 2018). Moreover, the falsification of consignment details by declaring lower values can reduce the chance of inspection by customs officials (Wyatt and Cao, 2015). This should especially be the case if customs officials systematically inspect consignments of higher value with the objective of maximizing tariff revenue.

7 Does illicit trade affect human health?

In our final exercise, we consider the implications of illicit trade on human health through the spread of zoonotic diseases. It is well known that contact with infected animals can transmit several diseases to humans. As reported in footnote 3, a large number of pathogens that can affect humans are zoonotic, and zoonotic diseases are responsible for many cases of human illnesses and deaths. Furthermore, there is abundant evidence that the prevalence of zoonotic diseases among emerging infectious diseases is linked to increasing volumes of animal trafficking and smuggling (Fisman and Laupland, 2010; Aguirre et al., 2020).[24]

We leave the question of whether illicit trade in live animals affects human health as an aside exclusively for data related reasons. EMPRES-i includes information on the number of humans infected and on the number of human casualties. The crossover of infections to humans is, however, very rare in the data. As displayed in the last row of Table A-3, only about one percent of infection cases in animal species are reported to also infect humans.

With this caveat in mind, in Table 7 we report the effect of missing imports on humans

[24]Pangolins – which are known to carry coronaviruses (Bale, 2020) and are believed to be the most heavily trafficked wild mammals in the world (Quammen, 2020) – are a prominent example. It is reported that almost almost nine hundred thousand pangolins have been smuggled during the past two decades, some of them dead, peeled of scales and frozen, others live (Quammen, 2020).

infected at both the intensive and the extensive margin, respectively using the number of human infections and a dummy equal to one if human infections related to an animal infection in country i, sector k and year t were reported. In columns (1)-(2) we estimate the effect at the intensive margin through PPML and discern no effect. In columns (3)-(4) we estimate the effect at the extensive margin through OLS (linear probability model). In both the specifications with i, k and t (column (3)) or ik and t (column (4)) fixed effects, missing imports have a positive and statistically significant effect on the likelihood of human infections. The point estimate implies that a one percent increase in missing imports is associated with 0.3 to 0.5 percentage point increase in the likelihood of human infections, which corresponds to a 30 to 50 percent increase relative to the sample mean. These results constitute preliminary evidence that illicit imports in addition to threatening animal biodiversity could also pose a risk to human health through spreading zoonotic diseases.

<< Table 7 about here >>

8 Conclusions

On October 18, 2004, two live eagles smuggled from Thailand were seized at Brussels International Airport. It was found that one of the two eagles had bilateral pneumonia, caused by Highly Pathogenic Avian Influenza (HPAI) H5N1 virus. Luckily, a screening performed in human and avian contacts indicated no dissemination occurred.

If this was a science fiction movie, its last sequence might display an episode of undetected smuggling of other live birds in another airport in Europe. The movie credits might then describe the consequences of the 2005 outbreak of avian influenza across Europe, in terms of human lives lost, specimen killed (either by the virus or by efforts to stop its spread), and economic costs. But this is not a movie. It is a realistic account of the first recorded case of H5N1 in the European Union (Van Borm et al., 2005). As argued by these authors, while this particular episode did not lead to any further contagion, it shows that illegal movements of live animals, in this case wild birds, are a major threat for the introduction of infectious diseases, such as highly pathogenic avian influenza.

Consistently with this case-study evidence, this paper has shown that illicit trade in live animals plays a significant role in spreading infectious diseases in animals. Using a dataset covering about 130 countries over a sixteen year period, we have shown that discrepancy in mirror trade statistics – used in the extant literature to uncover evidence of smuggling across various items – is systematically linked to spread of infectious diseases in the associated animal species. We have provided additional evidence that this relationship is likely to be driven by evasionary practices such as mis-classification or underpricing of the imported species.

Much of the public concern about animal diseases, of course, is about the associated risks for human health. We have provided some preliminary evidence that illicit imports, in addition to threatening animal health, could also pose a risk to human health through spreading zoonotic diseases. However, currently available data used in this study cover only few of those zoonoses that are responsible for most human illness and human cases. More research is needed to quantify the impact of illicit animal trade on human health, especially in light of the COVID-19 pandemic.

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Tables

Table 1: Missing imports as a proxy for illicit trade

Dependent variable	Missing imports	Confiscated (qty.)
	(1)	(2)
MFN tariff	0.001^{+}	
	(0.001)	
Missing imports (qty.)		0.781*
		(0.371)
Observations	8,653	334
No. of countries	146	56
R-squared	0.202	
Model	OLS	PPML

Notes: $^{+}$p<0.10, *p<0.05,**p<0.01. Dependent variable in column (1): difference between the log value of exports (augmented by one) reported by all exporting countries to importing country i in live animal category (HS heading) k in year t and the log value of imports (augmented by one) reported by country i from all countries in live animal category (HS heading) k in year t, sourced from UN COMTRADE. Dependent variable in column (2): number of imported units of live animal specimen which were confiscated by the customs authority in importer i in year t, sourced from the CITES Trade Database. MFN tariff is the most favoured nation tariff imposed by the importing country i on live animal category (HS heading) k in year t, sourced from UNCTAD TRAINS. Missing imports (qty.) is calculated as missing imports, using the import and export quantities rather than values, sourced from UN COMTRADE. Standard errors clustered at the country and year level in parentheses. Country, HS heading and year fixed effects included in column (1). Country and year fixed effects included in column (2). Years included: 2004-2019. HS headings included in column (1): 0101, 0102, 0103, 0104, 0105, and 0106.

Table 2: Estimations with importer, product, and year fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Missing imports	0.311**	0.273*	0.259+	0.343**	0.329**	0.373**	0.324*	0.347**
	(0.118)	(0.116)	(0.135)	(0.121)	(0.116)	(0.124)	(0.133)	(0.055)
Missing imports in ch. 02		0.641						
		(0.550)						
Missing imports in head. 0504			-1.032					
			(0.656)					
GDP per capita (logs)				-1.425				
				(1.167)				
Population (logs)					-1.210			
					(4.319)			
Health expenditure as % of GDP						0.352*		
						(0.157)		
Quality of port infrastructure							0.627	
							(0.584)	
Time to import (days)								0.144**
								(0.052)
Observations	9,053	9,038	8,101	8,878	8,878	7,931	7,418	5,365
No. of countries	136	136	123	135	135	129	123	128

Notes: +p<0.10, *p<0.05,**p<0.01. PPML regressions. Dependent variable: number of observed animal infection cases by importing country i, live animal category (HS heading) k and year t ($Infections_{ikt}$), sourced from FAO's EMPRES Global Animal Disease Information System (EMPRES-i). See notes to Table 1 for the description of Missing imports. Missing imports in ch. 02 are constructed as missing imports, with k being HS chapter 02 (Meat and edible meat offal). Missing imports in head. 0504 are constructed as missing imports, with k being HS heading 0504 (Guts, bladders and stomachs of animals other than fish). GDP per capita (logs) is the log of country i's GDP per capita in year t, sourced from IMF's World Economic Outlook data, October 2019 edition. Population (logs) is the log country i's population in year t, sourced from IMF's World Economic Outlook data, October 2019 edition. Health expenditure as % of GDP is country i's health expenditure as percentage of GDP in year t, sourced from the World Health Organization's Global Health Expenditure database. Quality of port infrastructure is country i's quality of port infrastructure in year t, sourced from the World Economic Forum's Global Competitiveness Report. Time to import (days) is country i's time associated with importing a standardized cargo of goods by sea transport, calculated in calendar days, in year t, sourced from the World Bank's Doing Business Indicators, 2006-2015 methodology. Standard errors clustered at the country and year level in parentheses. Country, HS heading and year fixed effects included in all specifications. Years included: 2004-2019 (columns (1)-(7)); 2006-2015 (column (8)). HS headings included: 0101, 0102, 0103, 0104, 0105, and 0106.

Table 3: Estimations with importer-product and year fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Missing imports	0.373**	0.318*	0.355*	0.416**	0.398*	0.472**	0.362*	0.412**
	(0.143)	(0.141)	(0.178)	(0.146)	(0.162)	(0.164)	(0.149)	(0.139)
Missing imports in ch. 02		0.625^{+}						
		(0.371)						
Missing imports in head. 0504			-1.080*					
			(0.533)					
GDP per capita (logs)				-1.492				
				(1.241)				
Population (logs)					-1.218			
					(5.292)			
Health expenditure as % of GDP						0.384		
						(0.235)		
Quality of port infrastructure							0.632	
							(0.601)	
Time to import (days)								0.148*
								(0.068)
Observations	5,691	5,682	5,117	5,538	5,538	4,894	4,728	2,918
No. of countries	134	134	122	133	133	128	123	126

Notes: $^{+}$p<0.10, *p<0.05,**p<0.01. PPML regressions. Dependent variable: number of observed animal infection cases by importing country i, live animal category k and year t ($Infections_{ikt}$), sourced from FAO's EMPRES Global Animal Disease Information System (EMPRES-i). See notes to Table 2 for the description of explanatory variables. Standard errors clustered at country and year level in parentheses. Country-HS heading and year fixed effects included in all specifications. Years included: 2004-2019 (columns (1)-(7)); 2006-2015 (column (8)). HS headings included: 0101, 0102, 0103, 0104, 0105, and 0106.

Table 4: Robustness checks

	Country-clustered standard errors		Excluding outlier years (2004, 2019)		No zeros' replacement in dependent variable		Missing imports in quantities (qty.)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Missing imports	0.311**	0.373**	0.315*	0.363**	0.338**	0.417**		
	(0.117)	(0.143)	(0.127)	(0.139)	(0.108)	(0.105)		
Missing imports (qty.)							0.047	0.169
							(0.093)	(0.145)
Observations	9,053	5,691	8,406	5,241	1,779	1,659	6,008	3,770
No. of countries	136	134	136	134	127	123	130	128

Notes: $^{+}$p<0.10, *p<0.05,**p<0.01. PPML regressions. Dependent variable: number of observed animal infection cases by importing country i, live animal category (HS heading) k and year t ($Infections_{ikt}$), sourced from FAO's EMPRES Global Animal Disease Information System (EMPRES-i). See notes to Table 2 for the description of missing imports, and notes to Table 1 for the description of missing imports (qty.). Standard errors (clustered at country level in columns (1)-(2), and at country and year level in columns (3)-(8)) in parentheses. Odd-numbered columns include country, HS heading and year fixed effects. Even-numbered columns include country-HS heading and year fixed effects. Years included: 2004-2019 (columns (1)-(2), (5)-(8)); 2005-2018 (columns (3)-(4)).

Table 5: Excluding observations with import bans, adding country specific time trends and MFN tariff

	Excluding observations with import bans		Country time trends		MFN tariff	
	(1)	(2)	(3)	(4)	(5)	(6)
Missing imports	0.301*	0.345*	0.226^{+}	0.265^{+}	0.371**	0.410**
	(0.131)	(0.146)	(0.132)	(0.151)	(0.121)	(0.141)
MFN tariff					0.011	-0.007
					(0.023)	(0.087)
Observations	8,652	5,356	9,053	5,691	8,218	5,070
No. of countries	136	134	136	134	131	129

Notes: $^{+}$p<0.10, *p<0.05,**p<0.01. PPML regressions. Dependent variable: number of observed animal infection cases by importing country i, live animal category (HS heading) k and year t ($Infections_{ikt}$), sourced from FAO's EMPRES Global Animal Disease Information System (EMPRES-i). See notes to Table 2 for the description of missing imports, and notes to Table 1 for the description of MFN tariff. Standard errors clustered at the country and year level in parentheses. Odd-numbered columns include country, HS heading and year fixed effects. Even-numbered columns include country-HS heading and year fixed effects. Columns (3)-(4) additionally include country-time trends. Years included: 2004-2019. HS headings included: 0101, 0102, 0103, 0104, 0105, and 0106.

Table 6: Mechanisms

	Misresporting				Underinvoicing	
	(1)	(2)	(3)	(4)	(5)	(6)
Missing imports	0.210**	0.160^{+}	0.230**	0.262**	-0.127	-0.802*
	(0.063)	(0.084)	(0.080)	(0.099)	(0.138)	(0.379)
High MFN tariff w.r.t. live animals (HS 01)	1.430**	1.592**				
	(0.523)	(0.586)				
High MFN tariff w.r.t. live animals (HS 01) × Missing imports	0.262*	0.519**				
	(0.118)	(0.189)				
High MFN tariff w.r.t. other animals (HS 0106)			1.457^{+}	1.437		
			(0.878)	(0.898)		
High MFN tariff w.r.t. other animals (HS 0106) × Missing imports			0.256*	0.252^{+}		
			(0.113)	(0.143)		
Differentiated HS heading × Missing imports					0.521**	1.265**
					(0.167)	(0.422)
Observations	8,218	5,070	7,208	4,538	9,053	5,691
No. of countries	131	129	133	131	136	134

Notes: $^{+}$p<0.10, *p<0.05,**p<0.01. PPML regressions. Dependent variable: number of observed animal infection cases by importing country i, live animal category (HS heading) k and year t ($Infections_{ikt}$), sourced from FAO's EMPRES Global Animal Disease Information System (EMPRES-i). See notes to Table 2 for the description of missing imports. High MFN tariff w.r.t. live animals (HS 01) is a dummy equal to one if the MFN tariff applied by country i in year t on HS heading k is larger than the average tariff on live animals (HS chapter 01) applied by importer i in year t, computed excluding HS heading k. High MFN tariff w.r.t. other animals (HS 0106) is a dummy equal to one if the MFN tariff applied by country i in year t on HS heading k, $k \in [0101, 0102, 0103, 0104, 0105]$, is larger than the MFN tariff applied by country i in year t on HS heading 0106 (Animals; live, n.e.c. in chapter 01), $\tau_{i\ell t}$, ℓ = 0106. Tariff data are sourced from UNCTAD TRAINS. Differentiated HS heading is a dummy equal to one if HS heading k differentiated, based on the Rauch (1999)'s (conservative) classification. Standard errors clustered at the country and year level in parentheses. Odd-numbered columns include country, HS heading and year fixed effects. Even-numbered columns include country-HS heading and year fixed effects. Years included: 2004-2019. HS headings included in columns (1)-(2) and (5)-(6): 0101, 0102, 0103, 0104, 0105, and 0106. HS headings included in columns (3)-(4): 0101, 0102, 0103, 0104, and 0105.

Table 7: Human cases

Dependent variable	Infections (humans)		Humans infected dummy	
	(1)	(2)	(3)	(4)
Missing imports	-0.157	0.237	0.005^{+}	0.003^{+}
	(0.285)	(0.214)	(0.002)	(0.001)
Observations	2,541	744	9,531	9,500
No. of countries	43	43	151	149
R-squared			0.111	0.408
Model	PPML		OLS	

Notes: $^{+}$p<0.10, *p<0.05,**p<0.01. Dependent variable in columns (1)-(2): number of observed human infection cases from diseases affecting live animal category (HS heading) k, by importing country i and year t, sourced from FAO's EMPRES Global Animal Disease Information System (EMPRES-i). Dependent variable in columns (3)-(4): dummy equal to one if the dependent variable in columns (1)-(2) is positive. See notes to Table 2 for the description of missing imports. Standard errors clustered at the country and year level in parentheses. Country, product and year fixed effects included in odd-numbered columns. Country-product and year fixed effects included in even-numbered columns. Years included: 2004-2019. HS headings included: 0102, 0103, 0104, 0105, and 0106 in columns (1)-(2); 0101, 0102, 0103, 0104, 0105, and 0106 in columns (3)-(4).

Appendices

A Appendix tables

Table A-1: Animal diseases in FAO EMPRES-i and animal species affected

Disease	Animal species affected
African horse sickness	Equine
African swine fever	Swine
Anthrax	Multiple
Bluetongue	Multiple
Bovine spongiform encephalopathy	Cattle
Bovine tuberculosis	Multiple
Brucellosis	Multiple
Brucellosis (Brucella abortus)	Multiple
Brucellosis (Brucella melitensis)	Multiple
Brucellosis (Brucella suis)	Multiple
Classical swine fever	Swine
Contagious bovine pleuropneumonia	Cattle
Equine infectious anaemia	Equine
Foot and mouth disease	Multiple
Glanders	Equine
Hendra Virus Disease	Multiple
Influenza - Avian	Avian
Influenza - Equine	Equine
Influenza - Swine	Swine
Japanese Encephalitis	Multiple
Leptospirosis	Multiple
Lumpy skin disease	Cattle
MERS-CoV	*Other diseases*
Newcastle disease	Avian
Peste des petits ruminants	Sheep and goat
Porcine reproductive and respiratory syndrome	Swine
Rabies	Multiple
Rift Valley fever	Multiple
Schmallenberg	*Other diseases*
Sheep pox and goat pox	Sheep and goat
West Nile Fever	Multiple

Notes: Left column: list of diseases with confirmed cases in the FAO's EMPRES Global Animal Disease Information System (EMPRES-i). Right column: World Organization of Animal Health (OIE)'s classification of animal diseases by species affected, sourced from OIE's 'Information on aquatic and terrestrial animal diseases'. See tab 'Type of animal' at `https://www.oie.int/en/animal-health-in-the-world/information-on-aquatic-and-terrestrial-animal-diseases/`. MERS-CoV stands for Middle East Respiratory Syndrome Coronavirus.

Table A-2: Correspondence between animal diseases in FAO EMPRES-i and HS headings

	HS heading						
Disease	0101	0102	0103	0104	0105	0106	N.A.
African horse sickness	199	0	0	0	0	1	0
African swine fever	0	0	20,812	0	0	1	76
Anthrax	11	211	32	34	1	31	103
Bluetongue	0	4,238	1	4,108	0	15	4,283
Bovine spongiform encephalopathy	0	37	0	0	0	1	1
Bovine tuberculosis	0	9	1	0	0	0	2
Brucellosis	0	99	7	252	4	0	96
Brucellosis (Brucella abortus)	0	23	0	2	0	0	0
Brucellosis (Brucella melitensis)	0	5	0	25	0	0	10
Brucellosis (Brucella suis)	0	3	14	0	0	1	1
Classical swine fever	0	0	2,246	0	0	0	4
Contagious bovine pleuropneumonia	0	202	0	1	0	0	0
Equine infectious anaemia	142	0	0	0	0	0	45
Foot and mouth disease	0	3,118	605	382	0	23	508
Glanders	45	0	0	0	0	0	9
Hendra Virus Disease	42	0	0	0	0	2	3
Influenza - Avian	0	0	0	0	29,298	2,940	39
Influenza - Equine	682	0	0	0	0	0	4
Influenza - Swine	0	0	141	0	10	45	9
Japanese Encephalitis	0	0	6	0	0	0	110
Leptospirosis	0	1	0	0	0	0	312
Lumpy skin disease	0	2,954	0	0	0	0	0
MERS-CoV	0	0	0	0	0	2,407	0
Newcastle disease	0	0	0	0	1,486	21	24
Peste des petits ruminants	0	0	0	3,100	0	6	7
Porcine reproductive and respiratory syndrome	0	0	384	0	0	0	0
Rabies	38	911	11	28	1	1,402	200
Rift Valley fever	0	171	0	372	0	21	459
Schmallenberg	0	1,136	0	2,190	0	3	8
Sheep pox and goat pox	0	0	21	1,113	0	0	0
West Nile Fever	443	1	0	0	6	63	27
Total	1,602	13,119	24,281	11,607	30,806	6,983	6,340

Notes: Left column: list of diseases with confirmed cases in the FAO's EMPRES Global Animal Disease Information System (EMPRES-i). Other columns: authors' classification of animal diseases by live animal category (HS heading) affected, based on data from FAO's EMPRES Global Animal Disease Information System (EMPRES-i), and information from USA Trade Online (`https://uscensus.prod.3ceonline.com/`). Each row assigns all the observations on each disease available in the FAO EMPRES-i database to Harmonized System (HS) headings 0101-0106 or to the non-assignable (N.A.) category if there is not sufficient information to make a precise assignment. HS heading 0101 includes horses, asses, mules and hinnies; HS heading 0102 includes bovine animals; HS heading 0103 includes swine; HS heading 0104 includes sheep and goats; HS heading 0105 includes poultry, fowls of the species Gallus domesticus, ducks, geese, turkeys and guinea fowls; HS heading 0106 includes live animals not elsewhere classified. MERS-CoV stands for Middle East Respiratory Syndrome Coronavirus.

Table A-3: In-sample descriptive statistics

Variable	Mean	Median	Std Dev	Min	Max
Confiscated (qty.)	2,428.21	2	21,707.26	0	379,520
Missing imports (qty.)	-0.35	-0.13	1.27	-5.86	3.26
Infections	5,597.71	0	120,725.90	0	7,763,993
Missing imports	0.09	-0.03	1.29	-8.48	9.72
Missing imports in ch. 02	0.13	0	0.67	-2.77	8.54
Missing imports in head. 0504	0.26	-0.01	1.04	-4.36	7.77
GDP per capita (logs)	9.07	9.11	1.39	5.14	11.70
Population (logs)	16.65	16.57	1.54	12.57	21.06
Health expenditure as % of GDP	6.98	6.93	2.49	1.60	17.20
Quality of port infrastructure	4.31	4.30	1.11	1.20	6.82
Time to import (days)	20.16	16.00	13.98	5.00	83.00
Missing imports (qty.)	-0.22	0	2.52	-18.69	10.89
MFN tariff	13.03	6.67	34.38	0	480.76
Infections (humans)	5.81	0	42.75	0	687
Declared imports (logs)	6.92	7.15	3.10	0	14.75
Variable	**Zeros**	**Ones**	**Std Dev**	**Min**	**Max**
Import ban	5,414	277	0.22	0	1
High MFN tariff w.r.t live animals (HS 01)	3,104	1,966	0.49	0	1
High MFN tariff w.r.t. wild animals (HS 0106)	2,529	2,009	0.50	0	1
Differentiated HS heading	2,639	3,052	0.50	0	1
Humans infected dummy	9,355	145	0.12	0	1

Notes: Descriptive statistics for Confiscated (qty.) and Missing imports (qty.) computed from the sample of column (2) of Table 1. Descriptive statistics for Infections, Missing imports and Import ban computed from the sample of column (1) of Table 3. Descriptive statistics for Missing imports in ch. 02 computed from the sample of column (2) of Table 3. Descriptive statistics for Missing imports in head. 0504 computed from the sample of column (3) of Table 3. Descriptive statistics for GDP per capita (logs) computed from the sample of column (4) of Table 3. Descriptive statistics for Population (logs) computed from the sample of column (5) of Table 3. Descriptive statistics for Health expenditure as percent of GDP computed from the sample of column (6) of Table 3. Descriptive statistics for Quality of port infrastructure computed from the sample of column (7) of Table 3. Descriptive statistics for Time to import (days) computed from the sample of column (8) of Table 3. Descriptive statistics for Missing imports (qty.) computed from the sample of column (8) of Table 4. Descriptive statistics for MFN tariff computed from the sample of column (4) of Table 5. Descriptive statistics for High MFN tariff w.r.t live animals (HS 01) computed from the sample of column (6) of Table 6. Descriptive statistics for High MFN tariff w.r.t. wild animals (HS 0106) computed from the sample of column (4) of Table 6. Descriptive statistics for Differentiated HS heading computed from the sample of column (6) of Table 6. Descriptive statistics for Infections (humans) computed from the sample of column (4) of Table 7. Descriptive statistics for Humans infected dummy computed from the sample of column (6) of Table 7. Descriptive statistics for Declared imports computed from the sample of column (2) of Table B-1. Import ban is a dummy equal to one if country i imposed an emergency Sanitary and Phytosanitary (SPS) measure to stop importing HS heading k in year t from any partner country, sourced from WTO Integrated Trade Intelligence Portal (I-TIP) data. See notes to tables 1, 2, 6, and 7 for the description of all other variables.

B Licit trade and disease burden

In this appendix, we consider the relationship between licit trade and animal infections. We show that this relationship is negative, and we argue that this result is consistent with an import demand-reducing effect of infections.

Columns (1)-(2) of Table B-1 replicate column (1) of Tables 2 and 3, respectively, with a different explanatory variable, namely licit trade, measured using reported imports: $\ln(1 + M_{ikt})$. Licit trade has a negative and statistically significant effect on the number of animal infections. This result is consistent with our explanation of reverse causality, i.e. a disease outbreak should negatively affect demand for imports of the associated animal specimen. An alternative explanation for the observed negative correlation between licit trade and the number of animal infections could be due to policy responses to disease outbreaks in the form of import bans. However, when restricting the sample by excluding observations with imports bans (columns (3) and (4) of Table B-1), the correlation remains negative and statistically significant. We take this as an indication that disease outbreaks reduce import demand, and this reverse causality feedback is likely responsible for the negative sign of the licit trade estimate.[25]

Table B-1: Licit trade

	Full sample		Excluding observations with import bans	
	(1)	(2)	(3)	(4)
Declared imports	-0.229^{+}	-0.350*	-0.311**	-0.482**
	(0.137)	(0.140)	(0.115)	(0.162)
Observations	9,524	5,903	9,113	5,562
No. of countries	136	134	136	134

Notes: $^{+}$p<0.10, *p<0.05,**p<0.01. PPML regressions. Dependent variable: number of observed animal infection cases by importing country i, live animal category k and year t ($Infections_{ikt}$), sourced from FAO's EMPRES Global Animal Disease Information System (EMPRES-i). Declared imports is the log value of imports (augmented by one) reported by country i from all countries in HS heading k in year t, sourced from UN COMTRADE. Standard errors clustered at the country and year level in parentheses. Odd-numbered columns include country, HS heading and year fixed effects. Even-numbered columns include country-HS heading and year fixed effects. Years included: 2004-2019. HS headings included: 0101, 0102, 0103, 0104, 0105, and 0106.

[25] Alternatively, in specification akin to columns (1)-(2) of Table B-1, we use mirror exports ($\ln(1 + X_{ikt})$) as a proxy for licit imports. The estimated association is once again negative, but the effect is smaller in magnitude and it is statistically not different from zero.

C Rauch's classification for live animals

In this section, we describe the assignement of the 'differentiated' dummy to HS headings, based on the conservative version of Rauch's (1999) classification.

HS headings 0101 and 0106 are unambiguously 'differentiated' (being coded as such by Rauch). HS headings 0102, 0103, and 0104 are unambiguously 'homogeneous' (being coded as 'goods traded on an organized exchange' by Rauch). Concerning HS heading 0105, six digit products containing live poultry weighting less than 185 grams (010511, 010512, and 010519 in the 2007 HS classification) are coded as 'differentiated', while six digit products containing live poultry weighting more than 185 grams (010594 and 010599 in the 2007 HS classification) are coded as 'goods traded on an organized exchange'. The choice to treat the heading as 'differentiated' was made based on the trade-weighted average of the one's associated to differentiated live poultry and the zero's associated to homogeneous live poultry (weights were computed using COMTRADE data on world trade in live poultry, averaged between 2007 and 2019). Since the trade-weighted average (0.6) is closer to one than to zero, we treat the heading 0105 as 'differentiated'.