Russian Counter-Sanctions and Smuggling: Forensics with Structural Gravity Estimation*

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Abstract

Trade and other economic sanctions are a common foreign policy instrument, but their imposition may induce smuggling. We develop and implement procedures to study smuggling after the food embargo imposed by Russia on Western countries after the annexation of Crimea in 2014. We construct predicted trade flows for the post-sanctions period using an estimated structural general equilibrium gravity model with many industry sectors and compare those predictions with actual trade flows. We identify a substantial value of suspicious trade flows which we associate with smuggling; especially importing banned goods through third countries such as Belarus. The structural gravity model systematically under-predicts trade volumes for country-product combinations used as channels for smuggling of the banned goods. We identify a quantity of smuggling equivalent to approximately ten percent of the pre-embargo trade flows.

JEL Classification: F10

Keywords: Conditional General Equilibrium, Sanctions, Structural Gravity Model, Trade.

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1 Introduction

Economic sanctions are a common foreign policy instrument. Countries initiating sanctions ("sanctioning countries" or "sender") usually seek to coerce behaviours or policies of the "sanctioned" or "target" countries. Travel bans, financial sanctions, trade restrictions, and military sanctions are the most common types of economic sanctions. The Global Sanctions Data Base (GSDB) records 1101 sanctions from 1950 to 2019, of which approximately 20 percent are trade sanctions (Kirilakha et al. (2021)). The frequency of sanctions fluctuates considerably, with the GSDB recording sharply increased sanction activity in the 1990s and 2010s (Figure 1), with the 1990s surge also present in the Threat and Imposition of Sanctions (TIES) database covering 1945 to 2005 (Morgan et al. (2014)).

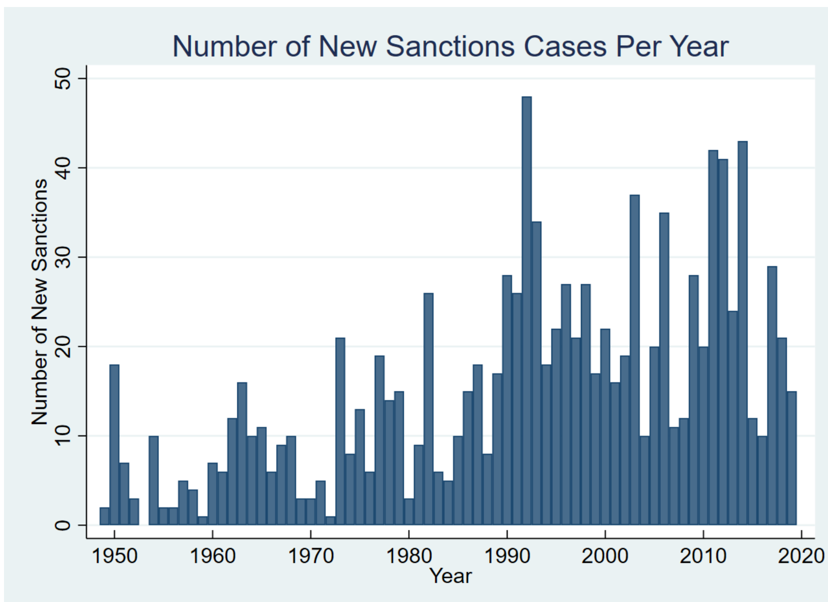

Figure 1

Sanctions may be evaded by smuggling directly between the target and sender or by indirect smuggling via a third country as a transshipping hub (Drezner (2000); Frankel (1982)). Relatively little literature studies the extent of smuggling during sanctions episodes. We study a sanctions episode following Russia's 2014 invasion of Ukraine. In response to Western sanctions, Russia placed counter-sanctions on a range of food exports from those countries, affecting roughly \$9 billion in trade. The Russian counter-sanctions mostly correspond very neatly to Harmonised System (HS) international trade categories, facilitating analysis.

Developments in trade models and quantitative trade policy analysis have long enabled us to estimate how trade sanctions will affect trade flows and welfare. These same developments also give us powerful tools for detecting smuggling, because the trade models generate predictions for what trade flows will be after the imposition of sanctions, and these predictions can be compared with realised trade flows. Since trade flows are usually measured and reported by two countries, the fingerprints of much smuggling activity may be apparent even if one country ceases to accurately report data. We develop and implement techniques for finding those fingerprints. We employ recent developments in estimating and simulating structural gravity models that developed following seminal papers by Anderson (1979) and Anderson and Van Wincoop (2003). We estimate structural gravity equations for approximately 1,000 HS 4-digit headings, generating detailed predicted trade values that we compare with actual 2015 trade data. We systematically study the deviations between actual and predicted trade values to find evidence of smuggling.

Russia's food embargo, which is a partial embargo, is a suitable natural experiment for this study for four reasons. First, the severity and scope of this episode increases the probability of identifying illegal trading activities.[1] The constraints of partial embargoes on trade are severe enough to incentivise smugglers to invest in constructing smuggling channels. Partial embargoes do not ban all trade with the target countries, potentially providing more avenues for smuggling. For example, smugglers might relabel sanctioned products to a similar but non-sanctioned category to pass customs enforcement of the sanctioning country. Second, relatively disaggregated trade data is available for almost all countries, enabling us to match trade flows to the sanctions list. Third, embargoes should decrease the trade of sanctioned goods to zero, simplifying the process of deriving the imputed amount of smuggling. Finally, this sanction episode was of considerable duration, is still active, and remains at the centre of public discourse. This research may help with more effective enforcement of economic sanctions. We identify around \$1bn to \$1.6bn in smuggled agri-food products.

A large body of literature on sanctions has developed in economics and political science; a recent overview can be found in Felbermayr et al. (2021). Political science studies are primarily concerned with whether sanctions achieve their political objectives and what factors determine their effectiveness, while economists tend to focus on the economic impacts of sanctions (Felbermayr et al. (2021)). Relatively few authors have explicitly studied smuggling. Frankel (1982) studied the effectiveness of the Embargo Act of 1807 using British trade statistics and concluded that enforcement became sufficiently effective so that smuggling was insignificant compared with previous trade. Crozet et al. (2021) found that the effect of trade sanctions on exporting firms is larger if those firms also serve a country adjacent to the target country, indirectly suggesting exporting through that adjacent country. Haidar (2017) studied Iranian firm-level data to establish that two-thirds of exports "destroyed"

[1] News agencies and the Russian government have already revealed the existence of smuggling after the imposition of the food ban; see Section 2.1.

by sanctions were deflected to third-countries, which may or may not indicate smuggling. Andreas (2005) argues that sanctions may bring about smuggling and the development of underground economies, which is supported by the study of trade and financial sanctions on Iran by Farzanegan (2013). A large volume of smuggling arose in Iran, although most of the smuggling was not directly connected to the sanctions but was a product of several price subsidies and a misalignment of the official exchange rate and the black-market exchange rate.

Several studies use empirical gravity models to estimate the effect of US economic sanctions on US aggregate bilateral international trade flows (Caruso (2003); Hufbauer et al. (2003); Yang et al. (2004)), while Frank (2017) extends this to study the trade effects of a more extensive set of sanctions. These studies find that sanctions tend to depress trade between the sender and target countries, but find mixed evidence on trade between the target and other countries. Larch et al. (2022) study the effect of sanctions on mining and energy trade, a sector frequently targeted by sanctions, and also find a significant reduction in trade between sender and target countries.

Our research is also related to studies that employ general equilibrium analysis to study the effects of international conflicts and trade policies, such as Glick and Taylor (2010) studying the cost of lost trade due to World Wars I and II, and Costinot and Rodríguez-Clare (2014) studying the welfare consequences of globalization. Anderson and Yotov (2016) employ a structural gravity model approach on 2 digit ISIC manufacturing sectors to estimate the general equilibrium trade and welfare effects of Free Trade Agreements (FTA). Felbermayr et al. (2020) use similar structural gravity modelling to estimate the general equilibrium effects of sanctions on aggregate bilateral trade and welfare, and also use that modelling to perform counterfactual analysis of the removal of a trade sanction. Our paper most directly descends from this line of analysis, and our methodology for constructing predicted trade flows most closely follows the conditional general equilibrium approach of Anderson et al. (2015).

Since our paper examines the difference between actual and predicted trade values to find evidence of smuggling, it is related to a strand of literature that detects smuggling or tariff evasion. Feenstra et al. (1999) and Feenstra and Hanson (2004) studied discrepancies between exporter and importer trade reports that might in part be due to tax and trade barrier evasion. Fisman and Wei (2004) and Javorcik and Narciso (2008) use those discrepancies to find evidence of tariff evasion, either by misclassifying products so they are charged a lower tariff rate or by under-reporting the value of imports. Fisman and Wei (2009) use the difference between the exporting country's recorded export and the importing country's recorded import to estimate the value of smuggling of cultural property and antiques. Berger and Nitsch (2008) find that gaps between exporter and importer trade reports are highly correlated with the level of corruption in the two countries, suggesting tariff evasion or smuggling. DellaVigna and La Ferrara (2010) study how stock prices respond to changed conflict intensities to detect illegal arms trade. Liu and Shi (2019) find evidence of Chinese firms evading anti-dumping duties by using intermediates in third countries.

Several papers also study the same Russian counter-sanctions that we study. Cheptea and Gaigné (2018) apply a triple difference econometric approach to estimate that the Russian embargo led to an 80 percent reduction in EU exports of banned products to Russia. Crozet and Hinz (2016) estimate that sanctions and counter-sanctions led to a 7.4 percent reduction in Russian exports and a 0.3 percent reduction in exports by Western sanctioning countries, with most of the latter effect in products NOT directly targeted by Russian retaliation. Hinz and Monastyrenko (2022) find that Russian consumers pay higher food prices due to their government's policy, leading to a significant loss of welfare. Bělín and Hanousek (2021) find that Russia's agri-food sanctions caused an 8 times larger decline in trade than Western sanctions on exports of oil and gas extraction equipment. Several scholars conduct computable general equilibrium analyses to estimate the impacts of the embargo on production, trade and welfare.[2] Ahn and Ludema (2020) study U.S.-EU sanctions against Russia and find that targeted firms suffered substantially in terms of revenue, value and employment relative to their non-targeted peers, though Russia was able to shield firms it considered "strategic".

Targeting individual firms is one example of "smart" sanctions designed to place pressure on specific groups and/or limit more widespread harm in the sender or target country. Besedeš et al. (2017) study financial sanctions and find that while they do depress capital flows, they are easily evaded if only a subset of countries applies them. Besedeš et al. (2021) examine firm-level data to find that financial sanctions have a limited effect on non-financial firms in the sanctioning country, so might legitimately be labelled "smart".

The remainder of the paper is structured as follows: Section 2 briefly introduces the sanction episode - the embargo and counter-embargo between Russia and the Western countries, and describes the data. Section 3 details our structural gravity modelling and the construction of trade discrepancies. Section 4 seeks to identify smuggling and smuggling mechanisms. Section 5 discusses limitations and potential future research, while Section 6 concludes.

[2] See, for example, Havlik (2014); Oja (2015); Kutlina-Dimitrova (2017); Boulanger et al. (2016); Gohin (2017).

2 Russian Agri-food Ban and Smuggling

2.1 Western Sanctions and Russian Counter-sanctions

Moret et al. (2016) and Crozet and Hinz (2016) provide a thorough description of the 2014 Russian-Ukranian crisis; we therefore limit our discussion of the crisis that led to Russian counter-sanctions. In 2008, the EU proposed a Stabilization and Association agreement to Ukraine, ratification of which was postponed multiple times until 2014 when the pro-Russian president of Ukraine, Viktor Yanukovych, announced that Ukraine quits this arrangement. This decision led to unrest and further riots in Ukraine, called "Euromaidan". In February 2014, president Yanukovich fled Ukraine and found asylum in Russia, while Ukraine was led by the interim government.

Following these events, Russian troops annexed Crimea in February and March of 2014. Additionally, there was unrest in Donetsk and Luhansk provinces of Ukraine; in May of 2022 the separatist governments of these two states announced independence from Ukraine and called themselves Donetsk and Luhansk People's Republics (DNR and LNR). These republics were recognized as independent states by the Russian government and were supported financially and militarily by Russia. The military conflict on the border between DNR, LNR, and Ukraine escalated. On July 17, Malaysian Airlines flight MH17 was shot down over the Donbas region, killing all 283 passengers and 15 crew members.[3]

US and European countries reacted to Russian interference with Ukranian sovereignty with two rounds of sanctions against Russia. These sanctions primarily targeted three sectors: finance, energy, and defence. The sanctions included travel bans on influential Russians, bans on transferring technology for energy extraction, and financial sanctions on some significant Russian institutions. Following the crash of MH17, these targeted sanctions were expanded to cover more individuals and entities, financial sanctions on state-owned banks, and embargoes on exports of goods including arms, other goods with military use, and equipment for the energy industry.[4,5]

In response to these sanctions, on August 6 president Putin signed an executive order on special economic measures to protect Russia's security, which banned imports of selected food and agricultural products from most countries that imposed sanctions on Russia. The embargo covered most meat, fish, dairy products, vegetables, and fruits, henceforth "agri-food" products.[6] The order was introduced for one year, but it has been repeatedly extended

[3]Crash of Malaysia Airlines flight MH17 Hrabove, Ukraine, 17 July 2014

[4]https://eur-lex.europa.eu/eli/reg/2014/833/oj

[5]https://home.treasury.gov/policy-issues/financial-sanctions/sanctions-programs-and-country-information/ukraine-russia-related-sanctions

[6]http://en.kremlin.ru/events/president/news/46404

with minor changes and remains active up to this date.

Since the embargo, Russian government declarations and news reports have revealed smuggling of banned agri-food products into Russia. Russia has repeatedly censured Belarus.[7] Russian officials have destroyed many banned agri-food products, suggesting that smuggling is likely a common phenomenon.[8] We will investigate how significant a phenomenon smuggling is and try to shed light on smuggling channels.

2.2 Data

The 2014 Decrees of the Russian Government N 778 and N 842 embargoed agri-food products that mostly map neatly into the 4-digit Harmonized System (HS) classification. Appendix Table A1 lists HS headings that are entirely or almost entirely embargoed. This facilitates analysis of the embargo using the Comtrade database and derivatives of that data such as the BACI database (Gaulier and Zignago (2010)).

While detailed monthly international trade data is available for many countries, there is no need for us to use that frequency. The effect of Russia's agri-food ban on reported data is readily apparent in annual UN Comtrade data, which is available for almost all countries. Figure 2 graphs reported exports of "embargoed" agri-food products to Russia for 2012 to 2020. A product is considered embargoed if it falls within one of the HS headings listed in Appendix Table A1. We graph two measures for each year: the solid bars are values reported by the Western countries subject to the sanctions; while the lighter bars are from Russian data.

The two series are roughly balanced from 2012 through 2014, but the relative values diverge from 2015, the first full year of the sanctions. Russian reported data soon becomes negligible, down from over $9 billion annually to as little as $30 million in 2016. Interestingly, the exports reported by the sanctioned countries are nearly seven times that size in 2016, and are nearly $200 million higher than Russian reported data every year from 2015 to 2020. A Fisman and Wei (2009) style measure of smuggling would pick up this number. Opportunities for smuggling might leave far more subtle fingerprints in international trade data. Consider trade in the embargoed HS 6-digit product 080930 Peaches, Including Nectarines, Fresh.[9] Figure 3 graphs Russian reported imports of peaches from embargoed countries and other sources for 2012 to 2020. Prior to the embargo, Russia sourced most of its peach imports

[7] Belarus appears to have wholeheartedly seized smuggling opportunities, see for example https://belarusdigest.com/story/belarus-and-russian-food-embargo-a-success-story/ and https://www.bbc.com/news/blogs-news-from-elsewhere-37166353.

[8] One example is https://www.bbc.com/news/world-europe-33818186.

[9] Yeliseyeu (2017) studied this example.

from the EU. After the embargo, these quickly disappeared in the Russian data, though other imports failed to make up for most of the embargoed trade until 2017.

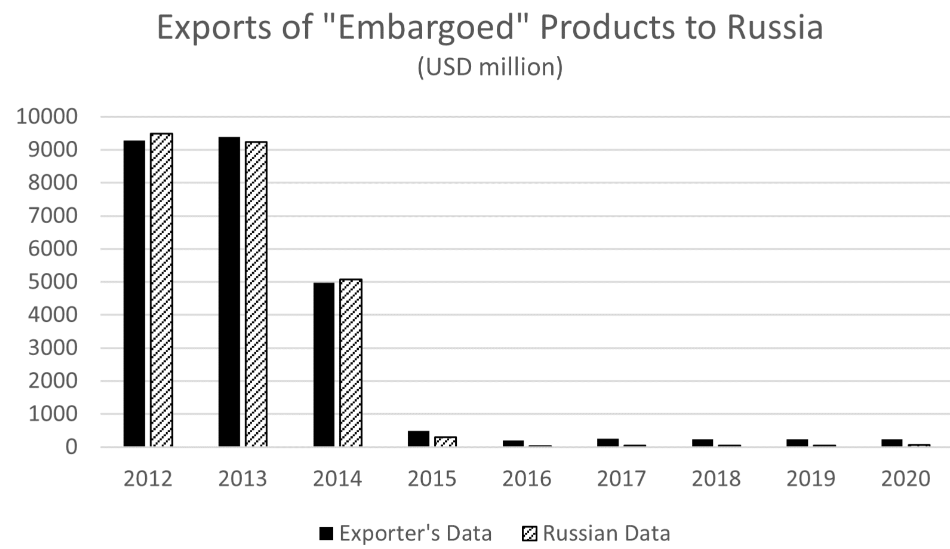

Figure 2

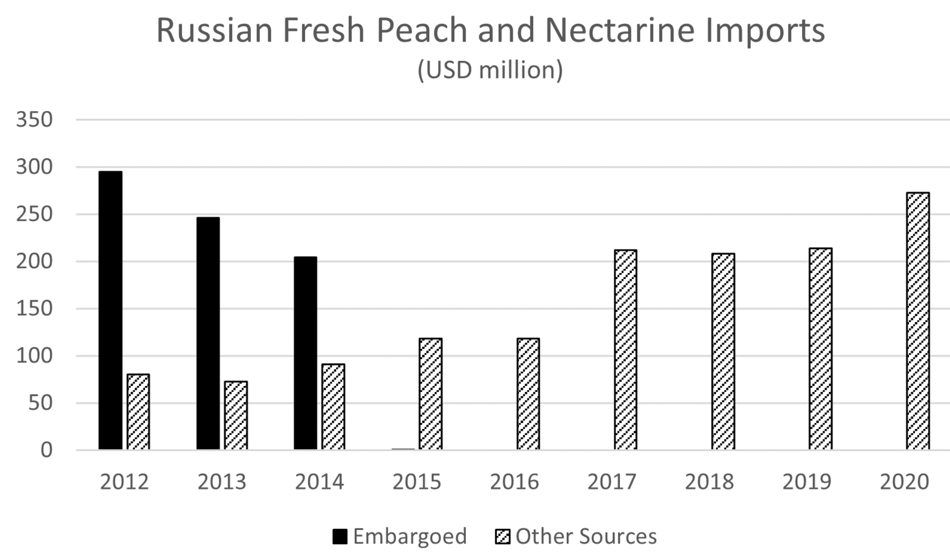

Figure 3

Now look to the curious behaviour of Belarusian reported data for the same period in Figure 4. Belarus, with a population 1/15th that of Russia, apparently absorbed much of the embargoed trade in 2014, before their new taste for imported peaches suddenly switched to sources not embargoed by Russia in 2015, with the value of this trade roughly comparable to the destroyed trade between the West and Russia.

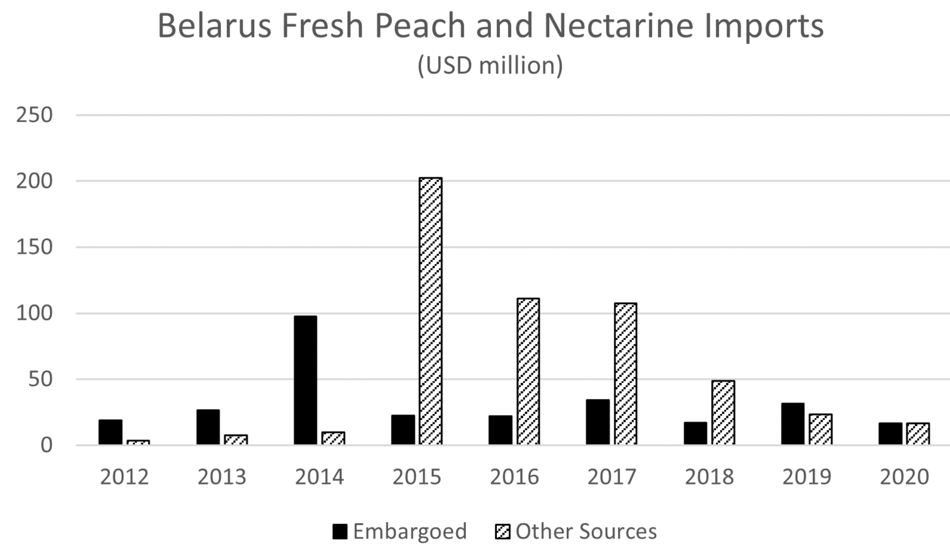

Figure 4

Closer examination of the Belarusian trade data reveals that it aligns especially poorly with data reported by the exporting countries. Of the top ten exporters to Belarus according to Belarusian data in Table 1, only three countries themselves report exports of peaches to Belarus, and even for these countries the values match poorly. Only two of the top ten exporters according to Belarusian data are subject to Russian sanctions. According to exporting countries' data, seven of the top ten exporters of peaches to Belarus are subject to Russian sanctions. The Belarusian data might not be entirely fictional; Belarus may well have been importing large quantities of peaches, but the origins are most likely countries subject to Russian sanctions, and the destination might not be consumers in Belarus.

Top 10 Exporters of Peaches to Belarus in 2015 ($m)		
Exporter	Belarusian Data	Exporter's Data
Greece	5.2	1.0
Brazil	5.6	0.0
Bosnia Herzegovina	9.6	0.0
Peru	9.8	0.0
Spain	14.7	2.9
Ecuador	16.4	0.0
Egypt	18.5	0.0
South Africa	23.5	0.0
Turkey	42.8	0.1
Morocco	64.5	0.0

Table 1

The trade of one possible transit country in just one embargoed HS 6-digit product may have involved smuggling equal in value to the entire Fisman and Wei (2009) measure of smuggling for all of the embargoed products. There is a need to develop a forensic method for statistically identifying smuggling that can detect a wider range of smuggling activity. We now turn to developing such a measure. We begin by estimating expected international trade flows following the imposition of sanctions. We need to commence with data that has not already been distorted by the sanctions; we use 2009 through 2013 international trade data to construct these estimates. It has long been noted that discrepancies exist between importers' and exporters' reports of trade flows,[10] sometimes for legitimate reasons such as trade costs and shipping times, sometimes to evade taxes or other trade restrictions, not to mention simple reporting and data collection errors. The most systematic approach to reconcile this reporting mismatch is by Gaulier and Zignago (2010), who produced the BACI trade database based on Comtrade data. They use a statistical approach to estimate the reliability of each country's trade reports, and then use those reliability estimates to weight each report.

We then employ structural gravity modelling following Anderson et al. (2015) to estimate counterfactual trade flows following the imposition of trade sanctions. The discrepancy between actual trade flows in 2015 (the first full year of data following the agri-food sanctions) and the counterfactual trade flows is our raw proxy for smuggling. Statistical analysis of these trade discrepancies will reveal whether they are systematically related to the trade sanctions, so that smuggling is a reasonable inference for some of these discrepancies. The exact manner by which observed trade differs from counterfactual trade flows can also shed light on smuggling channels.

One shortcoming of international trade data for structural gravity modelling is that it does not include information on purely domestic trade. Omitting domestic trade will affect our counterfactual exercise. We address this by including information on domestic trade flows for most food products from the Food and Agriculture Organisation's (FAO) food balance sheet data, while domestic output for other products is estimated using the Eora multi-region input-output table (Lenzen et al. (2012)). The FAO data is detailed, covers almost all sanctioned products, and can be freely downloaded from the FAO's website. We construct a correspondence that maps 93 FAO item codes for food to 133 HS 4-digit headings. We then construct ratios of the quantity of domestic trade to exports plus imports in the FAO data.[11] The Eora data is coarser, and roughly corresponds to 2-digit ISIC classifications, and we construct the ratio of the value of domestic trade to exports plus imports in the

[10]See Feenstra et al. (1999) for one example.

[11]There a small number of inadmissible (negative) values of this ratio. To reduce the risk of extreme valaues in our quantitative exercises, we constrain this ratio to lie between 0.05 and 20.

Eora data for each sector in each country. We give primacy to the FAO data, using Eora for other sectors, and multiply the ratio of domestic trade to exports plus imports by the sum of exports plus imports at the HS 6-digit level to get corresponding estimates of domestic trade.[12] Those HS 6-digit estimates are then aggregated to HS 4-digit headings.

3 Estimation of Smuggling

To estimate the amount of smuggling, we commence with the discrepancy between the observed trade flows in sanction periods and counterfactual trade flows in a hypothetical scenario where Russia imposes the embargo in a pre-sanction period. The counterfactual trade flows will quantify the expected changes in bilateral trade flows in the hypothetical scenario, including trade destruction, trade creation and trade deflection,[13] but not smuggling. On the other hand, the observed trade flows capture trade destruction, trade creation, trade deflection as well as smuggling. Therefore, the discrepancy is a proxy for the magnitude of the embargo-induced smuggling, where the quality of the proxy depends on how well the counterfactual quantifies the trade destruction, trade creation and trade deflection induced by the sanctions. Recent developments in the evaluation of trade policy have shown that structural gravity models can be used for counterfactual analyses to evaluate hypothetical trade policies (Anderson et al. (2015); Costinot and Rodríguez-Clare (2014)). We use the structural gravity model to compute counterfactual trade flows and obtain an estimate of smuggling. We briefly review the structural gravity model in Section 3.1 and the estimation procedure in Section 3.2.

3.1 Structural Gravity with Fixed Effects

Empirical gravity models of international trade have a long history, dating back to Ravenstein (1885)'s study of immigration patterns. Anderson (1979) provided the first theoretical foundation for the gravity model by assuming that consumers had identical Constant Elasticity of Substitution (CES) preferences over products that were differentiated by country of origin (Armington (1969)), which was further developed in Anderson and Van Wincoop (2003). Arkolakis et al. (2012) proved that a range of modern international trade models

[12] Unfortunately, Eora domestic trade data appears to be particularly poor for Belarus, dramatically understating Belarusian GDP and domestic trade. We use Belarusian input-output tables to improve that data.

[13] Bown and Crowley (2007) define these factors given an increase in the tariff of A against country B. Trade destruction refers to a decline in country B's exports to country A; trade deflection refers to an increase country B's exports to a third nation; trade creation refers to country A's increase in imports from a third nation.

provide foundations for a structural gravity model. We closely follow the CES-Armington formulation in Anderson et al. (2015), only applied to each sector. Consumers in each country have nested CES preferences, where the upper-tier is Cobb-Douglas across sectors, and the lower tier has the Armington-CES structure. Exports from country i to j in sector k at destination prices are:

$$X_{ij}^{k} = \frac{Y_i^k E_j^k}{Y^k} \left(\frac{t_{ij}^k}{\mathbf{\Pi}_i^k \boldsymbol{P}_j^k}\right)^{1-\sigma^k} \tag{1}$$

where t_{ij}^k are iceberg variable trade costs for exports from i to j; Y_i^k are country i sales to all destinations at destination prices; Y^k are worldwide sales at destination prices; E_j^k is expenditure in j; σ^k is the elasticity of substitution across varieties in sector k; and $\boldsymbol{P}_j^k$ and $\mathbf{\Pi}_i^k$ are, respectively, the "inward multilateral resistance" and "outward multilateral resistance" terms defined immediately below. Outward multilateral resistance aggregates country i's outward trade costs relative to destination price indexes, and is a measure of how remote a country is from its export markets:

$$\mathbf{\Pi}_i^{k\,1-\sigma^k} = \sum_j \left(\frac{t_{ij}^k}{\boldsymbol{P}_j^k}\right)^{1-\sigma^k} \frac{E_j^k}{Y^k} \tag{2}$$

Inward multilateral resistance is the CES price index for sector k and aggregates inward trade costs for each country, and measures how remote a country is from its import suppliers:

$$\boldsymbol{P}_j^{k\,1-\sigma^k} = \sum_i \left(\frac{t_{ij}^k}{\mathbf{\Pi}_i^k}\right)^{1-\sigma^k} \frac{Y_i^k}{Y^k} \tag{3}$$

The outward and inward multilateral resistance terms actually solve the set of equations given by equations (2) and (3) conditional on Y_i^k and E_j^k, and are therefore a conditional general equilibrium concept (Anderson et al. (2015)). Two countries will trade more with each other if they have low trade costs with each other or if they are more remote from the rest of the world. Consistent accounting for this intuition is a feature of theoretically consistent gravity models. The equilibrium supply price (exclusive of trade costs) is derived from market-clearing conditions and is given by Equation (4), where the parameter α_j^k can be thought of as an (inverse) taste or quality parameter in the CES utility function:

$$p_j^k = \left(\frac{Y_j^k}{Y^k}\right)^{\frac{1}{1-\sigma^k}} \frac{1}{\alpha_j^k \mathbf{\Pi}_j^k} \tag{4}$$

There are many empirical challenges to obtaining consistent estimates of the structural gravity model, while there are corresponding solutions to handle them. Many economists have contributed to the recommendations of properly accounting for the multilateral resistance terms.[14] The generally accepted rules are to use directional (exporter and importer) fixed effects when using a single cross-section of data, and to use exporter-time and importer-time fixed effects with panel data. To control for the endogeneity of trade policy, Baier and Bergstrand (2007) suggest including country-pair fixed effects. Silva and Tenreyro (2006) recommend using a PPML estimator to exploit the information in zero trade flows and to obtain better estimates given the heteroskedasticity present in trade data.

3.2 Estimation and Construction of the Trade Discrepancy Measures

In this section we describe how we construct the trade discrepancy measure for our further analysis. Our goal is to use pre-embargo data to construct predicted post-embargo trade flows. The first step of our analysis is the construction of predicted trade volumes in the absence of the embargo.[15] We estimate the standard gravity equation on 2009 to 2013 HS 4-digit data using high-dimensional PPML estimation using the command ppmlhdfe from Correia et al. (2020):

$$X_{ijt}{}^{k} = exp(\gamma_{ij}^{k} + \pi_{it}^{k} + \chi_{jt}^{k} + \beta^{k}\ln\tau_{ijt}^{k}) + \epsilon_{ijt}^{k}$$

where γ_{ij}^{k}, π_{it}^{k}, and χ_{jt}^{k} are country-pair, exporter-year, and importer-year fixed effects, and τ_{ijt}^{k} is one plus the advalorem tariff.[16] This specification not only allows us to obtain all of the estimates required for further procedures but also impose no structural form on the effects of control variables on the sectoral trade flows. We use the high dimensional fixed effects to replace the standard time-variant country and pairwise variables such as GDP and FTAs. We perform this analysis for each industry k separately, using trade data for 2009-2013. We then use our estimates of the fixed effects to construct predicted values of trade flows:

[14] See, for example, Feenstra (2004) and Olivero and Yotov (2012).

[15] Alternatively, we could have used trade flows from 2013 as a predictor of trade in 2015. This approach, however, has two major disadvantages. First, compared to predicted values, observed trade data includes an error term and, as a result, is generally a worse and noisier predictor of future trade flows. The second reason is that this approach utilizes only one year of data, while the predicted value approach allows us to use any available pre-embargo data.

[16] While the importer-year fixed effect should absorb any MFN tariff and the country-pair fixed effect should absorb any time-invariant preferential tariff, time-varying preferential tariffs are not absorbed by these fixed effects. We collect UNCTAD Trade Analysis Information System (TRAINS) data on advalorem-equivalent tariffs for 94 countries from the World Bank's World Integrated Trade Solution (WITS) site for 2005 to 2015. See the online Data Appendix for details. For the remaining importing countries, we assume that the fixed effects adequately capture their tariffs and set $\tau_{ijt}^{k} = 1$.

$$\hat{X}^k_{ijt} = exp(\hat{\gamma}^k_{ij} + \hat{\pi}^k_{it} + \hat{\chi}^k_{jt} + \hat{\beta}^k \ln\tau^k_{ijt})$$

In the next step, we construct the partial effect of the sanctions on trade volume. As our goal is to predict the effects of the embargo in 2015, we focus on the prediction for the last available pre-embargo flows, $\hat{X}^k_{ijt}$ for $t = 2013$. Note that the data for the previous years was still informative as it allowed us to estimate the country-pair specific component $\hat{\gamma}^k_{ij}$. Unlike most applications, where the effect of the intervention has to be estimated first, here we are dealing with an embargo and thus know the exact intended effect of this intervention.[17] The counterfactual flows in partial equilibrium $\hat{\hat{X}}^k_{ij}$ will then coincide with the predicted flows $\hat{X}^k_{ij}$ for unaffected industries and country-pairs and will be equal to 0 for flows from embargoed countries to Russia in embargoed sectors.

We then construct the general equilibrium ("GE") effects of the embargo. The logic behind the GE changes in trade flows in embargoed sectors is the following: partial equilibrium changes in trade flows lead to changes in both export sales and hence the output Y^k_i and imports, hence the expenditure E^k_j of directly affected countries. These changes then affect the outward and inward multilateral resistance terms for both directly and indirectly affected countries through equations (2) and (3). These indirect changes may be positive or negative depending on the pre-embargo trade patterns of the country.

We solve the system of equations (1)-(4) using the gegravity Stata implementation from Baier et al. (2019) separately for each industry k affected by the embargo and using elasticities at the HS 4-digit level provided by CEPII and estimated by Fontagné et al. (2022).[18] The GE counterfactual flows $\tilde{X}^k_{ij}$ coincide with the predicted flows for the non-affected sectors $\hat{X}^k_{ij}$, are equal to zero (and $\hat{\hat{X}}^k_{ij}$) for affected sectors and country-pairs, and differ from the previous values of trade flows for the bilateral flows in embargoed sectors that are not subject to the embargo.

$\tilde{X}^k_{ij}$ then represent the expected trade flows after the embargo and accounting for the GE adjustment. Now we construct the discrepancy in trade flows by comparing these expected trade flows with actual trade data from 2015. Note that $\tilde{X}^k_{ij}$ does not account for changes in total volumes of trade and in relative sizes of countries that happened between 2013 and 2015.[19] To account for these changes, we adjust expected trade volumes by the aggregate volume of trade of each country: $\tilde{\tilde{X}}^k_{ij} = \tilde{X}^k_{ij}\frac{X^{2015}_j}{\tilde{X}_j}$, where $X^{2015}_j \equiv \sum_{i=1}^{I}\sum_{k=1}^{K} X^{k,2015}_{ij}$ and

[17]Alternatively, we could have got identical estimates of the GE effect of the embargo by allowing trade costs between the affected countries to approach infinity.

[18]To reduce the risk of extreme values in our computations, we constrain elasticities to lie between 3 and 20.

[19]For example, the dollar value of Russia's aggregate trade and GDP decline in 2014 after oil prices and the value of the ruble fall.

$\tilde{X}_j \equiv \sum_{i=1}^{I} \sum_{k=1}^{K} \tilde{X}_{ij}^k$ are the total observed and counterfactual imports of country j.[20] We then define the raw discrepancy D_{ij}^k as the simple difference between the observed and predicted trade flows: $D_{ij}^k = X_{ij}^{k,2015} - \tilde{\tilde{X}}_{ij}^k$.

We also prepare to conduct comparisons similar in spirit to placebo tests. For our counterfactual exercise above, we used 2009 to 2013 data to estimate counterfactual trade flows following the imposition of an embargo, that we then compare to actual 2015 trade data. For our placebo exercises we bring everything forwards by two years, using 2007 to 2011 data to estimate trade flows for 2013, which we will compare with actual 2013 trade flows. To make our results comparable between 2013 and 2015, we use trade flows that were observed in both years. Ideally, our methods for identifying suspicious trade flows in 2015 will identify a far lower volume of suspicious trade flows in the 2013 comparison.

4 Detecting Smuggling

4.1 Suspicious Trade Triads into Russia

Motivated by our peek at Belarusian trade data, our first pass at detecting smuggling will focus on the rerouting of sanctioned products through transit countries. Such sanctions evasion is related to Liu and Shi (2019) finding evidence of anti-dumping duty evasion through use of intermediates in third countries. We initially examine the raw differential D_{ij}^k between actual 2015 trade data and our structural gravity model trade estimates. These raw values are simply ranked, and a trade triad involving a transit country (not being Russia or a Western country subject to sanctions) is considered suspicious if the following three conditions hold: (i) the export trade discrepancy D_{ij}^k from the transit country i to Russia is in the top 10 percent of all trade discrepancies; (ii) there is an export trade discrepancy in the same product k from a sanctioned country to i that also falls within the top 10 percent of all trade discrepancies; and (iii) product k is a sanctioned product. The twin-unlikelihood in (i) and (ii) is the essence of this measure.

For trade triads identified as suspicious, we take the potential quantum of smuggling to be the minimum of the outward trade discrepancy in (i) and the sum of the inward trade discrepancies in (ii), since exports from multiple sanctioned countries may be laundered through the same transit country. The value of these transactions is listed in column 1 of Table 2, while the number of suspicious flows is listed in column 1 of Table 3, with the top 10

[20] While it may seem appealing to perform this adjustment at the country-product level, such an adjustment would mostly eliminate our ability to detect smuggling that involves third countries such as Belarus. Revisiting our example of Belarusian peach trade in Section 2, note that scaling Belarusian peach trade in 2015 to equal 2013 values would mostly eliminate this episode.

transit countries listed along with the total for all transit countries. 207 suspicious triads are identified with a total value of \$665m. China and Belarus are the top two transit countries for these suspicious triads for both value and number.

We note, however, that this is a purely statistical procedure that would likely identify some transactions as suspicious even if no sanctions were imposed. We perform a placebo test by applying the same statistical approach to the discrepancy between 2013 trade data and structural gravity model trade estimates for 2013. The placebo test identifies a notably smaller set of transactions (95) worth a proportionally even smaller \$130m. The coincidence of unlikely imports of sanctioned products matched with unlikely exports of those same products to Russia surged following the imposition of the sanctions.

Top 10 Smuggling "Transit" Countries to Russia in 2015 (\$m)						
Transit Country	Raw	Raw Placebo	Normalised	Normalised Placebo	Residual	Residual Placebo
Belarus	265.8	45.1	265.3	5.9	262.8	5.2
China	140.5	27.3	67.0	0.0	67.0	0.0
Vietnam	31.5	7.2	30.0	4.4	25.8	4.8
Israel	23.6	1.8	19.2	0.0	19.2	0.0
Chile	21.1	0.9	0.0	0.0	0.0	0.0
Turkey	20.9	4.5	10.3	0.0	10.3	0.0
Thailand	17.5	1.8	1.4	1.8	1.4	1.8
India	17.1	7.3	0.9	0.6	0.9	0.4
Egypt	13.5	0.0	12.8	0.0	12.8	0.0
United Arab Emirates	11.5	0.0	0.0	0.0	0.0	0.0
ALL COUNTRIES	664.5	129.6	464.6	35.4	453.8	26.4

Table 2

Top 10 Smuggling "Transit" Countries to Russia in 2015 (Number of Suspicious Triads)						
Transit Country	Raw	Raw Placebo	Normalised	Normalised Placebo	Residual	Residual Placebo
Belarus	41	29	49	5	46	3
China	21	6	3	0	3	0
Vietnam	14	10	9	5	4	10
Turkey	13	4	2	0	2	0
Hong Kong	11	6	3	1	3	1
India	10	5	1	2	1	1
Egypt	10	0	3	0	2	0
Japan	10	8	0	0	0	0
Chile	9	1	0	0	0	0
Israel	8	1	5	0	5	0
ALL COUNTRIES	207	95	109	23	94	22

Table 3

We now seek to refine the procedure for identifying statistically unlikely trade triads. The procedure above took no account of differences between trade patterns for each bilateral trading relationship or each HS 4-digit product. This increases the risk that we label normal fluctuations in large trade relationships as suspicious. We now adapt the above procedure by first generating the absolute value of each trade discrepancy and then calculating two sets of standard deviations for the absolute discrepancies: for each importer-exporter pair; and for each HS 4-digit heading. We now study trade discrepancies exceeding \$100,000. We divide each such discrepancy by both of the corresponding standard deviations for the importer-exporter pair and for the HS 4-digit heading. These "normalised" discrepancies $\tilde{D}_{ij}^{k}$ are then ranked, and suspicious trade triads are then identified from this ranking. We report the results in columns 3 and 4 of Tables 2 and 3. The number of suspicious triads identified in 2015 falls by 47 percent to 109, but the number of suspicious triads in the placebo test falls even more substantially, by 76 percent to 23. We interpret this as suggesting that the slightly revised procedure is likely to give fewer false-positives when identifying suspicious trade triads. The value of suspicious triads falls more modestly, to \$465m for 2015 trade and to \$35m for the 2013 placebo.

We now make a further refinement to the procedure to further account for potential systematic features of the trade discrepancies. Our counterfactual trade values are generated from an estimated "gravity" model and externally estimated elasticities. Systematic forecast errors may themselves be related to gravity model variables. We regress the normalised discrepancies $\tilde{D}_{ij}^{k}$ on gravity variables (distance, contiguity, common language, colonial relationship) from the CEPII Gravity database (Conte et al. (2022)), tariffs from WITS, and full sets of exporter, importer, and HS 4-digit fixed effects:

$$\tilde{D}_{ij}^{k} = \beta_1 \ln Dist_{ij} + \beta_2 Cntg_{ij} + \beta_3 Lang_{ij} + \beta_4 Col_{ij} + \beta_5 Bdr_{ij} + \beta_6 \ln \tau_{ij}^{k} + \kappa_i + \mu_j + \zeta_k + \nu_{ij}^{k}.$$

The normalised trade discrepancies tend to be slightly larger for more distant country pairs, and slightly smaller for country pairs which are contiguous, share a common official language or a colonial relationship, or where trade is subject to higher tariffs. We then rank the residual trade discrepancies $\hat{\nu}_{ij}^{k}$ and identify suspicious trade triads from this ranking. The number of suspicious triads identified in 2015 and in the 2013 placebo test fall modestly to 94 and 22 respectively. The value of suspicious triads also falls modestly, to \$454m for 2015 trade and to just \$26m for the placebo.

We now conduct a further test of our methodology to reassure us that we are picking up smuggling behaviour and not some artifact of our data such as especially volatile 2015 trade patterns. We repeat the last refinement of our methodology but study residual trade discrepancies $\hat{\nu}_{ij}^k$ in products that were not subject to the agri-food sanctions. The procedure identifies 2,378 "suspicious" triads in 2015 worth \$6.7 billion compared with a similarly-large 2,697 "suspicious" transactions worth \$7.7 billion in the 2013 trade data. The uptick in suspicious triads appears to be confined to sanctioned products. We therefore believe that most of the suspicious triads we identify in agri-food products are true positives. While this trade may overlap with the nearly \$200m of smuggling that would be identified by a Fisman and Wei (2009) style estimate, there is no particular reason for it to do so, and it might be largely cumulative. We will later discuss how we believe we can further improve the true-positive rate, but we next turn to identifying other smuggling activity.

4.2 Suspicious Trade Triads into Belarus

Relative to its size, Belarus appears to be playing a large role in smuggling. Belarus is part of the Eurasian Customs Union with Russia, and the Belarus-Russia border appears to be quite porous. While we have seen that Belarus does not appear to be very truthful about the origins of its imports of agri-food products, the BACI data partially corrects for this because it is a weighted average of the importing country's trade report and the exporting country's trade report depending on the statistically estimated reliability of each trade report. Where Belarus's trade partners have more reliable data, BACI trade data will more closely resemble their reports. We repeat our suspicious trade triad analysis, only looking for goods "smuggled" into Belarus, from where they may find their way into Russia.[21] We report our results in Table 4. Using the residual trade discrepancies again seems to minimise the risk of false positives, with the value of 35 suspicious triads worth \$57m, while the procedure identifies 21 suspicious triads worth \$17m in the 2013 data.

We check whether this suspicious trade behaviour was evident in Belarus's imports of non-sanctioned products, which might indicate some legitimate reason reason for the behaviour. Applying the same methodology to non-sanctioned products shows 1,454 "suspicious" trade triads in 2015 worth \$1.8 billion, while the placebo test on 2013 data yields a slightly larger number, with 1,610 suspicious triads, though with a lower aggregate value of \$1.3 billion. Belarus's imports of sanctioned agri-food products is behaving very differently from its imports of other products as the pronounced uptick in suspicious trade triads is evident in sanctioned products but not in non-sanctioned products. We examined whether other members of the Eurasian Customs Union (Armenia, Kazakhstan, and Kyrgyzstan) were behaving similarly to Belarus, but we found no evidence of this.

[21] See Yeliseyeu (2017).

Top 10 Smuggling "Transit" Countries to Belarus in 2015 ($m)						
Transit Country	Raw	Raw Placebo	Normalised	Normalised Placebo	Residual	Residual Placebo
China	39.9	4.5	6.5	0.0	6.5	0.0
Brazil	24.1	0.0	21.9	0.2	21.9	0.0
Mexico	11.8	0.0	0.0	0.0	0.0	0.0
Turkey	11.0	1.4	0.6	1.4	0.6	1.4
Ukraine	10.9	4.2	10.1	0.0	10.1	0.0
South Africa	5.4	1.3	3.0	0.7	0.0	0.0
Peru	4.5	0.7	0.0	0.0	0.0	0.0
Bosnia-Herzegovina	4.4	0.0	4.6	0.0	4.4	0.0
India	2.7	3.9	1.8	1.0	1.8	1.2
Serbia	2.5	2.8	4.0	1.6	4.0	1.2
ALL COUNTRIES	129.9	31.8	61.5	17.7	56.9	16.7
Number of triads	58	43	41	24	35	21

Table 4

4.3 Relaxing Country of Origin

The Belarus peach and nectarine example in Section 2 suggests that Belarusian data can be very inaccurate about the origin of imports. If that is true for Belarus, or Russia, then despite the features of the BACI data, our trade triad measures will miss some smuggling through intermediate countries. To potentially capture more smuggling, we now relax our identification mechanism for suspicious trade triads. A trade triad involving a transit country (not being Russia or a Western country subject to sanctions) is now considered suspicious if the following three conditions hold: (i) the export trade discrepancy from the transit country i to Russia is in the top 10 percent of all trade discrepancies; (ii) there is an export trade discrepancy in the same product k from any country to i that also falls within the top 10 percent of all trade discrepancies; and (iii) product k is a sanctioned product. The twin-unlikelihood in (i) and (ii) is still the essence of this measure, but the measure now allows for mislabeling of the origin country in (ii). We present the results for suspicious triads into Russia in Table 5 and into Belarus in Table 6.

In both cases there is a substantial uptick in the value of suspicious trade triads in embargoed goods following the imposition of sanctions. Again, the procedure based on residual trade discrepancies appears to result in far fewer false-positives. The suspicious agri-food trade triads into Russia increase from 66 worth $78m in the 2013 placebo exercise to 259 worth $723m in the 2015 data. The potential value of the smuggling compared with Table 2 has increased by half. The value of suspicious agri-food triads into Belarus in Table 6 grows more dramatically, from $57m to $259m, but the placebo exercise generates a substantial number, though not value, of false-positives. These upticks are only evident for the sanctioned products. If we apply the same procedure to the non-sanctioned products, the number of suspicious trade triads into Russia is relatively stable, moving from from 4,722 cases worth $12.2 billion in the 2013 placebo exercise to 4,184 worth $14.5 billion in 2015, while those into Belarus decrease from 2,455 worth $1.4 billion in the 2013 placebo exercise to 1,709 worth $0.9 billion in 2015. Upticks in "suspicious" trade triads seem largely confined to sanctioned products.

Relaxing Origin: Top 10 Smuggling "Transit" Countries to Russia in 2015 ($m)						
Transit Country	Raw	Raw Placebo	Normalised	Normalised Placebo	Residual	Residual Placebo
Belarus	405.1	79.5	393.2	22.4	390.6	21.8
China	156.2	42.5	125.0	0.0	88.7	0.0
Kazakhstan	74.4	24.5	33.5	12.7	33.5	0.0
Vietnam	34.8	10.0	34.8	4.4	30.6	7.2
Chile	32.9	2.6	5.8	0.0	0.0	0.0
Turkey	29.9	4.5	13.5	0.0	13.5	0.0
Thailand	25.7	2.4	23.9	1.8	23.9	1.8
Israel	24.8	3.7	20.4	2.8	20.4	1.7
India	20.4	29.9	6.5	23.0	6.5	22.8
Egypt	17.7	0.0	14.1	0.0	13.9	0.0
ALL COUNTRIES	1004.8	248.9	784.1	101.6	722.7	78.3
Number of triads	679	314	333	76	259	66

Table 5

Relaxing Origin: Top 10 Smuggling "Transit" Countries to Belarus in 2015 ($m)						
Transit Country	Raw	Raw Placebo	Normalised	Normalised Placebo	Residual	Residual Placebo
China	83.7	5.6	69.3	2.4	69.9	0.0
Brazil	76.7	0.0	76.7	0.0	76.7	0.0
Moldova	33.9	2.3	34.7	3.2	34.7	3.2
Turkey	24.3	10.9	14.2	10.0	14.2	10.0
Ukraine	16.4	7.9	12.7	3.9	12.6	3.1
South Africa	13.2	6.0	8.4	2.9	1.9	2.2
Mexico	12.4	0.0	1.8	0.0	1.8	0.0
Bosnia-Herzegovina	8.1	0.0	8.3	0.0	8.1	0.0
Peru	7.8	0.7	7.8	0.0	3.4	0.0
India	7.7	4.2	8.2	2.8	7.7	3.0
ALL COUNTRIES	317.7	72.1	273.5	56.9	259.2	51.1
Number of triads	158	160	137	101	105	84

Table 6

4.4 Moving beyond Triads

Our forensic exercise employing both actual trade data and counterfactual trade data is detecting a pronounced uptick in suspicious trade triads involving sanctioned agri-food products, without a corresponding uptick in triads for non-sanctioned products. Further, the methodology has detected a special role for Belarus in smuggling, a role that has been corroborated by other reports (see discussion in Section 2). We interpret these findings as suggesting that there is substantial information content in our trade discrepancy measures when it comes to identifying smuggling. We will now move on from the triad methodology and instead directly study trade discrepancies into Russia and Belarus.

Our work on trade triads strongly suggested that our "residual" normalised trade discrepancies were the least likely to give rise to false positives in our identification of suspicious trade triads. We now focus on the top 1 percent of these residual normalised trade discrepancies and study the original value of the trade discrepancies associated with them for both sanctioned and non-sanctioned products and for 2015 (post-embargo) and 2013 (pre-embargo). Since we are no longer relying on the "twin unlikelihood" approach of the triad methodology, we narrow our attention to the most extreme discrepancies.

We summarise the results for Russia and Belarus in Table 7. Following Russia's agri-food product sanctions, the number of Russian HS 4-digit agri-food import lines in the top 1 percent of worldwide trade discrepancies increased from 0 to 4, with the associated value of the discrepancies increasing from 0 to $233m. For Belarus, the increase was much larger, with the number increasing from 7 to 20 and a twenty-fold increase in value from $32m to $654m. Of the 215 regions in the BACI trade data, Belarus ranked first for the increase in the number of sanctioned HS 4-digit agri-food import lines in the top 1 percent of worldwide trade discrepancies, while Russia ranked equal-second. For non-sanctioned products the proportional changes are much more modest, with a 3 percent increase in number for Russia but a 5 percent decrease in associated value, and a 32 percent decrease in number for Belarus but a 15 percent increase in value.

Beyond Triads: Top International Trade Discrepancies

Importer	Sanctioned HS	Top	Value 2015 ($m)	Number 2015	Value 2013 ($m)	Number 2013
Russia	Yes	1%	232.7	4	0.0	0
Russia	No	1%	2,623.3	66	2,754.1	64
Belarus	Yes	1%	653.9	20	31.5	7
Belarus	No	1%	489.1	39	426.9	57

Table 7

The extraordinary nature of the Belarus results strongly suggests that many hundreds of millions of dollars of embargoed products may have found their way into Russia via this channel. We now piece together our results to obtain overall estimates of the smuggling activity induced by the Russian counter-sanctions. We combine our estimates from Tables

5, 6 and 7 for the unlikely trade discrepancies identified using the residual normalised discrepancies. We delete duplicate observations, because Table 7 includes some trade flows that have already been counted in Tables 5 or 6. For 2015, our procedures label \$1.75 billion in agri-food trade imports by Belarus or Russia as being highly likely to be smuggling. Applying the same methodology to the pre-sanctions year of 2013, we label just \$160m as being highly likely to be smuggling, suggesting a false positive rate of around 10 percent. The simple difference between these values, \$1.59 billion, is one estimate of smuggling and is equal to 17 percent of pre-embargo trade.

A more conservative estimate of smuggling comes from giving more weight to the number of false positive transactions. In 2015 we found 374 trade trade discrepancies that were highly likely to be smuggling, with an average value of \$4.7m. In the 2013 comparison, our procedure labelled 152 trade discrepancies as smuggling, with an average value of \$1.1m. While this difference in average values suggests that false positives are more likely for smaller trade discrepancies, applying the 40 percent (152/374) false positive rate based on simple case counts to the \$1.75 billion in 2015 smuggling gives us a more conservative smuggling estimate of \$1.05 billion, or 11 percent of pre-embargo trade. While it would be possible to reduce this false-positive rate by raising the trade-discrepancy threshold for potential smuggling above our modest value of \$100,000, we would prefer to continue to improve the underlying modelling of trade flows to reduce the false-positive rate.

5 Discussion

We have found evidence of a significant amount of smuggling of banned agri-food items following the Russian embargo. Are there reasons to believe that we might be overstating smuggling? Yes. If international trade within HS 4-digit headings adjusts more flexibly than our model structures and parameters assume, then this will likely lead to an overstatement of smuggling because some actual trade flows may end up significantly exceeding predicted trade flows. One feature that we noticed when studying "false positives" in our placebo exercises was that the bulk of cases were molluscs, nuts and frozen fish. International markets for seafood may be especially well developed, and nuts may be especially substitutable. In either case, the international pattern of trade could reorganise quite quickly in response to sanctions or other market disruptions, and what we are detecting as smuggling could just be commodity markets quickly reallocating. We sought to reduce this risk by incorporating elasticity parameters σ^k estimated at the HS 4-digit level.

Another reason why we might over-estimate smuggling is because our model does not include intermediate inputs in an input-output structure like Caliendo and Parro (2015) or Caliendo et al. (2022). Our model does not capture all margins of international trade adjustment from the sanctions. The cost of using an input-output structure is the lack of sector detail in most input-output tables. What we gain from modelling intermediate inputs may be more than offset by the loss of sector detail. Since most of the embargoed agri-food products seem to be close to final goods, we decided that it was more valuable to keep the rich sector detail rather than model intermediate inputs. However, in future research we may be able to adapt trade models with intermediate goods to match more detailed trade data.

Our model also constrains substitution across HS 4-digit products to have a unit elasticity. If substitution across different HS 4-digit food products was greater, then this would also bias our results. A downwards bias in our smuggling estimates would often result, though this would depend on the precise substitution possibilities. Russia's embargo mostly affected relatively unprocessed food products, but did not affect many processed foods and some unprocessed food products. If consumers were more willing to substitute towards unaffected foods, then actual trade flows in embargoed products would tend to be *lower* than our model predicts, making it less likely that our procedure detects smuggling.

Are there any reasons why we might be underestimating smuggling? Yes. One argument is simply the reverse of an argument above; we may be overstating how flexible trade is in some products, so our model expects to see a substantial increase into Russia from some non-sanctioned sources. In this case, we may set the bar too high to statistically identify smuggling. But there are other more basic reasons. While we do not require data to be wholly accurate (in fact, inconsistencies can help us spot smuggling), we do require that the smuggled goods leave some fingerprint in data. In some sense it must always leave a fingerprint, since even a completely unrecorded smuggling transaction affects demand for legally traded products. However, we have chosen to identify smuggling from positive trade discrepancies, rather than infer smuggling from a much wider range of negative ones (the expected trade displaced by the smuggling). Non-reporting will often hinder our task regardless of the efforts of the creators of the BACI database. We leave as an open question whether the BACI database creators can, by understanding the motives for misreporting, improve on their estimates of detailed trade flows.

Besides non-reporting, there are other types of misreporting that we have not identified, in particular, misreporting of product code. Our analysis has focused on misreporting the true country of origin. We miss the potential of relabeling banned products to non-banned product codes. When we studied goods that we considered "similar" to the sanctioned goods, such as non-banned goods in the same or related HS 2-digit chapters, we did not see strong evidence of an uptick in large positive trade discrepancies, but we are necessarily restricted in our analysis because it is hard to pinpoint what the banned products might be relabeled as.

We further note that the only trade policy interventions that we explicitly modelled were MFN tariffs, preferential tariffs, and Russian counter-sanctions. While some other trade policy changes might be adequately modelled by our high-dimensional fixed effects, our modelling would be improved if we incorporated more policy data, including other sanctions data and special tariff measures, and especially including new policies affecting trade in agri-food products during our sample period.

Our procedure can be adapted to other trade sanctions episodes that can be readily mapped into international trade classifications. We are able to find evidence of smuggling because much trade data still contains very real information about trade flows. Better recording of export and import transactions by more countries would make it easier to find the fingerprints of smuggling, both because we should have a better idea of what trade should look like following the imposition of sanctions, and because it will be easier to detect departures from those expected patterns.

6 Conclusion

Recent developments in structural gravity modelling of international trade flows have enhanced our ability to model changes in international trade following a shock or a policy intervention. This improves our ability to analyse such shocks, with trade sanctions currently being a policy intervention of particular interest. We use structural gravity modelling at a detailed sector level to model the effects of the Russian agri-food embargo. We interpret deviations of observed trade flows from predicted trade flows as potential evidence of smuggling. There was a large uptick in large positive deviations for Russian and Belarusian imports in sectors subject to Russian sanctions, whereas trade in other sectors did not exhibit this pattern. This was partly corroborated by news reports of extensive smuggling. We interpreted the evidence as suggesting smuggling of around \$1.05 to \$1. billion in banned goods, or around 20 percent of the pre-embargo trade. Our procedures can be readily adapted to study smuggling in other trade sanctions episodes, especially if the trade sanctions map cleanly into an existing product classification.

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