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The COVID-19 pandemic and trade in agricultural products

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Abstract

In this study, we develop a structural gravity model to analyse the effects of the ongoing COVID-19 pandemic on international trade in food and agriculture. Using detailed data on trade flows, we estimate the trade impacts of the pandemic for major sectors in food and agriculture. Supply-side impacts on trade caused by reductions in labour tend to be largest in labour-intensive sectors such as meat processing and processed fruit and vegetables. The supply-side export effects are dwarfed by the demand-side import effects, as the recessionary impact of the pandemic drives significant decreases in imports, largely in processed goods and labour-intensive commodities.

KEYWORDS
agriculture, COVID-19, international trade, pandemic

1 | INTRODUCTION

The novel coronavirus disease (COVID-19) was first confirmed in Wuhan, China in December 2019 (Zhu et al., 2020). The infectious disease has rapidly spread worldwide within a short period of time, with the World Health Organization (WHO) officially declaring COVID-19 outbreak a global pandemic on March 11, 2020 (Cucinotta & Vanelli, 2020). As of July 2022, there had been more than 550 million cumulative confirmed cases globally, with over 6.3 million recorded deaths (WHO, 2022). The perilous situation induced large-scale social and behavioural changes as well as the introduction of unprecedented measures to control the spread, including travel restrictions, school and business closures and stay-at-home orders, which triggered a global economic downturn (Baldwin

& di Mauro, 2020; Coibion et al., 2020; Jordà et al., 2022; Lewis et al., 2020; Ludvigson et al., 2020) and financial market turmoil (Baker et al., 2020; Falato et al., 2021; Toda, 2020).

The disease has generated economic shocks in both demand and supply, with rippling effects on international trade in goods and services, including agricultural trade. On the supply side, distinct challenges emerged for farmers and processors in the wake of the pandemic. In particular, crowded working environments and clustering of workers were conducive for the quick spread of the virus, which became a major challenge for farming and processing value chains that depend on significant amounts of workers. This has in turn led to labour shortages during peak production and harvest periods, causing serious supply disruptions, product shortages and price increases for both food producers and consumers. These negative supply shocks ultimately limited the availability of commodities for export.

On the demand side, the outbreak scare, stay-at-home orders and resulting unemployment and falling income have altered consumer spending behaviour on food and agricultural products. This caused panic buying at retail outlets and plummeting sales in restaurants and other food service establishments. These forces have reverberated throughout the food supply chain, upending distribution channels and stranding food upstream due to order cancellations. The demand-side shocks have, therefore, also impeded the flow of commodities in the export market.[1]

Fearing that food supplies may be disrupted due to infection and containment measures, which may impede cropping and harvesting activities, several countries imposed export restrictions on agricultural products during the early stages of the pandemic (U.S. Congressional Research Service, 2020; Glauber et al., 2020).[2] In anticipation of export controls, the World Trade Organization (WTO), the UN Food and Agriculture Organization (FAO) and the WHO issued a joint statement on March 31, 2020, stating that: “Uncertainty about food availability can spark a wave of export restrictions, creating a shortage on the global market” (WTO, 2020a, 2020b). While many of the initial fears over food safety issues and food security have since subsided, leading to many governments allowing the restrictions to expire, uncertainty remains over the pandemic's continuing impacts on global food security and trade in food and agriculture (Laborde et al., 2020).

In light of these unprecedented disruptions to the global economy, it is essential to examine the adverse impacts of the COVID-19 pandemic on trade in food and agriculture, taking care to distinguish between the impacts arising from supply-based versus demand-based factors. Given the profound implications of the pandemic for global food security, understanding the trade implications of the COVID-19 outbreak is critical for both policy design and agricultural production.

To explore these issues, we develop a gravity model that incorporates both supply and demand channels to analyse the effects of the COVID-19 pandemic on international trade in food and agriculture. Specifically, we capture supply-side shocks arising from impacts on labour across countries and demand-side shocks arising from reductions in income. We highlight three factors that rationalise the use of the gravity approach over other methods for empirical trade modelling. First, the gravity model is marked by a high degree of success in empirically capturing the determinants of trade. Second, gravity is a theory-grounded structural relationship that can be established under a wide variety of theoretical settings (e.g. supply-based versus demand-based derivations). Third and finally, the gravity

[1]Given that the intent of the current study is to uncover the trade effects of COVID-19, we examine various types of primary agricultural commodities, rather than the trade-off between in-home versus out-of-home consumption, which can be analysed more appropriately using applied microeconomics and demand analysis models, as opposed to trade models.

[2]Examples include export restrictions by Russia, Kazakhstan, and Ukraine on wheat, Vietnam on rice, and Turkey on onions, lemons, and potatoes. For a complete list of export restrictions on food products linked to COVID-19, see https://public.tableau.com/app/profile/laborde6680/viz/ExportRestrictionsTracker/FoodExportRestrictionsTracker.

model hinges on data-derived parameters for trade policy modelling, in contrast with computable general equilibrium (CGE) models, which typically rely on assumed parameter values.

The structural equation obtained from this framework also accounts for differences in cross-country productivity, factor endowments and geographical barriers to trade. Based on this structural gravity framework, we estimate the trade impacts of the pandemic for 24 major sectors in food and agriculture using a detailed data set incorporating bilateral trade flows, labour use across countries and sectors and observed declines in national incomes resulting from the pandemic. This empirical analysis is comprised of two principal components.

First, we estimate the gravity equation of trade, which allows us to model bilateral trade at the sector level as a function of supply and demand in the exporting and importing country, respectively. Second, we obtain estimates at the sector level for the relationship between (i) output and employment and (ii) demand and income to conduct a set of counterfactual analyses based on the predicted labour and income effects of the pandemic. Combining the gravity (trade) estimates with the estimated supply and demand relationships (i.e. labour and income), we quantify the impact of the pandemic on trade in food and agriculture across both industries and countries.

In addition to offering a detailed, theoretically grounded characterisation of the COVID-19 pandemic's impacts on trade, our study makes several additional contributions. We combine a structural gravity model with a newly available data set on bilateral trade flows (the International Trade and Production Database; Borchert et al., 2021) to shed light on how infectious disease outbreaks impact international production, consumption and trade. We also offer novel estimates on the relationship between labour and production, as well as income and demand, across countries.

While our theoretical and empirical framework, and the assumptions adopted therein, are guided by the seminal work in the international trade literature, hence possessing the strengths as detailed above, we nonetheless acknowledge that the quality of our projections ultimately depends on our modelling decisions. Given the dynamic nature of the coronavirus pandemic, it is impractical to account for every possible channel through which COVID-19 induced changes affect trade, though we do capture several key supply-side and demand-side channels. Consequently, our analysis captures the main supply-side and demand-side disruptions and thus the findings that we present can serve as an approximation of COVID-19's impact on agricultural trade flows. Therefore, we emphasise that the reported estimates of the effects of the pandemic on agricultural trade are indicative of relative magnitudes rather than specific values.

The remainder of the study is organised as follows. Section 2 briefly reviews the developing literature on the trade impacts of the COVID-19 outbreak. Section 3 develops a structural gravity model of trade based on Eaton and Kortum (2002) and Chor (2010), which incorporates supply and demand factors such as productivity, endowments and other determinants of comparative advantage. Section 4 implements the gravity equation implied by the model to develop counterfactual analyses of COVID-19's impacts on trade. Finally, Section 5 offers concluding remarks.

2 | LITERATURE

The literature exploring the effects of COVID-19 pandemic on agricultural or general trade remains scant, but is gradually evolving. Existing studies are mostly descriptive in nature, offering early perspectives on the potential ramifications of COVID-19 on global trade and strategies in surmounting the pandemic. Baldwin and Tomiura (2020) review the supply disruptions and demand shocks caused by COVID-19 and discuss their potential effects on aggregate trade flows, particularly for manufactured goods and services (e.g. air travel and tourism), based on the experiences from prior global crises. Gruszczynski (2020) discusses the short- and long-term consequences of the pandemic for international trade, including foreign direct investment. This study also covers COVID-19-related trade policy measures, such as export controls over medical and food supplies and relaxations of some existing trade restrictions because of COVID-19. Evenett (2020) examines the policy-induced impediments to imports of medical supplies and states that trade policies should facilitate the flow of medical supplies to reach destinations where they are needed most.

Maliszewska et al. (2020) offer a scenario analysis of the implications of COVID-19 pandemic on international trade. Using a global computable general equilibrium model, the study simulates the impact of several COVID-19 related shocks, including decrease in demand for labour and capital, increase in international trade costs and drop in international tourism. This study finds that the biggest negative shock occurs in the output of domestic services and tourist services.

In the context of agricultural trade, Kerr (2020) provides a synopsis of the early effects of COVID-19-caused supply disruptions and demand shocks on trade in agricultural commodities. The study discusses the implications of two radically different potential reactions in the aftermath of the pandemic: first, increased international cooperation so that the global economy is better prepared for future global crises, particularly by keeping supply chains operating during crisis; and second, reduced international engagement and increased self-sufficiency so that dependence on foreign supplies is lessened. With regard to which of these two scenarios is likely to materialise, the author states that it "depends on how economies evolve in the wake of the COVID-19 pandemic." Further, Barichello (2020), studying the implications of the pandemic on Canada's agricultural trade, notes that trade in agricultural products will be less significantly affected due to low income elasticities of demand.

While most of the above studies provide descriptive exposition on the potential impacts of the pandemic on agricultural trade, few studies have yet offered rigorous quantitative evaluation of these effects.[3] In contrast, our study develops a theoretical model encompassing the important channels of the pandemic's effects and estimates a gravity model – one of the most empirically successful tools in economics (Anderson, 2010) – to quantify the magnitude of changes in trade in important agricultural commodities and processed products.

3 | THEORETICAL ANALYSIS

In this section, we describe a structural framework to quantify the effects of two distinct shocks inflicted by the COVID-19 pandemic on trade flows. Our modelling approach is similar in spirit to existing theoretical general equilibrium analyses of agricultural trade, for example, those of Reimer and Li (2010) and Costinot et al. (2016). This approach adapts the seminal work of Eaton and Kortum (2002) to model bilateral trade flows by accounting for cross-country differences in productivity, factor endowments, trade costs and gravitational forces. In doing so, we incorporate supply-side and demand-side shocks induced by the coronavirus pandemic. The supply-side shocks are incorporated in factor endowments (i.e. the impacts of the pandemic on labour), while the demand-side shocks are accounted for through income (i.e. the recessionary effects of the pandemic).

Suppose there are N countries, indexed as $n = 1, \ldots, N$ and K commodities, indexed as $k = 1, \ldots, K$. Let subscript i denote the exporting country and subscript n denote the importing country. On the

[3]With some exceptions, which generally analyse narrower aspects of agricultural trade than does our analysis: for example, Luckstead and Devadoss (2021) consider the impacts of COVID-19 on processed food trade, and Cao et al. (2020) examine the virus's ramifications for China's agricultural trade.

consumption side, the utility function of a representative consumer in country n is specified according to the constant elasticity of substitution (CES) function:

$$U_n = \left(\int_0^1 \left(q_n^k \right)^{\alpha} \mathrm{d}k \right)^{\frac{1}{\alpha}}, \tag{1}$$

where q_n^k is the quantity of commodity k and $\alpha \in (0, 1)$. The representative consumer's budget constraint is given by $\int_0^1 p_n^k q_n^k \, \mathrm{d}k = Y_n$, where p_n^k is the price of good k in country n and Y_n is the total income in country n. Maximisation of the utility function with respect to the budget constraint yields a demand function of the form:

$$q_n^k = \frac{Y_n}{P} \left(\frac{p_n^k}{P} \right)^{\frac{1}{\alpha - 1}}, \tag{2}$$

where $P = \left[\int_0^1 \left(p_n^k \right)^{\frac{-\alpha}{1-\alpha}} \mathrm{d}k \right]^{\frac{1-\alpha}{-\alpha}}$ is the price index.

On the production side, we assume the market for each good is perfectly competitive and that production technologies exhibit constant returns to scale. Given that all N countries can be potential producers of good k, we let p_{in}^k denote the price paid by importing country n for good k from country i (for $i = n$, p_{ii}^k is the price of domestic sales). The profit-maximisation problem of a representative producer in country i is specified as:

$$\pi_i^k = p_{in}^k q_{in}^k - \frac{c_i^k d_{in}^k}{z_i^k} q_{in}^k, \tag{3}$$

where c_i^k is the production cost of good k in exporting country i, d_{in}^k is the iceberg trade cost between two pairs of countries, which includes the transport cost between i and n, trade barriers, etc., and z_i^k is the productivity of country i in the production of good k. The first-order condition for profit maximisation yields the pricing rule $p_{in}^k = \frac{c_i^k d_{in}^k}{z_i^k}$.

In the spirit of Eaton and Kortum (2002), we consider productivity to be random and varying across countries. Specifically, productivity draws follow the Type II extreme value (Fréchet) distribution, with the cumulative distribution function (CDF) given by

$$F\left(z_i^k\right) = \exp\left(-T_i z^{-\theta}\right), \tag{4}$$

where $T_i > 0$ is the location parameter and $\theta > 0$ is the scale parameter. A higher value of T_i indicates that a country is likely to have higher productivity. In contrast, θ measures the variability of the productivity distribution, with a smaller value of θ implying larger variability of productivity and thus a greater degree of comparative advantage.

From the pricing rule, it is apparent that the distribution of z_i^k gives rise to the distribution of prices p_{in}^k. In particular, the CDF of p_{in}^k, denoted by $G_{in}^k(p)$, can be derived as a function of z_i^k as:

$$G_{in}^k(p) = \mathrm{Prob}\left(p_{in}^k \le p\right) = \mathrm{Prob}\left[\frac{c_i^k d_{in}^k}{z_i^k} \le p\right] = 1 - F\left[\frac{c_i^k d_{in}^k}{p}\right] = 1 - \exp\left(-T_i \left(\frac{c_i^k d_{in}^k}{p}\right)^{-\theta}\right) \tag{5}$$

Intuitively, $G_{in}^k(p)$ is the probability that country i will sell good k to country n at a price less than p. Given country n chooses to import from the lowest-price exporter, we let $G_n^k(p)$ represent the probability distribution that country n will buy good k at the lowest price (p_n^k) considering all prices offered by other countries, that is $p_n^k(z) = \min\left\{p_{1n}^k(z), p_{2n}^k(z), \dots, p_{Nn}^k(z)\right\}$. We can show that

$$G_n^k(p) = 1 - \prod_{i=1}^{N} \mathrm{Prob}\left(p_n^k \geq p\right) = 1 - \prod_{i=1}^{N}\left[1 - G_{in}^k(p)\right] = 1 - \exp\left[-\left(\sum_{i=1}^{N} T_i\left(c_i^k d_{in}^k\right)^{-\theta}\right)p^{\theta}\right]$$

Now, let π_{in}^k denote the probability that country i is the lowest-price exporter of good k to country n, that is $\pi_{in}^k = \int_0^\infty \prod_{s\neq i}\left(1 - G_{sn}^k(p)\right)\mathrm{d}G_{in}(p)$. Substituting $G_{sn}^k(p)$ and $G_{in}^k(p)$ with Equation (5) and re-arranging, we obtain $\pi_{in}^k = \int_0^\infty \prod_{s\neq i}\left(\exp\left(-T_i\left(\frac{c_i^k d_{in}^k}{p}\right)^{-\theta}\right)\right)dG_{in}(p)$, which can be further simplified to $\pi_{in}^k = \frac{T_i\left(c_i^k d_{in}^k\right)^{-\theta}}{\sum_{s=1}^{N} T_s\left(c_s^k d_{sn}^k\right)^{-\theta}}$ using the properties of the Fréchet distribution. Given that π_{in}^k equivalently represents the share of total expenditure on goods imported from country i (X_{in}^k) as a fraction of total expenditure (X_n^k), we arrive at the following equation:

$$\frac{X_{in}^k}{X_n^k} = \pi_{in}^k = \frac{T_i\left(c_i^k d_{in}^k\right)^{-\theta}}{\sum_{s=1}^{N} T_s\left(c_s^k d_{sn}^k\right)^{-\theta}}. \tag{6}$$

The share of country i's exports to country n depends on not only its own efficiency (T_i), production costs (c_i^k) and trade costs (d_{in}^k), but also those of all other competitors. In particular, country i's probability of exporting to country n increases if it is more productive, a lower cost producer and a lower trade-cost exporter relative to other countries. A small value of θ implies greater heterogeneity among countries and thus stronger comparative advantage. Two countries generally will have a larger volume of trade if they are dissimilar, that is if there is a greater disparity between their respective costs of production.

Taking the natural logarithm of both sides of Equation (6) and simplifying produces:

$$\ln X_{in}^k = \ln T_i - \theta \ln c_i^k - \theta \ln d_{in}^k - \ln\left(\sum_{s=1}^{N} T_s\left(c_s^k d_{sn}^k\right)^{-\theta}\right) + \ln X_n^k. \tag{7}$$

For empirical purposes, we define the trade cost as $d_{in}^k = \exp\left(\beta_d D_{in} + \zeta_{in} + \upsilon_{in}^k\right)$, where $\beta_d D_{in}$ is a linear combination of variables that captures iceberg costs (which measure real trade costs; the amount of a good that must be shipped for one unit of the good to arrive in a destination), D_{in} captures dyadic variables such as physical distance, linguistic ties, colonial links, border relationships and trade agreement status, and $\zeta_{in} + \upsilon_{in}^k$ captures idiosyncratic shocks on trade flows, with $\zeta_{in} \sim N\left(0, \sigma_\zeta^2\right)$ and $\upsilon_{in}^k \sim N\left(0, \sigma_\upsilon^2\right)$.

We also define the production cost of good k as $c_i^k = \prod_{f=0}^{F}\left(w_{if}\right)^{s_f^k}$, where $f = 0, 1, \dots, F$ denotes factors of production, w_{if} is the unit price of factor f and $s_f^k \in (0, 1)$ for $\sum_{f=0}^{F} s_f^k = 1$. Similar to Romalis (2004), we use the inverse of relative factor endowments, $\frac{V_{i0}}{V_{if}}$, to capture relative factor prices. Substitution of d_{in}^k and c_i^k in Equation (7) yields the main estimating equation:

$$\ln X_{in}^k = -\sum_{f=1}^{F} \theta\beta_f \left(\ln \frac{V_{if}}{V_{i0}}\right) s_f^k - \theta\beta_d D_{in} - \theta\zeta_{in} - \theta v_{in} + I_i + I_n^k, \tag{8}$$

where $I_i = \ln T_i$ is an exporter fixed effect and $I_n^k = -\theta\delta_k + \theta\mu_k - \ln\left(\sum_{s=1}^{N} T_s \left(c_s^k d_{sn}^k\right)^{-\theta}\right) + \ln X_n^k$ is an importer-commodity fixed effect.

The gravity equation given in Equation (8) captures the key gravity factors that determine bilateral trade between any two countries. As elaborated above, these determinants include productivity differences (captured by the exporter-and-importer fixed effects I_i and I_n^k), factor endowments (the endowments term V_{if}/V_{i0}) and trade costs (the term D_{in}). In essence, the gravity Equation (8) isolates the impact of supply factors (as measured by changes in the effective labour supply in the endowments term) and demand factors (as measured by changes in total expenditures by the importer). Thus, by embedding both supply and demand determinants of trade in a gravity framework (compared to, for instance, traditional gravity approaches focusing on one or the other), this formulation offers a general framework to examine the channels through which pandemic-driven shocks impact production, consumption and trade across countries. In our empirical analysis, we estimate this equation by controlling for bilateral-pair-specific fixed effects, which also accounts for time-invariant fixed effects for exporter and importer.

4 | EMPIRICAL ANALYSIS

Based on the gravity relationship obtained in Equation (8), we econometrically estimate the model using a detailed panel of bilateral trade flows at the commodity level and data on commodity-specific output, demand and trade costs. With the estimated parameters from the gravity model, we then conduct counterfactual analyses on the effects of the COVID-19 pandemic, delineating between supply and demand factors, which thereby allows us to quantify the impacts of the COVID-19 pandemic on international trade in food and agriculture.

4.1 | Gravity estimation

Our bilateral trade data is taken from the recently available International Trade and Production Database (ITPD) produced by the United States International Trade Commission (Borchert et al., 2021). The original data encompasses the bilateral trade flows of 234 countries, and we consider the 24 largest sectors in food and agriculture in the database. While our counterfactual scenarios on trade effects are based on the situation for 2020, the ITPD data only reports trade flows through 2016; therefore, we use the four most recent years of available data (2013–2016) to estimate the model's parameters. Table 1 gives the value of total world trade by sector as of 2016; in total, the sectors in our analysis reflect over $1 trillion in trade.

Following what has become standard in the empirical trade literature, we estimate the gravity equation using the Poisson pseudo-maximum likelihood (PPML) estimator advocated by Santos-Silva and Tenreyro (2006). The PPML approach is ideal for two reasons: first, by estimating the gravity

TABLE 1 Total world trade by sector, 2016 (billion USD)

Sector	Total trade	Sector	Total trade
Bakery products	30.6	Other agricultural products, nec	54.1
Beverages, nec	26.5	Other cereals	10.6
Chocolate and sugar confectionery	47.9	Other food products nec	90.8
Corn	32.0	Processed fruit & vegetables	70.5
Cotton	11.6	Pulses and legumes	11.6
Dairy products	70.0	Soft drinks; mineral waters	20.9
Eggs	3.6	Soybeans	55.7
Fresh fruit	85.7	Spices	10.3
Fresh vegetables	45.3	Starches and starch products	14.6
Grain mill products	35.7	Sugar	28.8
Meat and meat products	137.7	Vegetable and animal oils and fats	113.5
Nuts	24.6	Wheat	39.9

Note: Data from International Trade and Production Database (Borchert et al., 2021). See usitc.gov/data/gravity/itpde.htm for a more detailed breakdown of sector definitions.

equation with trade flows in levels (rather than logarithms), zero-trade flows between country pairs can be included in the estimation, and second, the PPML estimator is robust to heteroscedasticity in trade flows that is likely to bias the estimates from a log-linearized version of gravity.

The estimating equation corresponding to the gravity equation in the theoretical model, after exponentiating, is given by

$$X_{int}^{k} = \exp\left\{\alpha + \beta_1^k \ln X_{it}^k + \beta_2^k \ln X_{nt}^k + \lambda_{in}^k + \mu_t^k + \epsilon_{int}^k\right\}. \tag{9}$$

Of principal interest are the coefficients β_1^k and β_2^k; respectively, the export elasticity with respect to aggregate output and the import elasticity with respect to total consumption, each specific to sector k. By estimating the relationship between the exporter's total supply X_{it}^k and its labour input, and the importer's total demand X_{nt}^k and its national income, these coefficients will serve as the basis for our counterfactual analyses of supply-side and demand-side trade impacts of COVID-19.[4]

To account for other relevant gravity factors, including bilateral trade costs, exporter-and importer-specific determinants of trade, and sector-specific shocks, we further control for a robust assortment of fixed effects. This includes λ_{in}^k, a sector- and pair-specific dyadic fixed effect accounting for bilateral factors (including typical gravity variables such as distance, shared border, etc.) and a sector-year fixed effect μ_t^k. The dyadic effect λ_{in}^k additionally controls for exporter- and importer-specific unobserved factors that would otherwise be captured by exporter- and importer-specific fixed effects, and thus controls for endowments of other factors (such as land

[4]A concern might be raised about potential endogeneity between the dependent variable of bilateral exports and the right-hand side variables of total production and consumption. This is an issue common to nearly every study employing an empirical gravity approach; however, foundational work on gravity estimation by Hummels and Levinsohn (1995) and Frankel et al. (1997) show that this potential endogeneity bias does not significantly impact estimates on the relation between trade and production/consumption.

and capital), which we assume to remain largely fixed over the period of our data.[5] In addition, as proposed by Feenstra (2002), by controlling for exporter-commodity- and importer-commodity-specific factors, λ_{in}^{k} (at least partially) accounts for the multilateral trade resistance terms described in Anderson and van Wincoop (2003).[6]

Equation (9) is estimated in a pooled regression with sector-specific coefficients, the estimates for which are presented in Table 2. Standard errors are calculated using two-way clustering at the level of importer-year and exporter-year. Each of the estimates on the exporter supply and importer demand coefficients is significant at the alpha level of 0.01, likely owing to the large sample size in the estimation as well as the data being completely consistent with the theoretical gravity framework, that is with total supply and demand by country and sector appearing on the right-hand side.[7] Each of the estimated trade elasticities are inelastic and generally take reasonable values.

4.2 | Counterfactual analysis

With estimates of the gravity Equation (9), we turn to estimating the impacts of COVID-19 on international trade in food and agriculture by performing counterfactual analyses along the two supply and demand dimensions outlined earlier. We first consider effects from supply shocks owing to disruptions in the labour force, and second, effects from demand shocks arising from reductions in consumer income. Care should be taken in interpreting our findings because of potential changes in the structural parameters of the pre- and post-COVID-19 economy; however, as systematic post-pandemic data for the variables in our analysis do not yet exist, our results offer informed predictions on the likely impacts.

4.2.1 | Labour-Based supply effects

To estimate the labour market effects on trade via the supply channel, we must estimate the relationship between output and employment across countries and industries.[8] One of the principal ways through which the COVID pandemic has disrupted economic activity has been its significant disruptions in the labour force. The disease has been particularly impactful in many parts of food and agriculture, as early outbreaks caused numerous shutdowns in food processing facilities and caused disruptions to the farm labour supply.

[5]Dyadic fixed effects are perfectly collinear with separate exporter (i) and importer (n) fixed effects – and because dyadic fixed effects also account for pair (in) specific factors, for example distance, common language, or shared borders, they represent a much more rigorous specification than simply including i and n effects separately. And while in reality, the use of inputs such as capital and land varies across countries and industries even in a four-year time span, such inputs are typically less variable than labor. Further, suitable data at the sector- and country-level for these inputs is generally not available.

[6]The multilateral resistance terms reflect the barriers to a country's trade that are common across all of its partners (such as the country's remoteness from the rest of the world), as opposed to bilateral resistance terms that are specific to a single partner (such as geographical distance or tariff rates). While these terms vary over time, by controlling for long-run exporter- and importer-specific factors with our fixed effects approach, we account for the long-run aspects of these multilateral resistance terms.

[7]The majority of industry-level gravity studies employ GDP as a stand-in for aggregate sectoral production and consumption, or proxies such as the total value of food processing or crop production, owing to data on sector-specific production and consumption not generally being available. Our specification based on ITPD data improves on such approaches by including variables that directly align with their theoretical counterparts.

[8]Recovering many parameters using cross-country estimation is commonly encountered in empirical analysis. However, the inclusion of country fixed effects in each of our cross-country estimations ensures that we have controlled for underlying country-level idiosyncratic factors affecting the output-labor elasticity, which mitigates this concern.

TABLE 2 Estimated gravity coefficients by sector

Sector	Exporter supply (β_1^k) Estimate	SE	Importer demand (β_2^k) Estimate	SE
Bakery products	0.510[a]	(0.085)	0.763[a]	(0.060)
Beverages, nec	0.661[a]	(0.073)	0.831[a]	(0.076)
Chocolate and sugar confectionery	0.704[a]	(0.071)	0.726[a]	(0.072)
Corn	0.419[a]	(0.072)	0.715[a]	(0.056)
Cotton	0.565[a]	(0.074)	0.807[a]	(0.063)
Dairy products	0.726[a]	(0.067)	0.597[a]	(0.078)
Eggs	0.445[a]	(0.111)	0.567[a]	(0.112)
Fresh fruit	0.351[a]	(0.055)	0.773[a]	(0.051)
Fresh vegetables	0.294[a]	(0.061)	0.729[a]	(0.059)
Grain mill products	0.548[a]	(0.066)	0.724[a]	(0.057)
Meat and meat products	0.813[a]	(0.057)	0.453[a]	(0.090)
Nuts	0.693[a]	(0.052)	0.672[a]	(0.053)
Other agricultural products, nec	0.812[a]	(0.047)	0.723[a]	(0.058)
Other cereals	0.318[a]	(0.086)	0.813[a]	(0.086)
Other food products nec	0.658[a]	(0.070)	0.710[a]	(0.070)
Processed fruit & vegetables	0.681[a]	(0.061)	0.740[a]	(0.059)
Pulses and legumes	0.589[a]	(0.060)	0.603[a]	(0.046)
Soft drinks; mineral waters	0.593[a]	(0.076)	0.695[a]	(0.059)
Soybeans	0.449[a]	(0.076)	0.849[a]	(0.052)
Spices	0.658[a]	(0.068)	0.738[a]	(0.086)
Starches and starch products	0.658[a]	(0.087)	0.719[a]	(0.084)
Sugar	0.664[a]	(0.075)	0.691[a]	(0.071)
Vegetable and animal oils and fats	0.736[a]	(0.075)	0.828[a]	(0.042)
Wheat	0.432[a]	(0.066)	0.806[a]	(0.062)
Observations				788,286
Pseudo R^2				0.985
Pair-industry FEs				✓
Industry-year FEs				✓

Note: Standard errors clustered by exporter-year and importer-year in parentheses. Constant not reported.

[a]$p < .01$.

Our analysis of supply-side effects on trade is motivated by these labour force disruptions.[9] There are two aspects of these disruptions that inform our analysis. First, the severity of outbreaks of COVID-19 has varied substantially across countries due to differences in (among other factors) the timing of the disease's arrival, government policy responses and the effectiveness of countries' medical systems. Second, because we focus on several different sectors within food and agriculture, we should

[9]It is also conceivable that labor disruptions would impact a country's imports. First, supply-chain disruptions – such as a shortage of domestically produced beef owing to shutdowns at processing facilities – might encourage demand for foreign imports. Second, the labor-supply-driven effects of higher unemployment, whether driven by shutdown measures or economic downturns, will reduce aggregate consumer income, thus depressing import demand. We capture these impacts on import demand in our analysis of demand-side effects by considering forecasted reductions in overall economic activity by sector.

expect that labour-supply impacts will be different between relatively labour-intensive activities (such as food processing or fruit and vegetable production) and non-labour-intensive activities (such as the production of field crops). Further, differences in the labour intensity of production in advanced versus developing economies imply yet more scope for differences in potential labour impacts.

To account for these differences, we estimate the elasticity of output with respect to labour for each sector, allowing for different labour elasticities between advanced and developing countries.[10] Data on employment at the country-sector level is generally not available for the entire sample of countries in our analysis or for the most recent years. We, therefore, use data on output and labour inputs by sector and country from the EXIOBASE input–output tables (Merciai & Schmidt, 2018), which is compiled from primary sources on international production (FAO, 2020) and employment (ILO, 2020) in food and agriculture.

Using the four most recent years of EXIOBASE data (2008–2011), we estimate the following equation:

$$\ln X_{it}^{k} = \alpha + \gamma_1^k \ln L_{it}^{k} + \gamma_2^k \text{Developing}_i \times \ln L_{it}^{k} + \delta_i^k + \mu_t + \varepsilon_{it}^{k}, \tag{10}$$

which portrays gross output X_{it}^{k} in sector k in country i in year t as a function of the sector's employment L_{it}^{k} (the number of workers employed in the sector). Given differences in production techniques depending on countries' levels of development, we allow for different estimates of the output elasticity of labour in advanced ($\gamma_{Adv.}^{k} = \gamma_1^k$) versus developing ($\gamma_{Dev.}^{k} = \gamma_1^k + \gamma_2^k$) countries, where Developing_i is an indicator variable equal to one when exporter i is classified as a developing country.

To account for country-sector-specific factors that are largely invariant over time (such as inputs of capital and land), we include a country-sector fixed effect δ_i^k. The δ_i^k term also ensures that our estimation is based on within-country (versus between-country) variation, in that it controls for idiosyncratic differences in output-labour relationships across countries. In addition we include a year-specific fixed effect μ_t to account for time-specific determinants of output that are common across countries and sectors (e.g. technology improvements or macroeconomic shocks).

Equation (10) is estimated in a pooled regression, the estimates for which are presented in Table 3 (for brevity, we only present the point estimates, nearly all of which are significant at the 1–5% level; see Table A2 for the original estimation results). Because industries in EXIOBASE are sometimes defined at a more aggregate level than those in the ITPD trade data, we estimate the elasticity at the level of the EXIOBASE sector and assign the estimated elasticities to the more disaggregated ITPD sectors corresponding to each respective sector in EXIOBASE. The elasticities generally take values that accord with intuition – sectors that are relatively labour-intensive, such as meat processing, exhibit higher values, while non-labour-intensive sectors, such as cotton and soybeans, exhibit lower values. Further, estimates for advanced economies tend to be significantly lower than for developing economies.[11]

[10]We define advanced economies as those classified by the World Bank (2020) for the year 2020 as being high income, and developing as countries in the low, lower-middle, and upper-middle income classifications. See Table A1 for a full list of the countries in the analysis.

[11]Specifically, 10 out of the 13 elasticity estimates for the original EXIOBASE sectors exhibit lower values for advanced economies than for developing economies, and for two of the sectors for which the opposite is found (wheat and dairy products), the differences in the estimates are statistically insignificant. It is also the case that many of the countries in the developing country group (Argentina, Brazil, several Central and Eastern European countries) have relatively technologically advanced agricultural sectors, which accounts for the relative similarity between some of the estimates. A handful of the estimated labor elasticities, such as for labor inputs in wheat and egg production, take surprisingly high values. However, these estimates are (a) highly statistically significant (and thus precisely estimated), (b) inelastic (in line with intuition for these commodities), and (c) in the same range as the estimated elasticities for the other sectors. Because of this, and because our estimated supply-driven trade impacts for these sectors are not overly large, our estimates of these elasticities do not exert outsize influence on our broader results.

TABLE 3 Estimated output elasticities with respect to labour, by sector

Sector	$\gamma^k_{Adv.}$	$\gamma^k_{Dev.}$	Sector	$\gamma^k_{Adv.}$	$\gamma^k_{Dev.}$
Bakery products	0.24	0.65	Other agricultural products, nec	0.02	0.50
Beverages, nec	0.29	0.42	Other cereals	0.24	0.61
Chocolate and sugar confectionery	0.24	0.65	Other food products nec	0.24	0.65
Corn	0.24	0.61	Processed fruit & vegetables	0.24	0.65
Cotton	0.14	0.49	Pulses and legumes	0.02	0.50
Dairy products	0.23	0.17	Soft drinks; mineral waters	0.29	0.42
Eggs	0.60	0.84	Soybeans	0.10	0.32
Fresh fruit	0.17	0.29	Spices	0.02	0.50
Fresh vegetables	0.17	0.29	Starches and starch products	0.24	0.65
Grain mill products	0.24	0.65	Sugar	0.05[a]	0.18
Meat and meat products	0.78	0.30	Vegetable and animal oils and fats	0.09	0.32
Nuts	0.17	0.29	Wheat	0.55	0.35

Note: Entries give the elasticity of output with respect to labour for advanced versus developing countries based on estimation of Equation (10).

[a]The output elasticity of labour for sugar is assumed to be 0.05 (an arbitrary small value) because the point estimate for the elasticity is negative (but statistically insignificant).

Based on the above elasticities, we use data on COVID-19 infection rates as a proxy for the disruptions in the labour force across countries caused by the pandemic. We calculate these declines in the effective labour force based on the most recent (as of August 2020) Johns Hopkins University (2020) data, which records the incidence of confirmed cases of the virus across countries. While the virus varies considerably in its effects on individuals, complicating a simple one-to-one match between case numbers and impacts on the labour force, we assume that the per-capita incidence of cumulative confirmed cases is equivalent to the reduction in the labour force – that is, if one percent of a country's population has been affected by the virus, we assume a one percent reduction in labour for the country. And while it is not necessarily the case that the relationship between number of cases and number of lost workers is in reality an exact one, this approach accounts to some extent for the additional impact of lockdown and mitigation measures across countries in response to the severity of the observed outbreak.

Therefore, for each sector and country, we use (i) the computed reduction in labour supply from COVID-19 cases, (ii) the estimated elasticity of output with respect to labour and (iii) the estimated elasticity of exports with respect to output to compute the expected reduction in bilateral exports for each trading relationship. We then sum the computed impacts on bilateral exports by sector (again, calculated based on 2016 trade data, the latest year available in the ITPD database) in order to examine which sectors are expected to undergo the largest declines in trade from supply-side labour impacts.

Figure 1 presents these estimated impacts on total exports for each of the sectors in the analysis. Immediately apparent from the figure is that the largest impacts on trade arise in the meat-processing sector with $501 million in predicted supply-based trade losses. Given the profusion of early news stories on shutdowns at meat-processing plants, this comes as no surprise. Meat-processing industries and large meat-exporting countries such as the United States and Brazil were particularly hard hit relative to many other economic sectors in the early stages of the pandemic. Moreover, COVID's disruptions to this sector endured though most of 2020, as infection rates in US meatpacking facilities remained elevated well above infection rates in other parts of the economy (see ERS, 2021). However,

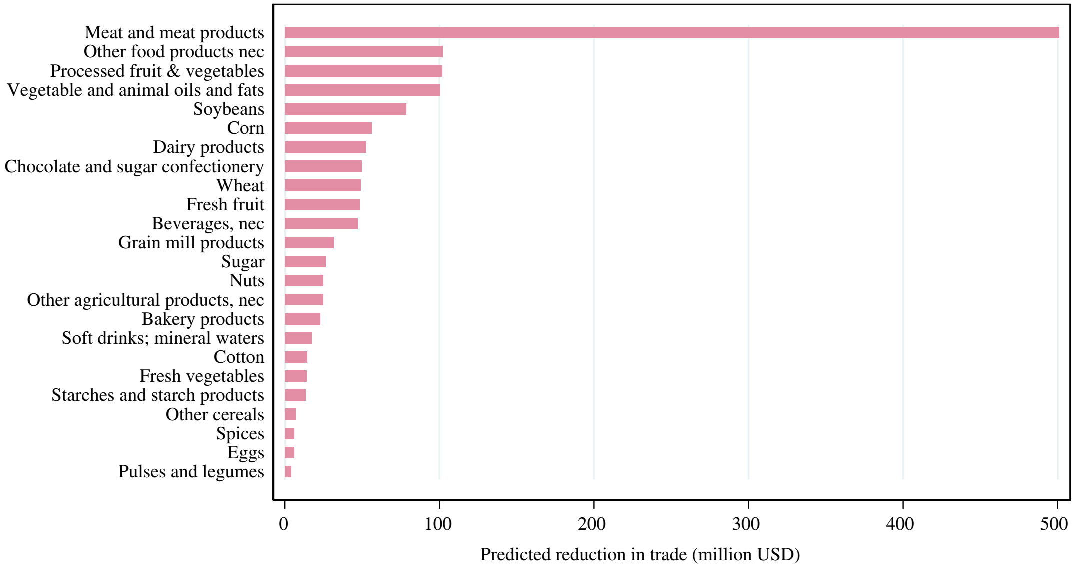

FIGURE 1 Supply-based trade reductions by sector

many of these outsize disruptions to the meat sector had largely been resolved by late 2020. Consequently, our results on supply-side trade impacts are most directly reflective of the mid- to late-2020 period, in which conditions in this sector were at their worst.

Processed food sectors, including "Other food products, nec" ($102 million in trade declines),[12] "Processed fruit and vegetables" ($102 million) and "Vegetable oils and animal fats" ($100 million) comprise the next largest losses, reflecting the significant negative impacts that outbreaks at processing facilities caused. Several primary commodities, including soybeans, corn and wheat, are also afflicted by reductions in trade. While such commodities are typically non-labour-intensive in advanced-economy producers, they are among the most-traded agricultural commodities, and any production impacts – even in small relative terms – are likely to engender significant impacts on total trade.[13]

Conversely, we find only negligible impacts on trade for some commodities, for example, cotton ($14 million), spices ($6.1 million) and eggs ($6 million). These findings likely reflect some combination of the non-labour-intensiveness of production of these commodities, the fact that they are traded in lower volumes than other sectors and that the principal exporters of these commodities have experienced comparatively minor outbreaks of COVID-19.

[12]"Other food products nec" consists of the ISIC industry codes 1075 (Manufacture of prepared meals and dishes) and 1079 (Manufacture of other food products nec).

[13]It is important to note that, for our results on supply-side trade effects, the magnitude of our estimated impacts (in their levels) is closely related to the volume of trade in each sector in the data. Specifically, it can be seen that the supply-side impacts by commodity found in Figure 1 track closely with the overall volume of trade for each commodity as shown in Table 1. Therefore, even for commodities such as corn or soybeans for which we estimate a comparatively low elasticity of output with respect to labor, the trade impacts that we quantify are necessarily related to the baseline volume of trade from which we calculate the counterfactual impacts of COVID. Consequently, even for primary commodities such as corn, wheat, and soybeans for which labor is of diminished importance in production, COVID-driven reductions in the effective labor supply can still yield trade impacts of significant magnitude. Moreover, while the supply-side effects for these commodities are sizable, they are modest relative to the total level of world trade in these commodities, and they are small relative to the demand-side trade impacts that we estimate.

4.2.2 | Income-based demand effects

For our second set of counterfactuals, we estimate the role of COVID-induced declines in consumer income on trade. As mentioned earlier, the COVID-19 pandemic caused an immediate and precipitous decline in economic activity, and with it a substantial decrease in employment and consumer incomes. To measure these impacts, we consider the relationship between GDP and aggregate demand by sector – as national incomes fall, some sectors are likely to observe significant declines in demand, while other sectors will have less elastic demand responses to income changes. The relationship that we estimate is given by

$$\ln X_{nt}^{k} = \alpha + \eta_1^k \ln \mathrm{GDP}_{nt} + \eta_2^k \mathrm{Developing}_n \times \ln \mathrm{GDP}_{nt} + \omega_k + \zeta_n + \mu_t + \varepsilon_{nt}^{k}, \tag{11}$$

where importer n's total consumption in sector k (X_{nt}^k, from the ITPD data) is a function of national income (GDP, from the World Bank) and industry-, importer- and year-specific fixed effects. The coefficients η_1^k and η_2^k reflect the income elasticity of demand by commodity, with effects differentiated between advanced versus developing countries (similar to the labour-output analysis, with $\mathrm{Developing}_n$ defined analogously to $\mathrm{Developing}_i$, $\eta_{Adv.}^k = \eta_1^k$ and $\eta_{Dev.}^k = \eta_1^k + \eta_2^k$) to account for non-homotheticity in income effects.

Table 4 presents the point estimates of Equation (11), nearly all of which are significant at the 1% level (see Table A3 for the full estimation results). Elasticities tend to be highest for primary commodities such as cotton, soybeans and cereals, and lowest for processed goods such as dairy products, grain mill products and processed fruit and vegetables, suggesting that larger economies tend to exhibit relatively higher demand for the former sectors.

As in the supply analysis, the demand-side counterfactual involves three components: (i) the reductions countries' national incomes during 2020, (ii) the estimated elasticity of consumption with respect to GDP by sector and (iii) the estimated elasticity of imports with respect to total consumption. In order to capture recessionary impacts on demand by sector, we employ observed percentage changes in real GDP in 2020 based on World Bank data. In conjunction, these elements allow us

TABLE 4 Estimated consumption elasticities with respect to GDP, by sector

Sector	$\eta_{Adv.}^k$	$\eta_{Dev.}^k$	Sector	$\eta_{Adv.}^k$	$\eta_{Dev.}^k$
Bakery products	0.36	0.92	Other agricultural products, nec	1.02	1.50
Beverages, nec	0.77	1.28	Other cereals	0.45	0.98
Chocolate and sugar confectionery	0.51	1.06	Other food products nec	0.47	1.02
Corn	1.02	1.44	Processed fruit & vegetables	0.41	0.98
Cotton	1.18	1.62	Pulses and legumes	0.79	1.22
Dairy products	0.47	1.01	Soft drinks; mineral waters	0.27	0.83
Eggs	0.77	1.25	Soybeans	1.37	1.85
Fresh fruit	0.81	1.30	Spices	0.67	1.17
Fresh vegetables	0.72	1.19	Starches and starch products	0.82	1.35
Grain mill products	0.33	0.83	Sugar	0.47	0.97
Meat and meat products	0.98	1.52	Vegetable and animal oils and fats	0.68	1.17
Nuts	0.77	1.31	Wheat	0.94	1.37

Note: Entries give the elasticity of aggregate demand with respect to GDP based on estimation of Equation (11). All estimates are significant at the $p < .01$ or $p < .05$ level.

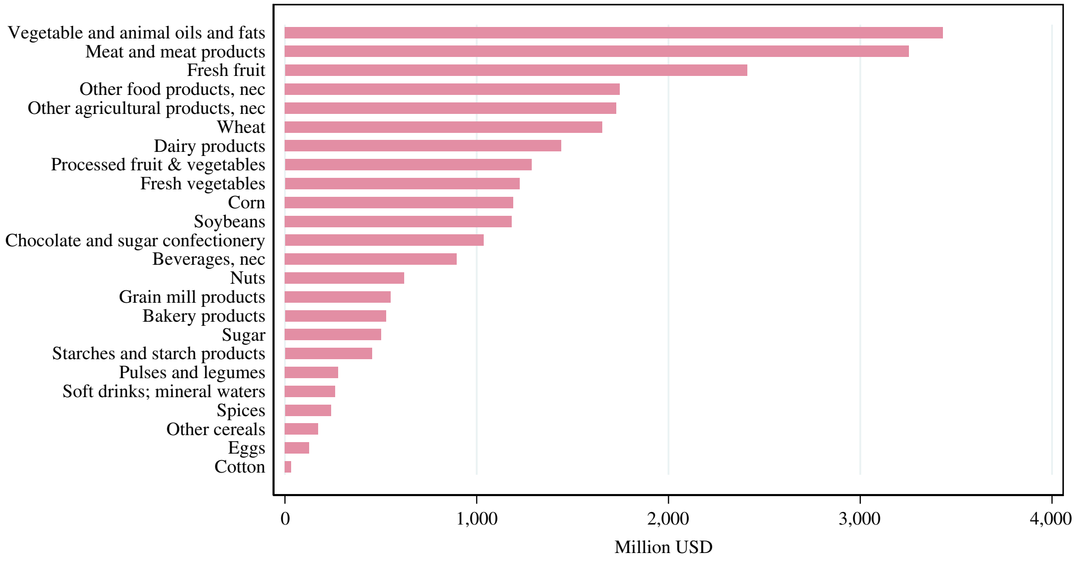

FIGURE 2 Demand-based trade reductions by sector

to compute the expected reduction in bilateral imports for each trading relationship, which when summed together, give the total demand-side effect on imports by sector.

Figure 2 depicts the estimated demand-side effects on trade across sectors. The demand-side effects are an order of magnitude larger than the supply-side impacts, reflecting the fact that significant declines in spending and consumption are likely to be more impactful than comparatively minor reductions in countries' effective labour supplies.

As seen in the figure, the large majority of demand-based trade impacts arise in processed sectors such as “Vegetable and animal oils and fats” ($3.4 billion in trade losses) and “Meat and meat products” ($3.2 billion), as well as primary commodities such as fresh fruit ($2.4 billion) and wheat ($1.6 billion). Such commodities are fundamental consumption items in nearly all countries, and with most countries experiencing severe economic downturns brought about by the pandemic, we estimate large declines in demand and trade in such sectors.

4.2.3 | Impacts by country

As a final exercise, we cumulate the sector-specific estimates for both exports and imports by country to determine which countries are expected to undergo the largest declines in exports or imports. These results reflect a combination of factors, chief among them the severity of the country's COVID-19 outbreak. Countries with the worst and longest lasting outbreaks are the ones likely to undergo the most significant impacts on both employment and income and thus the largest declines in trade. This logic is borne out in Figure 3, which depicts the predicted reduction in total exports (3a) and total imports (3b) by country for the 24 sectors in our analysis.

On the supply side, the countries with the largest outbreaks during 2020 clearly undergo the largest declines in exports from labour-based impacts. The United States – the site of the worst COVID-19 outbreak in the world – is expected to experience over $400 million in export losses, followed by Brazil with nearly $300 million in losses, and whose COVID-19 outbreak trails only the United

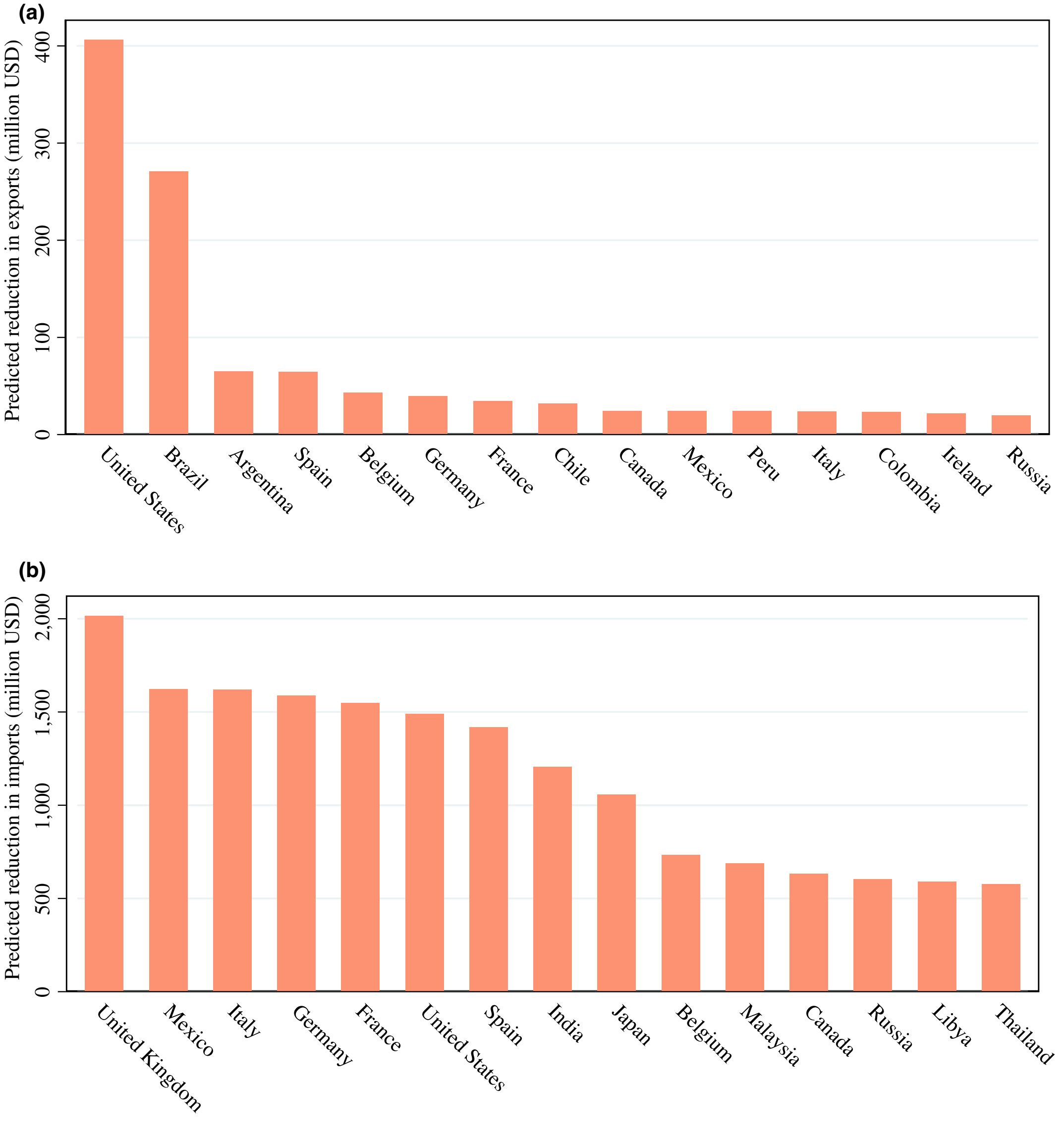

FIGURE 3 Trade impacts by country. (a) Supply-driven export declines by country. (b) Demand-driven import declines by country.

States in severity. Other large agricultural producers that experienced (or are experiencing) significant outbreaks, such as Argentina ($65 million) and Spain ($65 million), are subject to more muted export declines.[14]

[14]As was shown in our results on sector-level impacts in Figure 1, the largest supply-driven export impacts were found in the meat and meat products sector. To explore the degree to which this sector drives our findings on country-level impacts, we also compute the results from Figure 3 by excluding impacts from this sector. In doing so, we find that the patterns of trade impacts are largely consistent with the results that include this sector. The United States and Brazil undergo the largest trade impacts, though Brazil' s estimated reduction in exports of $205 million becomes larger than the reduction in US exports of $189.5 million. Other countries, including Argentina ($61.5 million), Spain ($26.8 million), Belgium ($25 million), and Peru ($23.9 million) experience impacts that are roughly comparable to (but naturally smaller than) the baseline results.

For the labour-based import demand effects, we find impacts that correlate closely with the severity of countries' COVID outbreaks during 2020. The United Kingdom, a country that was afflicted by multiple malignant and long-lasting outbreaks, shows declines that surpass those of other countries, with an estimated decrease in imports of $2.0 billion.[15] Mexico, as well as many large European (e.g. Italy, Germany and France) and Asian (e.g. India, Japan, Malaysia) countries that experienced lingering outbreaks and which enacted suppressive lockdown measures similarly experience large import declines.

To provide validation for our findings, we briefly compare our estimated trade impacts with observed reductions in trade during the 2019–2020 period (data from the BACI trade dataset from CEPII). In examining the observed trade data for 2020, we find many instances in which observed changes in trade between 2019 and 2020 closely align with our model's predictions. For example, the United States (the country for which we estimate the largest pandemic-induced reduction in exports) underwent noticeable year-over-year declines in the total exports of several major commodities, including chocolate and sugar confectionery ($322 million reduction in exports) fresh fruit ($160 million), fresh vegetables ($86 million) and wheat ($62 million). For Brazil (the country with the second largest reduction in exports) we estimate comparable declines for corn ($1.4 billion), nuts ($31 million) and chocolate and sugar confectionery ($23 million). Similarly, we observe large declines in imports of certain commodities for major markets that undergo large estimated changes in aggregate imports such as Mexico, which in reality experienced considerable declines in imports of meat ($515 million reduction in imports), dairy products ($250 million) and corn ($137 million).[16]

5 | CONCLUSION

The COVID-19 pandemic has had unprecedented impacts on the world economy and fears over its impacts have been particularly acute given the essential nature of the food and agriculture sector. As countries rely now more than ever on international trade to meet demand for food and agricultural products, and as export markets are of vital importance for producers, understanding the virus's impact on trade is essential in developing appropriate policy responses and ensuring global food security to meet the challenges of the pandemic.

In this paper, we develop a trade-gravity framework to quantify the pandemic's impacts across sectors and countries, considering both labour-driven supply impacts and income-driven demand impacts on trade. We develop a theoretical framework to guide our empirical analysis, which utilises a rich set of trade, labour and income data to estimate the gravity relationship and conduct several counterfactuals.

[15]The United Kingdom also completed its exit from the European Union in 2020, a non-COVID factor that likely contributed to the country's negative GDP growth in this period.

[16]It is important to note that the comparison of ex post year-to-year changes in observed trade volumes against our model's simulated predictions should be made with caution. Namely, our counterfactual exercise is based on a within-year analysis in which we compare the baseline predicted level of trade in a single year against a counterfactual predicted level of trade in that year, but under the counterfactual setting in which the pandemic had never occurred. Put differently, our analysis abstracts from other changes to international and domestic markets taking place over time before and during the pandemic period (e.g. Brexit, the US-China trade war) in order to isolate the specific trade impacts of the pandemic. Consequently, comparing observed year-to-year changes in trade volumes during the trade war period against our simulated predictions provides only a rough benchmark of our modelling accuracy.

Our findings can be summarised as follows. Supply-side impacts on trade caused by reductions in labour tend to be largest in labour-intensive sectors such as meat processing and processed fruit and vegetables, and arise because of significant outbreaks in large producers, such as the United States and Brazil, of such commodities. The supply-side export effects are dwarfed by the demand-side import effects, as our results suggest that the recessionary impact of the pandemic on consumption drove significant decreases in imports, largely in processed goods and labour-intensive commodities. All told, we predict several billion dollars of trade losses, suggesting that the pandemic has significant and severe negative implications for trade in food and agriculture.

The static nature of our model allows us to examine the counterfactual impacts of the COVID-19 pandemic on bilateral trade between countries, which is a standard approach in the trade literature. More research is warranted to understand the full extent of the COVID-19 induced shocks on trade. Future research in this area might analyse dynamic adjustment effects of the sectoral recovery in response to other shocks caused by the COVID-19 pandemic, such as supply chain disruptions (see Hobbs, 2020, 2021) and inaction of trade policy interventions, including sanitary and phytosanitary (SPS) measures (Evenett et al., 2022; WTO, 2020a, 2020b).

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DATA AVAILABILITY STATEMENT

The data used in the article is publicly available and the authors are willing to provide the data.

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APPENDIX A ADDITIONAL TABLES AND ESTIMATION RESULTS

TABLE A1 Sample countries and classification as advanced versus developing

Advanced countries			
Andorra	Denmark	Latvia	San Marino
Antigua and Barbuda	Estonia	Lithuania	Saudi Arabia
Aruba	Faroe Islands	Luxembourg	Seychelles
Australia	Finland	Macau	Singapore
Austria	France	Malta	Sint Maarten
Bahamas	French Polynesia	Mauritius	Slovakia
Bahrain	Germany	Nauru	Slovenia
Barbados	Gibraltar	Netherlands	South Korea
Belgium	Greece	New Caledonia	Spain
Bermuda	Greenland	New Zealand	St. Kitts and Nevis
British Virgin Islands	Guam	Northern Mariana Islands	Sweden
Brunei	Hong Kong	Norway	Switzerland
Canada	Hungary	Oman	Taiwan
Cayman Islands	Iceland	Palau	Trinidad and Tobago
Chile	Ireland	Panama	Turks and Caicos Islands
Croatia	Israel	Poland	United Arab Emirates
Curaçao	Italy	Portugal	United Kingdom
Cyprus	Japan	Qatar	United States
Czech Republic	Kuwait	Romania	Uruguay
Developing countries			
Afghanistan	Dominica	Liberia	Serbia
Albania	Dominican Republic	Libya	Sierra Leone
Algeria	Ecuador	Macedonia	Solomon Islands
American Samoa	Egypt	Madagascar	Somalia
Angola	El Salvador	Malawi	South Africa
Argentina	Equatorial Guinea	Malaysia	South Sudan
Armenia	Eritrea	Maldives	Sri Lanka
Azerbaijan	Ethiopia	Mali	St. Lucia
Bangladesh	Fed. States of Micronesia	Marshall Islands	St. Vincent and Grenadines
Belarus	Fiji	Mauritania	Sudan
Belize	Gabon	Mexico	Suriname
Benin	Gambia	Moldova	Swaziland
Bhutan	Georgia	Mongolia	Syria
Bolivia	Ghana	Montenegro	Tajikistan
Bosnia and Herzegovina	Grenada	Morocco	Tanzania
Botswana	Guatemala	Mozambique	Thailand
Brazil	Guinea	Myanmar	Timor-Leste

(Continues)

TABLE A1 (Continued)

Bulgaria	Guinea-Bissau	Namibia	Togo
Burkina Faso	Guyana	Nepal	Tonga
Burundi	Haiti	Nicaragua	Tunisia
Cabo Verde	Honduras	Niger	Turkey
Cambodia	India	Nigeria	Turkmenistan
Cameroon	Indonesia	North Korea	Tuvalu
Central African Republic	Iran	Pakistan	Uganda
Chad	Iraq	Palestine	Ukraine
China	Jamaica	Papua New Guinea	Uzbekistan
Colombia	Jordan	Paraguay	Vanuatu
Comoros	Kazakhstan	Peru	Venezuela
Congo	Kenya	Philippines	Vietnam
Costa Rica	Kiribati	Russia	Yemen
Cuba	Kyrgyzstan	Rwanda	Zambia
Côte d'Ivoire	Laos	Samoa	Zimbabwe
Dem. Rep. of the Congo	Lebanon	São Tomé and Príncipe	
Djibouti	Lesotho	Senegal	

Note: We define advanced economies as those classified by the World Bank (2020) for the year 2020 as being high income, and developing as countries in the low, lower-middle and upper-middle income classifications.

TABLE A2 Output elasticity of labour by sector (EXIOBASE sectors)

	Advanced countries $(\gamma^k_{Adv.})$		Developing countries $(\gamma^k_{Dev.})$	
Sector	**Estimate**	**SE**	**Estimate**	**SE**
Animal products nec	0.601[a]	(0.107)	0.838[a]	(0.104)
Beverages	0.292[a]	(0.074)	0.423[b]	(0.198)
Cereal grains nec	0.240[a]	(0.079)	0.608[a]	(0.169)
Crops nec	0.023[b]	(0.010)	0.496[a]	(0.116)
Dairy products	0.230[a]	(0.038)	0.167	(0.167)
Food products nec	0.241[a]	(0.060)	0.654[a]	(0.108)
Meat and meat products	0.776[a]	(0.137)	0.297	(0.183)
Oil seeds	0.102	(0.187)	0.316[c]	(0.174)
Plant-based fibres	0.144[a]	(0.035)	0.486[a]	(0.173)
Sugar	−0.008	(0.020)	0.181[a]	(0.057)
Vegetables, fruit, nuts	0.168[c]	(0.091)	0.294[b]	(0.128)
Vegetable oils and fats	0.091[c]	(0.053)	0.322[a]	(0.089)
Wheat	0.547[a]	(0.072)	0.353	(0.349)
Observations				2209
R^2				0.995
Country-industry FEs				✓
Year FEs				✓

Note: Estimates for the elasticity of output with respect to labour for advanced versus developing countries based on Equation (10). Standard errors clustered by country-year in parentheses.

[a] $p < .01$.

[b] $p < .05$.

[c] $p < .10$.

TABLE A3 Estimated consumption elasticity with respect to GDP by sector

Sector	Advanced countries $\left(\eta^{k}_{Adv.}\right)$ Estimate	SE	Developing countries $\left(\gamma^{k}_{Dev.}\right)$ Estimate	SE
Bakery products	0.357[a]	(0.123)	0.920[a]	(0.174)
Beverages, nec	0.768[a]	(0.123)	1.281[a]	(0.175)
Chocolate and sugar confectionery	0.512[a]	(0.122)	1.060[a]	(0.173)
Corn	1.018[a]	(0.123)	1.443[a]	(0.175)
Cotton	1.183[a]	(0.129)	1.619[a]	(0.176)
Dairy products	0.475[a]	(0.123)	1.015[a]	(0.173)
Eggs	0.767[a]	(0.125)	1.255[a]	(0.174)
Fresh fruit	0.814[a]	(0.123)	1.300[a]	(0.175)
Fresh vegetables	0.725[a]	(0.124)	1.192[a]	(0.175)
Grain mill products	0.331[a]	(0.122)	0.835[a]	(0.174)
Meat and meat products	0.985[a]	(0.124)	1.519[a]	(0.174)
Nuts	0.774[a]	(0.124)	1.306[a]	(0.173)
Other agricultural products, nec	1.019[a]	(0.124)	1.499[a]	(0.177)
Other cereals	0.452[a]	(0.123)	0.982[a]	(0.173)
Other food products nec	0.465[a]	(0.124)	1.018[a]	(0.173)
Processed fruit & vegetables	0.410[a]	(0.126)	0.976[a]	(0.173)
Pulses and legumes	0.787[a]	(0.123)	1.219[a]	(0.174)
Soft drinks; mineral waters	0.272[b]	(0.123)	0.831[a]	(0.173)
Soybeans	1.372[a]	(0.130)	1.848[a]	(0.176)
Spices	0.673[a]	(0.122)	1.170[a]	(0.174)
Starches and starch products	0.820[a]	(0.123)	1.348[a]	(0.172)
Sugar	0.466[a]	(0.122)	0.970[a]	(0.174)
Vegetable and animal oils and fats	0.683[a]	(0.123)	1.171[a]	(0.173)
Wheat	0.935[a]	(0.127)	1.374[a]	(0.177)
Observations				18,451
R^2				0.780
Industry FEs				✓
Country FEs				✓
Year FEs				✓

Note: Estimates for the elasticity of aggregate demand with respect to GDP based on Equation (11). Standard errors clustered by country-year in parentheses.

[a] $p < .01$.

[b] $p < .05$.