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Chapter Author(s): Shawn Arita, Jason Grant, Sharon Sydow, Jayson Beckman

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Has Global Agricultural Trade Been Resilient under COVID-19? Findings from an Econometric Assessment of 2020

Shawn Arita, Jason Grant, Sharon Sydow, and Jayson Beckman

10.1 Introduction

In 2020, the world economy suffered an immediate and significant global recession brought on by the coronavirus (COVID-19) pandemic. Global gross domestic product (GDP) shrank 3.2 percent (International Monetary Fund [IMF] 2021). In response to disease outbreaks, many national and sub-national governments imposed lockdowns, stay-at-home orders, and the promotion of remote business and education activities to thwart the spread of the virus. These actions contributed to significant disruptions of

Shawn Arita is a Senior Economist in the Office of the Chief Economist of the US Department of Agriculture.

Jason Grant is the W. G. Wysor Professor of Agriculture and Director of the Center for Agricultural Trade at Virginia Tech.

Sharon Sydow is a Senior Economist in the Office of the Chief Economist of the US Department of Agriculture.

Jayson Beckman is an Economist with the Economic Research Service of the US Department of Agriculture.

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non-essential businesses including restaurants, bars, shopping centers, and attractions.[1] Service and tourism industries have been particularly hard hit. For example, the year over year percentage change in weekly airline traffic plunged well over 50 percent for most industrialized nations in 2020 compared to 2019.[2] However, as countries have learned to manage the crisis, GDP forecasts for global economic growth in 2021 and 2022 have become more optimistic with forecasts of 6 and 4.9 percent growth, respectively (IMF 2021).[3]

In the early phases of the pandemic, initial 2020 forecasts for world trade were bleak. In April 2020, the World Trade Organization (WTO) forecasted declines in the value of real exports of −8.1 percent, −16.5 percent, and −20.4 percent under a V- (optimistic), U- (less optimistic), and L-shaped (pessimistic) set of economic recovery scenarios, relative to a baseline without pandemic (WTO 2020a).[4] However, even the most optimistic scenario turned out to overstate the actual decline in total trade in 2020, which, according to the WTO, was −5.3 percent (WTO 2021).[5] The WTO identified several reasons for the better-than-expected trade performance in 2020, including strong monetary and fiscal policies in many governments, business, and household innovation and adaptation that helped stabilize economic activity, and trade policy restraint (WTO 2021). While some trade restrictive measures were initially introduced when the pandemic began, including export restrictions for cereals, most of these measures were rescinded and new restrictions were not imposed. Countries also introduced trade facilitating measures in response to the pandemic, such as lowering import tariffs or taxes (Evenett et al. 2021).

Global trade in food and agricultural products also outperformed the WTO's initial projections, growing 3.5 percent in 2020. The smaller impact of the pandemic on global agricultural trade is likely related to several factors including a low-income elasticity of food demand, shipping channels that do not require substantial human interaction (i.e., bulk commodities), and the essential nature of the industry that many governments declared. Indeed, the WTO (2020b) describes agricultural trade during the COVID-19 pandemic as a "story of resilience" and one of the few "bright spots" in the

1. Experience with similar diseases (i.e., SARS, MERS, H1N1) reveals that while the human costs can be significant, the economic toll is due to the preventive behavior of individuals and the transmission control policies of governments (Brahmbhatt and Dutta 2008).

2. Flight data provided by Statista: https://www.statista.com/statistics/1104036/novel-coronavirus-weekly-flights-change-airlines-region/.

3. It should be noted that prior outlooks forecasted a larger contraction in GDP. In June 2020, the World Bank forecasted a 5.2 percent decline in global GDP growth; the International Monetary Fund (IMF 2020) projected a 4.2 percent decline. The World Bank forecasts growth of 5.6 percent in 2021 and 4.3 percent in 2022.

4. For agricultural exports, the projected decline was −6.5 percent, −11.2 percent, and −12.7 percent, respectively.

5. According to its latest projections, the WTO forecasts a growth in trade of 8.0 percent in 2021 and 4.0 percent in 2022.

global economy. Nevertheless, global food insecurity rose during the pandemic, with FAO estimating that 768 million people were facing hunger in 2020, 118 million more people than in 2019 (FAO et al. 2021).

While descriptive analyses may shed some light on the trade flow impacts of the pandemic, simple year over year changes are clouded by other confounding factors including ongoing animal disease challenges related to African swine fever (ASF) in pork and swine production, burgeoning feed demand by China related to a faster than expected recovery of its hog herd, policy changes such as the US-China Phase One trade agreement, and other factors. While global agricultural trade registered an overall increase in 2020, it is unclear to what extent COVID-19 affected trade flows conditional on other confounding factors. Identifying the pandemic effect from other factors is the key empirical objective of this paper.

A few studies have investigated the impacts of COVID-19 on international trade. Mallory (2020) analyzed early 2020 monthly data and found that beef and pork markets were temporarily impacted by lower exports during the initial onset of COVID-19, whereas grains and oilseeds markets were not affected. Friedt and Zhang (2020) estimate that the pandemic reduced Chinese exports by 40–45 percent during the initial wave. The authors estimate that China's domestic supply shocks contributed about 10–15 percent of the total reduction in Chinese exports, while international import demand shocks reduced the propensity of countries' purchases of Chinese exports by only 5–10 percent. Kejzar and Velic (2020) characterize the impacts of COVID-19 on supply chains in terms of the relative upstream or downstream position of an industry. Recently, Beckman and Countryman (2021) found that agricultural trade increased by 2.3 percent in 2020; but the information they present is at a highly aggregated level—and only accounts for total 2020 trade, without providing the decomposition done here. Arita, Grant, and Sydow (2021) provided a preliminary "early look" assessment of the impacts on agricultural trade using quarterly country-level data on imports of agricultural and non-agricultural commodities in a non-directional framework using data through August 2020. This paper builds off this analysis by using a more rigorous bilateral estimation framework across disaggregated agricultural commodities and market regions, adds non-agricultural and manufacturing trade to the analysis, and includes a longer time period (complete 2020 calendar year).

This article provides a comprehensive retrospective quantitative assessment of the impacts of COVID-19 on food and agricultural trade. Specifically, we develop a monthly reduced form, gravity-based model of bilateral agricultural and non-agricultural trade and econometrically assess different dimensions of the global pandemic effect. We examine the extent to which COVID-19 affected bilateral trade in 2020 relative to the pre-pandemic era, using high-frequency monthly data and detailed agricultural product sectors to account for the heterogeneous impact of the pandemic on economic outcomes and differences in underlying requirements of product distribution. As the governmental response to the pandemic was diverse and many countries experienced several surges of COVID-19 infections, we leverage variation in country-specific mobility restrictions and national lockdown stringency to identify trade impacts. To the best of our knowledge, this study is the first to systematically quantify the differential impacts of the pandemic on agricultural versus non-agricultural trade using a full calendar year of monthly data.

Our analysis aims to unpack various components of the COVID-19 pandemic effect on trade and is organized as follows. First, we examine the impacts of the overall agricultural sector and compare them to quantified impacts on the non-agricultural sector. Our estimated pandemic effect is decomposed between COVID-19 incidence rates, policy restrictions, *de facto* reduction in human mobility/lockdown effects and further between import demand and export supply disruptions. Second, we disaggregate impacts across product types and stratify which products were most affected by the pandemic compared to product sectors that were unaffected or even benefited from its indirect effects. Third, we illustrate the differential impact of the pandemic across countries with differing development levels and income classification, highlighting in particular the more severe impacts on low-income countries. Fourth, our analysis examines how the pandemic impacts on trade may have shifted throughout the year as industries learned to operate within the health and safety guidelines necessitated by the pandemic. Finally, we examine the pandemic's impact on the extensive margin of trade using monthly US port level shipments.

Potential impacts of trade restricting and trade facilitating policy responses to the pandemic were not incorporated into this analysis, although we believe that any positive or negative effects these measures had on agricultural trade during the period were likely minimal. First, these measures covered a relatively small share of total agricultural and food trade. Evenett et. al. (2021) estimate that export restraints applied to agriculture and food trade during January–October 2020 covered $39.4 billion (3 percent) of total 2019 trade, while import reforms covered $42.2 billion (4 percent). Second, Evenett et. al. (2021) found that trade policy intervention in food trade was not as geographically widespread and more likely to be temporary relative to medical products and personal protective equipment (PPE), which accounted for almost all of the COVID-19-related trade policy responses. Third, relatively stable food supplies and prices prior to the pandemic likely reduced the broad, open-ended use of export controls as observed in earlier periods (e.g., 2007/08 and 2010/11) when grain stocks were low, and prices spiked. Heterogeneous trade policy responses, both in terms of duration and type of measure, as well as some countries' concurrent use of both trade restricting and trade facilitating measures, adds a great deal of complexity to such an analysis.[6] While not the focus of this article, we view this topic as a fruitful area for further exploration, particularly looking at differential commodity effects.

10.2 COVID-19, Agricultural Markets, and Global Trade Trends

In this section, we provide an overview of the implications of COVID-19 on agriculture markets and trade. Specifically, we summarize the latest trade data and document the main stylized facts and trends before and during the global pandemic. Food and agricultural production and trade are generally considered an essential industry in most countries, which meant many agricultural workers, producers, wholesalers, retailers, and distributors were able to continue moving agricultural product through the supply chain (Chenarides, Manfredo, and Richards 2020). However, as Yaffe-Bellany and Corkery (2020) and Lusk, Tonsor, and Schulz (2021) found, the shuttering of restaurants, hotels, bars, entertainment attractions, and schools due to lockdown policies resulted in supply chain disruptions for certain agricultural products, leaving some producers with very few buyers. The COVID-19 pandemic is a complicated event because it affects both aggregate demand and supply and is dependent on the nature of the industry, the exposure of workers to illness (Luckstead, Nayga Jr., and Snell 2021), and the ability of supply chains to adapt to sharp changes in the way final products are consumed (i.e., food at home).

10.2.1 COVID-19 Trade Disruption Not Historically Large

Disruptions to food and agricultural trade resulting from economic, natural, or trade policy induced shocks are not new. Figure 10.1 plots the quarterly percent change of global agricultural and non-agricultural trade from 2005Q1 through 2020Q4. Figure 10.2 presents monthly values of global agricultural and non-agricultural trade during the 2018–2020 period. Several sharp declines in trade stand out. First, the Great Recession of 2007–2009 marked the most significant collapse in trade. Global manufacturing trade fell by 30 percent. Global agricultural trade fell by 20 percent (figure 10.1). However, the economic expansion period that followed was one of the longest on record. From 2009Q3 through 2014Q4, global agricultural and non-agricultural trade growth remained positive (the exception of 2012Q3 for non-agricultural trade). Second, beginning in 2015, world trade experienced a significant slowdown; commodity prices fell from their recent highs,

6. In a separate study, Ahn and Steinbach (2021) examined the determinants and factors that prompted countries to implement NTMs during the pandemic. Their study found that for the agricultural and food sector, the effects of COVID-19 cases were more correlated with facilitating trade than restricting it. Notably, they found a lower likelihood of trade-facilitating actions with domestic COVID-19 cases whereas they found a positive association for worldwide cases.

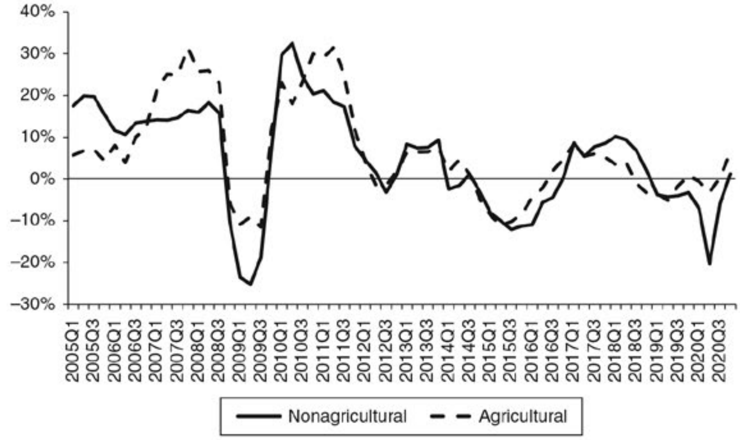

Figure 10.1 Changes in the growth of the value of global trade in 2020 not historically large

Note: Agricultural trade includes all HS codes defined under USDA's BICO definition of Agricultural and Agricultural-related goods. Non-agricultural trade includes all other HS codes.

Source: Author calculations using data from Trade Data Monitor, growth is in real terms.

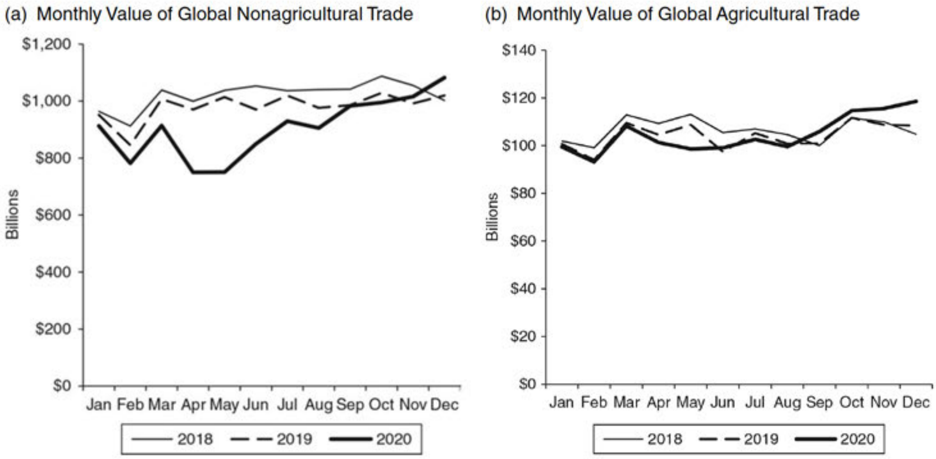

Figure 10.2 Non-agricultural trade plunged in 2020; agricultural trade relatively stable

Note: Agricultural trade includes all HS codes defined under USDA's BICO definition of Agricultural and Agricultural-related goods. Non-agricultural trade includes all other HS codes (not including trade in services). Trade values in real terms.

Source: Author calculations using data from Trade Data Monitor.

the US dollar appreciated, and the IMF lowered its forecast for global economic growth (see also UNCTAD 2016). These global macro factors led to a slowdown in global trade, with US and global agricultural exports falling more than 10 percent, a steeper contraction than currently observed under COVID-19 (figure 10.1). Third, in 2018, a trade dispute between the US and China and several other trading partners led to a significant escalation in applied tariffs and a resulting decline in US-China agricultural and merchandise trade (Crowley 2019; Bown 2018; Bown 2019; Amiti, Redding, and Weinstein 2019; Grant et al. 2021); nevertheless, global quarterly trade growth fell only slightly below zero.

10.2.2 Agricultural Trade Relatively Stable under COVID-19

Agricultural trade under COVID-19 has been relatively stable. Global agricultural trade fell 2 percent in 2020Q2 during the initial wave of COVID-19 infections and lockdowns; however, food and agricultural trade rebounded significantly during 2020Q3 and 2020Q4 and ended the year up. On the other hand, non-agricultural trade under the COVID-19 pandemic in 2020Q2 experienced the second largest contraction in global trade since 2005. Non-agricultural trade subsequently experienced a strong recovery in Q3 and Q4, but still remained down by the end of 2020.[7] The smaller impact on agricultural trade may reflect the relatively lower income elasticity of food demand, particularly for staple food items, and the structure of the agricultural global value chains which is less fragmented than manufacturing and other merchandise trade. Additionally, agricultural trade, which occurs more substantially through bulk marine shipments, is likely to be less susceptible to disruption to transport restrictions in other sectors that require more human interaction (WTO, 2020b). Interestingly, compared to the Great Recession of 2007–2009, when agricultural trade fell by large amounts, trade under the pandemic has remained stable, even though in both instances global GDP fell (and the decline in GDP was larger for COVID-19).

10.2.3 Uneven Changes in Agricultural Trade

While overall aggregate changes in agricultural trade have been generally stable, there are differences at the product and country level. Figure 10.3 presents the percentage change in 2020 trade flows (in value and volume) relative to 2019 across product sector categories and trading countries. Products used to make higher-end goods such as hides and skins, cotton, rubber, and nursery are among the sectors that saw the largest contraction in trade during the COVID-19 pandemic. These sectors are more likely to have a higher income elasticity of demand and thus are relatively more sus-

7. Non-agriculture does not include trade in services. In 2020, global trade in services fell over 20 percent, reflecting a much more significant effect from the pandemic than merchandise trade.

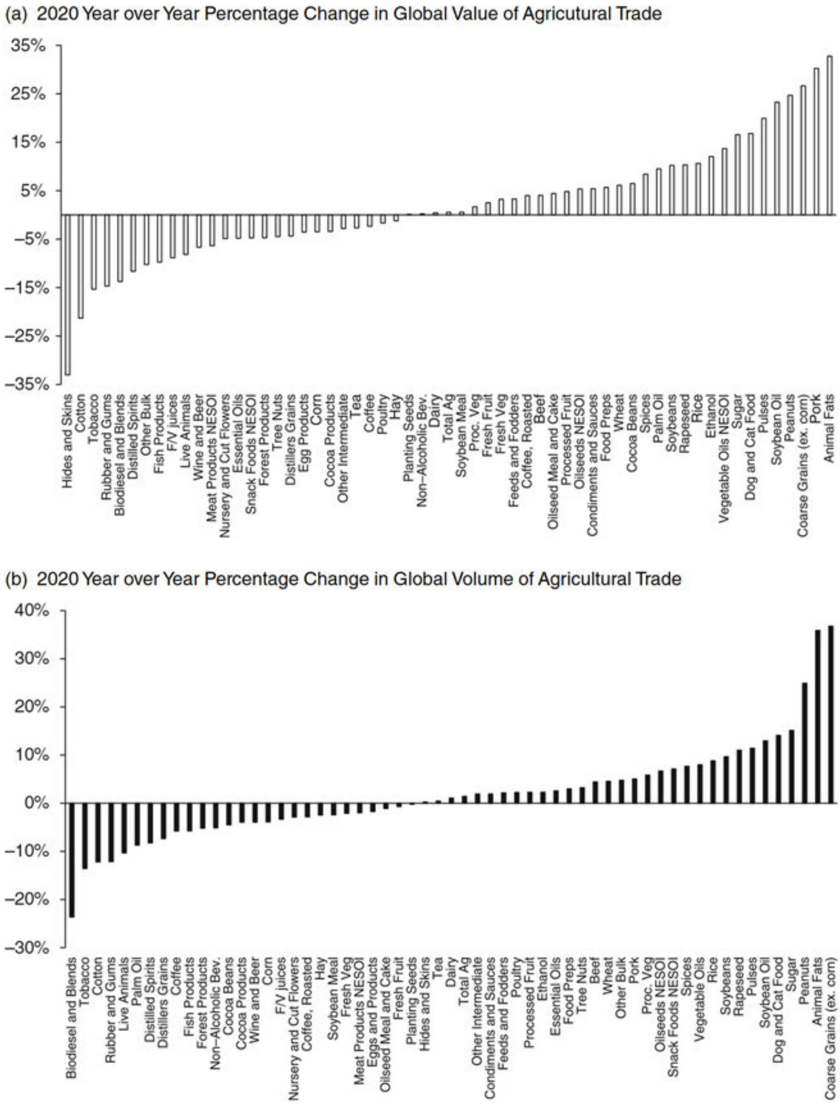

Figure 10.3 Uneven changes in the value and volume of global agricultural trade
Source: Author calculations using data from Trade Data Monitor. Trade values in real terms.

ceptible to aggregate demand shocks and lockdowns. Retail sales of clothing and textiles plummeted as clothing and apparel stores closed, weaker demand for retail purchases due to stay at home orders, and lower incomes as unemployment increased or workers became furloughed. Secondly, there is a clear dichotomy between food products more likely to be consumed at home versus those being consumed away from home. For example, trade in sectors characterized by high restaurant or food away from home consumption, such as seafood, poultry, and beef products (Binkley and Liu 2019), have declined globally. In comparison, trade in staple products such as cereal grains and protein crops, which are more likely to be consumed at home or serve as intermediate inputs for processing, has increased. Finally, the role of workers falling ill at meat packaging plants and plant closures in the US, Brazil, and other major meat exporting countries was also expected to weigh on exports due to temporary supply disruptions (Lusk, Tonsor and Schulz 2021). However, on an annual basis, figure 10.3 illustrates that beef, poultry, and especially pork increased significantly compared to 2019 trade values.

10.2.4 Other Agricultural Trade Shocks Occurring in 2020: Record China Import Demand, African Swine Fever (ASF), and Policy Changes

When examining year over year changes in trade, it is important to recognize that there are additional trade shocks that have occurred outside COVID-19. Simple year over year changes indicate that pork and oilseeds have experienced among the highest growth in 2020, an increase driven by ASF that has ravaged herd populations in China, Asia, and other parts of the world. China—which prior to ASF consumed almost half the world's pork supply—has faced severe supply shortfalls (down more than 20 percent since 2018), and has imported record amounts of pork, raising global prices.

As China's pig herd recovered and was further consolidated into more grain-fed operations, China's import demand for grains and oilseeds grew substantially with soybean imports expanding by an additional \$4 billion in 2020. Corn and coarse grain imports also surged on China's restocking efforts, increased demand from the larger and more grain intensive pig herd; wheat imports also increased as China has shifted some of the wheat grains to feed. The US-China Phase One agreement may also have supported further imports with selective waivers on retaliatory tariffs and liberalization of non-tariff measures on many key import sectors.

China, in fact, drives much of the overall observed global growth in 2020. Figure 10.4 shows that of the \$20 billion increase in global agricultural trade in 2020, China accounted for over 95 percent of that growth and fueled higher global commodity prices. Excluding increased China demand, the world would have experienced virtually zero agricultural trade growth in 2020. East-Asia (excluding China) and North America (excluding US) stand out in particular in terms of weak import growth.

10.3 Econometric Approach and Data

10.3.1 Econometric Model

Descriptive analysis suggests that agricultural trade has been generally stable under COVID-19. However, most of this assessment has relied on

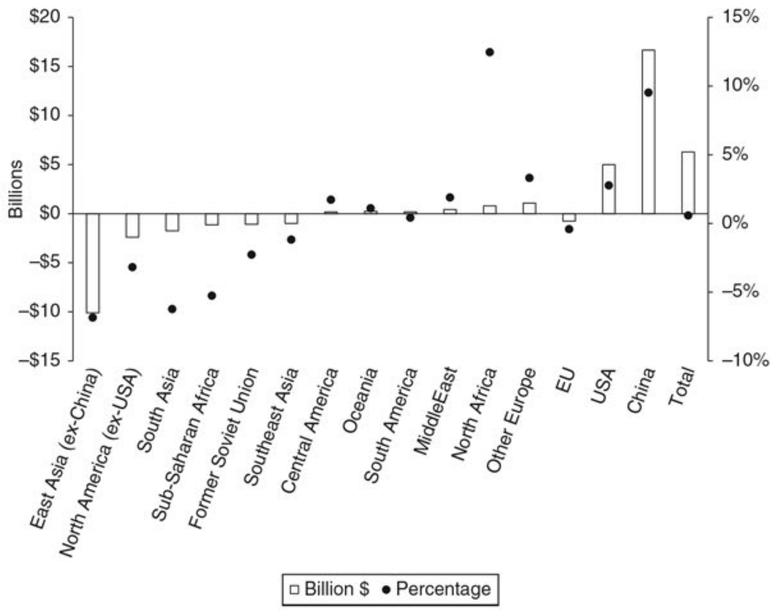

Figure 10.4 Agricultural trade growth in 2020 dominated by strong import demand in China. Figure shows change in value of agricultural imports year over year (2020 versus 2019).

Source: Author calculations using data from Trade Data Monitor, deflated into real dollars.

simple year over year changes that ignores confounding natural (i.e., ASF) and policy-induced (i.e., US-China Phase One) factors. To isolate the effect of COVID-19, we employ a rigorous monthly panel data econometric model of disaggregated product-line bilateral trade relationships. This approach exploits variation in country-and-month-specific indicators to estimate the (partial) direct trade effects of the pandemic-induced shock using a theoretically consistent model of bilateral trade flows at the product level as presented by Yotov et al. (2016), Peterson et al. (2013), Baldwin and Taglioni (2006), and Head and Mayer (2014). Following Grant et al. (2021), this approach is further extended by the use of a monthly dimension which provides a further source of within-year variation specific to many agricultural commodity exports. This framework has also been employed by Fajgelbaum et al. (2020) and Carter and Steinbach (2020), who investigated the impacts of the 2018–2019 trade war on manufacturing and agricultural product-line trade controlling for pre-trends and seasonality.

The gravity model used here is not fully structural as in Anderson and Yotov (2016) in conditional or full endowment general equilibrium (GE). By design, the GE gravity setup requires intra-national trade flows (i.e., trade with self) which is nearly impossible to obtain across months within years.

Thus, our results are consistent with best practices to estimate partial direct effects also advocated by Yotov et al. (2016) and Grant et al. (2021).

Denote exporting (importing) countries as i (j) and products, months, and years as k, m, and t, respectively. Using monthly panel data from January 2016 through December 2020 of bilateral-product-month relationships ($ijkm$), our baseline estimating equation to quantify the trade effect of COVID-19 on agricultural and non-agricultural exports is:

$$(1) \quad X_{ijkmt} = \exp\{\mu_{ijkm} + \pi_{it} + \varphi_{jt} + \kappa_{kt} + \xi_{mt} + \gamma_1 \text{Cov19}_{imt} + \gamma_2 \text{Cov19}_{jmt}\} + \varepsilon_{ijkmt},$$

where exp denotes the exponential function, X_{ijkmt} is the value of bilateral trade between exporting country i, importing country j, product group k, month m ($m = 1, 2, \ldots 12$), and year t ($t = 2016, 2017, \ldots 2019, 2020$). Equation (1) contains a comprehensive set of exporter-importer-product-month specific fixed effects,[8] μ_{ijkm}, designed to absorb all time-invariant product-and-month specific bilateral trade cost or natural trading partner effects.[9] Such trade cost factors include existing non-tariff measures (see Grant and Arita 2017; Ning and Grant 2019), transportation costs (i.e., distance), existing free trade agreements (i.e., US-Korea, China-Australia, etc.), bilateral applied tariffs, time-invariant natural, cultural and geographical factors, as well as within-year seasonality of supply and demand of product k. In addition to μ_{ijmk}, we also include importer-year (φ_{jt}), exporter-year (π_{it}), product-year (κ_{kt}) fixed effects, and month-year (ξ_{mt}) fixed effects, which are time varying, but not bilateral-specific, to control for changes in a country's overall inward or outward multilateral agri-food trade resistance (it, jt) and year-to-year fluctuations in global commodity prices (kt) or shifts in global agricultural trade patterns.

The direct and indirect effects of COVID-19 are captured from both the export and import side. Cov19_{imt} (Cov19_{jmt}) is an exporter-month-year (importer-month-year) specific COVID-19 variable designed to capture the influence of cases, deaths, lockdowns, and mobility impacts on an exporter's (importer's) trade with all partners. COVID-19 is a complicated multifac-

8. In their sensitivity analysis, Grant et al. (2021) included different degrees of fixed effects, with some specifications not including the full set of dummies (i.e., the exclusion of jt, kt, or mt). Results of their finding were generally robust to the different sets of fixed effects; however, the full set was viewed as being the most exhaustive in absorbing unobserved effects that would otherwise show up in the error term, and thus forms the basis of our estimations here. Estimates employing a smaller set of fixed effects (excluding π_{it}, φ_{jt}, and/or ξ_{kt}) were also performed and found to be largely robust to the full set of fixed effects. These estimates are available upon request.

9. For example, US-Canada, US-Mexico trade in many product lines is naturally higher than many other country-pairs in the model because of some shared border, language, cultural, and institutional similarities between USMCA/NAFTA partners. If we instead tried to leverage variation between country-pairs in the model for identification, we would miss the important fact that there are preexisting trends and trade relationships that are specific to country-pair-product and month (i.e., US exports of soybeans to China peak in the post-harvest fall season, whereas Brazilian soybean exports are counter-seasonal and peak in the US's spring planting season).

eted shock, and there is no single indicator that can reflect the entirety of its impact. Thus, we employ a battery of indicators attempting to capture different elements of its trade effect as discussed in the data section.

As suggested by Santos Silva and Tenreyro (2006), we adopt the Poisson-Pseudo-Maximum Likelihood PPML estimator because it retains the multiplicative theoretical structure of gravity type models (equation 1). It is also robust to unknown patterns of heteroskedasticity and allows the dependent variable to remain in levels (as opposed to logarithms) permitting the inclusion of zero trade flows in estimation. Zero trade flows are key in the context of assessing trade policy or pandemic-induced trade shocks at the product level, and for cases of thinner trade relationships among least developed economies for exports of certain processed food products. If the reason for zero trade is related to the COVID-19 pandemic in certain months, then omission of zero trade flows creates the classic sample selection bias leading to underestimation of trade impacts.

Finally, whereas equation (1) investigates the impact of COVID-19 on the value and volume (i.e., levels) of agricultural and non-agricultural trade, it may be the case that the pandemic's more severe disruptions occurred through supply chain logistical delays and reductions in the number of product shipments during heightened shutdown or mitigation periods to control the virus's spread. That is, the pandemic may have affected the extensive margin (number of product shipments) relatively more than the intensive margin (value or volume exported per product) of trade. US census trade data track monthly export shipments at district, port, and airport locations. In total we have monthly US export data for 353 ports and 52 airports for a total of 401 shipment localities.

Denoting ports as p, the extensive margin effect of COVID-19 is estimated as follows:

$$N_{pmt} = \exp\{\mu_{pm} + \alpha_t + \gamma_1 \mathrm{Cov19}_{smt}\} + \varepsilon_{pmt}\,, \tag{2}$$

where, N_{pmt} is the extensive margin of trade defined as the count of the number of product shipments to the world market from port p, in month m and year t. All port-level exports to the global market are included for the years 2017 and 2020 of monthly data.[10] We chose 2017 as the pre-pandemic reference year when evaluating the extensive margin to mitigate any potential slowdown in some port-level shipments of agricultural products due to the US-China trade dispute. During this dispute, some agricultural shipments halted, and certain products ended up in storage as the trade dispute continued. μ_{pm} and α_t are a comprehensive set of port-month and year fixed effects, respectively. In equation (1) the COVID-19 incidence rates, lockdown

10. Because of download restrictions when accessing port level shipment data, we do not include a bilateral trade dimension (i.e., port-by-destination market), and products are defined at the HS4-digit level.

policy stringency, and mobility indicators were defined at the country level. Because port locations can be mapped directly to US states, we employ COVID-19 case and death incidence, policy stringency, and mobility indicators at the state level. Specifically, in equation (2), $Cov19_{smt}$ represents state-specific COVID-19 cases, deaths, Oxford Policy Stringency and Google Mobility indices across months, where s, m, and t denote state, month, and year, respectively. If COVID-19 affected the extensive-product margin of trade—as measured by product throughput per port—then we would expect γ_1 to be negative (positive in the case of Google Mobility indicators).

10.3.2 Data

Monthly bilateral exports from January 2016 through December 2020 reported by 93 countries to 207 importing markets are retrieved from Trade Data Monitor.[11] The sample includes 57 agricultural and related product groups as defined by USDA's Bulk, Intermediate and Consumer-Oriented products (see appendix A and appendix B for a list of country sample and commodity grouping). Thus, an observation comprises a country pair, BICO product, month, and year. We also collect aggregate non-agricultural trade data from the same source. Given the nearly 5,000 HS6-digit product codes comprising non-agriculture, we aggregate all non-agricultural products into a single sector. While this likely masks some of the pandemic's effect on individual manufacturing sectors (i.e., vehicles and parts, aircraft, electronics), it does provide a benchmark comparison from which to judge the agricultural trade effects.

US port-level exports are retrieved from the US Census Bureau.[12] For each port we observe the monthly total value and shipping weight (i.e., volume) of exports for each HS4 product. Total export values and volumes are further broken out into the value of seaborne containerized vessel exports and the value of airborne exports to the world market. We have global exports for 428 port locations in the US and a total of 501,482 port-month observations comprising the years 2017 and 2020. The extensive margin of product throughput per port is the count of the number of HS4 product exports for each month in year t. In terms of total export values, the largest ports in 2020 were New Orleans, Houston, Oakland, and Los Angeles with \$19, \$17.7, \$15.1, and \$12 billion of total agricultural export values, respectively. However, in terms of containerized vessels, Oakland, Los Angeles, Long Beach, and New York City were the largest, with 2020 agricultural exports

11. Trade Data Monitor data are available by subscription at https://tradedatamonitor.com/. Exporter reported information was selected relative to importer reported information, since the former has arguably less data lag between transaction (time when trade sale occurred) and COVID-19 events. We also tested import reported information and found the results consistent with the export reported information.

12. Accessed at: https://usatrade.census.gov/.

of \$14.2, \$11.3, \$10.6, and \$7.4 billion. New York City, Miami, Boston, and Detroit saw the largest airborne shipments in 2020.

COVID-19 indicators used in this study are collected from the following sources:

i. *Direct outbreaks*: increase in the number of coronavirus cases or deaths reported in importing country *j* and exporting country *i* per million people (Johns Hopkins University). These data are available at: https://github.com/CSSEGISandData/COVID-19.

ii. *Policy response*: Oxford Policy Stringency Index in importing country *j* and exporting country *i*. The Oxford COVID-19 Government Response Tracker (OxCGRT) systematically collects information on several different common policy responses that governments have taken to respond to the pandemic on 18 indicators such as school closures and travel restrictions. It now has data for more than 180 countries. The Oxford Stringency Index ranges from 0–100. These data are available at: https://www.bsg.ox.ac.uk/research/research-projects/covid-19-government-response-tracker.

iii. *De facto reduction in human mobility/lockdown effect*: Community Mobility indicator in importing country [deviation from pre-COVID-19 baseline] using workplace and retail people traffic are retrieved from Google Mobility data, available at: https://www.google.com/COVID-19/mobility/.

Figure 10.5 presents the distribution of COVID-19 cases and death rates per million residents, the Oxford Policy Stringency Index and Google's Workplace Mobility indicator. The mean of COVID-19 cases per million residents is 1,575 with a median of 172. Andorra, Belgium, Czech Republic, Croatia, Luxembourg, Montenegro, and Serbia experienced average monthly COVID-19 cases per million residents greater than 25,000. These more extreme cases incidences occurred in October through December of 2020. Mean COVID-19 deaths per million residents is 27 with a median of 5 and a maximum of 766. Belgium, Bulgaria, Croatia, Slovenia, and San Marino all experienced COVID-19 death rates per million residents above 500, which occurred in March, April, November, and December 2020. The government lockdown stringency index as reported by Oxford has a mean of 56 and a median of 58, a minimum of 1 and a maximum of 100 (100 indicates complete lockdown). Ten countries imposed lockdown stringencies that exceeded 90 on the index: Argentina, Azerbaijan, Guatemala, Honduras, India, Jordan, Philippines, Serbia, the State of Palestine, and Slovenia. Interestingly, China, which was often highlighted as imposing strict lockdown measures, was not on the top-10 list. China's highest Oxford Policy reading was 80, and it imposed this level of stringency for 4 out of 12 months in 2020 (i.e., a longer duration of more stringent policies to stop the viral spread). By comparison, Argentina's reading of 100 on the Oxford indicator was imposed only in April 2020.

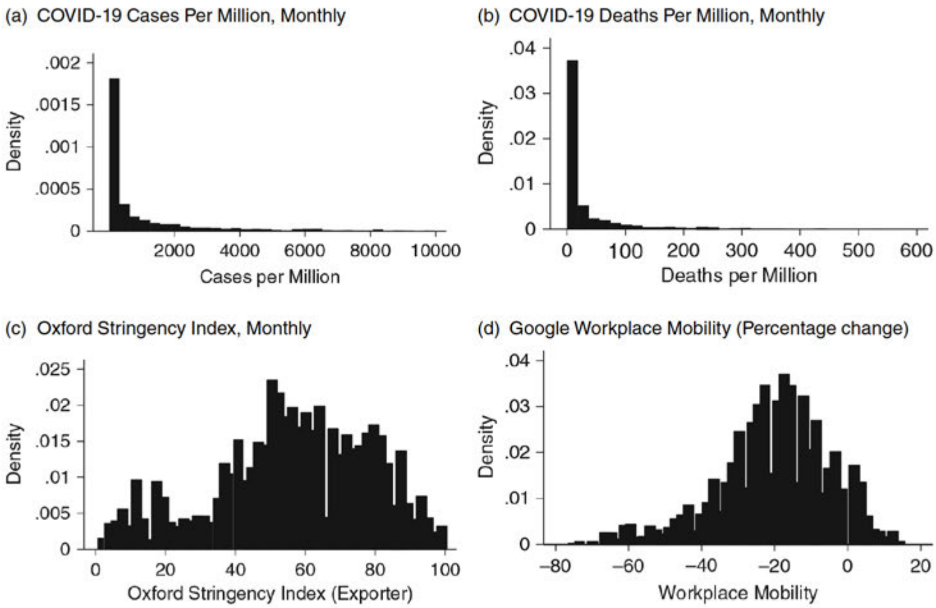

Figure 10.5 Distribution of COVID-19 cases, deaths, policy stringency and Google Mobility, March 2020 to December 2020

Source: Author calculations using cases and death rates data from Johns Hopkins University, Policy Stringency data from Oxford, and Workplace and Retail Mobility from Google. COVID-19 cases are truncated at 10,000 monthly cases per million residents to ease horizontal axis scaling. Similarly, monthly COVID-19 deaths per million residents care truncated at 600.

10.4 Econometric Results

The econometric results are organized according to different dimensions and components by which COVID-19 may be affecting international trade. Subsection one reports the overall effects on non-agriculture and agriculture. The second subsection presents the disaggregated effects on individual agricultural trade values and volumes. The third subsection examines the impacts across regions focusing in particular on how trade between low income countries were affected. In the fourth subsection we address within-year timing and dynamics of the COVID-19 trade effect. Finally, in the fifth subsection we estimate the extent to which COVID-19 indicators may have impacted the extension margin of US port shipments.

10.4.1 Estimated Sector Level Effects of Non-agricultural vs. Agricultural Trade

What is the effect of COVID-19 on global trade in 2020, holding other factors constant? Table 10.1 presents the aggregate sector level effects for

Table 10.1 **Estimated impact of COVID−19 on the value of bilateral trade: non−agricultural vs. agricultural goods**

VARIABLES	Non−Ag Goods value (1)	Ag value (2)	Non−Ag Goods value (3)	Ag value (4)	Non−Ag Goods value (5)	Ag value (6)	Non−Ag Goods value (7)	Ag value (8)	Non−Ag Goods value (9)	Non−Ag Goods value (10)
COVID Cases Exporter	−0.004***	0.002								
	(0.00)	(0.00)								
COVID Cases Importer	0.001	−0.003*								
	(0.00)	(0.00)								
COVID Deaths Exporter			−0.177**	−0.042					0.120*	−0.035
			(0.07)	(0.06)					(0.07)	(0.04)
COVID Deaths Importer			−0.167**	−0.248***					0.041	−0.085*
			(0.07)	(0.06)					(0.08)	(0.05)
Oxford Policy					−0.455***	−0.044			0.002	0.022
Stringency Exporter					(0.06)	(0.03)			(0.05)	(0.03)
Oxford Policy					−0.144***	−0.204***			0.072*	0.012
Stringency Importer					(0.04)	(0.05)			(0.04)	(0.03)
Google Workplace							0.396***	0.163***	0.443***	0.105**
Mobility Exporter							(0.05)	(0.04)	(0.07)	(0.05)
Google Retail							0.249***	0.143***	0.299***	0.135***
Mobility Importer							(0.03)	(0.02)	(0.05)	(0.04)
Observations	560,288	494,400	550,098	485,309	558,093	492,792	753,584	644,922	496,991	440,651

Note: The Dep. variable is value of trade estimated with PPML. Includes *ijm*, *it*, *jt*, *mt*, fixed effects. Standard errors are in parentheses and robust to clustering on *ijm*. *,**, and *** denote statistical significance at the 10, 5, and 1 percent levels, respectively. Estimated on monthly data from Jan. 2016 to Dec. 2020. Agricultural trade includes all HS codes defined under USDA's BICO definition of Agricultural and Agricultural−related goods; non-agricultural trade includes all other HS codes. Negative effect on trade is implied by a negative sign for cases and death counts and Oxford Policy Stringency and a positive sign for Google Mobility indices. Johns Hopkin's case/death counts are rescaled per a thousand, and Oxford Policy Stringency and Google Mobility indicators are rescaled to a 0−100 percent scale.

both the value of non-agricultural and agricultural trade for different indicators of the pandemic effect. All estimations include bilateral-month (i_{jm}), importer-year (i_t), exporter-year (j_t), and month-year (m_t) fixed effects. Since the estimates are performed at the overall sector level, product level fixed effects are omitted, and all standard errors are clustered by country-pair-and-month.[13]

Columns 1–4 report the estimated direct effect of the outbreak. The insignificant or small size of the coefficients suggests a very limited direct effect of the pandemic. For agricultural trade, a significant effect is found only on the death counts reported by the importing country. The coefficients in column 4 imply that each additional fatality per million people due to COVID-19 is associated with a 0.018 percent reduction in monthly agricultural trade. In our sample, the average number of new COVID-19 deaths reported per month, across all countries, is 27. Applying the estimated coefficient to the mean death count indicates that COVID-19 reduced agricultural trade by −0.5 percent, on average, throughout 2020. For non-agricultural trade, the direct COVID-19 effect for death counts is significant on both the exporter and importer side; however, the average effect implied by our coefficient estimates amounts to only a 1.1 percent reduction. The effect of COVID-19 case counts is largely negligible.

The stronger effect of the pandemic is more likely to be driven by the policy response of governments attempting to curb outbreaks and the mandatory and voluntary quarantining of individuals. The next set of results supports this. Columns 5 and 6 report the estimated impact of the Oxford Policy response. For non-agricultural trade, the coefficients are negative and statistically significant on both the exporter and importer COVID-19 indicator. A one unit increase in an importer's policy restrictiveness due to COVID-19 leads to reduction of agricultural trade of 0.2 percent. In 2020, the average importing countries' policy index was elevated to 52 percent. Applying our estimated coefficient to this average indicates that government policy response to COVID-19 reduced agricultural trade flows by 10 percent, on average. Similar to the direct effect, policy restrictions on the importer side were also negative and significant for agricultural trade, but not significant on the export side. The results may suggest that the COVID-19 effect may have been more significant through import demand channels rather than export supply. In contrast, exporter's policy response to COVID-19 is found to be much stronger for non-agricultural trade, which could be attributed to the more vulnerable supply chains occurring in non-agricultural trade that are typically longer and more complex than agricultural supply chains.

13. Estimates were also performed at the product level with product level fixed effects (using BICO codes). Results are provided in appendix C. The estimates on effects of the trade value with product effects are strongly robust to the estimates at the overall agricultural sector level. A separate set of estimates was also performed in terms of volumes, which was also found to be robust to the estimates in terms of value.

Columns 7 and 8 report the human mobility reduction/de facto lockdown effect of the COVID-19 using the Google Mobility indicators. Coefficients for the level of workplace mobility on the exporter side and retail mobility on the import side are positive for both non-agriculture and agriculture.[14] A 1 percent decrease in the level of workplace mobility for an exporter relative to the periods prior to COVID-19 led to a 0.4 percent reduction in non-agricultural trade and a 0.16-percent reduction in agricultural trade. In our sample the average level of workplace traffic fell by 17.8 percent under the pandemic, and retail traffic by 19.1 percent. Applying these averages to the estimated coefficients implies a 6 percent reduction in the average agricultural trade flow. By comparison, the de facto lockdown effect is about twice as large for non-agricultural trade.

Columns 9 and 10 report the results estimating all components jointly. We recognize that these variables may exhibit significant multicollinearity and thus several of the individual coefficients lose significance. Similar to the previous columns we find that the estimated effect is larger for non-agricultural than agricultural trade (twice as large). Interestingly, the COVID-19 effect seems to convey more significance on the import demand side for agricultural trade, whereas for non-agricultural trade it appears to impact export supply more severely.

It is also of interest to note the differences implied by the econometric findings relative to the simple year over year changes reported in the previous section. While year over year changes in global agricultural trade were up +2 percent in 2020, our econometric estimations (which control for other factors outside the pandemic) find statistically significant negative effects. The results suggest an approximate impact on the range of a 5–10 percent reduction in agricultural trade as predicted by the model due to COVID-19 direct and indirect factors. While two to three times smaller than non-agricultural trade, the results provide quantitative evidence that agricultural trade was not entirely resilient. Our findings also provide empirical support that policy restrictions and de facto lockdowns imposed by the importing countries are the main channels of trade loss.

10.4.2 Which Commodities Were Most Severely Impacted by the Pandemic?

In addition to some of the contrasting impacts of COVID-19 between agriculture and non-agriculture sectors, our earlier descriptive analysis also suggested noticeable differences within the agricultural sector. To understand how COVID-19 effects vary across individual product sectors, in this section we perform estimations at the commodity level as defined by USDA agricultural and agricultural-related (BICO) product groups. For these sets

14. Recall, Google Mobility indicators are in terms of deviations from a pre-pandemic benchmark, whereby reduced mobility implies a negative deviation. If reduced mobility is expected to decrease agricultural and non-agricultural trade, then we expect the sign on the mobility coefficients to be positive.

of estimations we estimate the joint effect of COVID-19, including direct (death counts per million), policy response (Oxford Policy Stringency), and de facto lockdown (Google Mobility) on both the importer and exporter side.[15] Case counts are not included in this specification due to the weak significance of these results found within the overall agricultural sector as reported in table 10.1.

Appendix D shows the estimation results, across individual commodities. The findings indicate very heterogeneous COVID-19 effects. In some commodities we find very large and significant negative effects, whereas others are found to carry insignificant or even positive effects. We find that 25 percent of the commodities suffered a significant negative effect from the incidence rate (death counts) impact of the pandemic, 50–55 percent from policy restrictions, and 35–40 percent from the de facto lockdown effect. In contrast, about 10 percent of the commodities are found to have experienced a positive impact from COVID-19, likely through demand shifting. Notably a slight majority of commodities (55–60 percent), were not found to be insignificantly affected by the pandemic.

Table 10.2 attempts to stratify the impacts of the pandemic across scenarios. It employs the coefficient estimates in table 10.3 and applies a one standard deviation shock to each of the COVID-19 effects (death counts, policy response, and de facto lockdown), and quantifies the resulting impact by commodities. The results are sorted from lowest to highest of the average impact across all indicators. Non-food agricultural commodities—hides and skins (−15 percent); ethanol (−10 percent); cotton (−7 percent); nursery flowers (−6 percent); rubber (−5 percent)—are found to have suffered the highest impacts. Certain meat products (−5 percent) and seafood (−5 percent), beef (−4 percent), poultry (−3 percent), and pork (−2 percent) also suffered among the most severe disruptions. Distilled spirits; tea; and sugar and sweeteners are among the other agri-food areas found to have been significantly negatively impacted.

It is of interest to note how our econometric results differ from simple year over year changes in other commodities. According to our estimates, global pork trade was reduced on average by 2 percent given a one standard deviation sized shock in COVID-19 policy restrictions and de facto lockdown effect. This stands in strong contrast to the over 20 percent increase in global growth as shown through simple year over year changes presented in section 10.2.3, which was driven by ASF. Rapeseed, which experienced an 11 percent increase in global trade in 2020, largely on confounding supply side shocks,[16] was found to be insignificantly impacted by COVID-19 in terms of the direct and indirect effects. Our estimation thus appears able to at least partially disentangle the COVID-19 effect for these commodities. For beef trade—

15. Estimations were also performed for individual sets of COVID-19 indicators and are available upon request.

16. For instance, EU rapeseed production suffered under droughts and disease, leading to a significant import demand increase in 2020 (Reuters 2020).

Table 10.2 **COVID−19 trade impact across commodities**

Product−group	1. Direct Effect (Deaths per million)	2. Policy Response (Oxford Stringency)	3. Human mobility reduction (Google)	4. Average (average of Direct, Policy Response, and Google Mobility effects)
Hides and skins	0%	−22%	−24%	−15%
Ethanol	−7%	−7%	−16%	−10%
Corn	0%	0%	−22%	−7%
Cotton	0%	−11%	−10%	−7%
Distilled spirits	−5%	−5%	−10%	−6%
Nursery flowers	−5%	−9%	−4%	−6%
Meat products NESOI	−3%	−8%	−5%	−5%
Essential oils	−6%	−4%	−5%	−5%
Rubber allied gums	0%	−4%	−11%	−5%
Fish products	−2%	−7%	−6%	−5%
Tea	0%	−6%	−9%	−5%
Sugars sweeteners		−6%	−7%	−5%
Forest products	0%	−3%	−9%	−4%
Beef	−3%	−3%	−6%	−4%
Cocoa beans	0%	−11%	0%	−4%
Poultry	−3%	−3%	−4%	−3%
Tobacco	−3%	−7%	0%	−3%
Snack foods NESOI	−1%	−3%	−3%	−3%
Coffee unroasted	2%	0%	−9%	−3%
Peanuts	0%	−8%	0%	−3%
Pork	−2%	−2%	−3%	−2%
Biodiesel blends	0%	0%	−6%	−2%
Wheat	−6%	0%	0%	−2%
Chocolate cocoa products	−1%	−3%	−1%	−2%
Hay	−5%	0%	0%	−2%
Eggs	0%	−4%	0%	−1%
Feeds fodders NESOI	0%	−4%	0%	−1%
Pet food	0%	−3%	0%	−1%
Processed vegetables	0%	−3%	0%	−1%
Spices	2%	−5%	0%	−1%
Food prep.	0%	−2%	0%	−1%
Other int. products	0%	−2%	0%	−1%
Fresh fruit	0%	0%	−1%	0%
Animal fats	0%	0%	0%	0%
Distillers grains	0%	0%	0%	0%
Fresh vegetables	0%	0%	0%	0%
Fruit vegetable juices	0%	0%	0%	0%
Non alcoholic bev	0%	0%	0%	0%
Palm oil	0%	0%	0%	0%
Pulses	0%	0%	0%	0%
Rapeseed	0%	0%	0%	0%
Soybean meal	0%	0%	0%	0%
Vegetable oils NESOI	0%	0%	0%	0%
Condiment sauces	1%	−2%	2%	0%
Processed fruit	1%	0%	0%	0%
Live animals	2%	0%	0%	1%
Dairy products	0%	3%	0%	1%
Oilseed meal	3%	0%	0%	1%
Tree nuts	0%	−8%	12%	1%
Coffee roasted extracts	1%	3%	0%	1%
Other bulk commodities	0%	5%	0%	2%

Table 10.2 **(continued)**

Product–group	1. Direct Effect (Deaths per million)	2. Policy Response (Oxford Stringency)	3. Human mobility reduction (Google)	4. Average (average of Direct, Policy Response, and Google Mobility effects)
Rice	4%	0%	4%	3%
Planting seeds	2%	5%	2%	3%
Soybean oil	9%	0%	0%	3%
Soybeans	0%	34%	0%	11%

Note: Impact applies cofficients estimated in table 10.2 to a one standard deviation shock of each COVID-19 indicator. One standard deviation is approximately equivalent to: Death counts-50 people per million; Oxford Policy Stringency-15 percent; and Google Mobility-10 percent. Column 4 is simple average of first three columns.

which had increased in 2020 relative to 2019—our results found a 4 percent decline given a one standard deviation shock, which is consistent with the supply chain disruptions that occurred in major producing countries.

We find that for many of the grains and oilseeds and prepared and processed foods there is a relatively small or insignificant effect. The stratification of estimated impacts seems to generally align with what has been found in the income demand elasticity literature. Non-food-related products are typically found to be the most sensitive to income shocks, followed by higher-value meat and specialty products, then staple grains and oilseeds. Consistent with the simple year over year changes, rice—a perennial staple food item—increased 4 percent given a one standard deviation COVID-19 incidence death rate or a one standard deviation in de facto lockdown effect. Soybeans are found to have a significant positive effect from the Oxford Policy restrictions. This could be attributed to increased demand driven by China's recovering herd size and thus reflecting a possible limitation in our approach to completely isolate the COVID-19 impact; however, the effect is insignificant in terms of death counts and de facto lockdown effect.

We also estimated the impact of COVID-19 on volume of trade. By focusing on volumes, we control for commodity price changes and isolate the impacts in terms of real changes in shipments.[17] Results are reported in appendix E and are found to be largely consistent with the estimations performed on values and roughly similar in magnitude.

10.4.3 Are Low Income Country Agricultural Trade Flows More Vulnerable to the Pandemic?

Concerns have been raised that COVID-19 may disproportionally affect low income countries more severely compared to high income countries. On the demand side, low income countries spend a much larger share of their

17. We note that our estimations on values do include month-time fixed effects, which at least partially controls for seasonality and price effects.

household budgets on food, and thus their purchases are more sensitive to income changes that may be caused by COVID-19. Further, low income countries may also be more vulnerable to supply chain disruptions. Ex-ante assessments indicate significant impacts on lower income countries. For example, using the USDA Economic Research Service Food Security model, Baquedano et al. (2021) found that 160 million additional people across the world may face insecurity as result of the COVID-19 pandemic.[18] Separately, the FAO estimated that an additional 118 million would become food insecure as a result of the pandemic (FAO et al. 2021). This section empirically examines whether we can detect any evidence of a disproportionate impact on low income country agricultural trade.

Table 10.3 performs the estimations according to selected subsamples which partition the data into income groups defined by the World Bank. Low income groups are defined as countries with a GNI per capita of less than \$4k, middle income countries \$4k–\$12.5k, and high income >\$12.5k. China, for example, is a middle income country. The results in table 10.4 report varying degrees of significance across the different specifications. Overall the differences across COVID-19 indicators and income groups tend to be mixed. The de facto level of lockdown for the importing country is generally larger for trade within low income countries relative to trade within high income countries. A 10 percent increase (approximately equivalent to a one standard deviation) of the de facto lockdown effect leads to a 5 percent reduction in low income to low income agricultural exports but only a 3 percent reduction for high income to high income trade. However, the effects of government policy responses is mixed. Low income to middle income agricultural exports are significant, but low income to low income agricultural exports are not significant. The overall results do not seem to provide compelling evidence that low income country agricultural trade was more severly impacted by the pandemic compared to agricultural trade between high income countries. However, we caveat that given the ongoing nature of the pandemic and rising COVID-19 outbreaks occuring in 2021 for several large developing nations, further research is warranted in assessing these differences. Finally, we also note that the coefficient on deaths per importer tends to be statistically significant (and negative) across all wealth/trade spectrums, while the coefficient on deaths per exporter is only significant in two scenarios (affecting exports to high income countries).

10.4.4 Pandemic Effects across Quarters

We also examine how COVID-19 impacted agricultural and non-agricultural trade during different periods of the pandemic. To perform

18. Study compares pre-pandemic forecasts from the ERS food security model to post-pandemic forecasts and finds an additional 160 million more insecure people in the post-forecast.

Table 10.3 **Impact of COVID−19 on the value of bilateral agricultural trade, by country income groups**

Level of Income	Low−Low (1)	Low−Mid (2)	Low−High (3)	Mid−Low (4)	Mid−Mid (5)	Mid−High (6)	High−Low (7)	High−Mid (8)	High−High (9)
COVID Deaths Exporter	−0.125	0.171	−0.080**	0.005	0.158	−0.154***	0.019	−0.020	−0.003
	(0.20)	(0.21)	(0.04)	(0.12)	(0.16)	(0.04)	(0.07)	(0.07)	(0.06)
COVID Deaths Importer	−0.077	−0.345**	−0.098**	−0.035	−0.230**	−0.138***	−0.331***	−0.327***	−0.258***
	(0.16)	(0.16)	(0.04)	(0.10)	(0.12)	(0.05)	(0.07)	(0.07)	(0.07)
Observations	184,546	194,227	255,460	241,435	249,147	297,309	319,875	325,724	358,712
Oxford Policy Stringency	−0.029	0.016	−0.094***	−0.146***	−0.064	−0.105***	0.054	0.020	−0.013
Exporter	(0.07)	(0.07)	(0.03)	(0.05)	(0.05)	(0.03)	(0.04)	(0.04)	(0.04)
Oxford Policy Stringency	−0.095	−0.336***	−0.022	−0.115**	−0.235***	−0.054	−0.289***	−0.257***	−0.229***
Importer	(0.06)	(0.09)	(0.03)	(0.05)	(0.07)	(0.03)	(0.07)	(0.06)	(0.07)
Observations	187,726	196,301	260,341	244,291	251,287	302,026	325,672	330,953	365,253
Google Workplace	0.258**	0.253***	0.166***	0.258***	0.335***	0.184***	0.077*	0.101**	0.124***
Mobility Exporter	(0.11)	(0.09)	(0.04)	(0.08)	(0.08)	(0.04)	(0.04)	(0.04)	(0.04)
Google Retail Mobility	0.217***	0.096	0.077***	0.154***	0.114**	0.099***	0.193***	0.169***	0.154***
Importer	(0.07)	(0.06)	(0.03)	(0.05)	(0.05)	(0.03)	(0.03)	(0.02)	(0.02)
Observations	289,913	251,152	318,745	346,947	308,473	364,132	449,892	427,673	467,559

Note: The Dep. variable is value of agricultural trade estimated with PPML. Includes *ijm*, *it*, *jt*, *mt*, fixed effects. Standard errors are in parentheses and robust to clustering on *ijm*. *,**, and *** denote statistical significance at the 10, 5, and 1 percent levels, respectively. Estimated on monthly data from Jan. 2016 to Dec. 2020. Agricultural trade includes all HS codes defined under USDA's BICO definition of Agricultural and Agricultural−related goods. Product groups defined by BICO codes. Income groups defined by World Bank Classification. High income countries have GNI per capita >$12.5k, Middle income $4–$12.5k, and Low Income <$4k. (1) Low−low means low income country exports to low income country, (2) low−mid means low income country exports to middle income country, and the rest of the columns follow accordingly. Negative effect on trade is implied by a negative sign for death counts and Oxford Policy Stringency and a positive sign for Google Mobility indices. For presentation purposes of the estimations, the Johns Hopkins case/death counts are rescaled per a thousand and Oxford Policy Stringency and Google Mobility indicators are rescaled to a 0−100 percent scale.

this analysis, we estimate quarter-specific regressions throughout 2020 for both the non-agricultural and agricultural sector. Table 10.4 reports the results. Columns 1–3 present the results using the number of deaths to explain agricultural and non-agricultural trade effects. The direct incidence rates are once again very limited and weak for both non-agricultural and agricultural trade. Columns 4–6 report the results using the Oxford Policy response. Here, the results are quite stark with a larger and more statistically significant negative COVID-19 effect under Q2 relative to Q3 and Q4. We also find that the de facto lockdown impact is most severely felt under Q2 and tends to lessen in Q3 and Q4. The joint effect indicates a similar finding.

We note that in some cases the effect is not only due to changes in the severity of COVID-19 indicators; it is also attributed to an attenuation of the COVID-19 effect across time. For instance, the coefficient results for the policy restrictiveness lessens from Q2 to Q4. We observe some similar weakening for the de facto coefficients, however, to a lesser degree. The results may suggest a learning effect whereby trade and supply chains may have adjusted to both the policy restrictions and de facto lockdown factors of COVID-19 following initial disruption in Q2.

10.4.5 Estimated Impacts along the Extensive Margin of US Agricultural Trade

In this final section, we consider whether the pandemic has impacted the number of agricultural product shipments passing through US ports. If the pandemic resulted in workers becoming ill, staying home, or mandatory shutdown of plants due to outbreaks of COVID-19, then perhaps the pandemic's effect on international trade is not necessarily through the value or volume of exports but in terms of the number of products exported as a measure of product throughput per port. US port-level data track product shipments in aggregate and by shipment method: containerized vessel versus airlifted shipments.

Table 10.6 presents the results after estimation of equation (2) using the Oxford Stringency Index of the policy response of state-level governments to the pandemic (Oxford), and percentage change in Google's Workplace Mobility (Workplace), also at the state level. Overall, the results suggest that US policy measures to contain the spread of the virus (Oxford) lead to a decrease in number of extensive product margin shipments per port (table 10.6, All Months, 2020). Across 428 port locations, the state-level Oxford Stringency index varies widely with a mean of 52 and a standard deviation of 24.[19] Thus a one (two) standard deviation increase in state governments' policy response to the de facto lockdown is representative of a 27 (92) percent increase around the mean. The results across all months in 2020 imply

19. The coefficient of variation is 0.46.

Table 10.4 **Effects of COVID−19 on the value of non−agriculture bilateral trade by quarter**

Quarter	Q2 (1)	Q3 (2)	Q4 (3)	Q2 (4)	Q3 (5)	Q4 (6)	Q2 (7)	Q3 (8)	Q4 (9)	Q2 (10)	Q3 (11)	Q4 (12)
COVID Deaths	−0.428***	−0.806***	−0.402***							0.110	−0.326**	0.126
Exporter	(0.13)	(0.17)	(0.11)							(0.11)	(0.15)	(0.08)
COVID Deaths	−0.377***	−0.408*	0.108							−0.204*	−0.119	0.208**
Importer	(0.13)	(0.24)	(0.09)							(0.11)	(0.16)	(0.09)
Oxford Policy				−0.662***	−0.473***	−0.530***				0.003	−0.004	−0.001
Stringency Exporter				(0.07)	(0.07)	(0.08)				(0.09)	(0.06)	(0.07)
Oxford Policy				−0.334***	−0.095**	0.020				−0.132*	0.076*	0.013
Stringency Importer				(0.04)	(0.05)	(0.05)				(0.07)	(0.05)	(0.05)
Google Workplace							0.458***	0.376***	0.577***	0.567***	0.367***	0.686***
Mobility Exporter							(0.07)	(0.06)	(0.08)	(0.12)	(0.09)	(0.11)
Google Retail							0.360***	0.278***	−0.002	0.228***	0.292***	0.161**
Mobility Importer							(0.04)	(0.03)	(0.04)	(0.07)	(0.05)	(0.08)
Observations	269,982	270,795	267,231	280,408	280,966	277,591	377,960	378,595	374,499	244,319	244,913	241,589

Note: The Dep. variable is value of agricultural trade estimated with PPML. Includes *ijm*, *it*, *jt*, *mt*, fixed effects. Standard errors are in parentheses and robust to clustering on *ijm*. *,**, and *** denote statistical significance at the 10, 5, and 1 percent levels, respectively. Estimated on monthly data from Jan. 2016 to Dec. 2020. Negative effect on trade is implied by a negative sign for death counts and Oxford Policy Stringency and a positive sign for Google Mobility indices. For presentation purposes of the estimations, the Johns Hopkins case/death counts are rescaled per a thousand and Oxford Policy Stringency and Google Mobility indicators are rescaled to a 0−100 percent scale.

Table 10.5 **Effects of COVID−19 on value of agriculture bilateral trade by quarter**

Quarter	Q2 (1)	Q3 (2)	Q4 (3)	Q2 (4)	Q3 (5)	Q4 (6)	Q2 (7)	Q3 (8)	Q4 (9)	Q2 (10)	Q3 (11)	Q4 (12)
COVID Deaths Exporter	−0.017	0.001	0.037							0.055	0.118	−0.042
	(0.07)	(0.13)	(0.15)							(0.06)	(0.11)	(0.08)
COVID Deaths Importer	−0.220***	−0.366**	−0.234*							−0.0836	−0.094	−0.025
	(0.07)	(0.15)	(0.13)							(0.06)	(0.16)	(0.08)
Oxford Policy Stringency Exporter				−0.123***	−0.038	−0.036				0.203***	0.077	0.000
				(0.04)	(0.04)	(0.06)				(0.06)	(0.05)	(0.06)
Oxford Policy Stringency Importer				−0.241***	−0.172**	−0.207**				−0.0012	−0.043	−0.005
				(0.06)	(0.07)	(0.10)				(0.05)	(0.05)	(0.05)
Google Workplace Mobility Exporter							0.259***	0.227***	0.244***	0.430***	0.262***	0.137
							(0.05)	(0.06)	(0.07)	(0.09)	(0.08)	(0.10)
Google Retail							0.121***	0.107***	0.058	0.091*	0.090	0.080
							(0.03)	(0.03)	(0.04)	(0.05)	(0.06)	(0.07)
Observations	237,977	238,163	235,525	247,517	247,527	245,162	323,281	323,814	320,767	216,309	216,452	214,024

Note: The Dep. variable is value of agricultural trade estimated with PPML. Includes *ijm*, *it*, *jt*, *mt*, fixed effects. Standard errors are in parentheses and robust to clustering on *ijm*. *,**, and *** denote statistical significance at the 10, 5, and 1 percent levels, respectively. Estimated on monthly data from Jan. 2016 to Dec. 2020. Negative effect on trade is implied by a negative sign for death counts and Oxford Policy Stringency and a positive sign for Google Mobility indices. For presentation purposes of the estimations, the Johns Hopkins case/death counts are rescaled per a thousand and Oxford Policy Stringency and Google Mobility indicators are rescaled to a 0−100 percent scale.

Table 10.6 **Extensive margin impacts at the US port level for agricultural shipments, all months, 2017 and 2020**

	No. Product Exports	No. Container Exports	No. Air Shipments	No. Product Exports	No. Container Exports	No. Air Shipments
All Months, 2020						
Oxford Policy Stringency	−0.079***	−0.070***	−0.117***			
	[0.010]	[0.019]	[0.017]			
Google Workplace Mobility				0.176***	0.126**	0.253***
				[0.022]	[0.040]	[0.034]
N	6,514	2,334	3,109	6,561	2,362	3,143
R^2	0.99	0.99	0.99	0.99	0.99	0.99
First Wave (Mar/Apr)						
Oxford Policy Stringency	−0.121**	−0.029	−0.188**			
	[0.037]	[0.073]	[0.065]			
Google Workplace Mobility				0.197***	0.069	0.298***
				[0.056]	[0.104]	[0.087]
N	1,109	389	546	1,116	393	551
R^2	0.99	0.99	0.99	0.99	0.99	0.99
Second Wave (Jul/Aug)						
Oxford Policy Stringency	−0.027	0.121	−0.245			
	[0.075]	[0.151]	[0.162]			
Google Workplace Mobility				0.420*	0.156	0.394*
				[0.173]	[0.290]	[0.246]
N	1,089	381	522	1,097	386	528
R^2	0.99	0.99	0.99	0.99	0.99	0.99
Third Wave (Nov/Dec)						
Oxford Policy Stringency	−0.075	0.039	−0.085			
	[0.084]	[0.101]	[0.148]			
Google Workplace Mobility				0.064	0.020	0.300*
				[0.133]	[0.249]	[0.173]
N	1,072	396	508	1,080	401	514
R^2	0.99	0.99	0.99	0.99	0.99	0.99

Note: The Dep. var. is the number of monthly agricultural product shipments per port for all US port localities including airports (No. of Product Exports); the number of containerized vessel exports per port (No. of Container Exports), and the number of airlifted shipments (No. of Air Shipments). All regressions include port−month and year fixed effects. *, **, *** denote statistical significance at the 10, 5, and 1 percent levels, respectively. Negative effect on trade is implied by a negative sign for Oxford Policy Stringency and a positive sign for Google Mobility indices.

a reduction of two (four) product shipments per port in 2020 on average for a one (two) standard deviation increase in the Oxford Stringency index. Similar results were obtained when evaluating the number of containerized product exports. For air shipments, however, the size of the coefficients is much more severe. Here, a one (two) standard deviation increase in state governments' Oxford Policy response is associated with three (six) fewer products transported by air per port.

The coefficients representing Oxford's state government response to the pandemic were generally larger during the first wave (First Wave, Mar/Apr) (with the exception of containerized exports). Thereafter, the effect of state governments' response on the extensive product margin of port-level shipments declined significantly in the second and third waves of the pandemic and became largely insignificant across modes of shipment. As reported previously, this could suggest a "learning effect" as workers and port managers better understood how to manage the policy restrictions necessitated by the pandemic. One exception is the coefficient on the policy response measured by the Oxford Stringency for air shipments during the second wave of the pandemic (−0.245). However, the coefficient is only significant beyond the 10 percent level (p-value = 0.13).

The remaining three columns in table 10.6 report the results using Google's Workplace Mobility indicator at the state level matched to port locations. Here, the pandemic's mean reduction in workplace mobility is 26 percent with a standard deviation across port-month locations of 8. The highest (absolute) reduction in workplace exceeding 60 percent occurred in Washington, D.C., Massachusetts, and New Jersey port locations. The results suggest that moving from a pre-pandemic mobility situation to the mean (−26 percent) results in five fewer product shipments per port overall and seven fewer product shipments that are transported by air. A one standard deviation move above the mean leads to two fewer shipments per port and four fewer air-transported product shipments. In contrast to the Oxford Policy impacts, the coefficient magnitudes tend to increase in the first and second waves of the pandemic. For example, during the summer wave (Second Wave, Jul/Aug) months, a further two standard deviation reduction in workplace mobility results in seven fewer product shipments per port overall and six fewer products transported by air. This translates to an approximate 10 percent contraction in the extensive margin of port-level agricultural trade in the US.

10.5 Conclusion

This study conducted a comprehensive one-year retrospective econometric assessment of the impact of the COVID-19 pandemic on global agricultural trade. Given the multifaceted nature of the pandemic's effect on domestic markets and global trade and supply chains, summarizing the pandemic's overall impact is challenging. However, several empirical findings are apparent as it relates to this pandemic and its effects on agricultural trade.

First, holding other factors constant, our estimates suggest that COVID-19 reduced overall agricultural trade by the approximate range of

5 to 10 percent, an effect two to three times smaller than our estimated effect for non-agricultural trade. The channels by which the pandemic has impacted agricultural trade is most evident through its de facto reduction in human mobility (voluntary or mandatory based) and secondly, government policy restrictions. Direct COVID-19 case and death count incidence was found to carry very limited association and quantifiable effects on trade. For agriculture trade, the negative impacts of the pandemic estimated by our model seem to be manifested more through import demand channels as opposed to export supply shocks.

Second, sharp differences in trade impacts were observed across agriculture commodities. However, the COVID-19 trade effect permeated in many non-food items (hides and skins, ethanol, rubber, cotton), which suffered the steepest trade losses. Meat products, including seafood, and higher-value agri-food products were also found to have been significantly negatively impacted. A few commodities experienced a positive impact, likely due to demand shifts for staple products (e.g., rice). Nevertheless, after an extensive empirical search the majority of agricultural commodities were not found to experience a significant trade impact from the pandemic, even when investigating quarterly within-year effects associated with various "waves" of the pandemic's more intense outbreaks and lockdown situations. We found evidence that trade flows adjusted to COVID-19 disruptions over time; however, for non-food items and some agricultural commodities, pandemic effects continued to persist through the end of 2020.

Third, several international organizations including the WTO and United Nations were concerned that the pandemic may impact low income developing countries relatively more because these countries may not be as well connected to global supply chains. However, we find limited and mixed evidence that low income and least developed countries' trade flows were more vulnerable to the COVID-19 shock, although future research should investigate this effect for key commodities of export interest to low income nations.

Finally, we found evidence that the pandemic impacted the extensive margin of agricultural trade. On average, product throughput as measured by the number of products exported per port per month fell by five overall and seven fewer products by air. At the mean, this suggests an 8 percent contraction in product shipments overall and 10 percent for products transported by air.

While this analysis shed light on the trade flow effects of the COVID-19 pandemic, the results should be put into perspective with the following caveats. First, the pandemic is still ongoing, and thus does not account for reemergence of outbreaks and ongoing surges occurring in 2021 and beyond. Second, the COVID-19 coefficients may be picking up other contemporaneous factors influencing bilateral trade not explicitly considered in this analysis. For example, several countries altered their export policies including export controls on products such as medical supplies, personal protective equipment (PPE), and some staple agricultural products. While many of these policies were temporary in nature (i.e., lasting only a month or two), the extent that these policies are correlated with the COVID-19 variables considered here could bias our estimates of the trade effects of de facto lockdown and immobility. Third, it would be interesting to disentangle monthly per capita income effects across countries in the sample that could be driving some of the results, particularly for higher valued nonfood items. For example, many of our COVID-19 government policy and de facto lockdown results were stronger on the import demand side, which could be the contemporaneous result of de facto lockdowns and declining per capita income. Although the 2020 (annual) income effect is absorbed by the importer-year fixed effect (jt), large monthly shocks to per-capita incomes are likely not well accounted for by country-time effects.[20] Additional variables that more fully describe within-year seasonality and international agricultural markets and food supply chains should improve the performance of gravity-based models at the monthly level. Finally, there may be important dynamics underlying the COVID-19 indicators and the time in which trade flows are recorded in the data. That is, there may be some incongruity between the time when COVID-19 cases, deaths, government responses, and decreased mobility indicators are surging, reflecting more serious phases of the pandemic and the time with which trade flow changes appear in countries' national statistics. On the other hand, while these lags may be important in the data and not fully captured in the current analysis, we tested alternative lag structures among the COVID-19 indicators with resulting estimates largely robust.[21]

To return to the original question posed in this article's title, Has global agricultural trade been resilient under COVID-19? The findings of our study suggest a *qualified* yes. Yes, this study did indeed find evidence of resilience, in that the econometric results found relatively small (but still statistically significant) negative effects of the pandemic that was robust along many dimensions of analysis and slices of the data—which could be interpreted as a testament of the stability of agricultural trade, at least in aggregate. However, we would also temper any broad conclusions given the high degree of evenness of impacts found by our analysis, which included evidence of severe disruptions for some sectors within agriculture. While the pandemic is still ongoing and direct and indirect effects continue to permeate across the international trading landscape, the findings summarized above offer useful empirical insights about how agricultural trade fares through a major global health crisis.

20. On the other hand, for many countries, income effects may have been stabilized, in part, through fiscal stimulus measures (IMF 2021).

21. Estimates available upon request.

Appendix A

Appendix 10A.1 List of countries in data set

Exporters			Importers			
Albania	India	Senegal	Afghanistan	Ecuador	Liberia	Saudi Arabia
Argentina	Indonesia	Serbia	Albania	Egypt	Libya	Senegal
Australia	Ireland	Singapore	Algeria	El Salvador	Lithuania	Serbia
Austria	Israel	Slovakia	Andorra	Estonia	Luxembourg	Sierra Leone
Bahrain	Italy	Slovenia	Angola	Ethiopia	Macao	Singapore
Belarus	Japan	South Africa	Argentina	Fiji	Madagascar	Slovakia
Belgium	Jordan	South Korea	Armenia	Finland	Malaysia	Slovenia
Belize	Kazakhstan	Spain	Australia	France	Maldives	Somalia
Bolivia	Kenya	Sri Lanka	Austria	French Polynesia	Mali	South Africa
Bosnia	Kosovo	Sweden	Azerbaijan	Gabon	Malta	South Korea
Botswana	Latvia	Switzerland	Bahamas	Gambia	Mauritania	Spain
Brazil	Lithuania	Taiwan	Bahrain	Georgia	Mauritius	Sri Lanka
Brunei	Luxembourg	Thailand	Bangladesh	Germany	Mexico	Sudan
Bulgaria	Macao	Turkey	Belarus	Ghana	Moldova	Swaziland
Canada	Madagascar	Ukraine	Belgium	Greece	Mongolia	Sweden
Chile	Malaysia	United Kingdom	Benin	Guatemala	Montenegro	Switzerland
China	Malta	United States	Bolivia	Guinea	Morocco	Syria
Colombia	Mauritius	Uruguay	Bosnia	Haiti	Mozambique	Taiwan
Costa Rica	Mexico	Zambia	Botswana	Honduras	Myanmar	Tajikistan
Cote d'Ivoire	Montenegro		Brazil	Hong Kong	Namibia	Tanzania
Croatia	Morocco		Brunei	Hungary	Nepal	Thailand
Cyprus	Mozambique		Bulgaria	Iceland	Netherlands	Togo
Czech Republic	Myanmar		Burkina Faso	India	New Zealand	Trinidad and Tobago
Denmark	Namibia		Cambodia	Indonesia	Nicaragua	Tunisia

(continued)

Appendix 10A.1 (continued)

Exporters		Importers			
Ecuador	Netherlands	Cameroon	Iran	Niger	Turkey
Egypt	New Zealand	Canada	Iraq	Nigeria	Turkmenistan
El Salvador	Nicaragua	Chile	Ireland	North Macedonia	Uganda
Estonia	North Macedonia	China	Israel	Norway	Ukraine
Ethiopia	Norway	Colombia	Italy	Oman	United Arab Emirates
Finland	Pakistan	Congo (DROC)	Jamaica	Pakistan	United Kingdom
France	Panama	Congo (ROC)	Japan	Panama	United States
Georgia	Paraguay	Costa Rica	Jordan	Papua New Guinea	Uruguay
Germany	Peru	Cote d'Ivoire	Kazakhstan	Paraguay	Uzbekistan
Ghana	Philippines	Croatia	Kenya	Peru	Venezuela
Greece	Poland	Cuba	Kuwait	Philippines	Vietnam
Guatemala	Portugal	Cyprus	Kyrgyzstan	Poland	Yemen
Honduras	Qatar	Czech Republic	Laos	Portugal	Zambia
Hong Kong	Romania	Denmark	Latvia	Qatar	Zimbabwe
Hungary	Russia	Djibouti	Lebanon	Romania	
Iceland	Saudi Arabia	Dominican Republic	Lesotho	Russia	

Appendix B

Appendix 10B.1 Agricultural and agricultural-related sectors defined by USDA (BICO) definition

BICO Product Category	BICO Aggregate Sector	HS6–digit Codes Comprising BICO Sectors
Coarse Grains	BULK	100200, 100290, 100300, 100390, 100400, 100490, 100700, 100790, 100820, 100829, 100840, 100850, 100860, 100890
Cocoa Beans	BULK	180100
Coffee (raw/unroasted)	BULK	090112, 090111
Corn (not for seed)	BULK	100590
Cotton	BULK	140420, 520100
Gums	BULK	130190, 400110, 400121, 400122, 400129
Oilseeds	BULK	120300, 120400, 120600, 120710, 120720, 120729, 120730, 120740, 120750, 120760, 120791, 120792, 120799
Other Bulk	BULK	100810, 100830, 121210, 121291, 121292, 121293, 140190, 140200, 140210, 140290, 140291, 140299, 140300, 140310, 140390, 140490, 400130, 500100, 500200, 530110, 530121, 530129, 530130, 530210, 530290, 530310, 530390, 530410, 530490, 530500, 530511, 530521, 530590, 530591, 530599
Peanuts/Groundnuts	BULK	120210, 120220, 120241, 120242
Pulses	BULK	071310, 071320, 071331, 071332, 071333, 071334, 071335, 071339, 071340, 071350, 071360, 071390
Rapeseed	BULK	120500, 120510, 120590
Rice	BULK	100610, 100620, 100630, 100640
Soybeans	BULK	120190
Tobacco	BULK	240110, 240120, 240130
Wheat	BULK	100110, 100119, 100190, 100199
	BULK	
Alcohol	CONSUMER	220290, 220291, 220299, 220300, 220410, 220421, 220422, 220429, 220430, 220510, 220590, 220600, 220810, 220820, 220830, 220840, 220850, 220860, 220870, 220890
Beef	CONSUMER	020110, 020120, 020130, 020210, 020220, 020230, 020610, 020621, 020622, 020629, 021020, 160250
Biodiesel	CONSUMER	382600
Cheese	CONSUMER	040610, 040620, 040630, 040640, 040690
Cocoa products	CONSUMER	180310, 180320, 180400, 180500, 180610, 180620, 180631, 180632, 180690
Coffee (roasted/processed)	CONSUMER	090121, 090122, 090140, 090190, 210110, 210111, 210112, 210130
Condiments	CONSUMER	210310, 210320, 210330, 210390, 220900
Dairy (excl. Cheese)	CONSUMER	040110, 040120, 040130, 040140, 040150, 040210, 040221, 040229, 040291, 040299, 040310, 040390, 040410, 040490, 040500, 040510, 040520, 040590, 170210, 170211, 170219, 190110, 210500, 350110, 350190, 350220, 350710, 980210

(continued)

Appendix 10B.1 **(continued)**

BICO Product Category	BICO Aggregate Sector	HS6-digit Codes Comprising BICO Sectors
Eggs	CONSUMER	40700, 40711, 40719, 40721, 40729, 40790, 40811, 40819, 40891, 40899, 350210, 350211, 350219, 350290
Ethanol	CONSUMER	220710, 220720
Food Preparations	CONSUMER	190120, 190190, 190211, 190219, 190220, 190230, 190240, 190300, 190410, 190420, 190430, 190490, 190590, 210410, 210420, 210690
Fresh Fruit	CONSUMER	080300, 080310, 080390, 080430, 080440, 080450, 080510, 080520, 080521, 080522, 080529, 080530, 080540, 080550, 080590, 080610, 080710, 080711, 080719, 080720, 080810, 080820, 080830, 080840, 080910, 080920, 080921, 080929, 080930, 080940, 081010, 081020, 081030, 081040, 081050, 081060, 081070, 081090
Fresh Vegetables	CONSUMER	070110, 070190, 070200, 070310, 070320, 070390, 070410, 070420, 070490, 070511, 070519, 070521, 070529, 070610, 070690, 070700, 070810, 070820, 070890, 070910, 070920, 070930, 070940, 070951, 070952, 070959, 070960, 070970, 070990, 070991, 070992, 070993, 070999
Fruit/Vegetable Juice	CONSUMER	200911, 200912, 200919, 200920, 200921, 200929, 200930, 200931, 200939, 200940, 200941, 200949, 200950, 200960, 200961, 200969, 200970, 200971, 200979, 200980, 200981, 200989, 200990
Nursery	CONSUMER	060110, 060120, 060210, 060220, 060230, 060240, 060290, 060299, 060310, 060311, 060312, 060313, 060314, 060315, 060319, 060390, 060410, 060420, 060490, 060491, 060499
Other Meat	CONSUMER	20410, 20421, 20422, 20423, 20430, 20441, 20442, 20443, 20450, 20500, 20680, 20690, 20810, 20820, 20830, 20840, 20850, 20860, 20890, 21090, 21091, 21092, 21093, 21099, 41000, 50400, 160100, 160210, 160220, 160290, 160300
Petfood	CONSUMER	230910
Pork	CONSUMER	020311, 020312, 020319, 020321, 020322, 020329, 020630, 020641, 020649, 021011, 021012, 021019, 160241, 160242, 160249
Poultry	CONSUMER	020710, 020711, 020712, 020713, 020714, 020721, 020722, 020723, 020724, 020725, 020726, 020727, 020731, 020732, 020733, 020734, 020735, 020736, 020739, 020741, 020742, 020743, 020744, 020745, 020750, 020751, 020752, 020753, 020754, 020755, 020760, 160231, 160232, 160239
Processed Fruit	CONSUMER	080410, 080420, 080620, 081110, 081120, 081190, 081210, 081220, 081290, 081310, 081320, 081330, 081340, 081350, 081400, 121230, 200600, 200710, 200791, 200799, 200811, 200820, 200830, 200840, 200850, 200860, 200870, 200880, 200891, 200892, 200893, 200897, 200899

Appendix 10B.1 (continued)

BICO Product Category	BICO Aggregate Sector	HS6-digit Codes Comprising BICO Sectors
Processed Vegetables	CONSUMER	071010, 071021, 071022, 071029, 071030, 071040, 071080, 071090, 071110, 071120, 071130, 071140, 071151, 071159, 071190, 071210, 071220, 071230, 071231, 071232, 071233, 071239, 071290, 071410, 071420, 071430, 071440, 071450, 071490, 121294, 121299, 200110, 200120, 200190, 200210, 200290, 200310, 200320, 200390, 200410, 200490, 200510, 200520, 200530, 200540, 200551, 200559, 200560, 200570, 200580, 200590, 200591, 200599
Snack Food	CONSUMER	170410, 170490, 190510, 190520, 190530, 190531, 190532, 190540
Spices	CONSUMER	090411, 090412, 090420, 090421, 090422, 090500, 090510, 090520, 090610, 090611, 090619, 090620, 090700, 090710, 090720, 090810, 090811, 090812, 090820, 090821, 090822, 090830, 090831, 090832, 090910, 090920, 090921, 090922, 090930, 090931, 090932, 090940, 090950, 090961, 090962, 091010, 091011, 091012, 091020, 091030, 091040, 091050, 091091, 091099
Tea	CONSUMER	090210, 090220, 090230, 090240, 090300, 210120
Tree Nuts	CONSUMER	080110, 080111, 080112, 080119, 080120, 080121, 080122, 080130, 080131, 080132, 080211, 080212, 080221, 080222, 080231, 080232, 080240, 080241, 080242, 080250, 080251, 080252, 080260, 080261, 080262, 080270, 080280, 080290, 200819
Distiller Dried Grains (DDGs)	INTERMEDIATE	230330
Essential Oils	INTERMEDIATE	330111, 330112, 330113, 330114, 330119, 330121, 330122, 330123, 330124, 330125, 330126, 330129, 330130, 330190, 330210
Fats	INTERMEDIATE	020900, 020910, 020990, 150100, 150110, 150120, 150190, 150200, 150210, 150290, 150300, 150500, 150510, 150590, 150600, 151610
Fodder	INTERMEDIATE	121300, 121410, 230210, 230220, 230230, 230240, 230250, 230310, 230320, 230670, 230800, 230810, 230890, 230990
Hay	INTERMEDIATE	121490
Hides & Skins	INTERMEDIATE	410110, 410120, 410121, 410122, 410129, 410130, 410140, 410150, 410190, 410210, 410221, 410229, 410310, 410320, 410330, 410390, 430110, 430120, 430130, 430140, 430150, 430160, 430170, 430180, 430190
Meal	INTERMEDIATE	120890, 230500, 230610, 230620, 230630, 230640, 230641, 230649, 230650, 230660, 230690

(*continued*)

Appendix 10B.1 (continued)

BICO Product Category	BICO Aggregate Sector	HS6−digit Codes Comprising BICO Sectors
Other Intermediates (i.e., flours, yeasts, saps, waxes, hairs)	INTERMEDIATE	050210, 050290, 050300, 050510, 050590, 050610, 050690, 050790, 051000, 051110, 090130, 110100, 110210, 110220, 110230, 110290, 110311, 110312, 110313, 110314, 110319, 110320, 110321, 110329, 110411, 110412, 110419, 110421, 110422, 110423, 110429, 110430, 110510, 110520, 110610, 110620, 110630, 110710, 110720, 110811, 110812, 110813, 110814, 110819, 110820, 110900, 121010, 121020, 121110, 121120, 121130, 121140, 121150, 121190, 130211, 130212, 130213, 130214, 130219, 130220, 130231, 130232, 130239, 140410, 151911, 151912, 151919, 151920, 152190, 180200, 210210, 210220, 210230, 210610, 230110, 230700, 350300, 350400, 350510, 350520, 350790, 382311, 382312, 510111, 510119, 510121, 510129, 510130, 510210, 510211, 510219, 510220
Palm Oil	INTERMEDIATE	151110, 151190, 151321, 151329
Seed	INTERMEDIATE	100111, 100191, 100210, 100310, 100410, 100510, 100710, 100821, 120110, 120230, 120721, 120770, 120910, 120911, 120919, 120921, 120922, 120923, 120924, 120925, 120926, 120929, 120930, 120991, 120999
Soy Meal	INTERMEDIATE	120810, 230400
Soy Oil	INTERMEDIATE	150710, 150790
Honey/Sugars	INTERMEDIATE	40900, 170111, 170112, 170113, 170114, 170191, 170199, 170220, 170230, 170240, 170250, 170260, 170290, 170310, 170390
Vegetable Oil	INTERMEDIATE	150810, 150890, 150910, 150990, 151000, 151211, 151219, 151221, 151229, 151311, 151319, 151410, 151411, 151419, 151490, 151491, 151499, 151511, 151519, 151521, 151529, 151530, 151540, 151550, 151560, 151590, 151620, 151710, 151790, 151800, 152110, 291570, 291615, 292320
Biodiesel	AG RELATED	382490, 382600
Distilled Spirits	AG RELATED	2208
Ethanol	AG RELATED	220710, 220712
Forestry	AG RELATED	4401−4421
Fishery	AG RELATED	All under Chapter 3, 50800, 50900, 51191, 1504, 1604, 1605, 230120

Note: In 2021, USDA changed its previous official definition of agriculture to follow the WTO definition of agriculture. Products including ethanol, distilled spirits, industrial alcohols, and others were added whereas other products (rubber, enzymes, and others) were removed from the USDA definition.

Appendix C

Appendix 10C.1 Estimated impact of COVID-19 on agricultural trade with product group effects: values vs. volume

VARIABLES	Value (1)	Volume (2)	Value (3)	Volume (4)	Value (5)	Volume (6)	Value (7)	Volume (8)	Value (9)	Volume (10)
COVID Cases Exporter	0.002**	0.006**								
	(0.00)	(0.00)								
COVID Cases Importer	−0.003***	−0.005**								
	(0.00)	(0.00)								
COVID Deaths Exporter			−0.037	−0.013					−0.040	−0.142**
			(0.04)	(0.09)					(0.03)	(0.07)
COVID Deaths Importer			−0.234***	−0.096					−0.070***	0.030
			(0.04)	(0.07)					(0.03)	(0.07)
Oxford Policy Stringency Exporter					−0.030	0.136***			0.024	0.249***
					(0.02)	(0.05)			(0.02)	(0.06)
Oxford Policy Stringency Importer					−0.204***	−0.312***			0.012	−0.050
					(0.03)	(0.05)			(0.02)	(0.04)
Google Workplace Mobility Exporter							0.147***	0.462***	0.091***	0.353***
							(0.02)	(0.07)	(0.03)	(0.07)
Google Retail Mobility Importer							0.135***	0.054*	0.131***	0.063
							(0.01)	(0.03)	(0.02)	(0.04)
Observations	8,296,198	8,053,593	8,103,927	7,867,905	8,287,412	8,044,391	9,731,967	9,417,002	7,418,663	7,202,455

Note: Estimated with PPML. Includes $ijkm$, it, jt, mt, kt, fixed effects. Standard errors are in parentheses and robust to clustering on $ijkm$. *,**, and *** denote statistical significance at the 10, 5, and 1 percent levels, respectively. Estimated on monthly data from Jan. 2016 to Dec. 2020. Agricultural trade includes all HS codes defined under USDA's BICO definition of Agricultural and Agricultural−related goods. Negative effect on trade is implied by a negative sign for cases and death counts and Oxford Policy Stringency and a positive sign for Google Mobility indices. For presentation purposes of the estimations, the Johns Hopkins case/death counts are rescaled per a thousand and Oxford Policy Stringency and Google Mobility indicators are rescaled to a 0–100 percent scale.

Appendix D

Appendix 10D.1 Product level estimates on the value of bilateral agricultural trade

	Animal Fats	Beef	Biodiesel Blends	Chocolate Cocoa Products	Coarse Grains	Cocoa Beans	Coffee Roasted Extracts
1. Direct Effect							
COVID Deaths Exporter	0.056	−0.158	0.226	−0.192**	−0.215	−0.133	0.296**
COVID Deaths Importer	−0.254	−0.611***	−0.188	−0.098	−0.688	0.519	−0.124
Observations	76,142	116,020	25,187	211,421	78,087	34,732	167,572
2. Policy Response							
Oxford Policy Stringency Exporter	0.164	−0.118	−0.185	−0.011	0.558	−0.710*	0.184**
Oxford Policy Stringency Importer	−0.155	−0.177*	−0.507	−0.205***	−1.449***	0.170	−0.084
Observations	78,051	118,557	25,995	215,637	80,311	35,853	171,734
3. Human Mobility Reduction							
Google Workplace Mobility Exporter	0.516	0.164	−0.696	0.147	−0.637	0.211	−0.070
Google Retail Mobility Importer	0.174	0.550***	0.580**	0.115**	−0.076	−0.125	−0.064
Observations	82,228	145,598	27,767	251,375	89,451	37,674	199,910

	Pet Food	Eggs	Essential Oils	Ethanol	Feeds Fodders	Fish Products	Food Preps
1. Direct Effect							
COVID Deaths Exporter	−0.012	−0.179	0.379	−0.498	−0.159	−0.126	−0.078
COVID Deaths Importer	−0.061	−0.198	−1.149**	−1.490***	−0.077	−0.382***	0.090
Observations	105,254	80,181	184,414	68,702	173,986	227,709	303,781
2. Policy Response							
Oxford Policy Stringency Exporter	−0.212*	−0.072	−0.153	−0.487*	−0.110	−0.220***	−0.011
Oxford Policy Stringency Importer	−0.008	−0.239**	−0.290*	−0.390	−0.236***	−0.252***	−0.119**
Observations	107,947	82,153	188,919	70,566	178,237	232,835	309,756
3. Human Mobility Reduction							
Google Workplace Mobility Exporter	0.118	−0.042	0.473*	1.608***	0.155	0.317***	0.089
Google Retail Mobility Importer	−0.130*	0.092	0.526***	0.152	0.082	0.283***	0.005
Observations	117,768	97,560	216,760	80,332	199,229	271,701	382,626

	Coffee Unroasted	Condiments & Sauces	Corn	Cotton	Dairy Products	Distilled Spirits	Distillers Grains
1. Direct Effect							
COVID Deaths Exporter	0.345**	0.192*	−0.129	−1.181	−0.063	−0.955***	0.430
COVID Deaths Importer	0.225	0.020	0.032	−0.566	0.027	−0.273	−0.910
Observations	83,748	184,663	59,471	38,100	220,479	166,756	13,665
2. Policy Response							
Oxford Policy Stringency Exporter	−0.143	0.007	0.467	−0.588	0.222***	−0.134	0.049

Appendix 10D.1 (continued)

	Coffee Unroasted	Condiments & Sauces	Corn	Cotton	Dairy Products	Distilled Spirits	Distillers Grains
Oxford Policy Stringency Importer	−0.147	−0.138***	−0.444	−0.712**	−0.054	−0.306**	0.198
Observations	86,240	188,779	61,164	39,296	225,336	170,772	14,124
3. Human Mobility Reduction							
Google Workplace Mobility Exporter	0.931***	−0.182**	2.162***	−0.220	−0.127*	0.661***	−1.280
Google Retail Mobility Importer	−0.080	0.071*	0.273	0.969***	0.044	0.326***	0.120
Observations	92,736	221,402	70,369	42,987	275,983	202,595	16,033

	Forest Products	Fresh Fruit	Fresh Vegetables	Fruit & Veg Juices	Hay	Hides & Skins	Live Animals
1. Direct Effect							
COVID Deaths Exporter	−0.052	−0.075	0.269	−0.201	−0.989**	−0.259	0.423*
COVID Deaths Importer	−0.160	−0.116	−0.078	0.182	−0.493	−0.195	−0.208
Observations	310,180	159,241	133,451	169,014	37,533	62,204	80,024
2. Policy Response							
Oxford Policy Stringency Exporter	−0.201**	−0.123	−0.041	0.025	0.218	−0.848***	0.226
Oxford Policy Stringency Importer	−0.089	0.079	0.112	0.028	−0.108	−0.593***	0.014
Observations	316,452	162,735	136,375	172,922	38,703	64,000	82,126
3. Human Mobility Reduction							
Google Workplace Mobility Exporter	0.535***	0.116	−0.150	−0.084	0.443	2.385***	−0.191
Google Retail Mobility Importer	0.320***	0.134**	−0.035	0.000	0.113	−0.222	−0.173
Observations	380,261	185,434	151,219	200,736	42,469	69,537	95,458

	Non Alcoholic Bev	Nursery flowers	Oilseed Meal	Oilseeds NESOI	Other Bulk Commodities	Other Intermediate Products	Palm Oil
1. Direct Effect							
COVID Deaths Exporter	0.122	−0.519***	−0.386	−0.144	−0.032	0.115	−0.708
COVID Deaths Importer	−0.066	−0.566***	0.696**	0.041	−0.45	−0.043	−0.667
Observations	158,127	141,315	58,379	121,014	110,573	287,332	57,463
2. Policy Response							
Oxford Policy Stringency Exporter	−0.13	−0.287***	−0.106	−0.328**	0.323*	−0.052	−0.439
Oxford Policy Stringency Importer	−0.057	−0.341***	0.289	−0.473**	−0.103	−0.102*	−0.291
Observations	161,849	144,396	60,090	124,142	113,770	293,298	58,884
3. Human Mobility Reduction							
Google Workplace Mobility Exporter	−0.098	0.142	0.651*	1.103**	0.419	0.002	0.952*

(continued)

Appendix 10D.1 (continued)

	Non Alcoholic Bev	Nursery flowers	Oilseed Meal	Oilseeds NESOI	Other Bulk Commodities	Other Intermediate Products	Palm Oil
Google Retail Mobility Importer	0.148*	0.427***	−0.074	−0.087	0.209	0.079*	0.249
Observations	193,836	159,582	65,416	136,655	122,999	348,556	68,484

	Rice	Rubber Allied Gums	Soybean Oil	Soybean meal	Soybeans	Spices	Sugars Sweeteners
1. Direct Effect							
COVID Deaths Exporter	0.896***	−0.594	1.783***	−0.53	1.044	0.415*	−0.176
COVID Deaths Importer	0.41	0.112	−0.99	0.106	0.103	0.181	−0.202
Observations	103,652	86,263	50,114	47,411	36,038	161,451	190,663
2. Policy Response							
Oxford Policy Stringency Exporter	0.352	0.091	0.603	0.273	2.269**	−0.322**	0.260**
Oxford Policy Stringency Importer	0.215	−0.245**	0.077	−0.315	−0.452	−0.025	−0.692***
Observations	105,938	88,931	51,769	48,867	37,193	165,348	194,986
3. Human Mobility Reduction							
Google Workplace Mobility Exporter	0.512	0.859***	0.024	−0.19	0.166	0.524*	0.702***
Google Retail Mobility Importer	−0.385**	0.285**	0.258	−0.099	−0.148	−0.221*	0.129
Observations	123,450	94,948	59,455	54,474	39,170	187,933	226,545

	Peanuts	Planting Seeds	Pork	Poultry	Processed Vegetables	Pulses	Rapeseed
1. Direct Effect							
COVID Deaths Exporter	−0.179	0.258	−0.242	−0.206	−0.037	−0.027	−0.714
COVID Deaths Importer	−0.038	0.318*	−0.421**	−0.620***	0.134	0.208	−0.741
Observations	41,250	134,570	102,010	115,777	215,209	112,846	22,038
2. Policy Response							
Oxford Policy Stringency Exporter	−0.12	0.312***	−0.085	−0.231**	−0.185***	0.095	−0.55
Oxford Policy Stringency Importer	−0.504*	0.005	−0.161*	−0.128	−0.046	0.144	−0.122
Observations	42,379	138,217	104,276	117,952	219,558	115,679	22,815
3. Human Mobility Reduction							
Google Workplace Mobility Exporter	0.684	0.154	0.008	0.129	−0.102	0.056	0.365
Google Retail Mobility Importer	0.065	−0.248***	0.262***	0.371***	0.065	−0.284	0.353
Observations	44,553	155,879	127,781	151,049	254,164	132,515	25,206

	Tea	Tobacco	TreeNuts	Vegetable Oils NESOI	Wheat	Processed Fruit	Snack Foods NESOI
1. Direct Effect							
COVID Deaths Exporter	−0.156	−0.012	−0.047	−0.038	−1.130**	0.253***	−0.261***

Appendix 10D.1 (continued)

	Tea	Tobacco	TreeNuts	Vegetable Oils NESOI	Wheat	Processed Fruit	Snack Foods NESOI
COVID Deaths Importer	−0.105	−0.583*	−0.164	−0.098	0.352	−0.011	−0.009
Observations	151,292	58,329	153,088	219,697	47,211	221,671	228,688
2. Policy Response							
Oxford Policy Stringency Exporter	−0.405***	−0.469*	−0.252**	0.069	−0.23	−0.051	−0.057
Oxford Policy Stringency Importer	−0.086	−0.327	−0.314**	−0.143	−0.128	−0.048	−0.217***
Observations	155,269	59,444	156,798	224,838	48,599	226,548	233,145
3. Human Mobility Reduction							
Google Workplace Mobility Exporter	0.882***	−0.595	−1.238***	−0.055	−0.274	0.058	0.338***
Google Retail Mobility Importer	−0.093	−0.039	0.278	−0.012	0.105	0.034	0.068*
Observations	176,436	64,246	180,071	260,656	57,168	258,467	278,045

Note: The Dep. variable is value of agricultural trade estimated with PPML. Includes *ijm, it, jt, mt,* fixed effects. Standard errors are in parentheses and robust to clustering on *ijm*. *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels, respectively. Estimated on monthly data from Jan. 2016 to Dec. 2020. Negative effect on trade is implied by a negative sign for cases and death counts and Oxford Policy Stringency and a positive sign for Google Mobility indices. For presentation purposes of the estimations, the Johns Hopkins case/death counts are rescaled per a thousand and Oxford Policy Stringency and Google Mobility indicators are rescaled to a 0−100 percent scale.

Appendix E

Appendix 10E.1 Product level estimates on the volume of bilateral agricultural trade

	Animal Fats	Beef	Biodiesel Blends	Chocolate Cocoa Products	Coarse Grains	Cocoa Beans	Coffee Roasted Extracts
1. Direct Effect							
COVID Deaths Exporter	0.320	0.055	0.375	−0.255**	−0.542	0.004	−0.132
COVID Deaths Importer	−0.260	−0.544***	−0.299	−0.029	−0.528	0.681	−0.555**
Observations	75,471	115,877	24,898	208,712	77,651	34,222	165,981
2. Policy Response							
Oxford Policy Stringency Exporter	0.334	−0.111	0.054	0.004	0.463	−0.293	0.216**
Oxford Policy Stringency Importer	−0.271	−0.280***	−0.525	−0.226***	−1.444***	−0.023	−0.404*
Observations	77,370	118,409	25,715	212,847	79,868	35,303	170,097
3. Human Mobility Reduction							
Google Workplace Mobility Exporter	0.391	0.223	−0.849	0.231**	−0.538	−0.075	−0.314
Google Retail Mobility Importer	−0.026	0.475***	0.603**	0.071	−0.077	0.091	0.143
Observations	81,508	145,175	27,423	247,953	88,974	36,973	197,752

	Pet Food	Eggs	Essential Oils	Ethanol	Feeds Fodders	Fish Products	Food Preps
1. Direct Effect							
COVID Deaths Exporter	0.031	−0.020	0.105	0.392	−0.026	−0.117	0.240***
COVID Deaths Importer	−0.122	0.136	−0.086	−1.642***	−0.000	−0.137	0.100
Observations	104,508	75,390	179,518	53,800	172,313	223,619	299,053
2. Policy Response							
Oxford Policy Stringency Exporter	−0.083	−0.129	−0.168	0.429	0.161	−0.211***	0.081
Oxford Policy Stringency Importer	0.018	−0.211	0.151	−0.088	−0.293**	−0.106	−0.143***
Observations	107,193	77,245	183,893	55,198	176,537	228,669	304,912
3. Human Mobility Reduction							
Google Workplace Mobility Exporter	0.120	0.244	0.066	1.436***	−0.075	0.308***	−0.220**
Google Retail Mobility Importer	−0.112**	−0.151	0.085	0.119	0.001	0.262***	−0.006
Observations	116,999	91,136	210,942	63,273	196,882	265,097	376,170

	Coffee Unroasted	Condiments & Sauces	Corn	Cotton	Dairy Products	Distilled Spirits	Distillers Grains
1. Direct Effect							
COVID Deaths Exporter	0.373**	0.225*	−0.147	−1.152	−0.430*	−0.708***	0.140
COVID Deaths Importer	0.303	0.040	0.152	−0.814	0.268*	−0.178	−0.582
Observations	82,490	182,143	59,165	36,745	218,151	132,072	13,611
2. Policy Response							
Oxford Policy Stringency Exporter	−0.011	0.225**	0.582	−0.570	−0.322	0.033	0.157

Appendix 10E.1 (continued)

	Coffee Unroasted	Condiments & Sauces	Corn	Cotton	Dairy Products	Distilled Spirits	Distillers Grains
Oxford Policy Stringency Importer	−0.183	−0.069	−0.483	−0.688**	0.031	−0.201**	0.191
Observations	84,935	186,182	60,847	37,876	222,946	134,787	14,065
3. Human Mobility Reduction							
Google Workplace Mobility Exporter	0.831***	−0.475***	2.425***	−0.081	0.219	0.379**	−0.695
Google Retail Mobility Importer	−0.135	0.016	0.235	0.889***	0.136	0.256***	0.064
Observations	91,335	218,223	69,941	41,103	272,460	161,182	15,923

	Forest Products	Fresh Fruit	Fresh Vegetables	Fruit & Veg Juices	Hay	Hides & Skins	Live Animals
1. Direct Effect							
COVID Deaths Exporter	0.006	0.473***	0.250	−0.201	−1.229**	0.520*	0.682***
COVID Deaths Importer	0.057	−0.099	−0.011	0.171	−0.551	−0.284	−0.280
Observations	293,722	157,168	131,147	156,415	37,222	57,417	65,553
2. Policy Response							
Oxford Policy Stringency Exporter	−0.299***	−0.027	0.020	0.098	0.336	−0.121	0.054
Oxford Policy Stringency Importer	−0.129	0.315***	0.334**	0.051	−0.050	−0.691***	0.079
Observations	299,561	160,613	134,010	159,835	38,390	59,056	67,184
3. Human Mobility Reduction							
Google Workplace Mobility Exporter	0.564***	0.067	0.672***	0.108	0.562	0.462*	0.027
Google Retail Mobility Importer	0.348***	−0.209**	−0.433***	−0.034	−0.088	0.289**	−0.122
Observations	357,380	182,128	147,855	184,676	42,101	63,993	77,345

	Non Alcoholic Bev	Nursery flowers	Oilseed Meal	Oilseeds NESOI	Other Bulk Commodities	Other Intermediate Products	Palm Oil
1. Direct Effect							
COVID Deaths Exporter	0.216	−0.361**	−0.305	−0.178	−0.303	0.191	−0.736
COVID Deaths Importer	−0.103	−0.446***	0.706**	−0.214	−0.862**	−0.070	−0.592
Observations	126,424	128,261	57,930	118,873	108,601	282,459	57,206
2. Policy Response							
Oxford Policy Stringency Exporter	−0.047	−0.246**	−0.028	−0.079	−0.264	0.232**	−0.423
Oxford Policy Stringency Importer	−0.094	−0.268**	0.224	−0.593**	−0.089	−0.291***	−0.251
Observations	129,010	131,003	59,627	121,926	111,745	288,339	58,602
3. Human Mobility Reduction							
Google Workplace Mobility Exporter	−0.111	0.069	0.498	1.737***	1.624***	−0.010	1.155**

(continued)

Appendix 10E.1 (continued)

	Non Alcoholic Bev	Nursery flowers	Oilseed Meal	Oilseeds NESOI	Other Bulk Commodities	Other Intermediate Products	Palm Oil
Google Retail Mobility Importer	0.080	0.433***	−0.109	−0.283	0.376	0.116*	0.153
Observations	154,390	144,581	64,813	133,809	120,087	341,771	67,997

	Rice	Rubber Allied Gums	Soybean Oil	Soybean meal	Soybeans	Spices	Sugars Sweeteners
1. Direct Effect							
COVID Deaths Exporter	1.788***	−0.091	1.631***	−0.776**	0.842	0.677***	−0.148
COVID Deaths Importer	−0.029	0.194	−1.016	0.220	0.053	0.479	−0.455
Observations	103,151	84,451	49,791	47,268	35,888	158,987	187,684
2. Policy Response							
Oxford Policy Stringency Exporter	0.670**	0.436*	0.577	0.250	2.090**	−0.315**	0.568***
Oxford Policy Stringency Importer	0.076	−0.271**	0.187	−0.273	−0.445	−0.115	−0.858***
Observations	105,431	87,062	51,444	48,726	37,032	162,815	191,957
3. Human Mobility Reduction							
Google Workplace Mobility Exporter	0.299	0.730**	0.160	0.021	0.519	0.090	1.249***
Google Retail Mobility Importer	−0.336**	0.217*	0.187	−0.214	−0.200	−0.025	0.105
Observations	122,523	92,988	58,940	54,243	38,807	184,788	221,962

	Peanuts	Planting Seeds	Pork	Poultry	Processed Vegetables	Pulses	Rapeseed
1. Direct Effect							
COVID Deaths Exporter	0.038	0.671	−0.199	−0.076	0.152	0.144	−0.211
COVID Deaths Importer	−0.003	−0.810*	−0.395*	−0.466***	0.426**	−0.245	−0.538
Observations	40,676	129,348	101,945	115,185	212,389	112,412	21,620
2. Policy Response							
Oxford Policy Stringency Exporter	−0.178	0.023	0.022	−0.072	−0.154	−0.315	−0.401
Oxford Policy Stringency Importer	−0.802***	−0.080	−0.231***	−0.117	−0.043	0.120	−0.146
Observations	41,776	132,826	104,202	117,341	216,644	115,222	22,391
3. Human Mobility Reduction							
Google Workplace Mobility Exporter	0.934*	0.608	−0.115	0.331**	0.111	0.111	0.096
Google Retail Mobility Importer	0.038	−0.289	0.338***	0.323***	0.083	−0.082	0.168
Observations	43,628	149,616	127,431	149,903	250,330	131,302	24,787

	Tea	Tobacco	TreeNuts	Vegetable Oils NESOI	Wheat	Processed Fruit	Snack Foods NESOI
1. Direct Effect							
COVID Deaths Exporter	0.110	0.193	0.073	−0.109	−1.285***	0.312***	0.041

Appendix 10E.1 (continued)

	Tea	Tobacco	TreeNuts	Vegetable Oils NESOI	Wheat	Processed Fruit	Snack Foods NESOI
COVID Deaths Importer	0.219	−0.544*	−0.319	0.052	0.454	−0.039	0.164
Observations	148,026	58,344	151,071	216,926	46,993	218,665	226,046
2. Policy Response							
Oxford Policy Stringency Exporter	−0.418***	−0.342	−0.207	0.106	−0.230	−0.133	0.101
Oxford Policy Stringency Importer	0.016	−0.401*	−0.617***	−0.119	−0.142	−0.211**	−0.302***
Observations	151,949	59,477	154,729	222,019	48,378	223,406	230,382
3. Human Mobility Reduction							
Google Workplace Mobility Exporter	0.985***	0.180	−1.381***	−0.081	−0.333	−0.115	−0.096
Google Retail Mobility Importer	−0.279**	0.128	0.164	−0.116	0.081	0.085	0.085
Observations	172,140	62,633	176,547	256,879	56,823	254,670	274,546

Note: The Dep. variable is value of agricultural trade estimated with PPML. Includes *ijm*, *it*, *jt*, *mt*, fixed effects. Standard errors are in parentheses and robust to clustering on *ijm*. *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels, respectively. Estimated on monthly data from Jan. 2016 to Dec. 2020. Negative effect on trade is implied by a negative sign for cases and death counts and Oxford Policy Stringency and a positive sign for Google Mobility indices. For presentation purposes of the estimations, the Johns Hopkins case/death counts are rescaled per a thousand and Oxford Policy Stringency and Google Mobility indicators are rescaled to a 0−100 percent scale.

References

Ahn, S., and S. Steinbach. 2021. "COVID-19 Trade Actions in the Agricultural and Food Sector." *Food Distribution Research Society* 52 (2): 51–75. https://www.fdrsinc.org/wp-content/uploads/2021/09/JFDR-July-2021-Full-Issue.pdf#page=55.

Amiti, M., S. J. Redding, and D. Weinstein. 2019. "The Impact of the 2018 Trade War on US Prices and Welfare." *Journal of Economic Perspectives* 33 (4): 187–210. https://www.aeaweb.org/articles?id=10.1257/jep.33.4.187.

Anderson, J. E., and Y. V. Yotov. 2016. "Terms of Trade and Global Efficiency Effects of Free Trade Agreements, 1990–2002." *Journal of International Economics* 99: 279–98. https://www.sciencedirect.com/science/article/pii/S0022199615001531.

Arita, S., J. Grant, and S. Sydow. 2021. "Has COVID-19 Caused a Great Trade Collapse? An Initial Ex Post Assessment." *Choices* Quarter 3. https://www.choicesmagazine.org/choices-magazine/theme-articles/agricultural-market-response-to-covid-19/has-covid-19-caused-a-great-trade-collapse-an-initial-ex-post-assessment.

Baldwin, R., and D. Taglioni. 2006. "Gravity for Dummies and Dummies for Gravity Equations." NBER Working Paper No. 12516. Cambridge, MA: National Bureau of Economic Research. https://www.nber.org/papers/w12516.

Baquedano, F., Y. Zereyesus, C. Christensen, and C. Valdes. 2021. "International Food Security Assessment, 2020–2030: COVID-19 Update and Impacts on Food Insecurity." USDA Economic Research Service: COVID-19 Working Paper

#AP-087. https://www.ers.usda.gov/webdocs/publications/100276/ap-087.pdf?v=3889.4.

Beckman, J., and A. Countryman. 2021. "The Importance of Agriculture in the Economy: Impacts from COVID-19." *American Journal of Agricultural Economics* 103 (5): 1595–1611. https://doi.org/10.1111/ajae.12212.

Binkley, J. K., and Y. Liu. 2019. "Food at home and away from home: commodity composition, nutrition differences, and differences in consumers." Agricultural and Resource Economics Review 48 (2): 221–252. DOI: https://doi.org/10.1017/age.2019.1.

Bown, C. P. 2018. "Trump's Trade War Timeline: An Up-to-Date Guide." Trade and Investment Policy Watch (blog). Peterson Institute for International Economics, April 19. https://www.piie.com/blogs/tradeinvestment-policy-watch/trump-trade-war-china-date-guide.

Bown, C. P. 2019. "US-China Trade War: The Guns of August." Trade and Investment Policy Watch (blog). Peterson Institute for International Economics, September 20. https://www.piie.com/blogs/trade-andinvestment-policy-watch/us-china-trade-war-guns-august.

Brahmbhatt, M., and A. Dutta. 2008. "On SARS Type Economic Effects during Infectious Disease Outbreaks." World Bank Policy Research Paper No. 4466. Washington, DC: World Bank. https://openknowledge.worldbank.org/handle/10986/6440.

Carter, C. A., and S. Steinbach. 2020. "The Impact of Retaliatory Tariffs on Agricultural and Food Trade. NBER Working Paper No. 27147. Cambridge, MA: National Bureau of Economic Research. https://www.nber.org/papers/w27147#:~:text=The%20results%20indicate%20that%20these,reorientation%20of%20international%20trade%20patterns.

Chenarides, L., M. Manfredo, and T. J. Richards. 2020. "COVID-19 and Food Supply Chains." *Applied Economic Perspectives and Policy* 43 (1): 270–79. doi.org/10.1002/aepp.13085.

Crowley, M. A. 2019. *Trade War: The Clash of Economic Systems Threatening Global Prosperity*. London: CEPR Press. https://voxeu.org/content/trade-war-clash-economic-systems-threatening-global-prosperity.

Evenett, S., M. Fiorini, J. Fritz, B. Hoekman, P. Lukaszuk, N. Rocha, M. Ruta, F. Santi, and A. Shingal. 2022. "Trade Policy Responses to the COVID-19 Pandemic Crisis: Evidence from a New Data Set. The World Economy 45 (2): 342–364.

Fajgelbaum, P., A. Khandelwal, W. Kim, C. Mantovani, and E. Schaal. 2020. "Optimal Lockdown in a Commuting Network." NBER Working Paper No. 27441. Cambridge, MA: National Bureau of Economic Research. https://www.nber.org/papers/w27441.

FAO, IFAD, UNICEF, WFP, and WHO. 2021. *The State of Food Security and Nutrition in the World 2021. Transforming Food Systems for Food Security, Improved Nutrition and Affordable Healthy Diets for All*. Rome: FAO. https://doi.org/10.4060/cb4474en.

Friedt, F., and K. Zhang. 2020. "The Triple Effect of COVID-19 on Chinese Exports: First Evidence of the Export Supply, Import Demand and GVC Contagion Effects." Center for Economic Policy Analysis, Covid Economics: Vetted and Real Time Papers. https://www.econbiz.de/Record/the-triple-effect-of-covid-19-on-chinese-exports-first-evidence-of-the-export-supply-import-demand-and-gvc-contagion-effects-friedt-felix/10012311905.

Grant, J., and S. Arita. 2017. "Sanitary and Phyto-sanitary Measures: Assessment, Measurement, and Impact." No. 938–2017–1828. International Agricultural

Trade Research Consortium (IATRC). https://iatrc.umn.edu/sanitary-and-phyto-sanitary-measures-assessment-measurement-and-impact.
Grant, J. H., S. Arita, C. Emlinger, R. Johansson, and C. Xie. 2021. "Agricultural Exports and Retaliatory Trade Actions: An Empirical Assessment of the 2018/2019 Trade Conflict." *Applied Economics Perspectives and Policy* 43 (2): 619–40. https://doi.org/10.1002/aepp.13138.
Head, K., and T. Mayer. 2014. "Gravity Equations: Workhorse, Toolkit, and Cookbook." *Handbook of International Economics* 4: 131–95. Elsevier. https://doi.org/10.1016/B978–0-444–54314–1.00003–3.
International Monetary Fund (IMF). 2020. World Economic Outlook Update, June. https://www.imf.org/en/Publications/WEO/Issues/2020/06/24/WEOUpdateJune2020.
International Monetary Fund. 2021. World Economic Outlook: Managing Divergent Recoveries. https://www.imf.org/en/Publications/WEO/Issues/2021/03/23/world-economic-outlook-april-2021.
Kejzar, K. Z., and A. Velic. 2020. "COVID-19, Trade Collapse, and GVC Linkages: European Experience." Center for Economic Policy Analysis, Covid Economics: Vetted and Real Time Papers. https://cepr.org/content/covid-economics-vetted-and-real-time-papers-0.
Luckstead, J., R. M. Nayga Jr., and H. A. Snell. 2021. "Labor Issues in the Food Supply Chain amid the COVID-19 Pandemic." *Applied Economic Perspectives and Policy* 43 (1): 382–400. doi.org/10.1002/aepp.13090.
Lusk, Jayson L., Glynn T. Tonsor, and Lee L. Schulz. 2021. "Beef and pork marketing margins and price spreads during COVID-19." Applied Economic Perspectives and Policy 43 (1): 4–23.
Mallory, M. L. 2020. "Impact of COVID-19 on Medium-Term Export Prospects for Soybeans, Corn, Beef, Pork, and Poultry." *Applied Economic Perspectives and Policy* 43 (1): 292–303. doi.org/10.1002/aepp.13113.
Ning, X., and J. H. Grant. 2019. "New Estimates of the Ad-valorem Equivalent of SPS Measures: Evidence from Specific Trade Concerns." Working paper. https://vtechworks.lib.vt.edu/handle/10919/95217.
Peterson, E., J. Grant, D. Roberts, and V. Karov. 2013. "Evaluating the Trade Restrictiveness of Phytosanitary Measures on US Fresh Fruit and Vegetable Imports." *American Journal of Agricultural Economics* 95 (4): 842–58. https://onlinelibrary.wiley.com/journal/14678276.
Reuters. 2020. "Rain to Help EU Rapeseed But Too Late to Avert French Area Drop." October 2. https://www.reuters.com/article/us-europe-grains-sowing/rain-to-help-eu-rapeseed-but-too-late-to-avert-french-area-drop-idUSKBN26N27F.
Santos Silva, J. M. C., and S. Tenreyro. 2006. "The Log of Gravity." *The Review of Economics and Statistics* 88 (4): 641–58. https://direct.mit.edu/rest/article/88/4/641/57668/The-Log-of-Gravity.
United Nations Conference on Trade and Development (UNCTAD). 2016. Key Indicators and Trends in International Trade 2016. https://unctad.org/en/PublicationsLibrary/ditctab2016d3_en.pdf.
World Bank. 2021. "Global Economic Prospects." World Bank Global Economic Prospects Report, January. https://www.worldbank.org/en/publication/global-economic-prospects.
World Trade Organization (WTO). 2020a. Methodology for the WTO Trade Forecast of April 8 2020. https://www.wto.org/english/news_e/pres20_e/methodpr855_e.pdf.
World Trade Organization (WTO). 2020b. "COVID-19 and Agriculture: A Story of

Resilience." Information Note, August 26. https://www.wto.org/english/tratop_e/COVID-19_e/agric_report_e.pdf.

World Trade Organization (WTO). 2021. "World Trade Primed for Strong but Uneven Recovery after COVID-19 Pandemic Shock." Press Release, March 31. https://www.wto.org/english/news_e/pres21_e/pr876_e.pdf.

Yaffe-Bellany, D., and M. Corkery. 2020. "Dumped Milk, Smashed Eggs, Plowed Vegetables: Food Waste of the Pandemic." *New York Times*, April 11. https://www.nytimes.com/2020/04/11/business/coronavirus-destroying-food.html.

Yotov, Y. V., R. Piermartini, J. A. Monteiro, and M. Larch. 2016. "An Advanced Guide to Trade Policy Analysis: The Structural Gravity Model." Geneva: World Trade Organization. https://www.wto.org/english/res_e/booksp_e/advancedwtounctad2016_e.pdf.