Essays on Price and Time in Trade and Household Production

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ABSTRACT

This dissertation consists of three chapters that estimate the elasticities regarding price and time in trade and household production. Chapters 1 and 2 estimate price elasticities. Chapter 1 estimates the one-factor-one-price elasticity of substitution (OOES)—or how the percentage change in the quantity of one good responds to the percentage change in the price (of itself or another good)—in an international trade context. Chapter 2 estimates the two-factor-one-price elasticity of substitution (TOES)—or the difference of percentage changes between two quantities with respect to the percentage change in the price of one good—in the context of household food production. Chapter 3 estimates the elasticity of export quantity and value with respect to delays in the time it takes to load or unload products at US ports.

Chapter 1 estimates the price elasticities in agricultural trade. Armington elasticities, the elasticity of substitution between goods from different countries, are key parameters in agricultural trade policy evaluation and welfare calculation. We estimate Armington elasticities for a selected basket of 38 agricultural commodities in 5 categories by compiling a sample of 118 countries' production and trade flows. Following and extending Feenstra et al. (2018), we estimate both the micro-elasticity of substitution between foreign sources of imports and the macro-elasticity of substitution between home and imported products at the commodity level. The median of the micro- and macro-elasticities are 6.4 and 5.0, respectively. Meat products have the lowest micro- and macro-elasticities, with the micro-elasticities ranging from 4.2 (pork) to 5.0 (poultry) and the macro-elasticities ranging from 2.9 (pork) to 4.5 (beef). Crops products have the widest range of Armington elasticities, with micro-elasticities ranging from 2.5 (pigeon peas) to 90.3 (peanuts), and macro-elasticities ranging from 1.2 (pigeon peas) to 20.1 (peanuts). In line with the literature, we find that 75 percent of the agricultural commodities have numerically smaller macro-elasticities than micro-elasticities, even though only 6 of them (pork, poultry, corn, peanuts, apples, and peppers) are statistically smaller at the 5 percent level. We explore the robustness of our estimates by slicing the sample into separate periods and importing countries. Finally, we discuss the policy implications of our estimates on predicting trade due to tariff changes and understanding welfare gains from agricultural trade.

Chapter 2 estimates the goods-time elasticity of substitution (EOS), the responsiveness of the difference between money and time in household production for change of opportunity cost of time (OCT). This chapter bridges the gap between literature that directly and indirectly estimates the goods-time EOS in household production. Inspired by the studies in environmental economics, we argue the opportunity cost of time in household production not only depends on wage but life-cycle dynamics and household demographics as well. We proceed with the estimation by two strategies: direct estimation of the household production, and the demand-supply approach borrowed from Feenstra's (1994) research on trade elasticities. Both strategies report the estimates are much larger than unit and closer to previous indirect estimates. We show our results are robust when applied to Aguiar and Hurst's (2007) sample, in which they employed the indirect estimation. The larger goods-time EOS indicates policies aiding households with money for groceries like the

Supplemental Nutrition Assistance Program (SNAP) are more sufficient, since money for certain groceries can more easily substitute for time in making meals.

Chapter 3 explores the elasticity of trade with respect to port congestion time. U.S. ports have struggled with significant supply chain congestion during the past two years. Anecdotal evidence shows the increasing port congestion brought substantial losses to U.S. exports, particularly agricultural shipments. However, previous studies are limited by the availability of explicit data on congestion times for unloading. This study first quantifies the association between port congestion days and U.S. agricultural exports, using monthly export data of top U.S. ports and their monthly average container and bulk shipments delays. We find one extra day delay of container shipments decreases U.S. agricultural monthly exports by 5 percent in quantity or 2 percent in value on average. That amounts to $63 million in monthly loss of export value on average, and Western U.S. ports are responsible for 69 percent of this total. The effect is most pronounced for the Western U.S. exports of bulk commodities, where congestion results in a 9 percent loss in quantity or 8 percent loss in value. For Eastern U.S., the most salient effect is on consumer commodities, with a loss of 3 percent in quantity and 3 percent in value. For the Gulf region, the largest effect is on bulk commodities, with a loss of 4 percent in quantity and 5 percent in value. The impacts of congestion on bulk shipments are both statistically and economically insignificant. However, we find some evidence that exporters substitute bulk cargoes with containers when bulk shipment delays at ports increase. The substitution of container shipments with bulk shipments, however, is unlikely.

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GENERAL AUDIENCE ABSTRACT

This dissertation explores price and time factors in trade and household production. All three chapters estimate the percentage change in a variable for the percentage change to some other variables (i.e., an elasticity). Chapter 1 estimates the elasticities in international agricultural trade. The core concept the first chapter relies on is the one-factor-one-price elasticity of substitution (OOES), or how the percentage change in the quantity of one good responds to the percentage change in the price (of itself or another good). Chapter 2 estimates the two-factor-one-price elasticity of substitution (TOES)—or the difference of percentage changes between two quantities with respect to the percentage change in the price of one good—in household food production context. The third chapter estimate the responsiveness of export quantity/value to time delays at port.

The first chapter examines how the demand for agricultural product imports will respond to price change. The study quantifies the responsiveness at two levels—micro and macro—using the Armington model, in which the product from each country is considered as a "variety". The micro-level elasticities capture the import demand responsiveness for a country of variety, say, Australian beef, when beef import price from Australia changes; The macro-elasticities capture the import demand responsiveness when, say, beef import prices from all countries change. We estimate both elasticities for a basket of 38 commodities, to shed light on policies such as "trade war" and multilateral trade agreements. In the median, one percent increase in price from a country of variety decreases 6.4 percent of demand for it; one percent decrease of price from all countries increases import demand by 5.0 percent.

The second chapter studies the substitutability between money and time in household production, or the goods-time elasticity of substitution (EOS), which captures the percentage change of money (for grocery purchases) relative to time (for food preparation and cleaning up, etc.) for the change of price of time. But what is the price of time in food production? Economists use the term opportunity cost of time (OCT), the highest value that household could spend their time on if not on food production. While most economists agree that OCT correlates with wage, this chapter argues the correlation differs by life cycle and household characteristics. What's more, OCT should also include non-wage factors like household characteristics. Maybe households with children in their middle age just value time with children more than the market wage. In this case, the value of time with children, instead of wage, could be their OCT in food production. Based on these arguments, the study estimates the goods-time EOS is much larger than in previous studies.

The magnitude of goods-time EOS has strong policy implications for policies like the Supplemental Nutritional Assistance Program (SNAP), which provides lower-income households money to buy groceries. If money and time are more substitutable, SNAP benefits will be more sufficient since money for certain groceries can more easily substitute for time in making meals. If goods-time EOS is small, however, SNAP benefits will be less sufficient, since the groceries are hardly substitutable for time in food production, and households still need to input a significant amount of time.

The third chapter considers the time factor in international trade. It leverages the bottleneck of the international supply chain, port delays, in past years to study the elasticity of trade with respect to port congestion time. The study focuses on U.S. agricultural exports of bulk shipments and container shipments. We estimate that each day of container shipment delay is associated with 5 percent decrease in export quantity and 2 percent decrease in export value. Compared with the estimates of micro-elasticities in Chapter 1, one-day delay of container shipment is equivalent to imposing extra 0.8 percent of tariff on U.S. agricultural products in the median. The effect of bulk shipment delay is muted. Chapter 3, combined with Chapter 1, sheds light on the price of time in agricultural trade.

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Chapter 1 Estimating Micro and Macro Armington Elasticities Among Agricultural Commodities

1.1 Background

Elasticities of substitution between agricultural products from different countries of sources, or Armington elasticities (Armington 1969), are vital in international trade policy evaluations. The direct policy implication of Armington elasticities is to infer the responsiveness of trade to cost/tariff change. The most recent example is the trade dispute, or so-called "trade war," between the U.S. and some of its significant trading partners, including North American Free Trade Agreement (NAFTA) members Canada and Mexico, China, and the European Union (E.U.). Countries repeatedly targeted U.S. exports of agricultural products for retaliation (See the recap by Grant, Ning, and Peterson 2018). The average tariff of the targeted U.S. exports in the "crop and animal products" sector increased most substantially by 24 percent in 2018 (Fajgelbaum et al. 2020)[1]. The micro-elasticities, the elasticity of substitution between varieties of products, are crucial to understanding how U.S. agricultural exports will change when such tariffs are imposed on U.S. agricultural products. The macro-elasticities, the elasticities of substitution between home

[1] The sectors are defined at NAICS-3 codes in Fajgelbaum et al. (2020)

and foreign products, provide implications for the change in total imports when the importing country lifts tariffs for all partners, such as when signing on the multilateral frameworks.

Estimates of Armington elasticities are also widely used to quantify the welfare effects of trade policies (Costinot and Rodríguez-Clare 2014). In the Computational General Equilibrium (CGE) or Applied General Equilibrium (AGE) models, welfare gains or losses in trade policy simulations depend crucially on Armington elasticity estimates (Wunderlich and Kohler 2018). An early example is the negotiation on agriculture in "Doha Round" launched by the 2001 Ministerial Declaration of WTO. Even though most of the assessments of an agricultural agreement in the "Doha Round" have concluded that developing countries benefit substantially from agricultural trade liberalization, the simulations of the gains are sensitive to the elasticities of substitution they choose in the agricultural sector (Bouët et al. 2005). Like the "Doha Round" assessments, evaluating the welfare change of trade wars requires consistent estimates of Armington elasticities of commodities in the agricultural sector.

Estimates of Armington elasticities in agricultural trade need to be updated. Early studies of Armington elasticities in the field of agricultural economics focused on specific commodities in a specific domestic market or from a specific origin, such as the elasticities of foreign demand for U.S. cotton (Babula 1987), the wheat trade (Johnson, Grennes, and Thursby 1979), and Japanese import elasticity of beef (Kawashima and Puspito Sari 2010). As the literature in this field progressed, attention turned mainly toward model specification issues but still within a rather narrow product or country categories (Alston et al. 1990; Davis and Jesen 1994; Davis and Kruse 1993; Moschini, Moro, and Green 1994). These efforts pushed the research toward the use of more flexible demand models, such as the Almost Ideal Demand System (AIDS) and Rotterdam models, to study import responsiveness (Andayani and Tilley 1997; Carew, Florkowski, and He 2004;

Chang and Chi 2002; Davis 1997; Irwin 2003; Muhammad, McPhail, and Kiawu 2012; Richards, van Ispelen, and Kagan 1997; Seale, Sparks, and Buxton 1992; Yang and Koo 1994). Some commodities, like meats, cotton, and apples, have been studied intensively, while others are under-analyzed.

International economists have studied trade elasticities for broader ranges of commodities. The methodology has mainly advanced in two directions: the demand-supply system approach that models the endogeneity of price, developed by Leamer (1981) and Feenstra (1994), and the gravity-like models that use exogenous variations of trade cost, such as tariff change (Fajgelbaum et al. 2020; Fontagné, Guimbard, and Orefice 2022). These studies embrace Armington models due to their adaptability to the development of new trade theory and the “new” new trade theory. They define products using Harmonized System (H.S.) Codes, typically at 4-digit, 6-digit, or higher disaggregated levels, but agricultural commodities of particular policy interests like beef could correspond to multiple H.S. 4-digit codes.

In this study, we adopt the Armington assumptions that each country of supply represents a variety of product, and use the demand-supply system to estimate the Armington elasticities of a selected basket of 38 agricultural commodities. The basket covers the most common commodities in categories of meats, crops, fresh fruits, fresh vegetables, and tree nuts. Many of them are under-explored in the literature. We attempt to obtain robust estimates of Armington elasticities for each commodity by using the production data of 118 importing countries and bilateral trade flows from the world to these countries during 1997-2017. To fulfill policy needs, we aggregate the bilateral trade flows and domestic production to the “commodity” level, consisting of single or multiple H.S. 4 or 6-digit codes. Our sample is, to our knowledge, the most comprehensive dataset with global agricultural production and bilateral trade flows matched at the commodity level.

The second contribution we make is to estimate both micro- and macro-elasticities at the commodity level. Most previous studies focus on estimating micro-elasticities but with limited attention to macro-elasticates. Traditional computable general equilibrium (CGE) models require the calibration of both micro- and macro-elasticities, with the latter assumed lower. Feenstra et al. (2018) incorporate the three-tier nested-CES structure of preferences in the Armington model. However, they estimate the macro-elasticities at the sector level instead of the commodity level.

We obtain valid estimates for 35 out of 38 commodities. The medians of the micro- and macro-elasticities are 6.4 and 5.0, respectively. Meat products have the lowest micro- and macro-elasticities, with the micro-elasticities ranging from 4.2 (pork) to 5.0 (poultry) and the macro-elasticities ranging from 2.9 (pork) to 4.5 (beef). Crops products have the widest range of Armington elasticities, with micro-elasticities ranging from 2.5 (pigeon peas) to 90.3 (peanuts), and macro-elasticities ranging from 1.2 (pigeon peas) to 20.1 (peanuts). In line with most of the literature, 75 percent of the agricultural commodities have numerically smaller macro-elasticities than micro-elasticities, even though only 6 of them (pork, poultry, corn, peanuts, apples, and peppers) are statistically smaller at the 5 percent level.

To test the robustness of our estimates, we divide our sample by periods and importing countries separately. The time span is sliced in the center; importing countries are grouped by OECD status. We find micro-elasticities center around similar values in subsamples to that in the full sample, whether we slice it by time or importing countries. The distribution of macro-elasticities is robust to the selection of sample periods but shifts by the selection of importing countries. We find OECD countries have a smaller median of macro-elasticity than non-OECD countries.

We apply our estimates to two exercises with policy implications. Firstly, we use the micro-elasticities to predict export value change due to tariff increases. Take the example of soybeans. We predict a 25 percent increase in tariff imposed by importing country on a specific exporter will result in 73 percent decrease in trade value, which is not far from the de facto number during the "trade war" between U.S. and China in 2018. Secondly, we apply our estimates of Armington elasticities and calculate the conceptual global welfare gain from agricultural trade. Our results show using micro-elasticities, instead of macro-elasticates, underestimates the global welfare gain by 26 percent on average.

The rest of the paper is organized as follows: In Section 1.2 we briefly review the methodology of estimating trade elasticates. Section 1.3 introduces our model setup. Section 1.4 elaborates our estimation strategy. Section 1.5 describes the data sources and the matching process. Section 1.6 presents the results of our estimation. In Section 1.7 we discuss the policy implications of our estimates. In Section 1.8 we conclude the paper.

1.2 A Brief Review of Methodology

This study employs the demand-supply system (Feenstra 1994; Leamer 1981) to estimate Armington elasticities in agricultural trade. Compared to the single-equation model of import quantity and price using time series, as is in Gallaway, McDaniel, and Rivera (2003), the demand-supply system recognizes the endogeneity of price and assumes errors in demand and supply curves are uncorrelated over time.

Feenstra (1994) first develops a robust demand-supply framework that estimates the elasticity of substitution among differentiated varieties from different supplying countries. The study introduces the exact price index and uses it to measure the unit cost of a product with changing varieties. The elasticity of substitution among varieties is a key parameter in the exact price index. The shortcoming of his study is that the unit cost derived from the CES utility function has only a single tier; therefore, it is limited in calculating the aggregate welfare change from introducing a new variety. Broda and Weinstein (2006) extend Feenstra's (1994) framework to a multiple-tier nested-CES structure. Overall welfare gain from variety change can be assessed using the extended framework, but with two underlying assumptions. First, the top-tier CES structure of foreign and domestic goods is symmetric, so the macro-elasticity between domestic and foreign categories is constant across products. Second, the framework concentrates on welfare gains from love of variety but with little attention to production behaviors. Feenstra et al. (2018) include the production side in the general equilibrium model by invoking Melitz (2003) model of heterogeneous firms. They also relax the assumption that macro-elasticity is constant across products and estimate the macro-elasticities combined with micro-elasticities.

Studies using Feenstra's framework share two common assumptions: First, demand and supply shocks are uncorrelated when aggregated over time for each import source. Therefore, 2-Stage Least Square (2SLS) estimation can be applied to identify the elasticities, using dummies of import sources as instruments. Second, for a given importing country, supply countries share the same supply elasticity. Soderbery (2015) relaxes the first assumption and argues limited information maximum likelihood (LIML) estimates are more robust in small samples or samples with outliers. Soderbery (2018) relaxes the second assumption and identifies heterogeneous supply elasticities by adding information on exporting countries' supply behaviors.

Besides the demand-supply system approach, the gravity models are commonly used to estimate Armington elasticities, which exploit exogenous variations in trade costs like tariffs

(Boehm, Levchenko, and Pandalai-Nayar 2020; Caliendo and Parro 2015; Fajgelbaum et al. 2020; Fontagné, Guimbard, and Orefice 2022; Hertel et al. 2007) or transportation costs (Hertel et al. 2007). These studies assume that variations of trade costs like tariffs and transportation costs are exogenous. However, trade costs are difficult to measure, and data on trade costs—say transportation costs—is not readily available for a wide range of products.

Compared to gravity models, the demand-supply system approach relies on readily accessible trade flows to identify Armington elasticities. Moreover, the demand-supply system allows for estimating multiple tiers of Armington elasticities, i.e., micro- and macro-elasticities, simultaneously, when the nested-CES utility is specified. Existing literature tends to understate the macro-elasticities because they take import price variation as exogenous (Hertel et al. 2007). Costinot and Rodrıguez-Clare (2014) argue that macro-elasticities, instead of micro-elasticities, are sufficient statistics for evaluations of welfare gain from trade, using autarky as counterfactual.

1.3 Model Setup

Our model setup modifies Feenstra et al. (2018)'s framework in three ways. First, we add an upper tier of global CES utility, C, that consists of the consumption of each country, j, in the world. For each country, the utility from consumption, C^j, has the same nested structure as in Feenstra et al. (2018). Figure 1.1 shows the diagram of the nested structure of the utility of country j. Our framework allows us to evaluate global welfare gain from trade by calculating the change of C from autarky. Second, we ignore the modeling of production behaviors in Feenstra et al. (2018) framework. They illustrate in the study that unit value is endogenous not only through variety change at supplying country level, but also through productivity of firms within each supplying country, using Melitz's (2003) heterogeneous firm productivity. Ignoring the production side does not change the econometric methodology for our purposes. Third, we extend their empirical strategy by determining micro- and macro-elasticities simultaneously, reducing their three-step estimation to one step. Feenstra et al. (2018) focus on only one importing country. Therefore, they estimate micro-elasticities, macro-elasticities, and micro- combined with macro-elasticities, consequently, in order to obtain robust estimates. With more importing countries in our sample, we directly proceed to the last step, micro- combined with macro-elasticities, without losing efficiency. We discuss this in more detail at the end of this section.

Let J denote the number of countries in the world, and G is the number of goods. A global representative consumer's utility is denoted as C, which is a CES function of each country's consumption, C^j.

$$C = \left[\sum_{j=1}^{J} (\xi^j)^{\frac{1}{\gamma}} (C^j)^{\frac{\gamma-1}{\gamma}} \right]^{\frac{\gamma}{\gamma-1}}$$

where ξ^j denotes each country's taste for agricultural products, and γ is the elasticity of substitution between countries. For each country j, a representative consumer consumes composite good C^j, which is a CES function of composite good g, C_g^j.

$$C^j = \left[\sum_{g=1}^{G} (\alpha_g^j)^{\frac{1}{\eta}} (C_g^j)^{\frac{(\eta-1)}{\eta}} \right]^{\frac{\eta}{\eta-1}}$$

where α_g^j denotes consumer's taste for good g, and η is the elasticity of substitution among agricultural products. One of the key assumptions in this study, as in Feenstra et al. (2018), is that good g produced at home and that of imports are not homogeneous for consumers. The composite good, C_g^j, consists of the third tier of the CES structure.

$$C_g^j = \left[(\beta_g^{jj})^{\frac{1}{\omega_g}} \left(C_g^{jj}\right)^{\frac{\omega_g - 1}{\omega_g}} + \left(1 - \beta_g^{jj}\right)^{\frac{1}{\omega_g}} \left(C_g^{Fj}\right)^{\frac{\omega_g - 1}{\omega_g}} \right]^{\frac{\omega_g}{\omega_g - 1}}$$

where C_g^{jj} and C_g^{Fj} are consumption of good g that relies on domestic supply and imports separately. ω_g is the macro-elasticity for good g, or elasticity of substitution between imports and home supply. While domestic production is assumed to be an individual variety, imports consist of multiple varieties from the rest of the world.

$$C_g^{Fj} = \left[\sum_{i=1, i \neq j}^{J} \left(\kappa_g^{ij}\right)^{\frac{1}{\sigma_g}} \left(C_g^{ij}\right)^{\frac{\sigma_g - 1}{\sigma_g}} \right]^{\frac{\sigma_g}{\sigma_g - 1}}$$

where κ_g^{ij} denotes country j's taste for variety i, and σ_g denotes the micro-elasticity, or the elasticity of substitution between varieties. The four-tier nested CES structure defines a system of canonical price indices. The global agricultural commodity price index is

$$P = \left[\sum_{j=1}^{J} \xi^j \left(P^j\right)^{1-\gamma} \right]^{\frac{1}{1-\gamma}}$$

which consists of the consumer price index (CPI) of agricultural commodities in each country, P^j.

$$P^j = \left[\sum_{g=1}^{G} \alpha_g^j \left(P_g^j\right)^{1-\eta} \right]^{\frac{1}{1-\eta}}$$

where P_g^j is a price index for agricultural commodity g in country j,

$$P_g^j = \left[\beta_g^{jj} \left(P_g^{jj}\right)^{1-\omega_g} + \left(1 - \beta_g^{jj}\right) \left(P_g^{Fj}\right)^{1-\omega_g} \right]^{\frac{1}{1-\omega_g}}$$

where P_g^{Fj} is the price index for imports of commodity g from the world to country j.

$$P_g^{Fj} = \left[\sum_{i=1, i \neq j}^{J} \kappa_g^{ij} \left(P_g^{ij} \right)^{1-\sigma_g} \right]^{\frac{1}{1-\sigma_g}}$$

where P_g^{ij} is the price of variety (country source) i of commodity g.

Solving the cost minimization problem with nested CES utility structure, we derive the demand of country j for commodity g, V_g^j; country j's demand for imports of commodity g, V_g^{Fj}; country j's demand for commodity g produced domestically, V_g^{jj}; and demand of country j for variety i of good g, V_g^{ij}, respectively. The conditional demand of country j for commodity g is:

$$V_g^j = E^j \alpha_g^j \left(\frac{P_g^j}{P^j} \right)^{1-\eta} \tag{1.1}$$

where E^j is the total expenditure of country j on agricultural commodities. By solving the top-tier cost minimization problem, we derive $E^j = E\xi^j \left(\frac{P^j}{P}\right)^{1-\gamma}$, where E is the global expenditure on agricultural commodities.

Demands at each tier can be solved inductively as follows.

$$V_g^{Fj} = V_g^j \left(1 - \beta_g^{jj}\right) \left(\frac{P_g^{Fj}}{P_g^j} \right)^{1-\omega_g} \tag{1.2}$$

$$V_g^{jj} = V_g^j \beta_g^{jj} \left(\frac{P_g^{jj}}{P_g^j} \right)^{1-\omega_g} \tag{1.3}$$

$$V_g^{ij} = V_g^{Fj} \kappa_g^{ij} \left(\frac{P_g^{ij}}{P_g^{Fj}} \right)^{1-\sigma_g} \tag{1.4}$$

Equation (1.4) shows that if all the values of trade and prices are correctly measured, micro-elasticity can be identified by equation (1.4) itself. Similarly, if the value of home supply, total imports, and price indices are measured correctly, either equation (1.2) or (1.3) can be used to identify macro-elasticity. To use all the information in equations (1.2)-(1.4), we transform the conditional demands into relative demands. Taking the ratio of equations (1.2) and (1.3), we have the macro demand for commodity g.

$$\frac{V_g^{Fj}}{V_g^{jj}} = \frac{1-\beta_g^{jj}}{\beta_g^{jj}}\left(\frac{P_g^{Fj}}{P_g^{jj}}\right)^{1-\omega_g} \tag{1.3'}$$

A more efficient way is to identify micro- and macro-elasticity in a single equation, which can be achieved by taking a ratio of equation (1.4) over (1.3),

$$\frac{V_g^{ij}}{V_g^{jj}} = \kappa_g^{ij}\,\frac{1-\beta_g^{j}}{\beta_g^{j}}\left(\frac{P_g^{Fj}}{P_g^{jj}}\right)^{1-\omega_g}\left(\frac{P_g^{ij}}{P_g^{Fj}}\right)^{1-\sigma_g} \tag{1.5}$$

If all the values of bilateral trade flows, home supply, and price indices are correctly measured, micro- and macro-elasticities can be determined simultaneously by estimating equation (1.5) alone.

1.4 Empirical Strategy

Two problems challenge estimation of equation (1.5): (1) the canonical price indices shown in the last section are never observed, and conventional price indices (unit values) have to be corrected for variety change; (2) prices are endogenously determined. To expand on the first challenge of measurement error of real price index, we apply Feenstra (1994)'s exact price index to correct for variety change.

$$P_{gt}^{Fj} = UV_{gt}^{Fj}\left(\frac{\lambda_{gt}}{\lambda_{gt-1}}\right)^{\frac{1}{\sigma_g-1}} = \prod_{i\in J_g}\left(\frac{UV_{gt}^{ij}}{UV_{gt-1}^{ij}}\right)^{w_{gt}^{ij}}\left(\frac{\lambda_{gt}}{\lambda_{gt-1}}\right)^{\frac{1}{\sigma_g-1}}$$

where UV_{gt}^{Fj} is the conventional price index to proxy P_{gt}^{Fj}, and J_g denotes the set of varieties commonly imported to country j during time t and $t - 1$. w_{gt}^{ij} is the weight of each variety in the set J_{gt}.

$$w_{gt}^{ij} = \frac{(s_{gt}^{ij} - s_{gt-1}^{ij})/(lns_{gt}^{ij} - lns_{gt-1}^{ij})}{\sum_{i\in J_{gt}}(s_{gt}^{ij} - s_{gt-1}^{ij})/(lns_{gt}^{ij} - lns_{gt-1}^{ij})}$$

λ_{gt} is the share of value of all commonly imported varieties over total value of imports in time t. Similarly, $\lambda_{gt-1}$is the share of value of all commonly imported varieties over total value of imports in time $t-1$.

$$\lambda_{gt} = \frac{\sum_{i\in J_g} V_{gt}^{ij}}{\sum_{i\in J_{gt}} V_{gt}^{ij}}, \text{ and } \lambda_{gt-1} = \frac{\sum_{i\in J_g} V_{gt-1}^{ij}}{\sum_{i\in J_{gt-1}} V_{gt-1}^{ij}}$$

Now we take logarithms of equation (1.5) on the right-hand side and left-hand side, and apply Feenstra (1994)'s first difference on the data, and use the exact price index to replace the canonical price indices in equation (1.5).

$$\Delta \ln\left(\frac{V_{gt}^{ij}}{V_{gt}^{jj}}\right) = \left(1 - \omega_g\right)\Delta \ln\left(\frac{UV_{gt}^{Fj}}{UV_{gt}^{jj}}\right) + \left(1 - \sigma_g\right)\Delta \ln\left(\frac{UV_{gt}^{ij}}{UV_{gt}^{Fj}}\right) + \varepsilon_{\mathrm{gt}}^{\mathrm{ij}} \qquad (1.6)$$

where $\varepsilon_{gt}^{ij} = \Delta \ln\left(\frac{\kappa_{\mathrm{gt}}^{\mathrm{ij}}\left(1-\beta_{\mathrm{gt}}^{\mathrm{j}}\right)}{\beta_{\mathrm{gt}}^{\mathrm{j}}}\right) + \left(1 + \frac{1-\omega_g}{\sigma_g - 1}\right)\Delta \ln\left(\frac{\lambda_{gt}}{\lambda_{gt-1}}\right)$. In equation (1.6), the error term, ε_{gt}^{ij}, consists of two parts in the right-hand side, a taste shock and the change of varieties, denoted by the first and the last term separately. Taste shocks can be exogenous to the model. However, the change of varieties can affect both unit values and values of imports. For example, a positive demand shock in country *j* will increase varieties of imports, pushing up import unit values and values. Therefore, co-movement of import unit values and values will dampen our estimates for elasticities if endogeneity is not addressed. Feenstra et al. (2018) incorporate other sources of endogeneity problems at the firm level, sub-variety level within each country of supply. A positive demand shock will also push less productive domestic and foreign firms to produce and export, driving up the unit cost even within a country of supply. We argue in this study that our simplified framework is sufficient to derive Feenstra et al. (2018)'s empirical strategy.

1.4.1 Micro Demand-Supply System

Re-arranging equation (1.6), with unit value ratio on the left-hand side, we obtain the inverse micro demand of country j for a good g imported from country i, which can be denoted as follows.

$$\Delta \ln\left(\frac{UV_{gt}^{ij}}{UV_{gt}^{Fj}}\right) = \frac{-\Delta \ln\left(\frac{V_{gt}^{ij}}{V_{gt}^{jj}}\right)}{\sigma_g - 1} - \frac{\omega_g - 1}{\sigma_g - 1}\Delta \ln\left(\frac{UV_{gt}^{Fj}}{UV_{gt}^{jj}}\right) + \frac{\varepsilon_{gt}^{ij}}{\sigma_g - 1} \tag{1.7}$$

where σ_g and ω_g are parameters of interests. The first difference of the variables eliminates country-specific but time-invariant tastes in preferences. The relative forms in the inverse demand equation are less sensitive to measurement errors. A direct way to overcome the endogeneity problem is to model the supply behavior. To be concise in model specification, we can assume that such demand shocks, unobserved in the error term in inverse demand function, simultaneously lead to supply price change. The reduced-form supply function, therefore, is constructed as:

$$\Delta \ln\left(\frac{UV_{gt}^{ij}}{UV_{gt}^{Fj}}\right) = \rho_{1g}\frac{\varepsilon_{gt}^{ij}}{\sigma_g - 1} - \rho_{2g}\frac{\omega_g - 1}{\sigma_g - 1}\Delta \ln\left(\frac{UV_{gt}^{Fj}}{UV_{gt}^{jj}}\right) + \delta_{gt}^{ij} \tag{1.7'}$$

where the response of supply price of variety from country i, to demand shocks, ρ_{1g}, must be non-negative and less than unit. ρ_{2g} denotes the response of supply price of country i, to country j's import price change. δ_{gt}^{ij} is the shock that only affects the supply of country i but not demand of country j. A reasonable assumption we impose is, as in Feenstra et al. (2018), error terms in the micro demand and supply equations are uncorrelated over time $E\left(\sum_t \varepsilon_{gt}^{ij}\,\delta_{gt}^{ij}\right) = 0, for\ i =$

$1, \dots, J, i \neq j$. The assumption implies we can simplify the micro demand-supply system by multiplying the errors of demand and supply equations. We first solve out ε_{gt}^{ij} and δ_{gt}^{ij} using equation (1.7) and (1.7), and multiply ε_{gt}^{ij} with δ_{gt}^{ij}.

$$Y_{gt}^{iF} = \sum_{n=1}^{2} \theta_{ng} X_{ngt}^{ij} + \sum_{n=3}^{4} (\omega_g - 1)\theta_{ng} X_{ngt}^{ij} + (\omega_g - 1)^2 \theta_{5g} X_{5gt}^{j} + \mu_{gt}^{ij} \qquad (1.8)$$

where

$$Y_{gt}^{iF} = \left[\Delta ln\left(\frac{UV_{gt}^{ij}}{UV_{gt}^{Fj}}\right)\right]^2$$

$$X_{1gt}^{ij} = \left[\Delta ln\left(\frac{V_{gt}^{ij}}{V_{gt}^{jj}}\right)\right]^2 \qquad X_{2gt}^{ij} = \left[\Delta ln\left(\frac{UV_{gt}^{ij}}{UV_{gt}^{Fj}}\right)\right]\left[\Delta ln\left(\frac{V_{gt}^{ij}}{V_{gt}^{jj}}\right)\right]$$

$$X_{3gt}^{ij} = \left[\Delta ln\left(\frac{UV_{gt}^{Fj}}{UV_{gt}^{jj}}\right)\right]\left[\Delta ln\left(\frac{UV_{gt}^{ij}}{UV_{gt}^{Fj}}\right)\right] \qquad X_{4gt}^{ij} = \left[\Delta ln\left(\frac{UV_{gt}^{Fj}}{UV_{gt}^{jj}}\right)\right]\left[\Delta ln\left(\frac{V_{gt}^{ij}}{V_{gt}^{jj}}\right)\right]$$

$$X_{5gt}^{j} = \left[\Delta ln\left(\frac{UV_{gt}^{Fj}}{UV_{gt}^{jj}}\right)\right]^2$$

The error term in equation (1.8) is a scaled multiplication of ε_{gt}^{ij} and δ_{gt}^{ij}, $\mu_{gt}^{ij} = \frac{\varepsilon_{gt}^{ij}\delta_{gt}^{ij}}{(\sigma_g - 1)(1-\rho_{1g})}$.

The reduced form-structural parameter system is shown below.

$$\theta_{1g} = \frac{\rho_{1g}}{(\sigma_g - 1)^2(1-\rho_{1g})} \qquad \theta_{2g} = \frac{2\rho_{1g} - 1}{(\sigma_g - 1)(1-\rho_{1g})}$$

$$\theta_{3g} = \frac{-(1 + \rho_{2g} - 2\rho_{1g})}{(\sigma_g - 1)(1-\rho_{1g})} \qquad \theta_{4g} = \frac{-(\rho_{2g} - 2\rho_{1g})}{(\sigma_g - 1)^2(1-\rho_{1g})} \qquad (1.9)$$

$$\theta_{5g} = \frac{-(\rho_{2g} - \rho_{1g})}{(\sigma_g - 1)^2(1-\rho_{1g})}$$

Equation (1.8) can be interpreted as a reduced-form micro demand and supply equation system. Inherited from the structural form demand-supply system, we impose the assumption $E\left(\sum_t \mu_{gt}^{ij}\right) = 0, for\ i = 1, \dots, J, i \neq j$ in equation (8). It simplifies the identification for σ_g and ω_g because if all the variables are suppressed by time dimension, the error term $\bar{\mu}_g^{ij} = 1/T \sum_t \mu_{gt}^{ij}$ no longer correlates with left-hand side variables in equation (1.10).

$$\bar{Y}_g^{iF} = \sum_{n=1}^{2} \theta_{ng}\bar{X}_{ng}^{ij} + \sum_{\{n=3\}}^{4} (\omega_g - 1)\theta_{ng}\bar{X}_{ng}^{ij} + (\omega_g - 1)^2\theta_{5g}\bar{X}_{5g}^{j} + \bar{\mu}_g^{ij} \qquad (1.10)$$

This is equivalent to using dummies of country sources, for each importing country and commodity, as instruments for right-hand side variables in equation (1.8). We proceed with the 2-Stage Least Square (2SLS) estimation sequentially. We first use the set of instruments (country dummies) to predict right-hand side variables in equation (1.8). Secondly, we estimate equation (1.10) by substituting (1.9) into (1.10) using Non-Linear Least Square (NLS) algorithm. This procedure alone yields robust results of σ_g but not ω_g. This is not surprising because the micro inverse supply function only addresses the co-movement of V_{gt}^{ij}/V_{gt}^{Fj} with $UV_{gt}^{ij}/UV_{gt}^{Fj}$, but identification of ω_g relies on addressing the endogeneity of $UV_{gt}^{Fj}/UV_{gt}^{jj}$.To obtain more efficient estimates of ω_g, we apply the same logic as in the micro demand-supply system to the estimates of ω_g in the macro demand-supply system.

1.4.2 Macro Demand-Supply System

Following the step of deriving inverse micro demand, we take the logarithm and first difference of equation (1.3) and substitute the price with Feenstra's (1994) exact price index. We then move the relative price to the left-hand side and obtain the inverse macro demand equation.

$$\Delta \ln\left(\frac{UV_{gt}^{Fj}}{UV_{gt}^{jj}}\right) = \frac{-\Delta \ln\left(V_{gt}^{Fj}/V_{gt}^{jj}\right)}{\omega_g - 1} + \frac{\varepsilon_{gt}^{Fj}}{\omega_g - 1} \tag{1.11}$$

where $\varepsilon_{gt}^{Fj} = \Delta \ln\left(\frac{1-\beta_{gt}^{j}}{\beta_{gt}^{j}}\right) + \left(\frac{1-\omega_g}{\sigma_g - 1}\right)\Delta \ln\left(\frac{\lambda_{gt}}{\lambda_{gt-1}}\right)$. The variety change, unobserved in the error term, correlates with both relative prices and values in equation (1.11), which biases the estimation of ω_g. We directly assume foreign supplying countries will respond to such unobservable shocks.

$$\Delta \ln\left(\frac{UV_{gt}^{Fj}}{UV_{gt}^{jj}}\right) = \rho^F \frac{\varepsilon_{gt}^{Fj}}{\omega_g - 1} + \delta_{gt}^{Fj} \tag{1.11'}$$

where ρ^F is the foreign supply coefficient, and δ_{gt}^{Fj} denotes the macro supply shock of country j. We assume the macro and supply shocks are uncorrelated over time, $E\left(\sum_t \varepsilon_{gt}^{Fj}\, \delta_{gt}^{Fj}\right) = 0, for\ g = 1, \dots, G$ and each importing country $j = 1, \dots, J$. To simplify the estimation of equations (1.11) and (1.11), we first solve out ε_{gt}^{Fj} and δ_{gt}^{Fj}, and then multiply them together and obtain the reduced form equation below.

$$Y_{gt}^{Fj} = \phi_1 X_{1gt}^{Fj} + \phi_2 X_{2gt}^{Fj} + \mu_{gt}^{Fj} \tag{1.12}$$

where

$$Y_{gt}^{Fj} = \left[\Delta ln\left(\frac{UV_{Fj}^{gt}}{UV_{gt}^{jj}}\right)\right]^2, X_{1gt}^{iF} = \left[\Delta ln\left(\frac{V_{gt}^{Fj}}{V_{gt}^{jj}}\right)\right]^2, X_{2gt}^{iF} = \left[\Delta ln\left(\frac{UV_{gt}^{Fj}}{UV_{gt}^{jj}}\right)\right]\left[\Delta ln\left(\frac{V_{gt}^{Fj}}{V_{gt}^{jj}}\right)\right]$$

and the reduced form-structural parameters are $\phi_1 = \frac{\rho^F}{(\omega_g - 1)^2(1-\rho^F)}$, and $\phi_2 = \frac{2\rho_F - 1}{(\omega_g - 1)(1-\rho^F)}$. Equation (1.12) can be interpreted as the macro demand and supply equation system, where $\mu_{gt}^{Fj} = \varepsilon_{gt}^{Fj}\delta_{gt}^{Fj}/(\omega_g - 1)$ is the scaled product of error terms in the demand and supply equations. Given the assumption in the macro demand and supply system, we further assume $E\left(\sum_t \mu_{gt}^{Fj}\right) = 0, for\ g = 1, \dots, G$and each importing country $j = 1, \dots, J$. This assumption adds more moment conditions to identifying macro-elasticities. Dummies of commodities can be used as instruments to identify the parameters in equation (1.12). In other words, when the dimension of t is suppressed, the error term, $\bar{\mu}_g^{Fj} = 1/T \sum_t \mu_{gt}^{Fj}$, is no longer correlated with left-hand side variables in equation (1.13).

$$\bar{Y}_g^{Fj} = \phi_1 \bar{X}_{1g}^{Fj} + \phi_2 \bar{X}_{2g}^{Fj} + \bar{\mu}_g^{Fj} \tag{1.13}$$

where we rely on the variation of importing country j to identify macro-elasticities for each commodity, ω_g. If the sample consists of only one importing country, as in Feenstra et al. (2018), estimating macro-elasticities at the commodity level is infeasible. Therefore, they impose the restriction that commodities within each sector share the common macro-elasticity. The identification assumption for macro-elasticities also adds information to equation (1.8). As macro-elasticities are identified, estimates on micro-elasticities will also be more precise.

The discussion above implies estimating equations (1.8) and (1.12) simultaneously can obtain robust estimates for both σ_g and ω_g. By doing so, we are effectively simultaneously estimating micro and macro demand-supply systems. To be specific, we proceed with the estimation in the following steps.

Step 1: Using dummies of country sources to predict right-hand side variables in equation (1.8).

Step 2: Using dummies of commodities to predict right-hand side variables in equation (1.12).

Step 3: Running NLS of equations (1.10) and (1.13) simultaneously using predicted variables from Steps 1-2.

Using the 2SLS-NLS estimation strategy, the standard errors of the point estimates on elasticities in Step 3 are not trustworthy. We use the bootstrap method and simulate 1,000 samples to obtain the standard errors for the point estimates.

Differentiating from Feenstra et al. (2018), our sample structure of multiple importing countries allows us to estimate micro- and macro-elasticities simultaneously for each commodity, using the abovementioned procedure. Feenstra et al. (2018) have to estimate micro-elasticities first and then pool the data for multiple commodities to identify their common macro-elasticity. Their final step is to estimate equations (1.8) and (1.12) simultaneously with each sector of commodities pooled together. Taking advantage of our data structure, we greatly simplify the estimation strategy.

1.5 Data

We use data from two sources: (1) Bilateral trade flows of agricultural commodities between the country pairs were obtained from U.N. Comtrade Database. Quantity and value of trade flows were aggregated to H.S. 6-digit level and reported by exporters. (2) We obtained global agricultural production and producer prices by country and commodity from Food and Agricultural Organization (FAO) online database, FAOSTAT. We matched the two data sources at the most disaggregated level according to their data collection description. When matching the trade data with home production, we took advantage of the reference matrix of FAO products to H.S. codes. In most cases, the commodities in FAOSTAT are referred to as single or multiple H.S. 6-digit products. Therefore, we were able to match the home production and price data with trade flows at 6-digit level and aggregate trade flows. When multiple commodities are referred to the same group of H.S. codes, we aggregated both home production/prices and trade flows so that they are matched at the same level. For example, apples have a single reference to H.S. 6-digit code, 080810. We simply matched U.S. imports of apples from all countries with annual domestic production at the single 6-digit level. In another more complex example, beef consists of two FAO products, "meat, cattle" and "meat, buffalo". Each of the FAO products corresponds to multiple H.S. 6-digit codes with overlap. In this case, we first aggregated FAO products to "meat, beef". We then pooled all H.S. 6-digit codes referred by "meat, cattle" and "meat, buffalo", and identified a subset of unique codes. We used this set of unique H.S. codes to match with trade flows.

Thirty-eight agricultural products in five categories were finally matched for 141 importing countries. For all the matched products, we calculated the aggregated quantity, value, and unit value of commodities imported from each supplying country to the importing countries in the sample, as well as the value of products that importing countries produce domestically and export to the world. As in previous studies, the total supply of each commodity is calculated as

$$Total\ Supply\ =\ (Production\ -\ Export)\ +\ Import$$

The share of home supply is measured as $(\mathrm{Production} - \mathrm{Export})/\mathrm{Total\ Supply}$,, and the share of imports is measured as $\mathrm{Import}/\mathrm{Total\ Supply}$. Our data spans from 1998 to 2017, which is also the time span of most products. We dropped the importer-commodity pairs that consist of less than 50 observations over this period. We also dropped the exporter-commodity pairs that consist of less than 20 observations over this period. After dropping missing values when creating the variables in equations (1.8) and (1.12), 118 importing countries remain in the sample. The list of countries can be seen in Table A1.1. Commodities in our sample are listed in Table A1.2.

Figure 1.2 depicts the value shares of agricultural imports over total "consumption." Most populous countries import a minimal share of agricultural products. For example, China imports 0.01 percent of its total agricultural consumption, and India imports less than 0.01 percent. In our sample, Malawi has the lowest share of 0.001 percent, and Equatorial Guinea has the highest share of 86.1 percent. The United States import 0.5 percent of total agricultural consumption.

1.6 Results

1.6.1 Main Results

We report the results in Table 1.1. One of the shortcomings of the 2SLS-NLS estimation is that the algorithm does not guarantee convergence. However, convergence issues are only a problem for three commodities (oranges, cauliflower/broccoli, and almonds), and thus, 35 out of 38 commodities have both valid micro- and macro-elasticities. All the estimations of commodities that converge show micro- and macro-elasticities greater than unit, which is consistent with the theoretical prediction. The overall estimates suggest that our estimation strategy of determining micro- and macro-elasticities simultaneously is robust in practice. The medians of the micro- and macro-elasticities across point estimations of products are 6.39 and 4.99, separately (Figure 1.3). The median of our estimates on micro-elasticities is greater than the previous studies that focus on downstream industries. Raimondi and Olper (2011) focus on food industries and report a median value of 4.32 for 4-digit ISIC industries. But the commodities we focus on in this study exclude processed food. Since we are the first study, to our knowledge, that estimates macro-elasticity at the commodity level, we cannot compare the median/mean of our results directly to previous studies. The most comparable results we find are reported by Feenstra et al. (2018), in which they present the sector-level macro-elasticity of food products is 4.08. Both our median and average of estimates are larger than this number.

Among the five categories of commodities, meat products have the lowest Armington elasticities on average (Table 1.1) . The micro-elasticities range from 4.23 (pork) to 5.01 (poultry), and the macro-elasticities range from 2.90 (pork) to 4.54 (beef). The bootstrap standard errors are all relatively small compared to the point estimates, indicating the estimates on Armington elasticities of meat products are precise.

Crops products have the widest range of point estimates on Armington elasticities. Pigeon peas have the smallest micro- (2.47) and macro-elasticities (1.17), while peanuts have the largest (90.30 and 20.06). However, these numbers could be misleading because the standard errors of the point estimates for these two commodities are so large that no statistical conclusion can be drawn. In contrast, the heavily traded crop commodities have precise point estimates. For instance, corn has point estimates of 4.35 vs. 3.22 for micro- and macro-elasticities, respectively, with both standard errors less than 0.5. Soybeans have point estimates of 5.28 vs. 5.51 for micro- and macro-elasticities, respectively, with both standard errors around unit. It is not surprising that estimates on heavily traded commodities are more efficient since they have a larger number of observations in the sample.

Ahmad, Montgomery, and Schreiber's (2020) review of Armington elasticities documents that gravity models tend to report larger estimates. Fontagné, Guimbard, and Orefice (2022) use the gravity model and variation of tariffs to estimate micro-elasticities for all H.S. 6-digit and 4-digit products. We extract 26 comparable commodities and list their estimates in Table 1.2. Consistent with the Ahmad, Montgomery, and Schreiber's (2020) review, they report a median of 7.12, around 19 percent larger than ours. Grant, Ning, and Peterson (2018) use the gravity model to estimate micro-elasticities for ten agricultural commodities. They report a median of 8.78, which is 33% larger than ours. Our estimates are directly comparable with Grant, Ning and Peterson (2018) for a subset of commodities. Eight out of nine comparable commodities have a much smaller estimate in our study (Table A1.3). The only exception is cotton. For cotton, we have a micro elasticity of 15.90, but Grant, Ning and Peterson (2018) report a number of 7.98. But our standard error is large, implying an imprecise point estimate for cotton.

Our results show around 75 percent of the commodities report larger micro-elasticities than macros. We further test whether it is supported by statistical evidence. The nested-CES preference suggests if micro-elasticities are not significant different from macro-elasticities, adding the tier of home supply and total imports is cumbersome. Micro-elasticities and the share of total imports are sufficient statistics for evaluating welfare gain from trade (Costinot and Rodrıguez-Clare, 2014). If the macro-elasticity is significantly smaller than the micro, the macro-elasticity, instead, is the sufficient statistics. The last two columns in Table 1.1 report the rejection of two nulls: $\sigma_g \leq \omega_g$ and $\sigma_g = 2\omega_g$ at 5 percent level. Our results show only 6 out of 35 commodities reject that $\sigma_g \leq \omega_g$. For commodities that reject $\sigma_g \leq \omega_g$, it is recommended to use ω_g in the evaluation of welfare gain. The last column further tests whether $\sigma_g = 2\omega_g$, which is a rule of thumbs in CGE models. 13 out of 35 reject the null.

1.6.2 Robustness Check

The estimation strategy of this study takes advantage of the "between variation" of data across importer-exporter pairs but downplays the "within variation" of these pairs over time. To test the sensitivity of our estimates to the selection of time span, we divide the sample equally by two periods, pre-financial crisis (1998-2007), and post-financial crisis (2008-2017). We plot the empirical distributions of subsample Armington elasticities in Figure 1.4. Our estimates are relatively robust to the time span in the sample. We find the distributions of micro-elasticities, for both pre- and post-financial crisis periods, present peak density at around six, which is consistent with our full sample results. The distribution of pre-financial crisis estimates is more dispersed due to some large estimates in the right tail. Soderbery (2010) suggests small number of periods will result in small sample biases. The empirical distributions of macro-elasticities resemble each other in shape, with that of the post-2008 estimates shifting slightly rightward. The medians of macro-elasticities for pre- and post-2008 subsamples are 4.97 and 5.50, separately.

Our estimates of Armington elasticities may vary by importing countries of distinct income levels. Figure 1.5 plots the empirical distributions of Armington elasticities by subsamples of countries' OECD statuses. For both subsamples, we find that the estimates of micro-elasticities center around similar values of six, despite the non-OECD subsample having a more dispersed distribution. The estimates of macro-elasticities differ significantly by OECD status. The median of the estimates for the OECD subsample is 4.25, 1.7 smaller than that of the estimates for the non-OECD subsample. The gap between estimates for OECD and non-OECD subsamples imply higher-income countries may be more difficult to substitute their agricultural imports than lower-income countries.

1.7 Policy Implications

Armington elasticities have multiple direct policy implications for agricultural trade. Most obviously, they uncover the short-term response of import values to tariff change.

According to Fajgelbaum et al. (2020), the micro-elasticity, $-\sigma_g$, represents the marginal percentage change of import value of commodity g, from source i to country j, due to one percentage change of tariff in the short term. Taking the logarithm of both sides in equation (1.4), the country i's demand for commodity g from exporter j can be written as follows.

$$lnV_g^{ij} = \alpha_g^{Fj} + (1 - \sigma_g) lnP_g^{ij} \tag{1.14}$$

where P_g^{ij} is, in fact, the price after tariff, and $V_g^{ij} = C_g^{ij} P_g^{ij}$. The term $\alpha_g^{Fj} = lnV_g^{Fj} - (1 - \sigma_g) lnP_g^{Fj}$. We denote tariff as T_g^{ij}.

$$P_g^{ij} = (1 + T_{gt}^{ij})P_g^{*ij}$$

where P_g^{*ij} is the price before tariff. Suppose the exporter i responds to the pre-tariff price.

$$lnP_g^{*ij} = \theta lnC_g^{ij} \tag{1.15}$$

where θ is inverse foreign export supply elasticity. Combing equation (1.14) and (1.15), we derive the pre-tariff export value from country i to j as follows.

$$lnV_g^{*ij} = -\frac{\sigma_g(1+\theta)}{1+\sigma_g\theta}\ln\left(1+T_g^{ij}\right) + \frac{\alpha_g^{Fj}(1+\theta)}{1-\sigma_g\theta}$$

where $V_g^{*ij} = C_g^{ij}P_g^{*ij}$. The export value of country i to j would change by $-\frac{\sigma_g(1+\theta)}{1+\sigma_g\theta}$ for marginal change of tariff on commodity g. With a horizontal supply curve, the marginal effect simplifies to $-\sigma_g$.

Taking the example of soybean—the foremost target of China's agriculturally-directed trade retaliation during the "trade war" with the U.S.—we predict an additional 25 percent increase in tariff will decrease Chinese imports of U.S. soybean by 73% $\left(= 1\text{-}e^{0.25\times(-5.28)}\right)$, using our coarse estimates of marginal effects. This coarse prediction has underlying assumptions that tariff increase leads to price change with the same percentage (a total pass-through or supply curve is horizontal), which are only likely to hold in the short term.[2] Recall the time span in our sample is from 1998-2017, before the "trade war". In 2018, actual U.S. soybean exports to China amounted to $3.1 billion, compared to $12.2 billion in the previous year, a dropped of 75 percent worth of value[3], which is not far from our coarse prediction of 73 percentage points. Macro-elasticities can be used in similar ways as $-\omega_g$ can be interpreted as the marginal percentage change of total

[2] Fajgelbaum et al. (2020) find they cannot reject supply elasticity equal zero using data from 2017:1-2019:4.
[3] Data Souce: USITC Executive Briefings on Trade.
https://www.usitc.gov/publications/332/executive_briefings/chinasoyebot.pdf

import value of commodity g by country j, due to one percentage change of import price index, ceteris paribus. Applications of Armington elasticities, in this case, are not counterfactual, thereafter, do not provide policy implications in the long term.

Transformed into trade elasticities, magnitudes of Armington elasticities determine our conceptual understanding of the welfare gains from trade. The counterfactual analysis calculates the welfare change of open economy j in status quo compared to its autarky status, i.e., country j has to sustain itself. Costinot and Rodrıìguez-Clare (2014) argue that total welfare gain from trade (compared to autarky), can be calculated by the following equation.

$$G_j = 1 - \prod_{g=1}^{G} \left(s_g^{jj}\right)^{\frac{\beta_g^{jj}}{\tau_g}} \tag{1.16}$$

where s_g^{jj} is the share of home supply for commodity g in country j; β_g^{jj} is the share of country j 's expenditure on commodity g over its total expenditure on agricultural commodities; $\tau_g = \sigma_g - 1$, is trade elasticity of commodity g. Equation (1.16) shows that s_g^{jj}, β_g^{jj} and τ_g are sufficient statistics to infer the welfare gain from trade. When macro-elasticities are specified, like in our case, $\tau_g = \omega_g - 1$. Equation (1.16) has underlying assumptions that: (1) the elasticity of substitution between any two agricultural commodities is unit so that C^j has a Cobb-Douglas form; (2) Production is completely competitive, and gains from trade originate from real consumption change.

Figure 3.61.6 and 1.7display our calculations of welfare gain from agricultural trade by country. Two observations are to be noted. (1) Large countries have lower welfare gain from agricultural trade, while small countries benefit more. For example, China and U.S. both have a welfare gain of less than 0.1%. Equatorial Guinea is the country in our sample that benefits most from agricultural trade, with a total welfare gain of 49%. This is not surprising because small countries have larger shares of agricultural imports. (2) Estimates of welfare gain are slightly more significant when using macro-elasticities than micro-elasticities. The global average welfare gain from trade is 26 percent larger using macro-elasticities than micro-elasticities.

The exercise of welfare calculation from trade has limitations. Firstly, the assumption that C^j has a Cobb-Douglas form can be relaxed and tested. Secondly, the welfare gain calculation in this exercise could be underestimated since our model setup only considers agricultural commodities as final goods in consumer's utility function. However, many of the commodities we focus on in this study, are likely to be inputs in the production of consumer goods as well. Participating in agricultural trade lowers the input prices, lowering the final product prices as well (Amiti et al. 2020).

1.8 Conclusion

This study replicates Feenstra et al.'s (2018) strategy of estimating micro- and macro-elasticities in the field of agricultural trade. Instead of the H.S. classification of products, we estimated the model at the commodity level corresponding to agricultural sectors. In addition to micro-elasticities, we estimate macro-elasticities at the nuanced commodity level as well, which is novel to the existed literature. Our estimates can be used to predict the responsiveness of trade value to tariff changes or welfare changes from trade policies.

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Figures and Tables

Figure 1.1 Structure of Nested-CES Preference in Armington Model

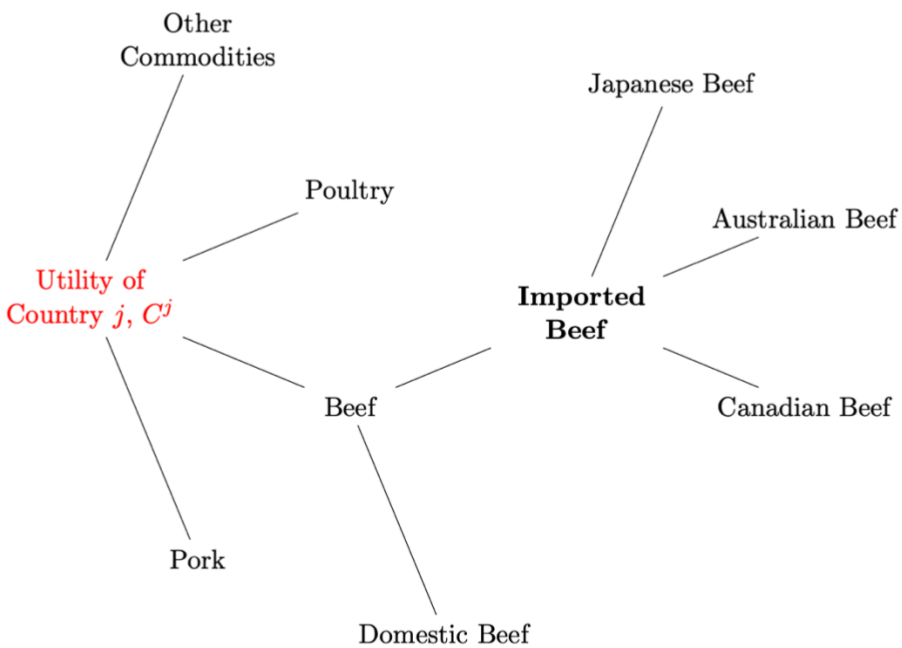
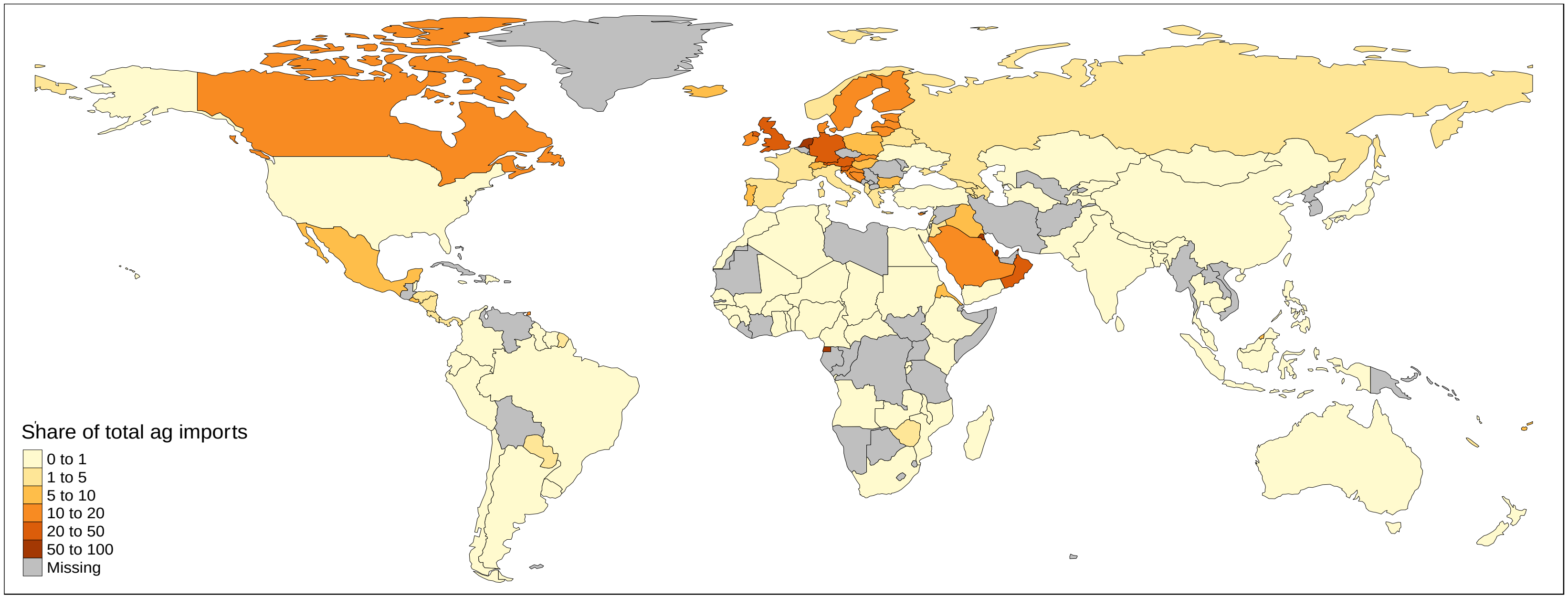
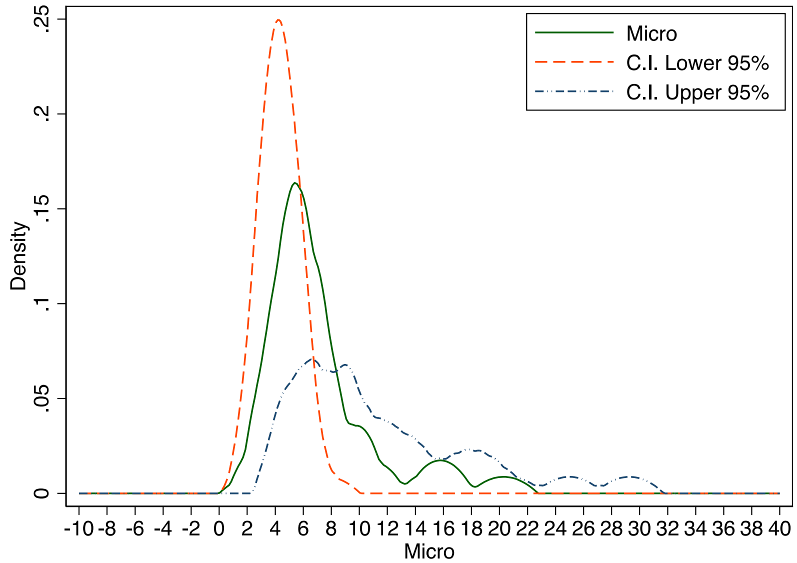


Figure 1.2 Global Value Shares of Agricultural Imports over Total Consumption

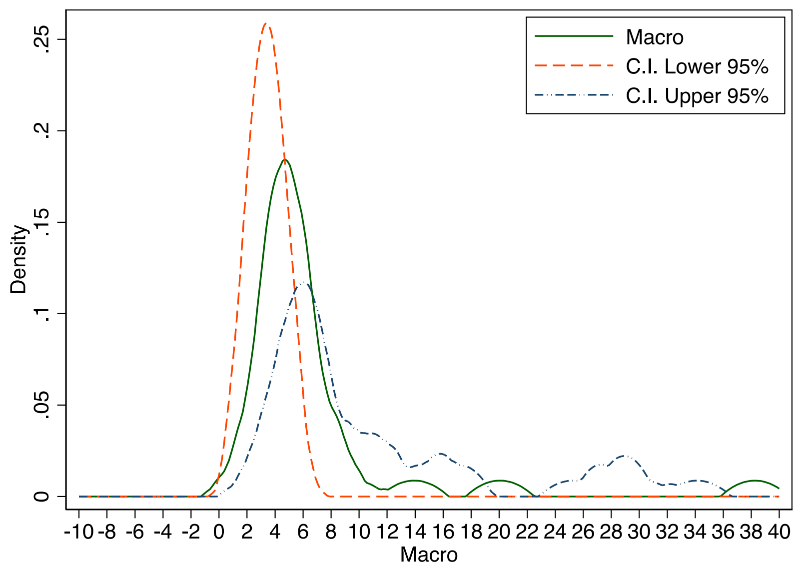


Notes: The value shares of agricultural imports are calculated as total value of agricultural imports over the sum of home supplies and imports.

Figure 1.3 Empirical Distributions of Micro- and Macro-Elasticities



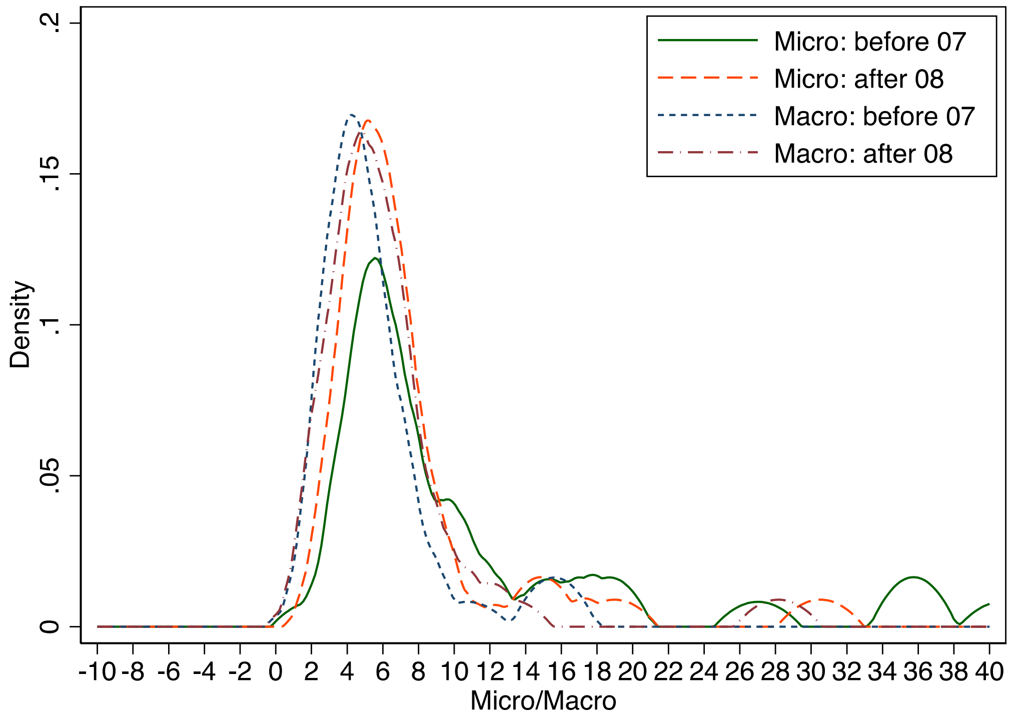
(a) Micro-Elasticities



(b) Macro-Elasticities

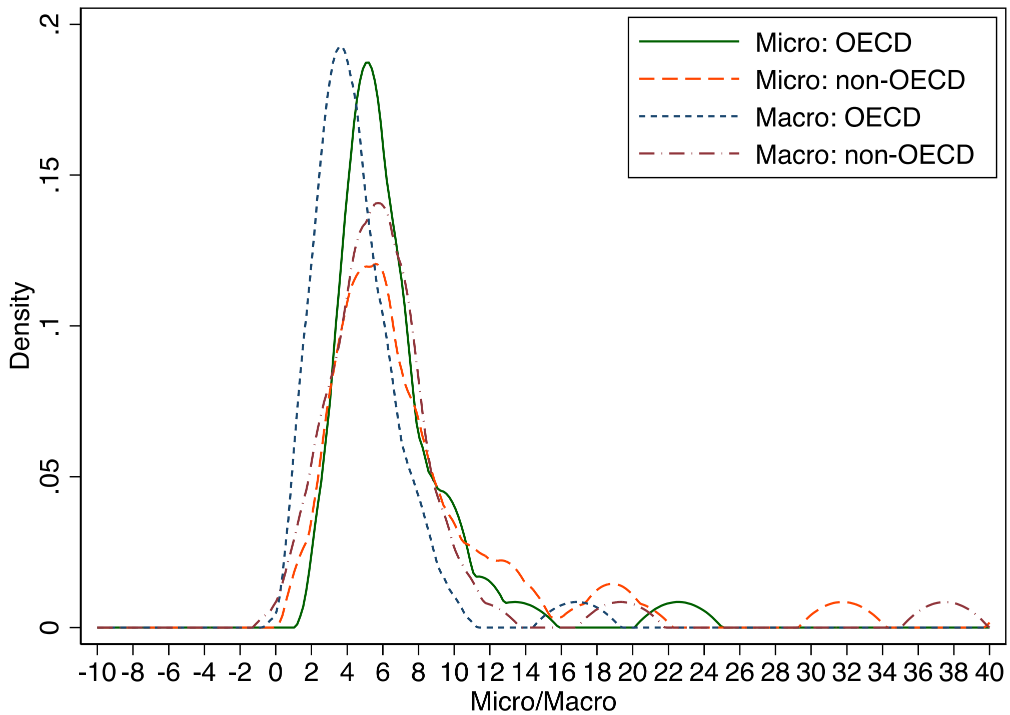
Notes: The solid lines are the empirical distributions of the point estimates of elasticities across commodities. The dashed lines are the empirical distributions of the 95% Confidence Interval (CI) lower bounds and upper bounds of the elasticities across commodities separately. C.I.'s of micro- and macro-elasticities are obtained by bootstrapping 1,000 samples.

Figure 1.4 Empirical Distribution of Micro and Macro-Elasticities by Subsamples of Periods



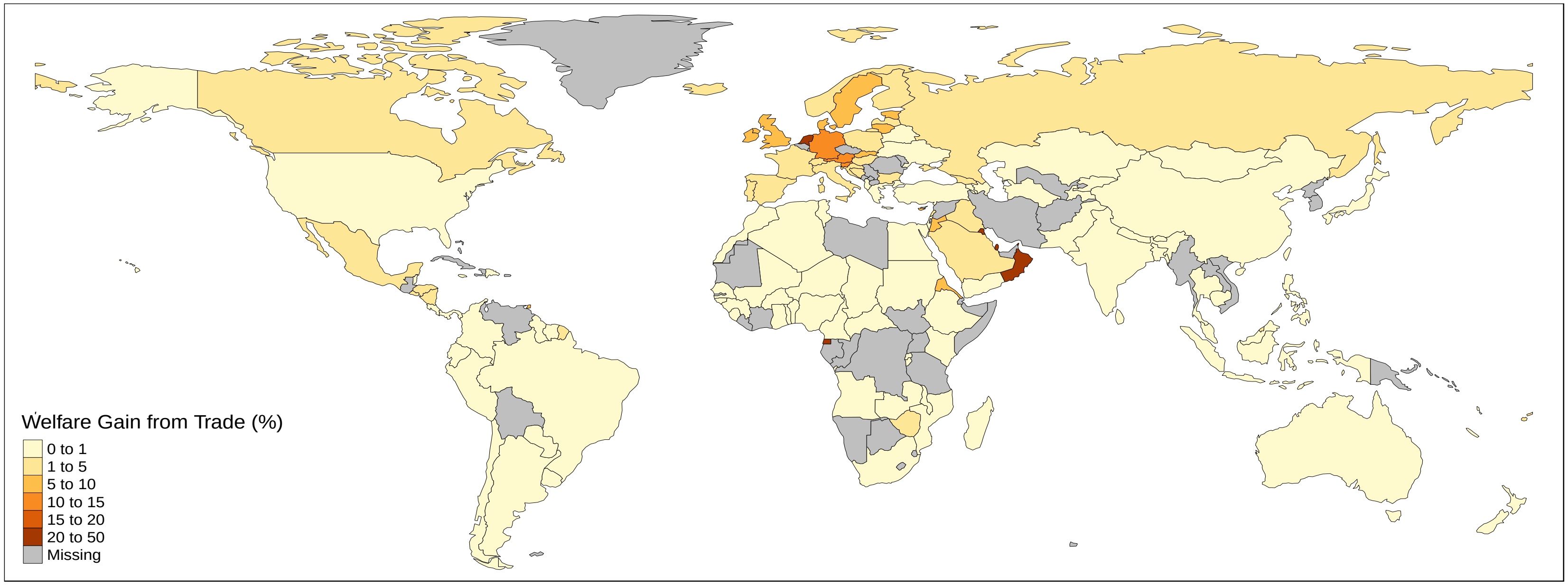
Notes: The figure presents the empirical distribution of the point estimates of elasticities across commodities, by subsamples of periods.

Figure 1.5 Empirical Distribution of Micro and Macro-Elasticities by Subsamples of Importing Countries



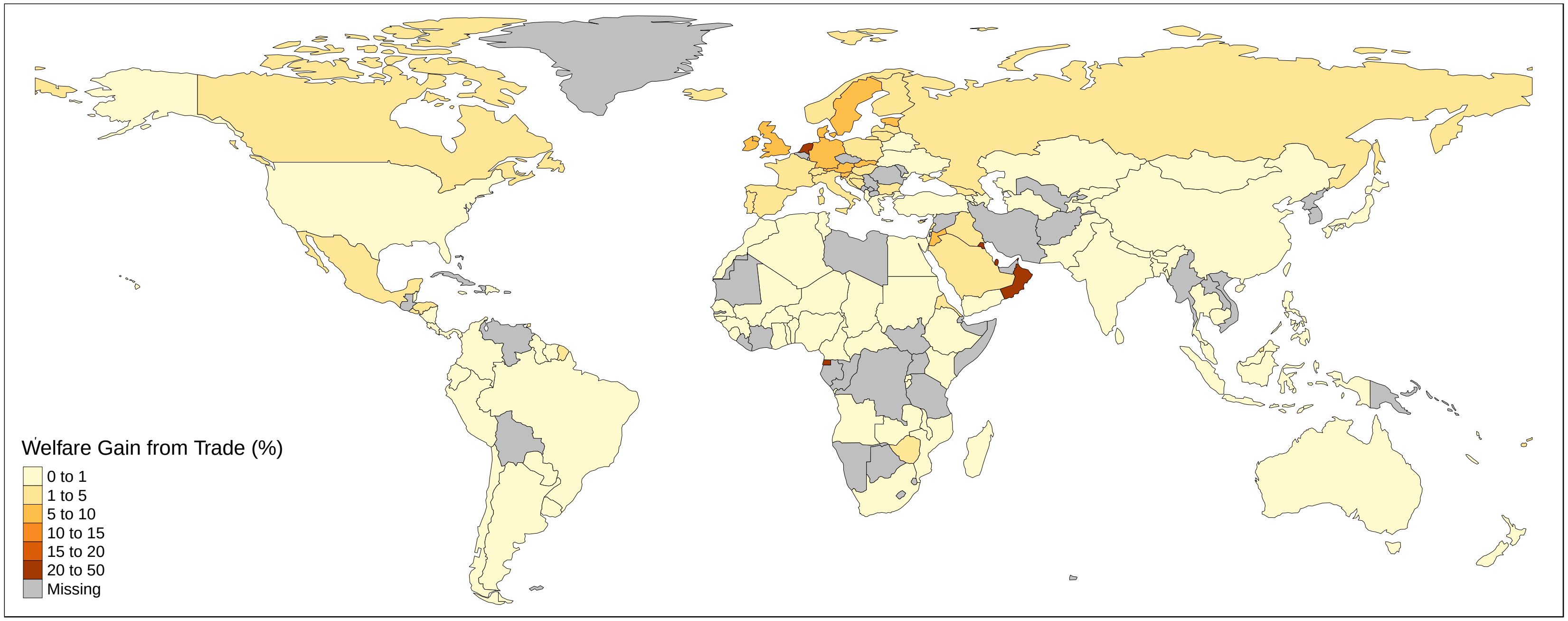
Notes: The figure presents the empirical distribution of the point estimates of elasticities across commodities, by subsamples of importing countries' OECD statuses.

Figure 1.6 Global Welfare Gains from Agricultural Trade Using Macro-Elasticities



Notes: Welfare gains from agricultural trade are calculated using equation (1.16), where shares of home supplies and shares of expenditures on each commodity are obtained using historical averages.

Figure 1.7 Global Welfare Gains from Agricultural Trade Using Micro-Elasticities



Notes: Welfare gains from agricultural trade are calculated using equation (1.16), where shares of home supplies and shares of expenditures on each commodity are obtained using historical averages.

Table 1.1 Estimates on Micro- and Macro-Elasticities

Category	*Commodity*	*Sigma*	*S.E.*	*Omega*	*S.E.*	*Rejection of Null (Y = 1)*	
						$\sigma_g \leq \omega_g$	$\sigma_g = 2\omega_g$
Meat	Beef	4.39	0.50	4.54	1.25	0	1
	Pork	4.23	0.33	2.90	0.71	1	0
	Poultry	5.01	0.48	4.08	0.62	1	1
Crops	Beans	6.40	2.21	6.87	1.89	0	1
	Chickpeas	9.23	43.79	3.55	32.31	0	0
	Corn	4.35	0.27	3.22	0.25	1	1
	Cotton	15.90	32.82	8.02	4.39	0	0
	Lentils	4.25	5.39	7.97	6.32	0	0
	Peanuts	90.30	64.36	20.06	7.22	1	0
	Peas	20.29	34.27	13.94	11.07	0	0
	Pigeon Peas	2.46	39.89	1.17	16.26	0	0
	Rice	3.19	5.83	3.23	4.97	0	0
	Sorghum	6.67	5.11	1.87	0.18	0	0
	Soybeans	5.28	1.03	5.51	1.27	0	1
	Tobacco	15.66	27.13	4.13	0.50	0	0
	Wheat	4.09	0.33	5.00	0.68	0	1
Fresh Fruit	Apples	6.88	4.38	4.11	0.31	1	0
	Berries	5.80	37.23	9.62	52.09	0	0
	Cherries	11.58	11.54	5.44	1.70	0	0
	Grapefruit	8.90	8.29	6.75	4.55	0	0
	Grapes	8.93	2.49	5.22	0.58	0	0
	Lemons	69.45	58.79	38.25	12.15	0	1
	Melons	6.55	5.61	4.80	1.19	0	0
	Peaches	5.36	5.71	6.44	2.37	0	0
	Pear	7.24	1.47	5.37	0.85	0	1
	Strawberries	6.10	0.89	4.88	0.53	0	1
Fresh Veg.	Carrots & Turnips	6.39	3.48	4.58	0.60	0	0
	Lettuce	4.42	7.94	2.74	3.96	0	0
	Onions	5.54	0.82	4.20	0.34	0	1
	Peppers	5.52	0.80	5.02	0.60	1	1
	Potatoes	5.85	0.85	4.99	0.66	0	1
	Sweet Potatoes	3.30	1.94	4.49	2.24	0	0
	Tomatoes	6.75	0.80	5.66	0.72	0	1
Tree Nuts	Pistachios	10.44	37.93	7.31	4.84	0	0
	Walnuts	6.57	4.74	4.71	2.06	0	0
Total	35					6	13

Notes: S.E. stands for standard errors. Standard errors of micro- and macro-elasticities are obtained by bootstrapping 1,000 samples.

Table 1.2 Comparison of Micro-Elasticities with CEPII Estimates

Category	*Products*	*This Study*	*CEPII*
Meats	Pork	4.23	15.80
	Poultry	5.01	4.20
Crops	Corn	4.35	4.60
	Cotton	15.90	13.70
	Peanuts	90.30	7.20
	Rice	3.19	7.50
	Sorghum	6.67	4.98
	Soybeans	5.28	7.20
	Wheat	4.09	3.60
Fresh Fruit	Apples	6.88	5.30
	Berries	5.80	12.80
	Cherries	11.58	38.50
	Grapefruit	8.90	20.70
	Grapes	8.93	6.90
	Melons	6.55	14.80
	Peaches	5.36	9.01
	Pear	7.24	5.90
	Strawberries	6.10	5.01
Fresh Veg.	Carrots & turnips	6.39	10.50
	Lettuce	4.42	7.90
	Onions	5.54	3.60
	Peppers	5.52	6.80
	Potatoes	5.85	3.70
	Sweet Potatoes	3.30	7.04
	Tomatoes	6.75	5.30
Tree Nuts	Walnuts	6.57	12.10
Overall Median		5.98	7.12
Overall Mean		9.64	9.41

Notes: The CEPII estimates are obtained from Fontagné, Guimbard, and Orefice's (2022) results. See project website: http://www.cepii.fr/CEPII/en/bdd_modele/bdd_modele_item.asp?id=35

Appendix Tables

Table A1.1 List of Importing Countries of in the Sample

Africa	*Asia*	*Europe*	*Oceania*	*North America*	*South America*
Algeria	Armenia	Albania	Australia	Antigua and Barbuda	Argentina
Angola	Azerbaijan	Austria	Fiji	Barbados	Brazil
Cameroon	Bangladesh	Belarus	New Zealand	Canada	Chile
Congo	Brunei Darussalam	Bosnia and Herzegovina		Costa Rica	Colombia
Egypt	Cambodia	Bulgaria		Dominican Republic	Ecuador
Equatorial Guinea	China, Hong Kong SAR	Croatia		El Salvador	Paraguay
Ethiopia	China, mainland	Denmark		Honduras	Peru
Gambia	Cyprus	Estonia		Jamaica	Suriname
Ghana	Georgia	Finland		Mexico	Uruguay
Guinea	India	France		Nicaragua	
Kenya	Indonesia	Germany		Panama	
Madagascar	Iraq	Greece		Saint Lucia	
Malawi	Israel	Hungary		Trinidad and Tobago	
Mali	Japan	Iceland		United States of America	
Mauritius	Jordan	Ireland			
Morocco	Kazakhstan	Italy			
Mozambique	Kuwait	Latvia			
Niger	Kyrgyzstan	Lithuania			
Nigeria	Lebanon	Malta			
Rwanda	Malaysia	Netherlands			
Senegal	Maldives	Norway			
South Africa	Mongolia	Poland			
Togo	Nepal	Portugal			
Tunisia	Oman	Russian Federation			
Zambia	Pakistan	Slovakia			
Zimbabwe	Philippines	Slovenia			
	Qatar	Spain			
	Saudi Arabia	Sweden			
	Singapore	Switzerland			
	Sri Lanka	Ukraine			
	Tajikistan	United Kingdom			
	Thailand				
	Turkey				
	Viet Nam				
	Yemen				

Table A1.2 List of Commodities in the Sample

Animal Products	*Crops*	*Fresh Fruit*	*Fresh Veg.*	*Tree Nuts*
Meat, beef	Cotton	Apples	Carrots and turnips	Almonds
Meat, pork	Corn	Berries	Cauliflower/broccoli	Pistachios
Meat, poultry	Rice	Cherries	Lettuce	Walnuts
	Sorghum	Grapefruit	Onions	
	Wheat	Grapes	Peppers	
	Peanuts	Lemons	Potatoes	
	Soybeans	Melons	Sweet Potatoes	
	Beans	Oranges	Tomatoes	
	Chick peas	Peaches		
	Lentils	Pear		
	Peas	Strawberries		
	Tobacco (Unmanufactured)			

Table A1.3 Comparison of Micro-Elasticities with Grant, Ning and Peterson (2018)

	GNP (2018)	*This Study*
Soybean	6.54	5.28
	(2.42)	(1.03)
Wheat	7.98	4.09
	(0.86)	(0.33)
Corn	13.01	4.35
	(3.50)	(0.27)
Rice	16.56	3.19
	(1.11)	(5.83)
Sorghum	29.17	6.67
	(8.58)	(5.11)
Cotton	4.74	15.9
	(1.11)	(32.83)
Apple	13.04	6.88
	(1.29)	(4.38)
Beef	8.87	4.39
	(0.37)	(0.50)
Pork	5.42	4.23
	(0.40)	(0.33)

Notes: GNP (2018) represents for Grant, Ning and Peterson (2018). Standard errors are in parenthesizes.

Chapter 2 Measuring the Opportunity Cost of Time and the Goods-Time Elasticity of Substitution in Food Production

2.1 Introduction

The household production model predicts that consumers can substitute goods for time in household production (Becker 1965). It is exceedingly important to understand the goods-time elasticity of substitution (EOS) in household production because it provides strong implications for economic and policy issues, such as child development, health production, and welfare program effectiveness (Baral, Davis, and You 2011; Davis 2014). For instance, the Supplemental Nutritional Assistance Program (SNAP) subsidizes expenditure on food for low-income households. Given SNAP benefits, larger goods-time EOS implies the household has greater food sufficiency since having more money to buy groceries would require *less* of a change in time the more substitutable money is for time. The elasticity also provides implications on how much households substitute food at home (FAH) with food away from home (FAFH) after being subsidized (Davis 2014). FAFH strongly correlates with obesity, which public policy on household food security and welfare should consider.

The magnitude of goods-time EOS remains an empirical issue. It had been difficult to estimate until recent years with the release of the American Time Use Survey (ATUS) launched in 2003. Estimates of goods-time EOS diverge in strategies. Direct estimation of household production function has shown it is rather difficult to substitute goods for time. No matter whether food consumption time is considered as input or not, the goods-time EOS is far less than unit (Baral, Davis, and You 2011; Hamermesh 2008). A recent study by Canelas et al. (2019) compares the substitutability between time and money for five commodity groups in two developing countries, and finds the substitution is most inelastic in eating among all the commodity groups. Conversely, studies using the indirect estimation strategy report goods-time EOS are much larger than unit (Aguiar and Hurst 2007). This study attempts to bridge the gap between these two strands of literature.

The assumption of opportunity cost of time (OCT) is vital for directly/indirectly estimating household production function and goods-time EOS. Most of the existing studies that directly estimate household production function assume the OCT in home production is equal to the wage rate (Baral, Davis, and You 2011; Hamermesh 2008). The assumption can be relaxed in two directions: incorporating household heterogeneity of OCT, and a component uncorrelated with wage, which could achieve different estimates of EOS. Alternatively, indirect estimation of goods-time EOS circumvents the reliance on wage data but not the assumption on OCT. Aguiar and Hurst (2007) use household tradeoff behavior between grocery shopping time and price to infer their OCT in grocery shopping and apply it to *all* household production activities, which is a strong assumption as there is no reason to expect the EOS to be the same for all household production activities (Davis 2014)

Studies in another field, the evaluation of environmental amenities, have advanced in directly modeling OCT in recreational activities, or the shadow value of time. The existing studies justify the flexible form of OCT from two perspectives. McKean, Johnson, and Taylor (2012) incorporate a two-step model based on McConnell-Strand model (McConnell and Strand 1981) that allows for the fraction of wage to depend on consumers' socio-economic backgrounds. Larson and Lew (2014) extend McConnelle-Strand model by relaxing the assumption of efficient labor market and allowing over- and under-employed statuses, which incorporates a random unobservable term in OCT that depends on workers' socio-economic backgrounds.

While there are many different theoretical frameworks that could be used to motivate a more general OCT than just the wage rate, this paper introduces the two-step decision-making framework to household production, to demonstrate how a flexible form of OCT that consists of both wage and non-wage components could arise. The household makes an ex-ante life-cycle decisions on market and household labor supply in the first step, which suggests OCT in household production be a fraction of wage. In the second step, household faces idiosyncratic shocks in labor market/household production, underlining the OCT should include an unobserved non-wage component. Both steps, we assume, depend on life-cycle dynamics and demographics, which are heterogeneous across households.

We proceed with two strategies that rely on wage data to estimate goods-time EOS: direct estimation and the demand-supply approach. The direct strategy, following Baral, Davis, and You (2011) and Hamermesh (2008), explicitly models OCT but with a more flexible form and estimates the ratio of input demands (i.e. food expenditures to time in food production). The demand-supply approach innovatively borrows the idea from Feenstra (1994) and overcomes the endogeneity problem of wage, arguing that households naturally are both consumers and suppliers of food products. This is, to our knowledge, the first to apply Feenstra's (1994) strategy for estimating household production. Using both strategies, we find goods-time EOS is much greater than unity, which is more in line with previous studies using indirect estimation strategies. We also find the demand-supply approach reports greater estimates than the direct estimation strategy but keeps the pattern of relative magnitudes using different measurements for household production time and food expenditure. Finally, we apply our demand-supply strategy to Aguiar and Hurst's (2007) sample and obtain a similar estimate to using our sample.

The rest of the paper is arranged as follows: Section 2.2 describes the theoretical framework of two-step decision-making process on household production; Section 2.3 introduces the two empirical strategies; Section 2.4 describes the data we use in this study; and Section 2.5 and 2.6 show results and draw conclusions, respectively.

2.2 Theoretical Model

The property of separation of household production from consumption is key for model setup, which determines whether household production can be modeled independently from household consumption. To satisfy the separation property of household production, domestic good is necessary to be perfectly marketable (Chiappori 1997). While it is acknowledged that foods can be bought and consumed in restaurants, restaurant foods are rarely perfect substitutes for homemade foods, due to household preference heterogeneity on taste, health, and quality. Household preferences not only differ by socio-economic status, but also evolve over life cycle. Firstly, our simple life-cycle framework relaxes the assumption of perfect separation of household production, in which we motivate that household preference heterogeneity and life-cycle decision-making process are the two reasons why OCT in household production doesn't simply comprise wage rate. Secondly, we are aware that labor supply is not upward sloping or perfectly elastic in the short run, say from week to week, so individuals cannot adjust labor input constantly between job and household production according to wage rate. The stickiness of labor market input underlies that, even though OCT in household production depends on wage rate, it varies from time to time. Such a structure of OCT naturally entails a two-step decision-making on labor input and household production. The next section shows demonstrates why such a decision structure leads to the OCT not being equivalent to the wage rate as is often assumed.

In the first step, household uses ax-ante information to determine life-cycle consumption of numeraire good (c), household products (y), and time allocations to household production (h) and leisure (l) at each period, k, after current age, t. In step two, household faces idiosyncratic shocks and determines ad hoc time allocation and consumption. The idea that household makes ex-ante decisions on consumption and time allocation can be described as a life-cycle utility maximization process.

$$max\colon V = \sum_{\{k=t\}}^{T} \psi^k U(c_{ik}, y_{ik}, h_{ik}, l_{ik}; Z_i) \tag{2.1}$$

$$s.t.\colon y_{ik} \leq f(h_{ik}, x_{ik}) \tag{2.2}$$

$$\sum_{k=t}^{T} [(c_{ik} + w_{ik} l_{ik} + W_{ik} h_{ik} + p_{ik} x_{ik}) - (w_{ik} T_{ik}^0 + I_{ik}^0 + P_{ik} y_{ik})] \leq A_{it} \tag{2.3}$$

where inequalities (2.2) and (2.3) are technology constraints of household production and life-cycle budget constraint separately. ψ denotes the time discount factor. p_{ik} is the price of purchased groceries, and x_{ik} is the amount of composite good that consists of purchased groceries. P_{ik} is the price of food sold in restaurants but similar to homemade food, and y_{ik} is the amount of homemade food consumed by household. In our framework, prices of groceries and restaurant food are exogenous to households. w_{ik} and W_{ik} denote the OCT in leisure and household production separately, where the former is market wage rate and the latter is to be determined. I_{ik}^{0} denotes household unearned income. The household utility is conditional on its characteristics, Z_i, which is a set of backgrounds that are assumed to be invariant to age, such as gender, education, etc.

The first-order conditions (F.O.C.s) of household utility maximization problem are:

$$l: w_{it} = \psi^t \frac{U_t}{\mu_{it}} \tag{2.4}$$

$$y: \frac{\lambda_{it}}{\mu_{it}} = P_{it} + \psi^t \frac{U_y}{\mu_{it}} \tag{2.5}$$

$$h: W_{it} = \psi^t \frac{U_h}{\mu_{it}} + \frac{\lambda_{it} f_h}{\mu_{it}} \tag{2.6}$$

$$x: p_{it} = \frac{\lambda_{it} f_x}{\mu_{it}} \tag{2.7}$$

where λ_{it} is the multiplier on technology constraint, which is also the shadow value of homemade food. Similarly, μ_{it} is the shadow value of wealth at age t, i.e. $\mu_{it} = dV_{it}/dA_{it}$. In our model, we assume all decision makings on consumption and time allocation have interior solutions. Hence, expressions (2.4)-(2.7) must be equalities.

Equation (2.5) shows the shadow value of homemade food depends on both market price (if it is marketable) and preference. In our study, we assume $U_y > 0$, which means household values homemade food greater than market food. Equation (2.6) shows the OCT in household production depends on household marginal utility/disutility of time in household production and marginal shadow value product of time in household production. If household enjoys food preparation, the OCT is larger than marginal value product. Equation (2.7) describes the condition at equilibrium that the marginal shadow value product of grocery input must be equal to its price.

To elaborate on the relationship of OCT in household production with respect to wage rate, we take a ratio of equations (2.6) and (2.4) and substitute λ_{it} by equation (2.5). Therefore, the ax-ante OCT in household production can be denoted as follows.

$$W_{it}(Z_i, w_{it}) = \left(\frac{U_h}{U_l} + \frac{\psi^t U_y + P_{it}\mu_{it}}{\psi^t U_l} f_h\right) w_{it} = \rho(Z_i, \mu_{it}) w_{it} \tag{2.8}$$

Equation (2.8) shows that ex-ante OCT in household production does not equal wage rate in general but is a function of wage rate and household characteristics. It equals wage rate only when the term in the bracket on the right-hand side coincidentally equals one. It is sufficiently true if, for instance, (1) the household member has neither utility nor disutility in household production, and (2) home products (food at home) are perfect substitutes to market products (restaurant food), $U_y = 0$. The first condition is hard to fulfill if household members do enjoy home production more than work, ceteris paribus. The second condition requires home products are always replicable by the market. It is very likely that the value in the bracket does not equal to unit, but equals to a value conditioning on household characteristics, Z_i, and the marginal utility of wealth, μ_{it}. If μ_{it} is constant over the life cycle, as in MaCurdy (1981) and Heckman and Macurdy (1980), ρ is fixed over the life cycle, though heterogeneous across households. If μ_{it} is time-variant during the life cycle, as in Altonji (1986), ρ depends on not only household characteristics but also age in life.

By solving the utility maximization problem using ax-ante information, households choose optimized consumption $\bar{c}_{ik}$, leisure $\bar{l}_{ik}$, and meals consumed at home $\bar{y}_{ik}$ for each period $k = t, \ldots, T$. After entering the labor market, household faces idiosyncratic shocks, which is observed by household members but unobservable to researchers. The shocks come from family or labor market, making households spend unexpectedly less or more on household production than they planned. This happens when households unexpectedly have a new child member, the child is sick and needs extra care, or household members are experiencing a difficult/smooth week on their jobs.

In this step, households are not able to adjust labor supply and consumption at the margin, but only expenditure on groceries and time in household production. Moreover, the OCT in household production is pre-determined at the beginning of age t, W_{it} must be taken as given in adjusting food expenditure and time allocation, thereafter, denoted by $\overline{W}_{it}$. Households minimize their total expenditure with ad hoc information.

$$min\colon p_{it}x_{it} + \bar{c}_{it} + w_{it}\bar{l}_{it} + \overline{W}_{it}h \tag{2.9}$$

$$s.t.\colon\ f(h_{it}, x_{it}) \geq \bar{y}_{it} \tag{2.10}$$

$$\bar{h}_{it} \geq (\ or\ \ \leq) h_{it} \tag{2.11}$$

The OCT in household production is borrowed from the first step and pre-determined. The inequality constraint (2.11) describes the shock to a household, where the inequality can have either a positive or negative direction. Denote π_{it} and ϕ_{it} as the multipliers on the constraint (2.10) and (2.11) separately, which represent the extra value for "saving" meals at home and household production time, respectively. The F.O.C.s of the cost minimization problem are:

$$h\colon \pi_{it}f_h = \overline{W}_{it} + \phi_{it} \tag{2.12}$$

$$x\colon \pi_{it}f_x = p_{it} \tag{2.13}$$

where OCT in household production—on the right-hand side of equation (2.12)—becomes the sum of a pre-determined component that depends on wage rate and an undirected component that is unobservable to researchers. Since $\bar{h}_{it}$is pre-determined by both household characteristics and life-cycle dynamics, $\phi_{it}$is also conditional on household characteristics and household members' age.

To estimate the goods-time EOS, we specify the household production technology as a CES function of purchased groceries and time input.

$$f(h_{it}, x_{it}) = k\left[\alpha x_{it}^{\frac{\sigma-1}{\sigma}} + (1-\alpha)h_{it}^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{2.14}$$

where k is the shifter and σ denotes the goods-time EOS. Take a ratio of equations (2.12) and (2.13), substitute the marginal product of time and groceries with their functional form using technology (2.14), and re-arrange the terms.

$$\ln\frac{x_{it}}{h_{it}} = \sigma\ln\left(\overline{W}_{it} + \phi_{it}\right) - \sigma\ln p_t + \sigma\ln\frac{\alpha}{1-\alpha} \tag{2.15}$$

where we take logarithms on both sides of the equations. The challenge to estimating equation (2.15) is that the quantity of composite grocery input x_{it} is unobserved on the left-hand side. So is the price index p_t. But we observe household total expenditure on groceries and food, which can be used to replace the unobserved quantity of groceries. It is useful to rewrite equation (2.15) as follows.

$$\ln\frac{E_{it}}{h_{it}} = \sigma\ln\left(\overline{W}_{it} + \phi_{it}\right) + (1-\sigma)\ln p_t + \sigma\ln\frac{\alpha}{1-\alpha} \tag{2.16}$$

where $E_{it} = x_{it}p_t$, which denotes household i's total expenditure on groceries and food at age t. Direct estimation of equation (2.16) requires correct measurement of not only wage and OCT, but expenditure and time use in food production as well. The next section discusses measurement errors on both left and right-hand sides of equation (2.16).

2.3 Econometric Model

2.3.1 Measurement Error

Previous studies that direct estimate equation (2.16) highlight two problems of wage data: (1) the endogeneity of wage, and (2) missing wage data of retirees or those who are not in the labor force.

Heckman's (1979) selection model is used to impute the exogenous wage rates, as in Baral, Davis, and You (2011) and Hamermesh (2008). Household demographics, such as age and gender, are used to predict the exogenous wage. The underlying assumption is that household demographics only affect food expenditure per unit time through wage, which does not hold in equation (2.16). This study takes another approach—explicitly modeling OCT with a functional form that includes both wage and household demographics—to overcome the endogeneity caused by measurement error.

The second challenge of estimating equation (2.16) is the measurement error of weekly household hours in food production, h_{it}. A typical time use survey, such as the American Time Use Survey (ATUS), records household time use in a 24-hour window, whereas, the survey asks about weekly expenditure and wage. The typical measurement of h_{it}, E_{it} and w_{it} above entails a mismatch of the unit on the left-hand side and right-hand side. This scaling effect is not problematic when the empirical model is in linear form, or when weekly hours in food production are a constant scaleup of day hours, regardless of ATUS survey days. In the former case, the scaling factor is absorbed by the constant in a linear model, which only affects the efficiency of estimates on goods-time EOS, but not consistency. In the latter case, adding a constant term in OCT can address the measurement problem of h_{it}. The estimation of equation (2.16) does not apply to each of the cases. Firstly, equation (2.16) is in non-linear form. The measurement error of the independent variable causes estimation bias, as is the measurement error of the dependent variable. Secondly, it is reasonable to suspect that household food production time varies from weekdays to weekends. The ATUS sample is randomized by day, and around 50 percent of the households are surveyed on weekends (You and Davis 2019). Simply augmenting the daily time by seven to obtain weekly hours could manually create measurement errors in food production time.

To address the endogeneity of wage as well as measurement error of OCT, we propose two strategies to estimate σ. In our first strategy, we impute weekly food production time and allow a more flexible form of OCT to overcome the measurement error in left-hand side and right-hand side separately. We then proceed with non-linear least square (NLS) estimation of equation (2.16) directly. In our second strategy, we classify measurement error as a source of endogeneity and estimate a demand-supply system. The thought originates from Feenstra (1994)'s seminal work on estimating trade elasticities.

2.3.2 Direct Estimation of Goods-Time EOS

Because our sample has a cross-sectional structure, we treat t as the age group that household i belongs to, instead of the age during the life cycle. Equations (2.8) and (2.12) suggest both life-cycle dynamics and household demographics affect OCT. Let $Z^0 = \{Z_i, t\}$ denotes all the factors we consider in our estimation, which includes age, gender, educational levels, and the number of children. We use these factors to classify the households into groups. We now denote the total number of demographic cells as G, and g as the demographic cell that a household belongs to.

$$\ln\frac{E_{ig}}{h_{ig}} = \sigma \ln\big(\rho_g(Z^0)w_{ig} + \phi_g(Z^0)\big) + \alpha_0 + \varepsilon_{ig} \tag{2.17}$$

where $a_0 = \sigma ln[\alpha/(1-\alpha)] + (1-\sigma)p$ denotes the constant term. ε_{ig} is the error term. Equation (2.17) allows households to have heterogeneous OCT, which consists of a heterogeneous fraction of wage rate and a heterogeneous "wage-invariant" component. The direct estimation of equation (2.17) proceeds in the following steps.

Step 1: Impute weekly household food production time, h_{ig}, using a linear regression model and household characteristics Z^1 and dummies of ATUS survey day. Z_1 includes (a) dummies of nine age groups (25-69) with five years as bin width; (b) gender; (c) numbers of children within the household and their interactions; (d) dummies of four educational levels: high school, some college, college degree and higher than college degree; (e) dummies of race and minority: white, black, Asian and Hispanic; (f) dummies of household location: metropolitan area or not, dummies of population size range of the metropolitan area, state of residence; (g) dummies of survey day: Monday to Saturday, dummies of survey month, the dummy of a holiday.

Step 2: Proceed with NLS estimation for equation (2.17) using imputed weekly hours. We allow ρ_g and ϕ_g to vary by age, gender, educational levels, and number of children.

Step 3: The standard errors are wrong because we used imputed weekly hours in the second step. To correct standard errors, we used bootstrap and simulated 1,000 samples to calculate them.

Identification of σ in equation (2.17) relies on the correct specification of the functional form of OCT. The Advantage of the direct estimation strategy is we can evaluate life-cycle OCT in food production, including the share of wage-related cost and non-wage cost.

2.3.3 The Demand-Supply Approach

The direct estimation for σ is feasible. However, it relies on the assumption that equation (2.17) is correctly specified. An alternative strategy is to avoid modeling the structure of OCT in food production, while addressing the endogeneity of wage at the same time. Take the first-order Taylor series approximation of equation (2.17) at $\rho_g w_{ig}$.

$$\begin{aligned}\ln\frac{E_{ig}}{h_{ig}} &= \sigma\ln\left(\rho_g w_{ig}+\phi_g\right)+\alpha_0+\varepsilon_{ig}\\ &\approx \sigma\ln\rho_g w_{ig}+\frac{\sigma\phi_g}{\rho_g w_{ig}}+\alpha_0+\varepsilon_{ig} \qquad (2.17')\\ &= \alpha_0+\sigma\ln\rho_g+\sigma\ln w_{ig}+\frac{\sigma\phi_g}{\rho_g w_{ig}}+\varepsilon_{ig}\end{aligned}$$

where the second line is a first-order Taylor series approximation at $\rho_g w_{ig}$ of the OCT conditional on household characteristics Z^0. As in the last line of equation (2.17), when we run the regression using wage rate and household demographics as regressors, estimation on σ will still be biased because the term remaining in the right-hand side, $\frac{\sigma\phi_g}{\rho_g w_{ig}}$, is correlated with both wage rate and food expenditure. The Taylor series approximation, therefore, transforms the measurement error problem of OCT into an endogeneity problem. This is only one way to argue the endogeneity of wage rate. Another way is to analyze it in a demand-supply framework. The regression equation of expenditure-time ratio on wage can be derived from a cost minimization of household production behavior, assuming separation of production from consumption. Therefore, it describes household demand for labor input in food production. The higher one's time value (wage) is, the less time input in food production one demands. We demean the variables in the last line of equation (2.17) by group means, re-arrange the terms, and move wage to the left-hand side.

$$\Delta \ln w_{ig} = \frac{1}{\sigma}\Delta \ln \frac{E_{ig}}{h_{ig}} + \frac{\xi_{ig}}{\sigma} \tag{2.18}$$

where Δ denotes data after demeaning, and $\xi_{ig} = -(\Delta\frac{\sigma\phi_g}{\rho_g w_{ig}} + \Delta\varepsilon_{ig})$. Unobserved demand shocks, varying by household demographics, affect both wage and time in food production, therefore, bias the estimate of σ in equation (2.18). We overcome the co-movement by assuming household time allocation will respond to the demand shocks, and that they will adjust their time input in household production. We propose a reduced form supply of household production time in equation (2.19):

$$\Delta \ln w_{ig} = \eta\frac{\xi_{ig}}{\sigma} + \delta_{ig} \tag{2.19}$$

where η is the response of food production time supply with respect to demand shocks. δ_{ig} denotes the labor market shocks, or supply shocks for household production. The demand-supply system for household production time has the assumption that overall shocks in demand and supply side are uncorrelated, $\sum_g \sum_{i \in g} \xi_{ig}\delta_{ig} = 0$, in equation (2.18)-(2.19). We further assume this holds for each demographic cell $g = 1, \dots, G$, which can be used as moment conditions to identify the system.

$$E\left(\sum_{i \in g} \xi_{ig}\delta_{ig}\right) = 0, for\ g = 1, \dots, G$$

A similar assumption was made by Feenstra (1994) and Feenstra et al. (2018), who used the demand-supply framework to identify the elasticity of substitution between varieties of products from country sources, or Armington elasticity, in international trade. Following their procedure, we multiply ξ_{ig} with δ_{ig} in equation (2.18) and (2.19) separately, and derive the following equation.

$$Y_{ig} = \theta_1 X_{1ig} + \theta_2 X_{2ig} + \mu_{ig} \tag{2.20}$$

where

$$Y_{ig} = \left(\Delta \ln w_{ig}\right)^2$$

$$X_{1ig} = \left(\Delta ln \frac{E_{ig}}{h_{ig}}\right)^2$$

$$X_{2ig} = \left(\Delta \ln \frac{E_{ig}}{h_{ig}}\right)(\Delta \ln w_{ig})$$

and $\mu_{ig} = \frac{\xi_{ig}\delta_{ig}}{\sigma(1-\eta)}$, $\theta_1 = \frac{\eta}{\sigma^2(1-\eta)}$, $\theta_2 = \frac{2\eta-1}{\sigma(\eta-1)}$. Equation (2.20) simplifies the identification of the demand-supply system, because σ and η can be recovered from the reduced form parameters. Inherited from the demand-supply system, we assume $E\left(\sum_{i \in g} \mu_{ig}\right) = 0, for\ g = 1, \dots, G$. Let N_g denote the number of observations within demographic cell g.

This moment condition highlights when aggregating errors within demographic cells in equation (2.20), $\overline{\mu}_g = \left(\frac{1}{N_g}\right) \sum_{i \in g} \mu_{ig}$, the error term no longer correlates with right-hand side variables.

$$\overline{Y}_g = \theta_1 \overline{X}_{1g} + \theta_2 \overline{X}_{2g} + \overline{\mu}_g \tag{2.20'}$$

where we suppress the dimension of i and take averages of each variable within demographic cells. Since $\overline{\mu}_g$ no longer correlates with right-hand side variables, OLS estimation can obtain unbiased estimates of θ's, and σ can be obtained by numerically solving out the structural form of θ's.

The procedure discussed above can be summarized by a 2SLS estimation, where dummies of demographic cells are used as instruments for right-hand side variables in equation (2.20). Formally, we describe the empirical strategy in two stages below.

Step 1: Proceed 2SLS to estimate θ's in equation (2.20), using demographic cells as dummies to predict right-hand side variables

Step 2: Solving out σ numerically by using the structural form of θ's.

To obtain consistent estimates, we include dummies of survey days (Monday-Saturday), in addition to dummies of cells, as instruments for right-hand side variables. Demographic cells are divided by age groups, gender, college degree and the presence of children, thereafter, the number of cells is 72. Standard errors are obtained using bootstrap methods with 1,000 samples.

This strategy can be applied to Aguiar and Hurst's (2007) sample. They use grocery shopping time and price data to identify goods-time EOS in household production, assuming the OCT in grocery shopping and household production are the same. In comparison, we rely on accessible wage data in our framework.

2.4 Data

We obtained the data on household food production time from the Bureau of Labor Statistics American Time Use Survey (ATUS). The ATUS randomly selects households from those who have finished their last interview of the Current Population Survey (CPS)[4], and selects one respondent from each household to record his/her time diary of a day. We restricted the sample to only single-headed households, to circumvent the imputation of spouse's wage and time in food production for dual-headed households. We measured food preparation time in two ways: One includes food preparation (ATUS Code 020201), presentation (ATUS Code 020202), and cleaning up (ATUS Code 020203), grocery shopping (ATUS Code 070101), and travel related to grocery shopping (ATUS Code 180701), but excludes time on eating and drinking; The other includes time on eating and drinking (ATUS Code 110101) as well. We simply refer to the former measurement as "food preparation time", and the latter as "food consumption time", in the following of this paper.

Data on food expenditure were obtained from CPS Food Security Supplements (FSS) survey in December of each year. It asks correspondents for their households' total food expenditure during the reference week and usual week separately. Therefore, we matched the ATUS 2006-2008 data with FSS data in December 2005, December 2006, and December 2007. To approximate the food expenditures during the ATUS survey closely, we matched the ATUS 2006-2008 waves data with the FSS data if it is the last wave of survey of CPS households.[5]

[4] CPS participating households typically complete eight interviews during 16 months. After the first four interviews during successive four months, households gap for eight months, and participate in another four interviews.

[5] ATUS interviews usually happen two to five months after last interviews of CPS.

The measurements of food expenditure-time ratio, therefore, consist of four combinations: reference week expenditure over preparation time, reference week expenditure over consumption time, usual week expenditure over preparation time, and usual week expenditure over consumption time. The data we use is the same as in Baral, Davis and You (2011).

2.5 Results

Table 2.1 presents the results of directly estimating equation (2.17) using reference week food expenditure data. We report the results under three scenarios. In each column, we employ different restrictions on parameters: a fixed fraction (ρ) of wage as OCT in column 1; heterogeneous fractions ($\rho_g(Z^0)$) of wage as OCT in column 2; and includes heterogeneous unobserved OCT ($\phi_g(Z^0)$) in column 3. Panel A reports the results using reference week expenditure over preparation time as the measurement for the right-hand side variable in equation (2.17), while Panel B uses food consumption time to construct the dependent variable. Numbers of observations differ in Panel A and B because more missing values are reported using the first measurement.

When imposing the restriction that ρ is universal for all households, the coefficient on the OCT, goods-time EOS, presents a negative value, no matter which measurement we use for food production time. This is inconsistent with Becker's (1965) prediction that goods and time are substitutes in household production. Allowing heterogeneous ρ_g that depends on household demographics, the estimate of σ turns positive when excluding consumption time from the measurement of food production time, but it remains negative when including it. Further incorporating unobserved household OCT, the estimates of goods-time EOS increase to over unit. But measurements of household production time—preparation time versus consumption time—

result in a large discrepancy in the estimates. Using preparation time leads to an estimate of 1.82, 80 percent larger than the estimate (1.01) using consumption time. This discrepancy is not novel in the literature. Baral, Davis and You (2011) justify it in theory and find the discrepancy is around 70 percent. All the estimates, except the one using consumption time in column 2, show statistical significance at 1 percent level. We refer to the measurement of preparation time combining with most flexible assumption of OCT (column 3 in Panel A) as our baseline results.

We find the correlation of OCT with wage is weakest for middle-aged adults, while their non-wage OCT is substantial. Figure 2.1 displays the life-cycle change of OCT associated with wage, using the estimates from baseline results. Households with adults aged between 25 and 29 are normalized as the control group. Interestingly, we find a U-shape life-cycle change of $\hat{\rho}_g$, reaching the bottom at around age 45-49. This is in stark contrast with labor studies that document the inverse U-shape of the life-cycle wage rate. Our estimates show OCT of household production doesn't change in proportion to life-cycle wage growth. Correlation of OCT with age decreases by 12 percent in middle age between 45 and 49, compared to young adults aged between 25 and 29. Figure 2.2 displays the life-cycle change of non-wage OCT in household production, compared with adults aged between 25 and 29. We find an inverse U-shape of life-cycle non-wage OCT, which peaks around age between 45 and 49.

We mirror the estimation in Table 2.1 by replacing the reference week food expenditure with the usual week answer and report the results in Table 2.2. The results are very similar to their counterparts in Table 2.1, but with a slight difference in column 3. Using usual week expenditure lowers our baseline estimate of EOS slightly by 5 percent (from 1.82 to 1.73), and lowers the estimate using food consumption time by 10 percent (from 1.01 to 0.91). This same pattern of relative magnitude is consistent with Hamermesh (2008).

Columns 1-4 in Table 2.3 proceed with our demand-supply estimation and report the results using the four measurements of food expenditure over household production time separately. Three observations are noteworthy: Firstly, all the point estimates of EOS in Table 2.3 are much larger than the baseline counterparts in Table 2.1 and Table 2.2. Secondly, the relative magnitude patterns in Table 2.1 and Table 2.2—between reference week and usual week, and preparation time and consumption time—persist in the demand-supply estimation. Thirdly, the estimates are not sensitive to preparation/consumption time but are so to reference/usual week expenditures. Goods-time EOS estimate is 3.64, using reference week food expenditure over preparation time, just the double estimate reported under baseline setting in Table 2.1. Using the alternative measurement of consumption time slightly shrinks the point estimate by 0.3. However, replacing the measurement of food expenditure with the usual week answer substantially shrinks the point estimate to 2.52 (see column 2), a more than 30 percent decrease from the reference week estimate in column 1. The last scenario, using measurement of usual week expenditure over consumption time, reports the smallest point estimates of 2.31 in column 4. Still, the magnitude is more than doubling the counterpart using the direct estimation strategy (see column 3, Panel B, Table 2.2).

Our demand-supply strategy can be applied to Aguiar and Hurst (2007)'s sample. They matched the household scanner data of grocery items from 1993 to 1995 with 2003 ATUS, at the demographic group level (see Aguiar and Hurst, 2007, for more details on data processing). The average grocery shopping amount within each group was used as the proxy for weekly food expenditure, which is more comparable to the FSS usual week answer in our sample. Restricting their sample to single-headed households, we obtain a point estimate of 2.39 for goods-time EOS, which is very similar to the estimates using our sample and the usual week expenditure. By assuming households have the same OCT in grocery shopping and household food preparation, Aguiar and Hurst (2007) report point estimates of goods-time EOS ranged from 1.78 to 2.18 for all households. Our strategy circumvents this assumption but obtains an estimate close to theirs.

2.6 Conclusion

Studies on goods-time elasticity of substitution in household production usually measure the opportunity cost of time as a fixed fraction or estimable fraction of wage. We argue that OCT is heterogeneous among households due to life-cycle dynamics, and households have unobserved fixed costs in household production. We develop two strategies, the direct estimation, and the demand-supply approach, to recover goods-time EOS. Empirical results show that allowing unobserved fixed cost in household production, goods-time EOS estimates become larger than unit. Demand-supply estimates are even larger than direct NLS estimates. We replicate the demand-supply estimation using Aguiar and Hurst's (2007) sample and obtain similar results. The study suggests neglecting the heterogeneity of the OCT among households and fixed costs in household production may lead to a severe underestimation of goods-time EOS, which have crucial implications for policy making.

The goods-time EOS is a typical two-factor-one-price elasticity of substitution (TOES), which generally measures the difference of percentage changes between two quantities with respect to the percentage change in the price of one good (Chambers, 1988). A positive estimate determines that money and time are substitutes in food production, and a larger estimate means they are more substitutable (Davis and Gauger, 1996; Davis and Shumway, 1996).

What are the implications of goods-time EOS on policies that aim to increase food sufficiency of lower-income households? Let’s assume two extreme cases: perfect substitutes and perfect complements. Figure A2.1 is a simplified model with two inputs, money and time. With perfect substitutes, the isoquant of household products is a straight line, as shown in Figure A2.1. With perfect complements, the isoquant of household products is an L-shape. Policies, say SNAP benefits, subsidize household grocery expenditure, but they can hardly buy time directly for households. Suppose the initial point before subsidy is A, where both isoquants intersect. Let $M' - M^0$ denotes the SNAP benefits. With perfect complements, i.e., goods-time EOS is zero, the point moves from A to B, but household product isoquant does not move at all, which means household has the same food sufficiency as before subsidy. If households want to improve food sufficiency, they must change time in food production greatly. Conversely, with perfect substitution between goods and time, i.e., EOS is infinitely large, the isoquant line moves from y to y', which greatly improve food sufficiency. In this case, households don't need to change time in food production at all. The analysis indicates that, the greater goods-time EOS, the more sufficient SNAP benefits will be.

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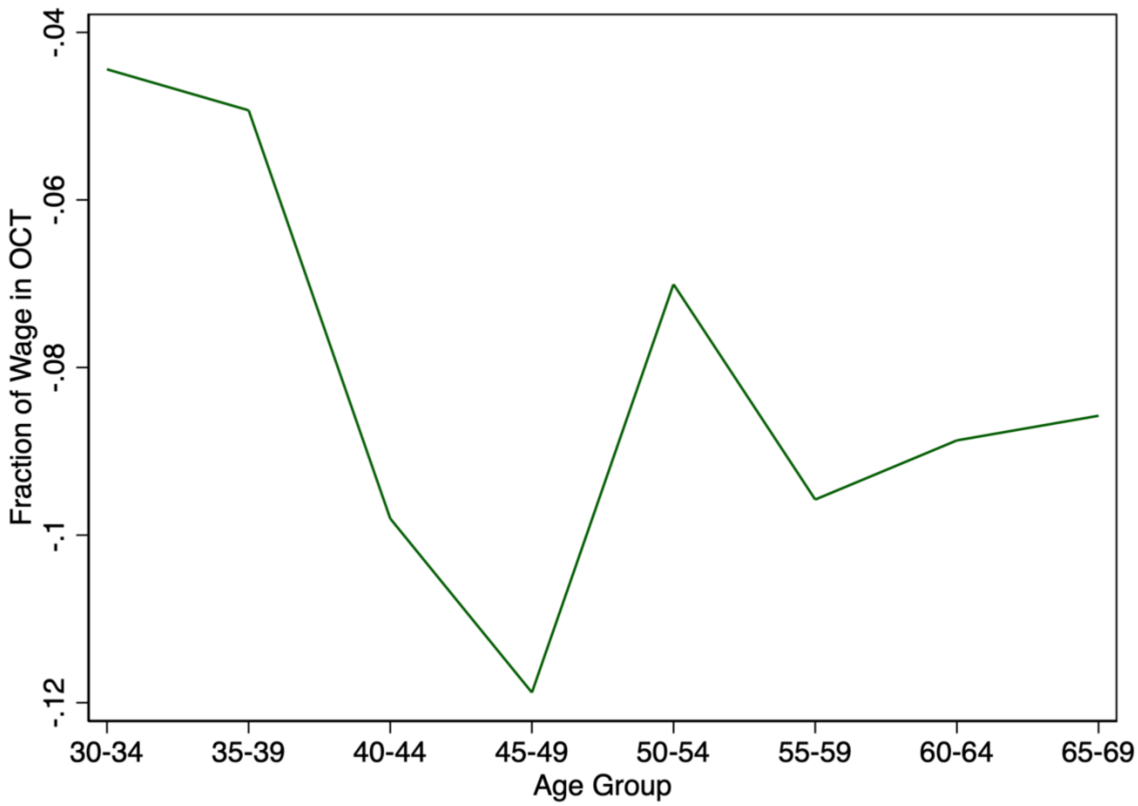
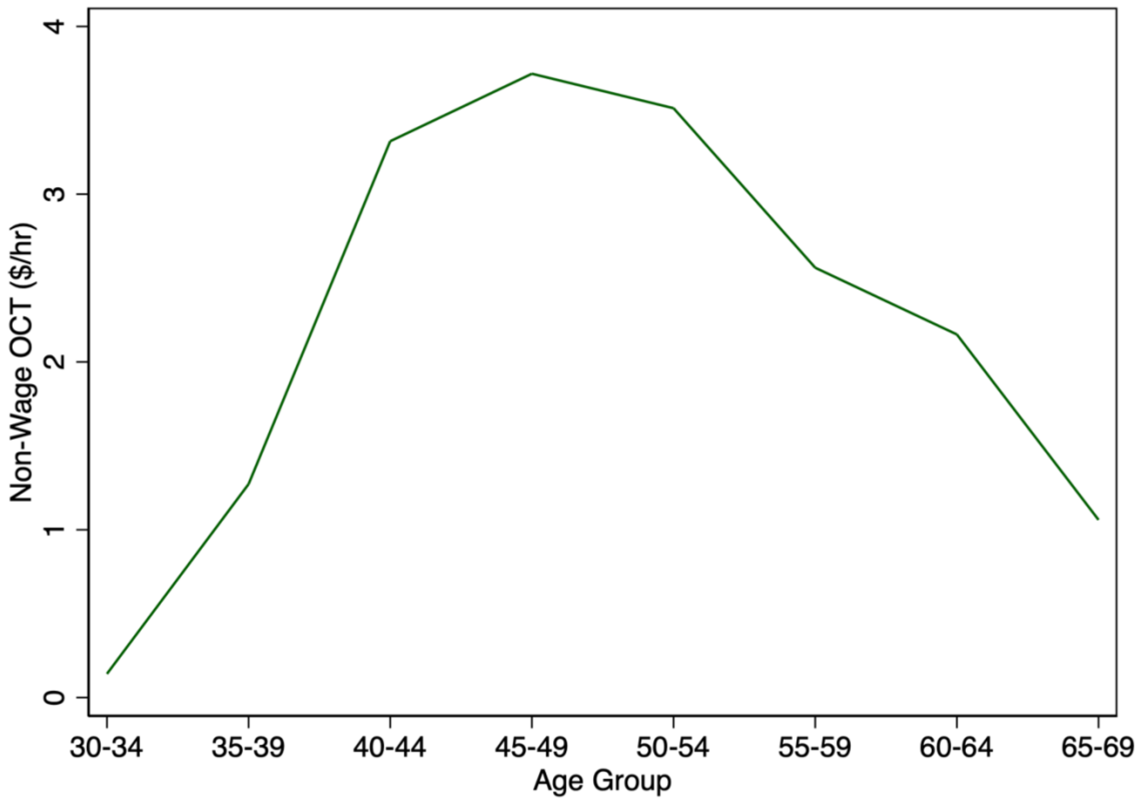
Figures and Tables

Figure 2.1 Fraction of Wage in OCT over Life Cycle: Normalizing Age 25-29 as Zero



Notes: The figure presents the point estimates of ρ_g over life cycle, normalizing the value for age group 25-29 as zero.

Figure 2.2 Non-Wage OCT over Life Cycle: Normalizing Age 25-29 as Zero



Notes: The figure presents the point estimates of ϕ_g over life cycle, normalizing the value for age group 25-29 as zero.

Table 2.1 Direct Estimates of Goods-Time EOS Using Reference Week Food Expenditure

OCT	ρw	$\rho_g(Z^0)w$	$\rho_g(Z^0)w + \phi_g(Z^0)$
	(1)	(2)	(3)
Panel A: Without Consumption Time			
sigma	-0.21	0.17	1.82
	(0.07)	(0.009)	(0.32)
N	2061	2061	2061
Panel B: With Consumption Time			
sigma	-0.22	-0.21	1.01
	(0.04)	(0.13)	(0.33)
N	2077	2077	2077

Notes: Standard errors are in parentheses. Standard errors are obtained by bootstrapping 1,000 samples.

Table 2.2 Direct Estimates of Goods-Time EOS Using Usual Week Food Expenditure

OCT	ρw	$\rho_g(Z^0)w$	$\rho_g(Z^0)w + \phi_g(Z^0)$
	(1)	(2)	(3)
Panel A: Without Consumption Time			
sigma	-0.22	0.17	1.73
	(0.07)	(0.01)	(0.61)
N	2070	2070	2070
Panel B: With Consumption Time			
sigma	-0.09	-0.21	0.91
	(0.04)	(0.08)	(0.44)
N	2083	2083	2083

Notes: Standard errors are in parentheses. Standard errors are obtained by bootstrapping 1,000 samples.

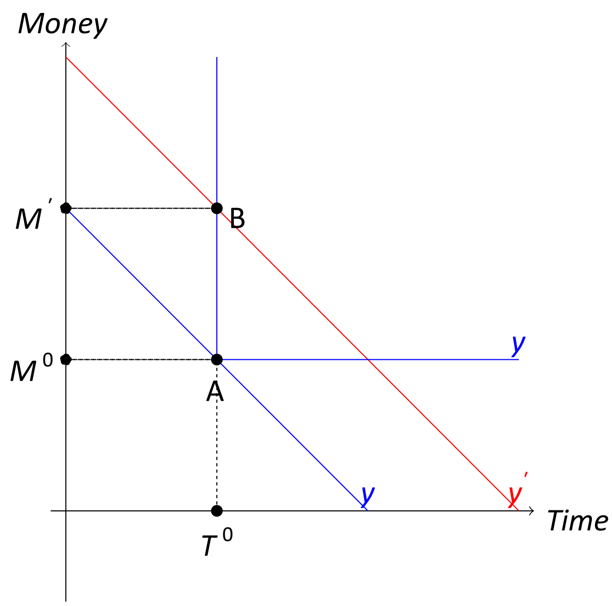
Table 2.3 Demand-Supply Estimates of Goods-Time EOS

	Our Sample				*AH (2007)*
	(1)	(2}	(3)	(4}	(5)
sigma	3.64	2.52	3.34	2.31	2.39
	(1.09)	(1.17)	(0.93)	(0.70)	(1.05)
N	1146	1147	2020	2025	2631
Reference Week	Y		Y		
Usual Week		Y		Y	Y
W/ Consumption time			Y	Y	

Notes: AH (2007) represents for the sample in Aguiar and Hurst (2007). Standard errors are in parentheses. Standard errors are obtained by bootstrapping 1,000 samples.

Appendix Figures

Figure A2.1 Perfect Substitutes and Perfect Complements between Money and Time



Chapter 3 : What A Difference A Day Makes: Impacts of Port Congestion on U.S. Agricultural Exports

3.1 Introduction

"It's like taking ten lanes of freeway traffic and squeezing them into five [when the cargo gets here]."

Gene Seroka, Executive Director, Port of Los Angeles, October 2, 2021[6]

U.S. and global ports experienced increasing congestion and delays prior to COVID-19. These delays and related supply chain disorders, however, were amplified in 2021 and have continued into 2022 following a strong resurgence of economic activity following nearly two years of COVID-19 lockdowns and remote work and business schedules. The high-speed growth of seaborn shipments—driven pronouncedly by container modes increased at a ten percent rate annually since 1990—is mismatched by port capacity expansion (Fruth and Teuteberg 2017). These challenges were exacerbated by recent increases in socio-economic uncertainties, including trade protectionism associated with the U.S.'s abrupt reversal towards China and other key trading partners, and lockdown effects caused by the COVID-19 pandemic. As a consequence, global port

[6] Reuters (2021), available at: https://www.reuters.com/business/autos-transportation/containergeddon-supply-crisis-drives-walmart-rivals-hire-their-own-ships-2021-10-07/

delays, surpassed 1.5 days on average by the end of 2021. As major hubs of seaborne vessel traffic, China and U.S. ports were significantly affected (Komaromi, Cerdeiro, and Liu 2022). At the end of 2021, port delays in China increased by more than three days compared to the average levels in 2019, and the U.S experienced a rise of more than eight days of delay (Komaromi, Cerdeiro, and Liu 2022). The literature suggests port congestion could impede exports of commodities because shipping time constitutes part of the non-tariff (time) costs of international trade (Hummels and Schaur, 2013).

U.S. ports, especially California ports, have long been performing at the bottom in terms of shipping delays compared to the rest of the world. Los Angeles ranked 337 out of 351 among global ports in 2021, and Long Beach ranked 341 (Carter, Steinbach, and Zhuang 2021). Before the pandemic, container ship waiting times at California ports were twice that at major east coast ports (Carter, Steinbach, and Zhuang 2021). The gap further widened after 2020, reaching over nine days of delay in May 2021 (Carter, Steinbach, and Zhuang 2021). Due to the delay and the huge difference in freight rates between importing and exporting shipments, exports from California ports faced severe shortages of empty containers because more liners could still make profits and earn higher freight rates by returning to partner countries without loading U.S. export cargo.

An obvious question is: what is the impact of such delays on the value of agricultural exports? Through an event study strategy that compares exports before and after May 2021—a "break" point in time chosen by the authors when port container congestion started worsening—Carter, Steinbach, and Zhuang (2021) estimate California's containerized agricultural export value dropped by 17% from May to September 2021, a loss of $2.1 billion.

Other recent studies have examined the effects of economic factors that impact port performance and international trade. Using the same event study strategy, Steinbach (2022) extends Carter, Steinbach, and Zhuang's (2021) research to broader product categories shipped by containers from all U.S. ports. Steinbach (2022) finds U.S. exports decreased by 7.8 percent in value and 11.8 percent in quantity after May 2021. Consistent with Carter, Steinbach, and Zhuang (2021), Steinbach (2022) sees the effects of Western port delays are most saliant among all regions, and chemical products had the most export value loss. Arita et al. (2022) is one of the first studies to examine the impact of COVID-19 induced lockdown measures in 2020 on U.S. agricultural export. They use Oxford Stringency Index and Google's Workplace Mobility as proxies for U.S. state-level policy response to contain the virus and find the stringency of the policy response is negatively correlated with many non-food categories such as hides and skins, cotton, rubber, essentials oils, but had a more muted impact on key staple bulk commodities such as wheat, corn, and rice.

Our study distinguishes itself from previous studies in three important aspects. First, to our knowledge, this is the first study to use port congestion data (or days in delay)to directly examine the congestion-time elasticity of trade with respect to shipment delays, including both container and bulk shipment methods of transport, on U.S. agricultural exports.[7] Instead of focusing on the supply chain shocks due to COVID-19 in 2021, we ask the more general question of how large the U.S. agricultural export volume response is to one additional day of port congestion. The answer to this question can directly inform policymakers who are interested in evaluating the benefits and costs of improving port capacity and management.

[7] In this study, we measure port congestion as days in delay for unloading, which may not represent "congestion" days. Because some time of delays can be expected to be normal even without any congestion, which will be discussed later in the Conclusion section.

Second, we explore the heterogeneity of the effects and test the dependency of port congestion effects on port regions and product categories within a unified, single-equation model. The data we use include all monthly export quantity/value of agricultural products from the top 31 ports in the U.S., from 2016 to 2021, and the congestion days by transportation modes of each port in each month as well. We employ a reduced-form gravity-based model that allows us to control for high-dimensional fixed effects that should rule out common short-term shocks, policy responses unrelated to port congestion, and geographic and historical trade patterns. Adding all-level interactions of port region and product dummies with congestion time, we test three hypotheses: (a) We test whether the estimate of percentage effect (the coefficient on the congestion variable) is independent of port regions and products in general, the null hypothesis that all the differences in the percentage trade response to an additional day of congestion between East, Gulf and West ports, and the difference between consumer, intermediate and bulk commodities are simultaneously zero. (b) We test whether the percentage effect depends on port regions, with the null hypothesis that all differences of percentage effects between Eastern or Gulf regions and Western region equal zero. (c) We test the dependency of congestion effect on products, with the null hypothesis that all differences of percentage effects between intermediate or consumer commodities and bulk commodities equal zero. Finally, we test the substitutability between bulk and container shipping modes (i.e. inter-modal substitutability) for agricultural products, which is likely to happen when one transportation mode faces unexpected delays.

Our results provide new evidence that containerized agricultural exports are relatively elastic (i.e., sensitive) to port congestion. One extra day delay of container shipments decreases U.S. agricultural monthly exports by 5 percent in quantity or 2 percent in value on average. Transformed into trade volumes, that is 140 thousand M.T. fewer monthly exports of agricultural products and an average $63 million monthly loss in export value. Consistent with existing studies, we find Western ports shoulder most of the burden across all regions, around 69 percentage points of total marginal loss in value. Across products, bulk commodities exports contribute the largest share of loss, accounting for more than 46 percent of total marginal loss in value. The effects on the Western region's exports of bulk commodities are most pronounced; one day delay of container shipments leads to 9 percent loss in quantity and 8 percent loss in value, well above the global effects. For the Eastern region, the most salient impact is on consumer commodities, with a loss of 3 percent in quantity and 3 percent in value. For the Gulf region, the largest effect is on bulk commodities, with a loss of 4 percent in quantity and 5 percent in value.

In contrast, the effect of bulk shipment delay is negligible and statistically insignificant. Importantly, we find that very little of the losses from vessel container shipments due to congestion are compensated by bulk shipments. In other words, we find no evidence of inter-modal substitutability—the idea that bulk shipments can be substituted for container shipments impacted by congestion. This is likely due to the existing infrastructure and product-specific logistical frictions in the system that make it difficult to take a shipment of, say, bell peppers that require refrigeration during export and put it on a bulk vessel. However, we also find it possible to substitute bulk shipments with containers when bulk shipping delays increase.

Additionally, this study contributes to the maritime economics literature that discusses port capacity and resilience to uncertainties. Studies in this area have shown port congestion accounts for more than 65 percent of container shipping unreliability (Notteboom 2006). Investment in port capacity, both physical and digital infrastructure, could improve the performance of addressing uncertainties (Fruth and Teuteberg 2017; Russell, Ruamsook, and Roso 2022). This study reveals one of the underlying economic costs of under-investment in port capacity.

The rest of the paper is organized as follows. Section 3.2 introduces our data sources and begins by summarizing key facts about U.S. ports and their export patterns. In Section 3.3 we present the empirical framework and identification strategy to quantify the effects of port congestion. The results are discussed in Section 3.4 and in the final section we conclude.

3.2 Data

Our data have six dimensions: port locations, shipping modes, importing countries, products, year, and month. We compiled monthly U.S. port exports/imports data with port congestion information for the purposes of our analysis. We downloaded the monthly port exports/imports data, consisting of around 400 ports in the United States, from the Census Bureau of Foreign Trade accessed through Trade Data Monitor. The data includes all coast-to-coast trade flows of commodities at the H.S. 6-digit level and their value, shipping weight, transportation mode, and partner country for each month and year in the sample. We selected the 31 largest agricultural exporting and importing ports in terms of trade volumes in our sample. These ports account for nearly 95 percent of U.S. agricultural trade. Port congestion data of bulk and container shipments were provided by Thomson Reuters REFINTIV Eikon shipping information database. [8] Finally, the combined export data comprise trade flows from 31 U.S. ports to 72 partner countries (importers), 748 HS 6-digit products, spanning from 2016 to 2021. We summarize the export flows of the data in the following section.

[8] Please see the full description of the shipping data through the link. https://www.refinitiv.com/en/financial-data/commodities-data/shipping-data

3.2.1 Where to Export?

Cargo shipped to different partner countries used different ports and different shipping modes. To depict the general picture of the trade flows, we collapsed the data from U.S. port regions to partner regions worldwide. Ports are divided into four regions: Eastern (E), Gulf (G), Inland (I) (predominantly Canada and Mexico), and Western (W) (See Table A3.1 for the ports in each region). Partners of trade flows are classified into 11 regions in the world: Africa (AFR), Central America (CAM), China (CHI), E.U. Countries (EUR), Middle East (MIE), North America (NAM), Other Asian Countries (OAS), Oceania Countries (OCE), Other European Countries (OEU), South America (SAM), Southeast Asia (SEA), (See Table A3.2 for countries in each partner regions).

Figure 3.1 gives an initial snapshot of international trade flows from U.S. ports to the rest of the world in 2016. A few facts stand out. Firstly, Western ports export the largest value of agricultural products over all four port regions. About 49% of total exports from Western ports are destined for Southeast Asian countries. China is the second-largest destination, accounting for 22% of export value. Secondly, for Inland ports, more than 97% of exports in value arrive in North American trade partners Canada and Mexico. Thirdly, for Gulf and Eastern ports, exports ships dispersedly to all regions of the world. But still, a significant share, 28% of the total export value departing from Eastern ports, arrives in China. The largest three buyers of U.S. agricultural exports are North America, Southeast Asia, and China.

Does the export pattern in Figure 3.1 persist over time? Figure 3.2 shows that the U.S. port region's monthly share of export value remained stable over the year 2016-2021. The graph shows exports from Gulf and Western coasts have seasonal patterns coinciding with the underlying seasonality in bulk commodity production and export in northern hemispheric countries. At the same time, those from Eastern and Inland ports are relatively stable over seasons.

Disentangling exports by BICO aggregate (BICOA) sectors (bulk, intermediate, and consumer-oriented commodities), the results are consistent with the overall story but with a few heterogeneous patterns (see Figure 3.3). BICO is the USDA Foreign Agricultural Service (FAS) designated classification of agricultural products into three categories: bulk, intermediate and consumer-oriented commodities. The bulk commodities include corn, wheat, rice, soybeans, grain sorghum, etc.; The consumer goods include fresh fruits and vegetables, alcohol, chocolate, pasta, noodles, soups, spices, etc.; The intermediate products include fodder, hay, soybean oil and meal, etc. Please see Table A3.3 for all the commodities within the three categories.

Our analysis in Figure 3.3 shows that, first, seasonal patterns differ by commodities. They are most discernible for bulk products in all ports except Inland ports. Perhaps not surprisingly, intermediate and consumer goods exports are less prone to seasonal volatility. Second, even within port regions, destinations of exports differ by commodities. For Eastern ports, exports of bulk commodities to Southeast Asia account for around 40 percent of the total share, but exports of consumer commodities to the same destinations account for less than 20 percent. The share of intermediate goods is around 25 percent. However, Eastern ports shipped the largest share of their intermediate goods to E.U. countries and substantial bulk commodities to Southeast Asia and China as well. Almost all Inland ports' cargos, regardless of commodities, depart for North America. For Western ports, nearly all the exports of bulk and intermediate commodities are received by destinations in Southeast Asia and China. Meanwhile, a substantial amount of consumer goods exports depart for Southeast Asia, the E.U., and other Asian countries. Very few–but an increasing amount of them over time–goes to China.

3.2.2 By What Means to Export?

Figure 3.4 presents the historical share of export value by port regions and transportation modes. As shares of shipping modes differ by port regions. air transportation is negligible in all port regions for agricultural exports.

For Eastern ports, container shipments were increasing over the past six years, from 75 percent of the total value share of exports in 2016 to around 90 percent in 2021. Container shipments in Western ports were relatively stable over time but with larger oscillation in the recent two years. The value share of container shipments dropped to a historically low of 56 percent in October 2021. For Gulf coastal ports, bulk shipments dominated over other shipping modes and remained stable for all time. For Inland ports, ground transportation dominates over all other modes.

Shipping modes differ by commodities as well (see Figure 3.5). Overall, consumer commodities have the highest share of container shipments, while bulk commodities have the lowest.

3.2.3 Port Congestion by Means

Because of certain data limitations and availability, this study focuses on analyzing bulk, and containerized shipping modes. Our data have information on delays for only bulk and container shipments. Therefore, Inland ports, dominated by ground shipments, are dropped from analysis in this section. Air shipments in the other three port regions are dropped as well.

We present the regional averages of port congestion (i.e. delay days) data. The regional congestion days are the arithmetic averages of port congestion days within each region after merging with trade data, which is equivalent to weighting the congestion data by frequencies of port-level shipments. The last two columns in Table A3.1 show the within-region share of shipments for each port by transportation modes. In the West, Los Angeles exports the largest overall share of 27 percent of container shipments. In the Gulf, Huston exports more than 75 percent of all container shipments. In the East, New York has the largest share of 22 percent of all container shipments.

Figure 3.6 presents the monthly port congestion days by region and transportation methods. Firstly, bulk congestion is similar across all regions. Overall, bulk congestion is heavier than container, except for some short-term shocks in Western and Gulf coastal ports. Average bulk shipping congestion is around three days. Meanwhile, the variation of congestion days has been increasing since 2019, especially in Eastern and Gulf ports. Western port congestion of bulk shipments has been worsening since 2020. Secondly, container shipment congestion varies across regions. It is lowest in Eastern ports and highest in Western ports, both experiencing a substantial increase in recent years. Consistent with the news, Western ports have been most vulnerable to container congestion since 2019. At the end of 2021, the container congestion in Western ports reached a historically high of around ten days on average.

Figure 3.7 displays the median of the monthly congestion days of the world partner ports. Bulk transportation congestion was maintained well below three days even in recent years. Container congestion reached the highest in the first half of 2020, likely due to COVID-19 pandemic lockdowns. But the highest point of partners' container congestion on the median is around 1.5 days, much smaller than U.S. ports during the same period.

In Figure 3.8, we attempt to visualize the potential correlation between U.S. port congestion and agricultural exports. To rule out the seasonality of congestion, we compare congestion days by month in different years and by different port regions and shipping modes. We also aggregated the monthly export quantities at each port region by bulk or container shipment. The size of the point represents the total export quantity (in log million metric tons). We find the pattern of congestion is consistent with Figure 3.6. For container shipments, we also find that export quantities are much smaller in some abnormal seasons with extra port congestion. For instance, the average container congestion days reached around 19 in Gulf ports in June 2020 due to the pandemic, compared to less than one day in the same month before the pandemic. Total containerized agricultural exports in that month were 92 thousand MT in 2020, a 36 percent decrease from the average of the same month from 2018 to 2019, and a 43 percent decrease from the average of the same month from 2016 to 2017. For other port regions, the levels of point sizes are too coarse to discern any correlation between port congestion and export volume. Take, for example, Western ports. The average container congestion was 4.3 days in June 2020, compared to around 1.5 days from 2018 to 2019. Total containerized agricultural exports were 1.8 million M.T. in June 2020, a 10 percent decrease from the average of the same month from 2018 to 2019, which is difficult to discern from the point sizes in Figure 3.8. For bulk shipments, total exports do not explicitly correlate with congestion days.

The coarse analysis above suggests some initial correlations between congestion and U.S. agricultural exports. However, the preceding qualitative analysis did not attempt to hold other factors constant. For this, we need a more formal model predicting port-level bilateral trade, which we develop in the next section.

3.3 Estimation Strategy

We use more sophisticated econometric methodologies to formally explore the association between port congestion and agricultural exports. We removed observations of Air and Inland transportation methods from the sample to focus on vessel container and bulk shipments. Consistent with the last section, we also dropped export flows of live animals since most cross-border trade in live animals occurs between the U.S., Canada, and Mexico.

The effects of port congestion on U.S. agricultural exports may be heterogeneous in multiple dimensions. Both existing studies and our summary analysis have shown that congestion is much heavier in Western ports (Komaromi, Cerdeiro, and Liu, 2022). Steinbach (2022) uses the event study method and finds that the effects of congestion vary by ports and products. Following previous studies, we examine the heterogeneity of port congestion effects in two dimensions: port regions and products.

Our original data consist of six dimensions: p as U.S. port, s as transport or shipping mode, j as importer country, k as H.S. 6-digit product, t as exporting year, and m as exporting month. The data are unbalanced over time: some large and busy ports like Los Angeles constantly ship almost every product over time, but the small ports like Longview in Washington export very few containerized products between 2016 and 2021. The non-random missing values—congested ports are less likely to have missing values—could lead to a biased estimation of port congestion with an unbalanced panel. However, policymakers are likely more interested in the aggregate bottleneck effect of port congestion within the U.S. or a region instead of the congestion effect of a single port on average, which has more implications on port competitiveness (Yeo, Roe, and Dinwoodie 2008). Consequently, our interest is at a more aggregate level but one which will allow for some heterogeneous effects. Estimating the model at the aggregate level of data may address these concerns.

We aggregated the data in three dimensions: port, product, and importer. The data dimensions, before and after aggregation, are presented in Table A3.4. Consistent with our summary analysis, ports were aggregated into three regions: East, Gulf, and West Coast. Products were classified into three categories: bulk, intermediate, and consumer products, according to their position in the supply chain. Importers of U.S. products were aggregated into three routes: Asia-Pacific, America (including North and South America), Europe & Africa. Destinations are classified simply by Pacific and Atlantic routes, while exports to North and South America can arrive through either route.

Following Arita et al. (2022), Grant et al., (2021), and Steinbach (2022), we use a non-linear panel regression model to estimate the effects of port congestion on U.S. agricultural exports.

$$X^{s}_{pjktm} = \exp\left(\alpha_{pkm} + \mu_{jkt} + \eta_{pjk} + \phi_{ktm} + \beta_1^{*} CONG^{s}_{ptm}\right) + \varepsilon_{pjktm} \quad (3.1)$$

where s denotes the transportation modes, including bulk and container modes. Export volume, X^{s}_{pjktm}, is measured by quantity or value. $CONG^{s}_{ptm}$ denotes the congestion days of container shipments. α_{pkm}, μ_{jkt}, η_{pjk}, and ϕ_{ktm} denote high-dimensional fixed effects separately. We run the regression separately with bulk shipments and container shipments.[9]

As with all econometric models, we attempt to address the endogeneity problem caused by the correlation of unobservables with port congestion in the model specification. Port congestion could be a proxy for under-investment in port capacity, suggesting that the unobservables correlated with both port capacity and export volume be controlled. Russell, Ruamsook, and Roso (2022) develop a capacity framework that consists of four components: seaside interface capacity, platform capacity, landside interface capacity, and system-wide capacity. Each component comprises both static capacity, such as the dock/berth system that remains unchanged in the short

[9] The chow tests reject that bulk and container congestion have the same coefficients and intercepts with P-values of less than 0.001, when regressing on export quantity and value separately.

run; and adjustable capacity, including pilotage or towage service capacity that can be adjusted in the short run.

Three main sources of unobservables could correlate with both port static/adjustable capacity and exports: the demand side, the supply side, and factors that correlate with both demand and supply. We expect the demand for U.S. agricultural products to be common for all ports but could vary by country, products, and time, which can be controlled by adding importer-product-year fixed effects, μ_{jkt}. The supply-side unobservables that correlate with port capacity are assumed to be invariant for all importers but vary by ports, products, and seasons. Agricultural production is constrained by geographics, climate, and seasonality. Reasonably, port static capacity may be larger if it locates closer to production origins; the adjustable capacity may be even larger during the harvest season. Therefore, port—product—month fixed effects, α_{pkm}, are added to equation (1). Time invariant trade costs, like transportation costs from a port to its partners, are likely to correlate with both port capacity and exports, which are controlled by η_{pjk}. Lastly, time-varying shocks, like COVID-19 lockdowns, could affect both port adjustable capacity and exports through the channels of both demand and supply (Arita et al., 2022). We assume these effects are common for all U.S. ports and their partners, therefore, can be absorbed by product-year-month fixed effects, ϕ_{ktm}.

Our analysis coincides with Yotov et al. (2016) 's gravity model specification that recommends including importer-time, exporter-time, and country pair fixed effects, where μ_{jkt} resembles the importer-time fixed effects and η_{pjk} mimics the country pair fixed effects.

Since we concentrate on only one exporter—the US, which comprises multiple ports—in our study, exporter-time fixed effects are mimicked by two components: country-level exporter-time fixed effects, ϕ_{ktm}; and port-level "exporter-time" fixed effects, α_{pkm}. The identification assumption is the fixed effects absorb all the unobservables correlated with both port capacity and export flows. Besides the congestion days of U.S. ports, we have the data on partner ports' monthly average congestion days, which can be used as controls in the robustness checks. Following Yotov et al. (2016), we employ the Poisson-Pseudo-Maximum Likelihood (PPML) model to estimate equation (3.1) because it reserves the multiplicative structure inherent in the structural gravity model (Silva and Tenreyro 2006). Additionally, the PPML estimation allows zero trade flows in some months due to the crucial nature of agricultural seasonality. Standard errors of the estimation are clustered at the port-importer-product level.

During our sample period, tariffs changed dramatically. In 2018 and 2019, partner countries, including China, E.U., Turkey, and India, had imposed extra tariffs on U.S. agricultural products. These tariffs descended significantly between 2020 and 2021, led by the phase one deal between U.S. and China. If tariff changes cofound with port congestion, our estimates on port congestion effects will be biased. We do not find such correlation between port congestion and dramatic tariff changes in Figure 3.6. The congestion days of U.S. ports were at the same level during dramatic tariff increases in 2018 and 2019, compared to 2016 and 2017. Western port delays, however, continuously climbed up in 2019, which is unlikely to be driven by tariff increases.

To explore the heterogeneous effects of port congestion among products and port regions, we estimate a model akin to equation (3.1) but with interactions of congestion with port region dummies and product dummies.

$$\begin{aligned} X^s_{pjktm} = \exp\,(&\alpha_{pkm} + \mu_{jkt} + \eta_{pjk} + \phi_{ktm} + \beta_1 CONG^s_{ptm} + \\ &\beta_2 CONG^s_{ptm} E_p + \beta_3 CONG^s_{ptm} G_p + \beta_4 CONG^s_{ptm} ITM_k + \beta_5 CONG^s_{ptm} CSM_k \\ &+ \gamma_1 CONG^s_{ptm} E_p ITM_k + \gamma_2 CONG^s_{ptm} E_p CSM_k \\ &+ \gamma_3 CONG^s_{ptm} G_p ITM_k + \gamma_4 CONG^s_{ptm} G_p CSM_k) + \varepsilon_{pjktm} \end{aligned} \tag{3.2}$$

where E_p and G_p are dummies indicating Eastern and Gulf coastal port regions separately. ITM_k and CSM_k denote intermediate and consumer products separately. Equation (3.2) consists of all-level interactions of congestion, port region dummies, and product dummies. The marginal effects of congestion can be seen through the following equation.

$$
\begin{aligned}
Marginal\ Effect = \frac{\partial X^s_{pjktm}}{\partial CONG^s_{ptm}} \\
&= \exp(.)\,(\beta_1 + \beta_2 E_p + \beta_3 G_p + \beta_4 ITM_k + \beta_5 CSM_k \\
&+ \gamma_1 E_p ITM_k + \gamma_2 E_p CSM_k + \gamma_3 G_p ITM_k + \gamma_4 G_p CSM_k) \\
&\approx \bar{X}^s_{pjktm}(\beta_1 + \beta_2 E_p + \beta_3 G_p + \beta_4 ITM_k + \beta_5 CSM_k \\
&+ \gamma_1 E_p ITM_k + \gamma_2 E_p CSM_k + \gamma_3 G_p ITM_k + \gamma_4 G_p CSM_k)
\end{aligned} \tag{3.3}
$$

where the marginal effect is usually calculated on the average export quantity/value, $\bar{X}^s_{pjktm}$. The marginal effect of port congestion depends not only on parameters but also on dummies of port regions and products. When all dummies are switched off, the marginal effect of congestion is $\bar{X}^s_{pjktm}\beta_1$, which is the baseline effect, or the effect of congestion on Western region's exports of bulk commodities. The parameter, β_1, can be interpreted as the percentage change of exports on average for the Western region. β_2 denotes the difference of the percentage effects between Eastern and Western region's exports of bulk commodities, which can be obtained by switching on and off $E_p$andβ_3 can be interpreted similarly. β_4 (β_5) denotes the difference of the percentage effects between the Western region's exports of bulk and intermediate (consumer) commodities, which can be obtained by switching on and off $ITM_k(CSM_k)$. The γ's can be interpreted as the conditional difference of percentage effects between the interaction of dummies and their corresponding conditionals. Take γ_1 as an example. Conditioning on $E_p = 1$, $\beta_4 + \gamma_1$ denotes the difference of percentage effects between Eastern region's export of intermediate and bulk commodities. Alternatively, conditioning on $ITM_k = 1$, $\beta_2 + \gamma_1$ denotes the difference of percentage effects between Eastern and Western regions' exports of intermediate commodities. Other γ's can be interpreted similarly. We list the interpretations of parameters in the third column of Table 3.1.

If there is no heterogeneity in either dimension of port regions or products, we expect that the effects of congestion do not depend on port regions or products. All the differences in percentage effects compared with baseline effects equal zero, meaning congestion has the same impact across all port regions and products. This thought leads us to test the following hypothesis.

$$H_0^1: \beta_2 = \beta_3 = \beta_4 = \beta_5 = \gamma_1 = \gamma_2 = \gamma_3 = \gamma_4 = 0$$

Rejecting the null hypothesis H_0^1 means congestion effects display general heterogeneity in the dimensions of port regions or products. We can further test the dependency of congestion effects on either dimension. If there is no heterogeneous effect across port regions, the differences in percentage effects between port regions should equal zero, or $\beta_2 = \beta_3 = 0$. Furthermore, all the conditional differences of percentage effects between port regions should also equal zero. For instance, conditioning on intermediate goods, $ITM_k = 1$, the differences of percentage effects between Eastern or Gulf regions and Western regions should equal zero separately. In other words, $\beta_2 + \gamma_1 = 0$ and $\beta_3 + \gamma_3 = 0$. Conditioning on consumer commodities, $CSM_k = 1$, we should obtain $\beta_2 + \gamma_2 = 0$ and $\beta_3 + \gamma_4 = 0$. Combining all the parameters restrictions, the following hypothesis can test the independence of congestion effects on port regions.

$$H_0^2: \beta_2 = \beta_3 = \gamma_1 = \gamma_2 = \gamma_3 = \gamma_4 = 0$$

Rejecting the null hypothesis H_0^2 means there are general heterogeneous effects across port regions.

Similarly, we test the independency of congestion effects across products with the null hypothesis that all the differences and conditional differences of percentage effects between products equal zero.

$$H_0^3: \beta_4 = \beta_5 = \gamma_1 = \gamma_2 = \gamma_3 = \gamma_4 = 0$$

Rejecting the null hypothesis H_0^3 means there are general heterogeneous effects across products.

If all the null hypotheses, H_0^1-H_0^3, are rejected, the congestion effects are heterogeneous in both dimensions.

3.4 Results

3.4.1 Main Results

We report the estimation results of equation (3.1) in Table 3.2, where we impose the restriction that port congestion has the same effects across all the port regions and products.

Columns 1-4 present the coefficients of port congestion on U.S. agricultural export quantity, which can be interpreted as the average percentage change of exports due to one more day of congestion. We find the effect of port congestion on containerized agricultural exports is substantial: On average, one extra day of congestion at the port decreases monthly export quantity by around 5 percent, and the point estimate is statistically significant at 1 percent level (see column 1). The effect remains unchanged when additionally controlling for partner ports' congestion time in column 2. In contrast, the estimates of bulk transportation congestion effects display much smaller magnitudes and statistical insignificance (see columns 3-4).

Consistent with Steinbach (2022), we observe the effects on export value are smaller than on quantity. One extra day of port congestion decreases monthly containerized agricultural export value by 2 percent on average, less than half of the effects on quantity. Because value can be defined as unit value times quantity, this accords with the intuition that the price effect of congestion would increase, thus offsetting the quantity effect to some extent. Specifically, the percentage effect of port congestion on unit values can be recovered by taking a difference between the percentage effects on value and quantity. In our case, one extra day of container shipment delays increases unit values of U.S. agricultural exports by 3 percent (=5%-2%) on average. The point estimates are statistically significant at 1 percent level, with or without control of partner congestion (see columns 5-6). The last two columns in Table 3.2 show estimates of bulk transportation congestion effects approximate zero on export value and draw inconclusive statistical significance.

3.4.2 Robustness Checks

China was the largest buyer of U.S. agricultural products in 2020. The "trade war" between U.S. and China had the most prominent effects on U.S. agricultural exports. U.S. agricultural exports to China dropped substantially during 2018 and 2019 and recovered swiftly after 2020 due to the Phase One Deal. To rule out the effects of China, we excluded it from the importers in our sample and re-aggregated the data. We present the results in Panel A, Table 3.3. Excluding China from the sample doesn't change our main findings. The effects of container congestion on export quantity (column 1) and value (column 3) are very similar to their counterparts in Table 3.2. The effects of bulk congestion are again close to zero and statistically insignificant.

The trade frictions during 2018 and 2019 affected not only China but other U.S. trade partners like E.U. and NAFTA members as well. We further test the robustness of our results by excluding the years 2018 and 2019 from our sample. The results are reported in Panel B, Table 3.3. The coefficients are very similar to their counterparts in Table 3.2. Table 3.3 shows that our main findings are neither driven by China as a significant importer nor the trade frictions between the U.S. and the rest of the world.

3.4.3 Heterogeneity

To explore heterogeneous effects among port regions and products, we estimated equation (3.2) by measurements of export volume and transportation methods and report the results in Table 3.4. Results in columns 1 and 3 highly suggest effects of container shipment congestion depend on both port regions and products. Measuring export volume by the quantity of weight in column 1, hypotheses H_0^1 - H_0^3 are all rejected at 1 percent statistical significance level, supporting heterogeneities in both dimensions. Replacing the outcome by export value of dollars, column 3 shows similar pattern of heterogeneities to column 1.

Columns 2 and 4 in Table 3.4 report the results of bulk shipment congestion effects. While estimation on the restricted model of bulk shipment congestion shows both statistically and economically insignificant results (in Table 3.2), the hypothesis test results of H_0^1 (in columns 2 and 4, Table 3.4) show the restricted model cannot be rejected at 1 percent statistical significance level. Additionally, neither hypothesis H_0^2 nor H_0^3 is rejected at 1 percent significance level, implying neither heterogeneous effects across port regions nor products are supported by data.

3.4.4 Marginal Effects

To connect this study to policy implications, we calculate the marginal effects of port congestions on average. According to equation (3.3), the marginal effect equals the multiplication of average export with the percentage change. In this section, we focus on heterogeneous marginal effects of each port region and product, therefore, we calculate the marginal effects by multiplying the average of each subgroup with their specific coefficients in Table 3.1. We concentrate on container shipment because its congestion effects on U.S. agricultural exports are both economically and statistically significant. The marginal effects are calculated using the heterogeneous coefficient estimates (Table 3.1 and Table 3.4) and subgroup monthly average as given in equation (3.3).

Figure 3.9 presents the marginal effects of container congestion on agricultural export quantity, measured by metric tons (M.T.). Panel (a) presents the recovered subgroup coefficients, and Panel (b) presents the marginal effects. All coefficients and marginal effects are negative in directions. Western ports are most vulnerable to container shipment congestion, reporting the largest coefficients and marginal effects. Bulk commodities are most vulnerable across the products shipped from Western ports. To be specific, one extra day of congestion in Western ports decreases monthly exports of bulk commodities by 9 percent, or monthly 47 thousand M.T. on average. The coefficient on intermediate goods shipped from Western ports stays next to bulk commodities, and the coefficient on consumer goods is the least. Transformed into marginal effects, one extra day of congestion in west ports incurs 39 thousand M.T. fewer exports of intermediate goods and 21 thousand M.T. fewer consumer goods. Summing up the marginal effects within each port region, the effects are 107 thousand M.T. for Western ports, 29 thousand M.T. for Eastern ports, and 4 thousand M.T. for Gulf coastal ports.

The coefficients of congestion on export value across subgroups, along with the subgroup marginal effects, are mixed in directions (see Figure 3.10). While the coefficients for bulk and intermediate commodities in Eastern ports and consumer goods in Gulf coastal ports are positive, none of them show statistical significance. This is because contemporaneously with congestion, we have seen one of the largest upticks of price inflation since the early 1980s. All the other subgroups report negative coefficients and marginal effects. Consistent with the marginal effects on export quantity, the marginal effects on export value are largest in Western ports, and the loss of bulk commodities export value is the greatest among products shipped from Western ports. One extra day of congestion decreases monthly bulk commodities export value by 8 percent in the Western region on average. The monthly average value of bulk commodities departing from the Western region is \$392 million. Therefore, one extra day of congestion leads to \$32 million of monthly loss. The marginal loss of export value on average amounts to \$44 million concerning all products in Western ports, the largest among all three regions. The marginal losses in the Eastern and Gulf coastal regions are \$15 million and \$5 million separately. Summing up the marginal effects in all regions, the United States' monthly agricultural export loss amounts to \$63 million on average if container congestion time at all ports increase by one day. The marginal effects of each subgroup can be seen in Table A3.5.

3.4.5 Substitution of Transportation Modes

Importers value the timeliness and quality of shipments. In our sample, we show bulk shipments have a longer delay than container shipments on average. Beyond shipping time, container shipments are more likely to fulfill the special needs of cargos, such as the cold chain facility used to keep meats frozen. The relative timeliness of container shipments and stricter shipping conditions required by container cargos may imply that it's unlikely to substitute container shipments with bulk. However, the substitution of bulk with container shipments is more plausible. We would overestimate the marginal loss of container congestion if exporters can substitute container shipments with bulk modes easily. With perfect substitutability, we may observe a high correlation between congestion days of bulk and container shipments. In our sample, the correlation coefficient is as low as 0.13, meaning substitution of shipping modes is not frequent, if possible.

We formally tested the substitution across transportation modes by running regressions on both container and bulk shipping congestion days.

$$X_{pjktm}^{s} = \exp\,(\alpha_{pkm} + \mu_{jkt} + \eta_{pjk} + \phi_{ktm} + \beta_1^B CONG_{ptm}^{BULK} + \beta_2^C CONG_{ptm}^{CONTAINER}) + \varepsilon_{pjktm} \tag{3.4}$$

where $CONG_{ptm}^{BULK}$ and $CONG_{ptm}^{CONTAINER}$ denote the delays of bulk and container shipments separately. We estimate equation (3.4) for exports of each transportation mode individually and report the results in Table 3.5.

As expected, we find it is possible to substitute bulk shipments with containers, but not vice versa. Column 1 shows one extra day of bulk shipment congestion increases containerized agricultural export quantity by around 2 percent on average, while the coefficient on container shipment congestion remains unchanged compared with that in Table 3.2. Measuring the outcome by export value, instead, results in much smaller substitutional effects and statistical insignificance (see column 3), which implies the original bulk cargos substituted with container shipments have much lower unit values than the original container shipments. For the results of exports by bulk shipment, neither bulk congestion nor container congestion has statistically meaningful effects, underling it is more difficult to substitute container shipments with bulk shipments (see columns 2 and 4).

The results in Table 3.4 imply our estimates of the containerized exports loss due to congestion can barely be compensated by bulk shipments.

3.5 Conclusion

This study provides novel evidence of the marginal effects of port congestion on U.S. Agricultural exports. We summarized top U.S. ports' monthly export data and average congestion days. Given the data, we employed the gravity-like estimation strategy and PPML algorithm to formally test the marginal effects of port congestion on U.S. agricultural exports.

Our results confirm containerized shipments are sensitive to congestion, while bulk shipments are much less so. Among products, bulk commodities are most vulnerable to container shipment congestion: One more day of congestion reduced monthly exports of bulk commodities by 60 thousand M.T. and a $29 million loss in value. The loss of bulk commodities export value accounts for 46 percent of the total loss of all commodities. Among ports, the Western region contributes the most loss measured by both value and quantity. The marginal loss of one extra day of container congestion in Western ports is worth monthly $44 million, accounting for 69 percent of the total loss across all ports. We find exporters may turn to container shipping modes when bulk shipment congestion increases, but the substitution of the other way around is much more unlikely.

Our study has limitations. The measurement of port congestion, the time delays of unloading at ports, may not reflect the "true" congestion. Because even during normal seasons, delays don't shrink to zero days. Further studies may define what normal delays are and what the threshold of congestion is, to focus on abnormal congestion effects.

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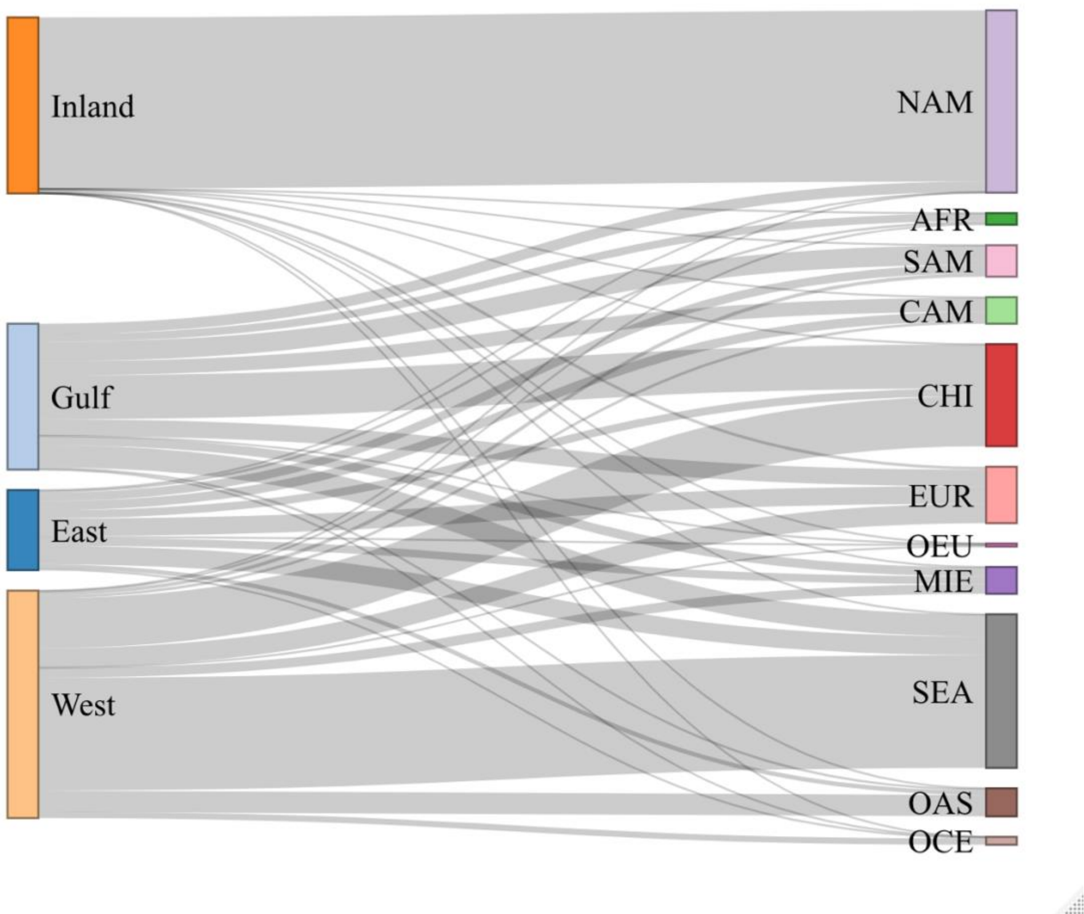
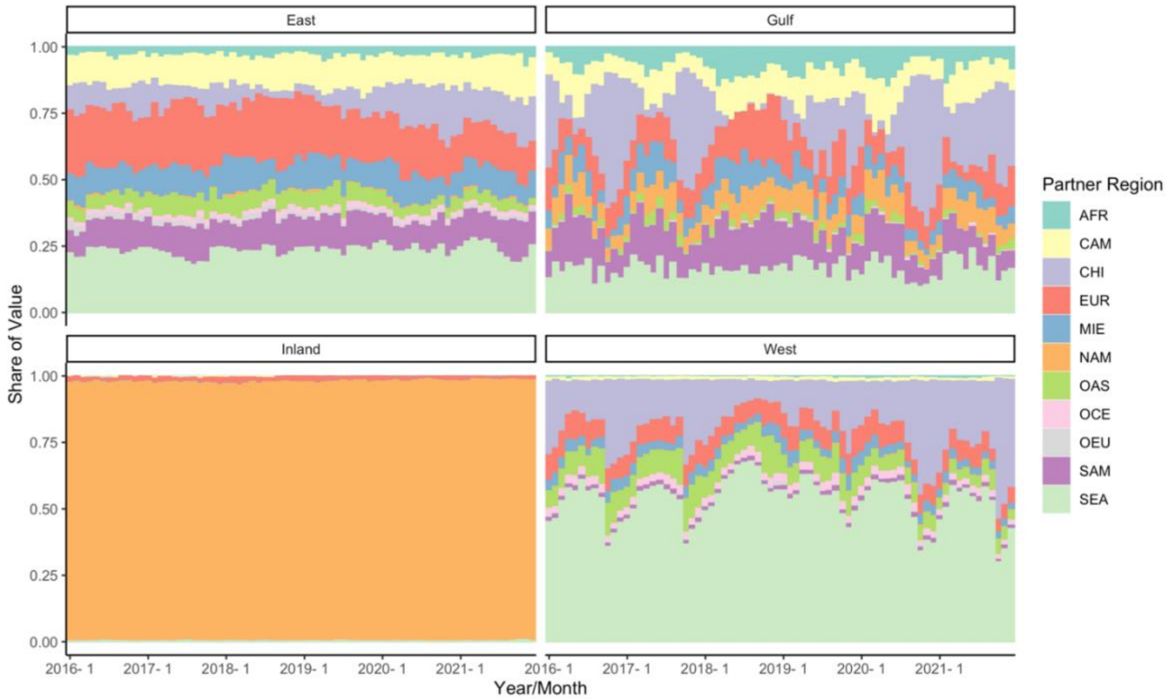
Figures and Tables

Figure 3.1 U.S. Agricultural Exports Flows from Port Regions to Destinations in 2016



Source: Author tabulations using U.S. census trade data track.
Notes: Export values of top 31 U.S. ports are aggregated to port regions and their partners' regions. Partners' regions include North America (NAM), Africa (AFR), South America (SAM), Central America (CAM), China (CHI), E.U. Countries (EUR), Other European Countries (OEU), Middle East (MIE), Southeast Asia (SEA), Other Asian Countries (OAS), Oceania Countries (OCE) (See Table A2 for countries in each partner regions).

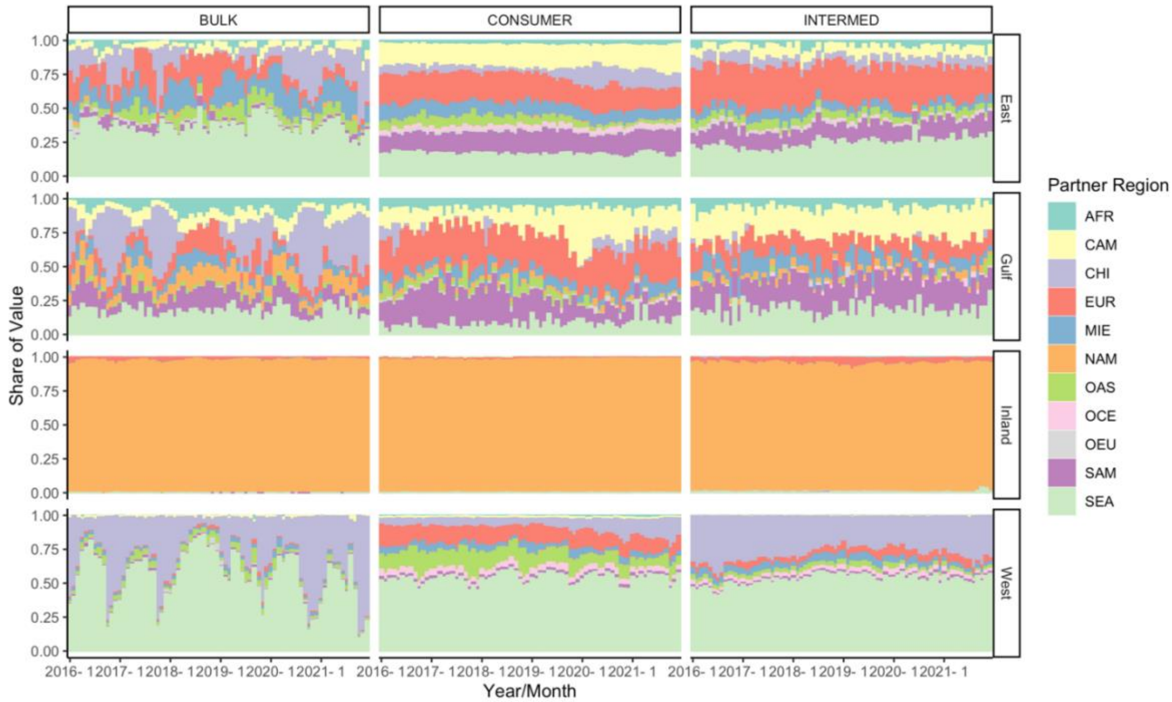
Figure 3.2 Value Shares of Destinations by Port Region: 2016-2021



Source: Author tabulations using U.S. census trade data track.

Notes: Export values of top 31 U.S. ports are aggregated to port regions and their partners' regions. Partners' regions include North America (NAM), Africa (AFR), South America (SAM), Central America (CAM), China (CHI), E.U. Countries (EUR), Other European Countries (OEU), Middle East (MIE), Southeast Asia (SEA), Other Asian Countries (OAS), Oceania Countries (OCE) (See Table A2 for countries in each partner regions).

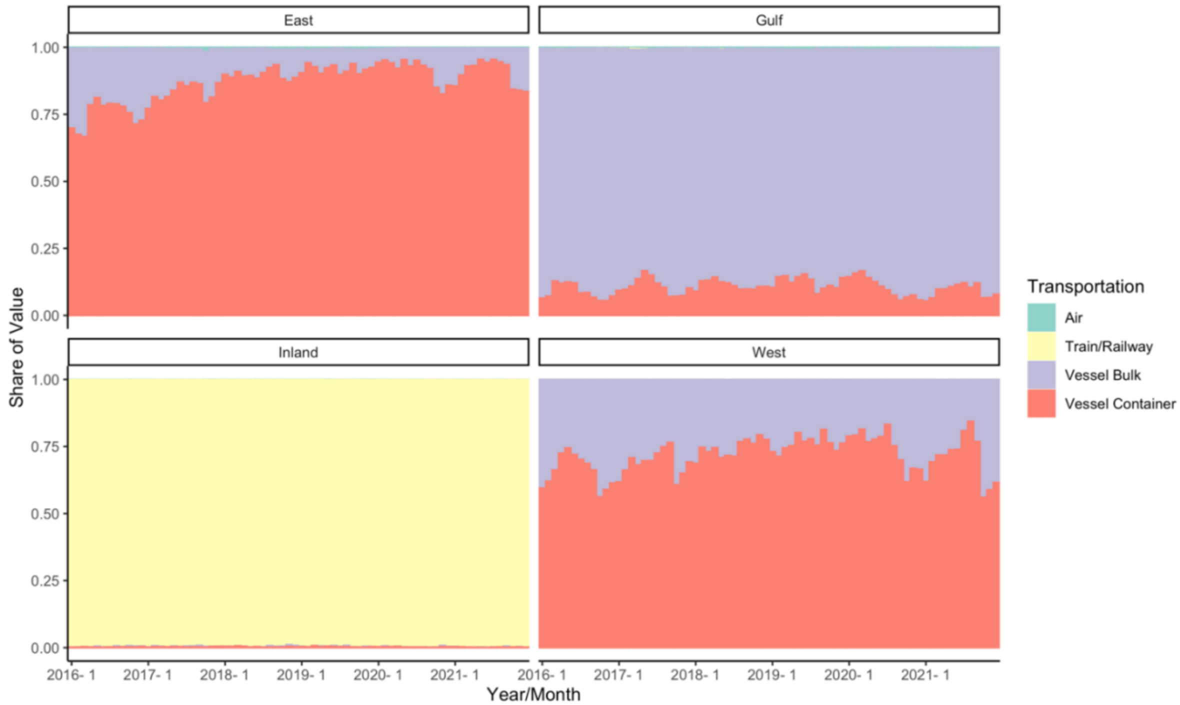
Figure 3.3 Value Shares of Destinations by Port Region and BICOA: 2016-2021



Source: Author tabulations using U.S. census trade data track.

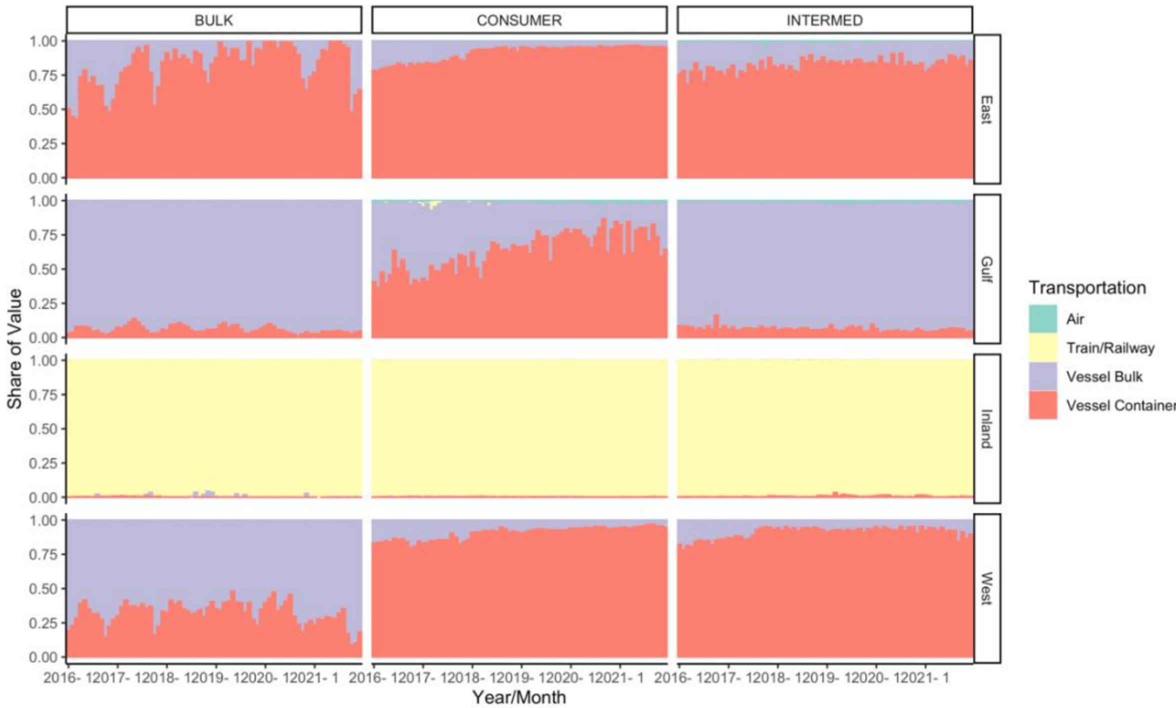
Notes: Export values of top 31 U.S. ports are aggregated by products, port regions, and their partners' regions. Partners' regions include North America (NAM), Africa (AFR), South America (SAM), Central America (CAM), China (CHI), E.U. Countries (EUR), Other European Countries (OEU), Middle East (MIE), Southeast Asia (SEA), Other Asian Countries (OAS), Oceania Countries (OCE) (See Table A2 for countries in each partner regions).

Figure 3.4 Export Value Shares of Transportation Modes by Port Region: 2016-2021



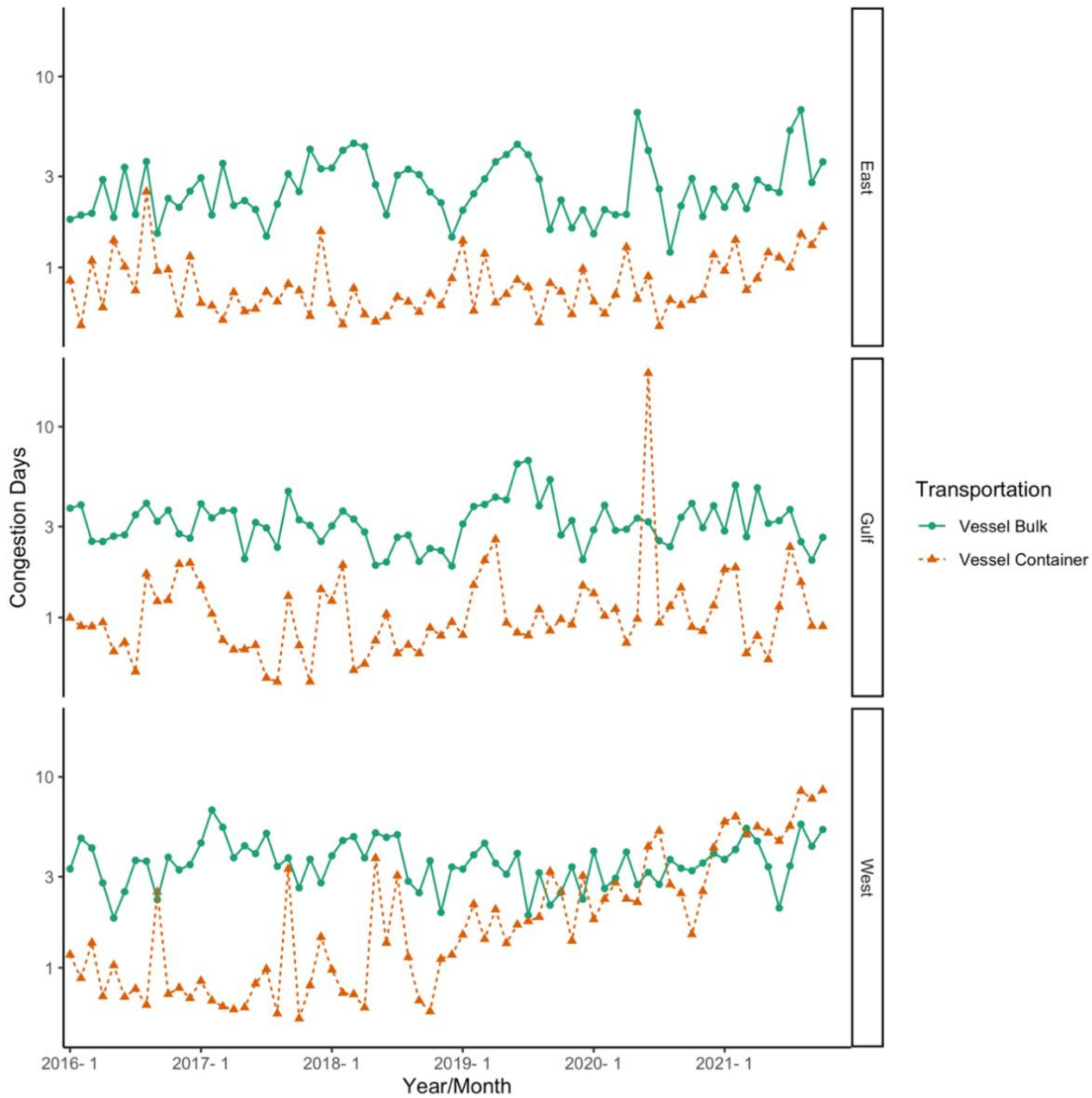
Source: Author tabulations using the sample of this study.

Figure 3.5 Export Value Shares of Transportation Modes by Port Region and BICOA



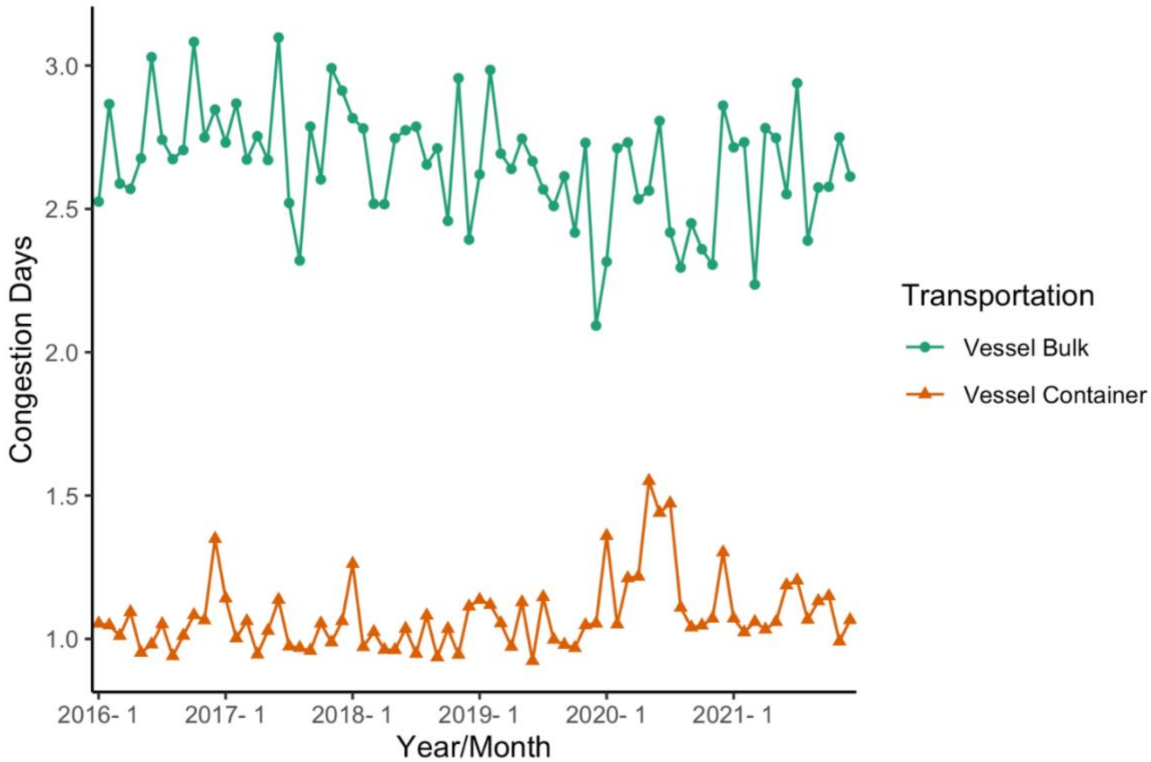
Source: Author tabulations using the sample of this study.

Figure 3.6 Average Congestion Days by Port Region and Transportation Mode



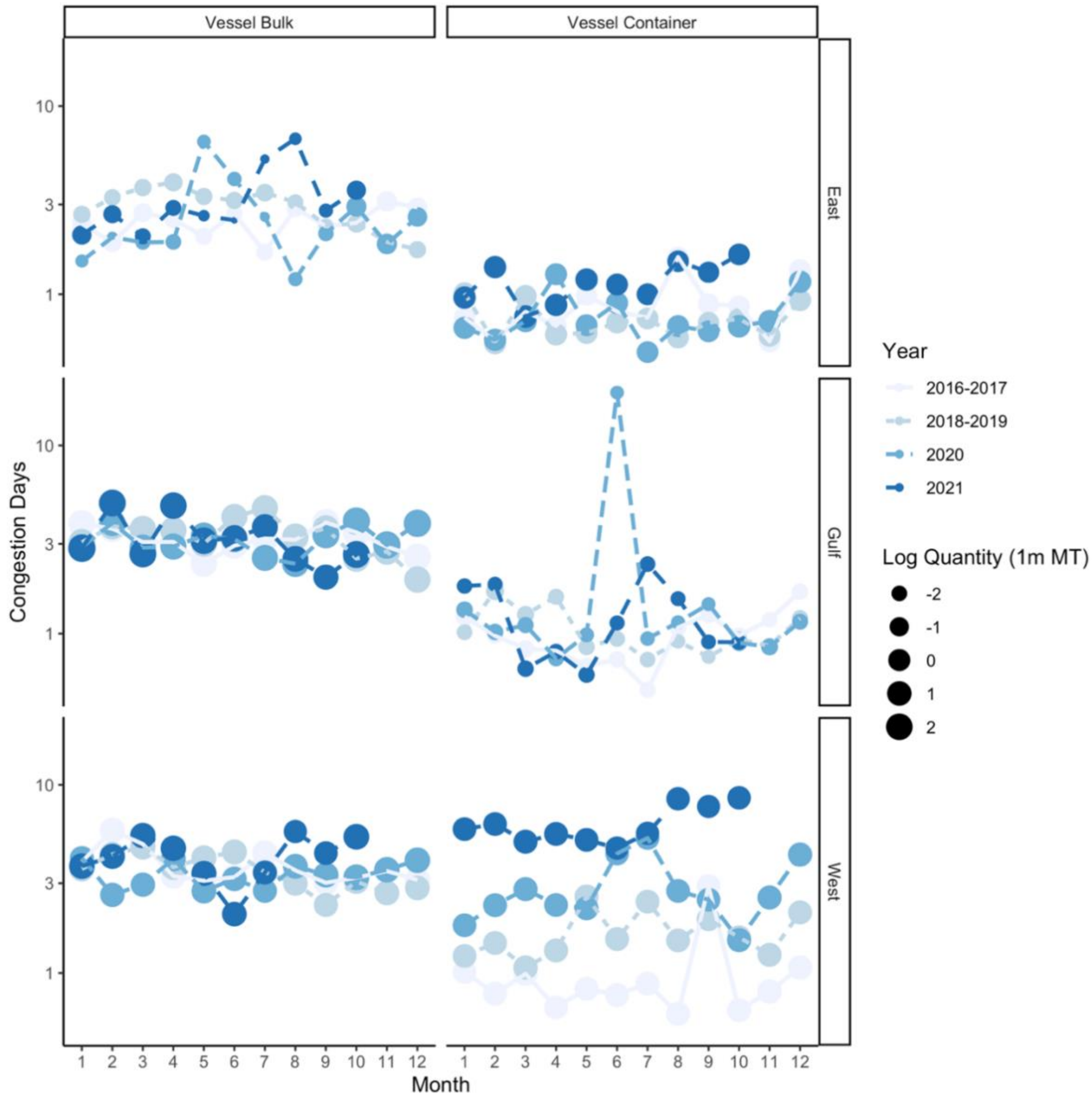
Source: Author tabulations using the sample of this study.

Figure 3.7 Partner Ports' Median Delays by Transportation Mode



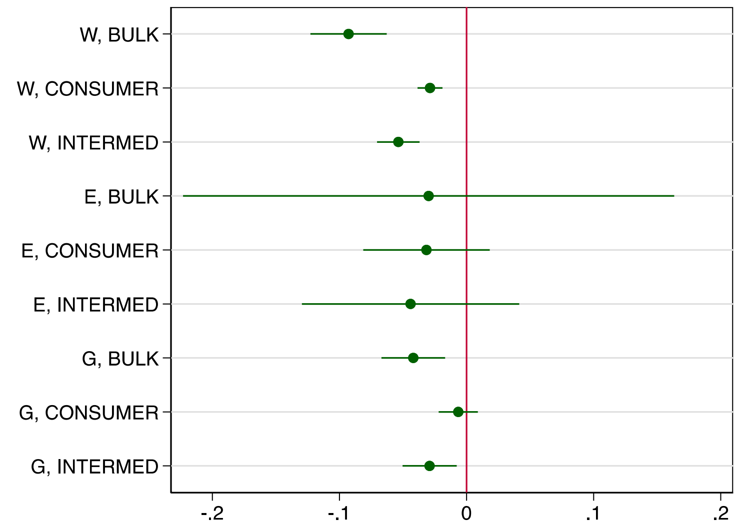
Source: Author tabulations using the sample of this study.

Figure 3.8 Correlation of U.S. Port Congestion and Agricultural Exports

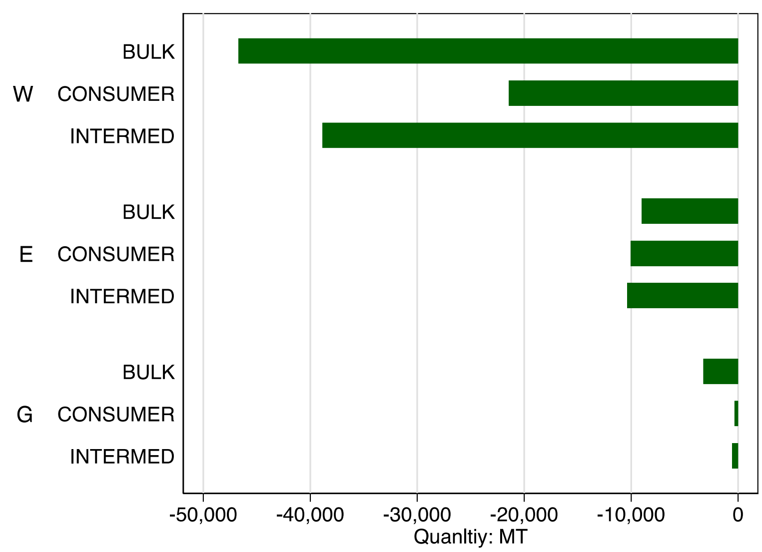


Source: Author tabulations using the sample of this study.
Notes: The sizes of the points represent the log values of monthly total export quantities (in 1 million MT).

Figure 3.9 Heterogeneous Coefficients and Marginal Monthly Loss on Export Quantity



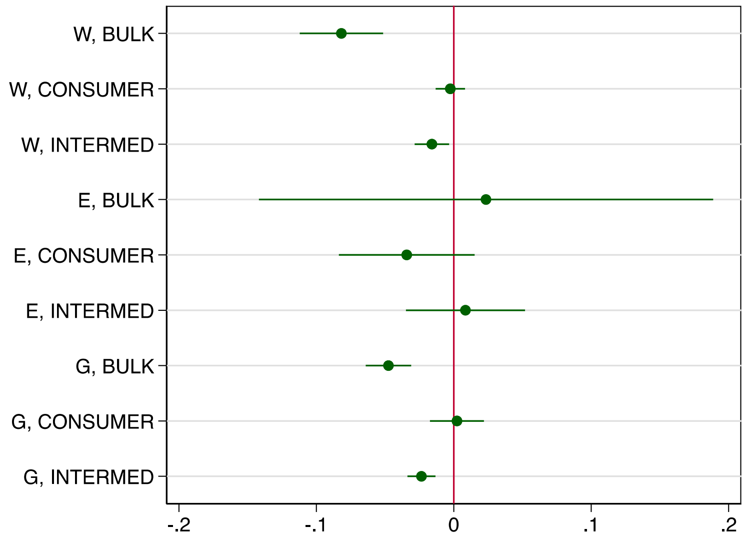
(a) Coefficients



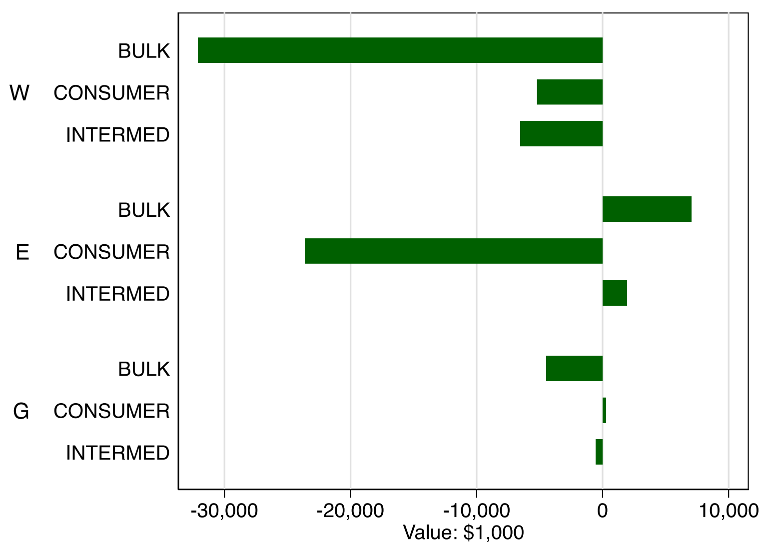
(b) Marginal Monthly Loss

Notes: The subgroup coefficients are recovered using Table 3.1 and the results in Table 3.3. The marginal effects are evaluated by the multiplication of the subgroup average with their coefficients on congestion.

Figure 3.10 Heterogeneous Coefficients and Marginal Monthly Loss on Export Value



(a) Coefficients



(b) Marginal Monthly Loss

Notes: The subgroup coefficients are recovered using Table 3.1 and the results in Table 3.3. The marginal effects are evaluated by the multiplication of the subgroup average with their coefficients on congestion.

Table 3.1 Heterogeneous Coefficients of Subgroups across Port Regions and Products

Port Region	Product	Coefficient
West	Bulk	β_1
East	Bulk	$\beta_1 + \beta_2$
Gulf	Bulk	$\beta_1 + \beta_3$
West	Intermediate	$\beta_1 + \beta_4$
West	Consumer	$\beta_1 + \beta_5$
East	Intermediate	$\beta_1 + \beta_2 + \beta_4 + \gamma_1$
East	Consumer	$\beta_1 + \beta_2 + \beta_5 + \gamma_2$
Gulf	Intermediate	$\beta_1 + \beta_3 + \beta_4 + \gamma_3$
Gulf	Consumer	$\beta_1 + \beta_3 + \beta_5 + \gamma_4$

Notes: The last column presents the coefficient of each subgroup using parameters in equation (3.2)

Table 3.2 Port Congestion and U.S. Agricultural Exports: Full Sample Results

Dependent:	*Quantity*				*Value*			
Shipment:	*Container*		*Bulk*		*Container*		*Bulk*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CONG	-0.051***	-0.051***	0.020	0.018	-0.020***	-0.020***	0.005	0.004
	(0.006)	(0.006)	(0.020)	(0.021)	(0.005)	(0.005)	(0.020)	(0.020)
Partner Congestion		-0.008		0.029		0.006		0.021
		(0.026)		(0.026)		(0.025)		(0.026)
Observations	1890	1890	1890	1890	1890	1890	1890	1890

Standard errors in parentheses
** p<0.10, ** p<0.05, *** p<0.01*
Notes: All the columns control for three-tuple fixed effects, including port-product-month, importer-product-year, port-importer-product, product-year-month fixed effects. CONG measures the average congestion days (corresponding to the shipment modes in each column) of U.S. port regions, divided by West, East, and Gulf coast. Partner congestion is a measure of the average congestion days of partners of each port region, corresponding to the shipment modes in each column.

Table 3.3 Robustness Check on Port Congestion and U.S. Agricultural Exports

Dependent:	*Quantity*		*Value*	
Shipment:	*Container*	*Bulk*	*Container*	*Bulk*
	(1)	(2)	(3)	(4)
Panel A: China Excluded				
CONG	-0.048***	0.006	-0.013**	-0.014
	(0.006)	(0.015)	(0.005)	(0.015)
Observations	1890	1890	1890	1890
Panel B: 2018-2019 Excluded				
CONG	-0.055***	0.017	-0.021***	0.021
	(0.007)	(0.024)	(0.006)	(0.024)
Observations	1242	1242	1242	1242

Standard errors in parentheses

** p<0.10, ** p<0.05, *** p<0.01*

Notes: Panel A excludes China from importers before aggregating the data. Panel B excludes years from 2018 to 2019 from the data. All the columns control for three-tuple fixed effects, including port-product-month, importer-product-year, port-importer-product, product-year-month fixed effects. CONG measures the average congestion days (corresponding to the shipment modes in each column) of U.S. port regions, divided by West, East, and Gulf coast.

Table 3.4 Port Congestion and Agricultural Exports: Heterogeneous Effects

Dependent:	*Quantity*		*Value*	
Shipment:	*Container*	*Bulk*	*Container*	*Bulk*
	(1)	(2)	(3)	(4)
$CONG$	-0.093***	0.023	-0.082***	0.027
	(0.013)	(0.031)	(0.012)	(0.034)
$CONG \times E$	0.063	0.032	0.105	-0.108
	(0.084)	(0.069)	(0.076)	(0.074)
$CONG \times G$	0.051***	-0.010	0.034**	-0.011
	(0.018)	(0.052)	(0.016)	(0.057)
$CONG \times ITM$	0.064***	-0.013	0.079***	-0.035
	(0.014)	(0.054)	(0.013)	(0.044)
$CONG \times CSM$	0.039**	-0.019	0.066***	-0.017
	(0.016)	(0.068)	(0.013)	(0.059)
$CONG \times E \times ITM$	-0.066	-0.168*	-0.137*	0.033
	(0.087)	(0.092)	(0.080)	(0.083)
$CONG \times E \times CSM$	-0.053	-0.046	-0.081	0.014
	(0.093)	(0.099)	(0.079)	(0.093)
$CONG \times G \times ITM$	-0.029	0.066	-0.029*	0.049
	(0.020)	(0.091)	(0.018)	(0.084)
$CONG \times G \times CSM$	-0.026	0.044	-0.042**	0.027
	(0.021)	(0.087)	(0.017)	(0.083)
Hypothesis Tests:				
H_0^1	48.93	13.38	59.65	17.00
	(0.000)	(0.100)	(0.000)	(0.030)
H_0^2	23.67	11.56	12.18	14.48
	(0.001)	(0.073)	(0.058)	(0.025)
H_0^3	31.16	7.87	59.45	0.69
	(0.000)	(0.248)	(0.000)	(0.995)
Observations	1890	1890	1890	1890

Standard errors in parentheses
** p<0.10, ** p<0.05, *** p<0.01*

Notes: All the columns control for three-tuple fixed effects, including port-product-month, importer-product-year, port-importer-product, product-year-month fixed effects. CONG measures the average congestion days (corresponding to the shipment modes in each column) of U.S. port regions, divided by West, East, and Gulf coast. E and G are dummies of Eastern and Gulf coastal port region separately. ITM and CSM are dummies of intermediate and consumer goods separately. Both chi-squared values and p-values (in parentheses) of hypotheses tests are presented.

Table 3.5 Substitutional Effects of Transportation Modes and Agricultural Exports

Dependent:	*Quantity*		*Value*	
Shipment:	*Container*	*Bulk*	*Container*	*Bulk*
	(1)	(2)	(3)	(4)
Container Congestion	-0.053***	-0.011	-0.020***	-0.000
	(0.006)	(0.011)	(0.006)	(0.010)
Bulk Congestion	0.017***	0.022	0.002	0.005
	(0.006)	(0.020)	(0.005)	(0.019)
Observations	1890	1890	1890	1890

Standard errors in parentheses
** p<0.10, ** p<0.05, *** p<0.01*
Notes: All the columns control for three-tuple fixed effects, including port-product-month, importer-product-year, port-importer-product, product-year-month fixed effects. "*Container Congestion"* measures the average congestion days of container shipments in U.S. port regions, divided by West, East, and Gulf coast. "*Bulk Congestion"* measures the average congestion days of bulk shipments in each port region.

Appendix Tables

Table A3.1 U.S. Ports and Port Regions in the Sample

		Share of Shipments within Regions (%)	
Port	*State*	*Vessel Container*	*Vessel Bulk*
West (9)			
Kalama	WA	0.00	0.18
Long Beach	CA	24.02	24.06
Longview	WA	0.01	0.13
Los Angeles	CA	26.59	26.48
Oakland	CA	25.54	25.55
Portland	OR	0.20	0.33
Seattle	WA	12.32	12.05
Tacoma	WA	11.22	11.01
Vancouver	WA	0.09	0.21
Gulf (4)			
Baton Rouge	LA	0.01	2.51
Gramercy	LA	0.08	4.06
Houston	TX	75.49	64.15
New Orleans	LA	24.43	29.29
East (8)			
Baltimore	MD	4.34	4.34
Charleston	SC	7.59	7.54
Miami	FL	20.04	19.66
New York	NY	21.55	21.86
Newark	NJ	6.88	7.01
Norfolk-Newport News	VA	11.73	11.78
Port Everglades	FL	16.27	16.01
Savannah	GA	11.59	11.80
Inland (10)			
Blaine	WA	6.04	6.31
Buffalo-Niagara Falls	NY	26.81	24.87
Champlain-Rouses Point	NY	0.49	3.96
Detroit	MI	11.68	11.57
Port Huron	MI	54.98	53.28

Table A3.2 Partner Regions and Partner Countries in the Sample

Partner Region	*Partner Country ISO*	*Partner Country*	*No. of Countries*
AFR	CIV; CMR; DZA; EGY; GHA; KEN; MAR; NGA; SEN; TUN; ZAF; ZWE	Ivory Coast; Cameroon; Algeria; Egypt; Ghana; Kenya; Morocco; Nigeria; Senegal; Tunisia; South Africa; Zimbabwe	12
CAM	CRI; DOM; GTM; HND; JAM; NIC; PAN; SLV	Costa Rica; Dominican Republic; Guatemala; Honduras; Jamaica; Nicaragua; Panama; El Salvador	8
CHI	CHN	China, Mainland	1
EUR	AUT; BLX; CHE; DEU; DNK; ESP; FIN; FRA; GBR; GRC; HUN; IRL; ITA; NLD; PRT; ROM; SWE	Austria; Benelux; Switzerland; Germany; Denmark; Spain; Finland; France; United Kingdom of Great Britain and Northern Ireland; Greece; Hungary; Ireland; Italy; Netherlands; Portugal; Romania; Sweden	17
MIE	ARE; ISR; JOR; PAK; SAU; TUR	United Arab Emirates; Israel; Jordan; Pakistan; Saudi Arabia; Turkey	6
NAM	CAN; MEX	Canada; Mexico	2
OAS	BGD; HKG; IND; LKA	Bangladesh; China, Hong Kong SAR; India; Sri Lanka	4
OCE	AUS; NZL	Australia; New Zealand	2
OEU	NOR; POL; RUS; UKR	Norway; Poland; Russian Federation; Ukraine	4
SAM	ARG; BRA; CHL; COL; PER; PRY; TTO; URY; VEN	Argentina; Brazil; Chile; Colombia; Peru; Paraguay; Trinidad and Tobago; Uruguay; Venezuela, Bolivarian Republic of	9
SEA	IDN; JPN; KOR; MYS; PHL; SGP; THA; TWN; VNM	Indonesia; Japan; Korea, Republic of; Malaysia; Philippines; Singapore; Thailand; China, Taiwan; Vietnam	9

Table A3.3 BICO Products in the Sample

BICOA	*BICO*	*No. of Products*
BULK	COARSEGR; COCOABEANS; COFFEEUN; CORN; COTTON; GUMS; OILSEED; OTHBULK; PEANUTS; PULSES; RAPESEED; RICE; SOYBEANS; TOBACCO; WHEAT	15
CONSUMER	ALCOHOL; BEEF; CHEESE; CHOCOLATE; COCOPROD; COFFEE; CONDIMENTS; DAIRY; EGGS; ETHANOL; FOODPREP; FRESHFRT; FRESHVEG; FVJUICE; NURSERY; OTHMEAT; PETFOOD; PORK; POULTRY; PROCFRT; PROCVEG; SNACKFOOD; SPICES; TEA; TOBACCO; TREENUTS	26
INTERMED	COCOPROD; DAIRY; DDGS; ESSOILS; FATS; FODDER; HAY; HIDESKINS; MEAL; OTHBULK; OTHINTERMED; PALMOIL; SEED; SOYMEAL; SOYOIL; SUGAR; VEGOIL	17
LIVEA	LIVEA	1

Table A3.4: Dimensions of the Data Before and After Aggregation

Dimension (Subscript)	*Before Aggregation*	*After Aggregation*
p	Ports (31)	Port Region (3)
j	Importer (74)	Importer Region (3)
k	H.S. 6-digit Product (748)	BICOA (3)
t	Year (6)	Year (6)
m	Month (12)	Month (12)

Table A3.5 Estimated Trade Loss Due to One Extra Day of Container Congestion

Port Region	*BICOA*	*Value ($1,000)*	*Quantity (M.T.)*
West	BULK	-32077	-46725
	CONSUMER	-5205	-21439
	INTERMED	-6506	-38864
	Subtotal	-43788	-107028
	Subtotal Share	69%	76%
East	BULK	7036	-9008
	CONSUMER	-23618	-10018
	INTERMED	1921	-10360
	Subtotal	-14662	-29386
	Subtotal Share	23%	21%
Gulf	BULK	-4462	-3249
	CONSUMER	268	-346
	INTERMED	-541	-563
	Subtotal	-4736	-4158
	Subtotal Share	7%	3%
Total		-63185	-140572