A Tractable Model of Trade with Flexible Cost Structure *

Konstantin Kucheryavyy† Ruo Shangguan‡

U of Tokyo and HSE University Waseda University

November 29, 2021

Abstract

We introduce variable marginal costs of exporting in a heterogeneous firms trade model *à la* Melitz (2003). In our setup, the marginal costs of exporting depend on the quantity shipped in addition to the standard iceberg trade costs. Under the Pareto distribution of firms' productivities, our model implies a tractable gravity equation and an expression for welfare gains from trade, for which the Arkolakis *et al.* (2012) formula for gains from trade is a special case. This costs structure can be micro-found through a firm's inventory management problem, and the key parameter can be estimated using the frequency of shipment of exports. Under the log-normal distribution of firms' productivities, we calibrate all trade costs using Chinese transaction-level data. The ad-valorem equivalent rate for logistics costs is minor for productive firms, but it is substantial for less productive firms.

Keywords: trade costs, heterogeneous firm model, welfare gains from trade

JEL classification: F12, F13, F14

*We are grateful to Michal Fabinger, Hidehiko Ichimura, Taiji Furusawa, Peter Schott, Sam Kortum, Yoichi Sugita, and the seminar participants at the Online Workshop on International Trade and FDI at Kobe University, the Asia Pacific Trade Seminar at the University of Tokyo, EEA-ESEM , ETSG, Purdue University, JEA Autumn Meeting for insightful discussions. Konstantin Kucheryavyy acknowledges financial support of JSPS Kakenhi Grant Number 20K13476 as well as financial support of the HSE University Basic Research Program.

†Graduate School of Public Policy, University of Tokyo. Email: kucher@pp.u-tokyo.ac.jp

‡Institute for Empirical Research in Organizational Economics, Waseda University. Email: roy1312@gmail.com

1 Introduction

The structure and magnitude of trade costs have important implications for various questions in international trade. To name a few: how firms make entry decisions, how much they sell in each destination, and what price they charge for the products exported. Answers to these questions, in their turn, have important implications for the magnitudes of welfare gains from trade. In this paper, we study how a richer trade costs structure introduced into a heterogeneous firms trade model *à la* Melitz (2003) affects our understanding of these questions. In the model, firms need to pay logistics costs to export, in addition to iceberg trade costs and fixed trade costs. The level of required logistics costs is a power function of the quantities traded. As a result, marginal trade costs depend on the exported amount of goods.

The first contribution of this paper is to derive the formula for welfare changes under a richer trade cost structure. Because in this model, iceberg trade cost is no longer the only variable trade cost, it is natural to expect the logistics costs to play a significant role. In the symmetric two-country world, we show that the pass-through of zero-profit cutoff into welfare depends on the quantity elasticity of logistics costs and the elasticity of substitution, instead of pass-through elasticity equal to one in the case of no logistics costs. Notably, the sufficient statistics of gains from trade are composed of three elasticities, the trade elasticity (i.e., the elasticity of relative trade with respect to the iceberg trade costs), the demand elasticity, and the quantity elasticity of logistics costs. Under the assumption that firm-level productivity follows the Pareto distribution, we further derive the explicit formula for gains from trade. The resulted formula is simple and includes the ACR formula for gains from trade as a particular case. The result illustrates the importance of the microstructure of trade costs in addition to the macro restrictions proposed in Arkolakis *et al.* (2012, ACR).

We use the extended economic order quantity model proposed in Fabinger and Weyl (2018) to micro-found the logistics costs through an inventory management problem. In this problem, each firm chooses an optimal frequency of shipment that balances the transaction costs and the inventory costs. Intuitively, if shipment frequency is high, the total transaction cost, which is the sum of transaction costs across shipments, will be increased. While at the same time, frequent shipments keep the inventory level, and therefore storage costs, at a low level.

The micro foundation provides a straightforward way to estimate logistics cost elasticity via linear regression of log shipment frequency on log trade volume. Using the data on the universe of international trade transactions of Chinese exporters, we find the elasticity of logistics costs to be 0.6, which confirms the finding in Fabinger and Weyl (2018) and shows a clear rejection of the hypothesis of constant marginal trade costs, a standard assumption in the literature. With the estimated trade costs elasticity, we compare the prediction of gains from trade, measured by the change in real income associated with moving to autarky, between the ACR formula and our formula. On average, we observe 11.5% lower welfare gains from trade.

To further evaluate the impact of a different trade cost structure, we calibrate the trade costs from observed trade flows assuming that productivity parameters across firms follow a log-normal distribution, an assumption also used by Fernandes *et al.* (2019) and Head *et al.* (2014). More specifically, we match the firm-level distributions of export sales and shipment frequency across origin-destination pairs. The distributions of firm-level shipment frequency help us to identify the parameter that governs the magnitude of logistics costs. We find that logistics costs play a more significant role for less productive firms. For instance, for simulated firms that export from Guangdong Province to the US, the logistics costs account for 4.7% of revenue for the 25th-quantile firm. On the other hand, they account for 13.8% of revenue for the 75th-quantile firm in the productivity distribution.

Using the calibrated model, we calculate the implied level of iceberg costs for each firm at each destination such that the restriction that the logistics costs are zero and the variable profits remain at the same level. Then the difference between the implied and the calibrated iceberg trade costs can be viewed as the ad valorem equivalent rate of logistics costs. Similar to the revenue share, we find that the impact of logistics costs are highly heterogeneous across firms. For example, for simulated firms that export from Guangdong Province to the US, while the 25th-quantile firm incurs the logistics costs with an ad valorem equivalent rate of 5.7%, the 75th-quantile firm pays an ad valorem rate of 15.0% for the logistics costs. Taking the average of the implied iceberg trade costs across firms for each origin-destination pair and calculate the correlation between distance and the averages, we find that introducing logistics costs helps to reduce the distance elasticity of the iceberg trade costs. Thus our study contributes to the understanding of the distance elasticity of trade.

Our analysis builds on Arkolakis *et al.* (2012, ACR) and Melitz and Redding (2015, MR). In their seminal paper, ACR shows that under some conditions, the welfare gains from trade for a large class of models can be summarized by two statistics, namely the expenditure share on domestic goods and the trade elasticity. In a paper closely related to ACR, MR derives the formula of welfare gains from trade in a heterogeneous firm model under less restrictive assumptions. We extend their results under a different microstructure of trade costs.

The current paper contributes to the vast literature on trade costs, particularly the literature that studies implications of trade cost structure beyond the iceberg cost. Hummels and Skiba (2004) famously document evidence supporting the "Washington apple" effect, where high-quality goods tend to be shipped further away, a vital implication of the per-unit trade costs. The same paper also found that the elasticity of freight costs to price is less than one, which is against the assumption of the iceberg cost. However, using the transaction-level import data of Columbia, Lashkaripour (2020) found that the elasticity of transport costs to price is close to one, so the iceberg cost provides a semi-accurate representation of transport costs. In another paper that explores the implications of per-unit cost, Irarrazabal *et al.* (2015) estimated that the average magnitude of the additive trade costs is about 14% of the median price.

Similar to the papers assuming constant per unit trade costs, trade costs in our model depend on the quantity traded. However, the constant marginal cost per unit is only a limiting case in our model that we essentially rule out by restricting parameter values. With the proper restriction on parameter values, we can derive an explicit formula for welfare changes in response to trade cost changes in a rich environment with heterogeneous firms and asymmetric countries, which is important progress compared to the previous papers.

Another strand of literature explores the implications of trade cost per shipment. Alessandria *et al.* (2010) use cost per shipment to explain lumpiness in international trade transactions, and show that the inventory consideration is important in understanding the price responses to large devaluation of currency. Hornok and Koren (2015a,b) document that per shipment cost, as measured by World Bank's Doing Business survey, is associated with less frequent shipments, and build a homogeneous firm model to assess the welfare impacts of per shipment barriers. Kropf and Sauré (2014) estimate the magnitude of fixed cost per shipment using an extension of the standard Melitz model. Blum *et al.* (2019) show that the per-shipment costs could significantly affect the quality choice of firms. Therefore the countries with lower per shipment costs have a comparative advantage in producing high-quality goods.

Our paper also uses the frequency of shipments to identify trade costs, but we do not impose that cost per shipment is constant. The simple inventory management problem underlies our micro-foundation gives an explicit formula of the optimal shipment frequency, which significantly facilitates the estimation and is absent in the model assuming exponential inventory depreciation. However, to keep the analysis tractable, we abstract from demand uncertainty.

2 A Trade Model with Flexible Trade Costs

In this section, we introduce the theoretical model. To make the intuition clearer, we first restrict the model to a closed economy in Section 2.1, then discuss the impact of a more flexible cost structure on welfare gains from trade in two symmetric countries in Section 2.2. To simplify notation, we normalize wage to 1 in both sections. Finally, in Appendix A, the model is generalized to an environment with asymmetric countries.

2.1 Closed Economy

The setup of demand is the same as the Melitz (2003) model. The consumers in the economy are homogeneous. Each individual maximizes a constant elasticity of substitution (CES) utility function by choosing consumption quantities across a variety of goods. The utility maximization problem leads to the revenue function[1]

$$X_d(q) = Aq^{\nu_R}, \tag{1}$$

where q is the consumption quantity, $0 < \nu_R < 1$ is related to the elasticity of substitution between varieties, σ, through the relation $\nu_R = \frac{\sigma-1}{\sigma}$. Let L and P denote the total population and price index in the economy, the parameter A, defined as $A = P^{\nu_R}L^{1-\nu_R}$, summarizes the market condition.

Each firm takes a marginal cost draw, denoted by a, from a distribution $G(a)$. The production technology features constant return to scale, so that the total variable production costs for producing q units is aq. To deliver the product to the final consumer, the firm needs to incur logistics costs, which is equal to

$$C_{LT}(q) = B_d q^{\nu_L}, \tag{2}$$

where B_d is a parameter determining the level of logistics costs in the domestic market, ν_L determines how fast the logistics costs increase with quantity shipped. We make the following assumption about ν_L:

Assumption 1. $0 \le \nu_L < \nu_R$.

The introduction of logistics costs is our main departure from the literature. Under Assumption 1, the marginal logistics costs is decreasing in quantity. Depending on the value of ν_L, logistics costs capture the implications of different trade cost structures. When $\nu_L = 0$, the logistics costs become constant and can be merged with the fixed costs, therefore in that case, the model reduces to the standard Melitz model. Because of this, and for

[1] See Appendix A for a more detailed specification of preferences.

the analytical tractability, we assume that fixed costs are zero for the theoretical discussion. When we perform quantitative analysis in Section 3, we remove the restriction of zero fixed costs to match the extensive margin of trade flows observed in the data. As a limiting case, when $\nu_L = 1$, the logistics costs per unit are constant. Thus it becomes additive trade costs emphasized by several papers in the literature of trade costs (e.g., Hummels and Skiba 2004, Irarrazabal *et al.* 2015). Appendix C.1, provides a micro-foundation of the logistic costs via an inventory management problem.

The profit function of a firm with marginal cost equal to a is therefore

$$\pi = Aq^{\nu_R} - B_d q^{\nu_L} - aq, \tag{3}$$

which implies a first-order condition

$$\frac{\partial \pi}{\partial q} = A\nu_R q^{\nu_R - 1} - B_d \nu_L q^{\nu_L - 1} - a = 0, \tag{4}$$

and a second-order condition

$$\frac{\partial^2 \pi}{\partial q^2} = A\nu_R\left(\nu_R - 1\right) q^{\nu_R - 2} - B_d \nu_L \left(\nu_L - 1\right) q^{\nu_L - 2} < 0. \tag{5}$$

We can use the first-order condition (4) to express

$$a = A\nu_R q^{\nu_R - 1} - B_d \nu_L q^{\nu_L - 1}. \tag{6}$$

This expression implies that a can be thought of as a function of q, i.e., $a\left(q\right)$. This is one of the key insights that significantly simplifies the theoretical analysis that follows. Combining expression (6) for a together with the condition that firm should earn non-negative profits, gives

$$A\left(1 - \nu_R\right) q^{\nu_R} - B_d\left(1 - \nu_L\right) q^{\nu_L} \geq 0.$$

So that using Assumption 1, firm's profits are nonnegative if and only if $q \geq q_d^*$, where

$$q_d^* \equiv \left[\frac{B_d (1 - \nu_L)}{A (1 - \nu_R)} \right]^{\frac{1}{\nu_R - \nu_L}} \tag{7}$$

is the zero-profit quantity. Next, the second-order condition (5) holds if and only if

$$q^{\nu_R - \nu_L} > (q_d^*)^{\nu_R - \nu_L} \frac{\nu_L}{\nu_R},$$

which holds for any $q \geq q_d^*$ under Assumption 1. Finally, it is straightforward to check that $a'(q) < 0$ if and only if the second-order condition (5) holds.

Hence, $a(q)$ is a monotone function defined for all $q \geq q_d^*$ that provides a one-to-one mapping between firm's marginal cost a and the optimal quantity q. This, in turn, implies that there is a unique profit-maximizing quantity q for each cost $a \in (0, a_d^*)$, where $a_d^* \equiv a(q_d^*)$.[2] In addition, we can write the optimal quantity $q = q(a)$ without causing confusion.

The introduction of positive ν_L impacts the relative prices between firms having different productivity. When $\nu_L = 0$, it is easy to verify that the relative price is equal to the relative productivity. When $\nu_L > 0$, the same proportion of advantage in marginal cost translates into a bigger difference in prices, due to the ability of taking advantage of the scale of economy in the transportation technology by productive firms. To see this more formally, consider two firms with $a_1 < a_2$, so that firm 1 has higher productivity. By Equation (6) and the monotonicity of $a(q)$,

$$\frac{a_1}{a_2} > \left(\frac{q_1}{q_2} \right)^{\nu_R - 1} = \frac{p_1}{p_2},$$

where the equality follows from the definition of price, $p(q) = X_d(q)/q = Aq^{\nu_R - 1}$.[3]

[2] Throughout the paper, we assume that the support of marginal cost is large enough that there is active selection of firms.

[3] On the other hand, observe that the markup is equal to

$$\frac{p(q)}{VC'(q)} = \frac{1}{\nu_R},$$

where $VC(q)$ is the total variable cost that includes both logistics and production costs. This shows that the

To solve the model, use the free entry condition

$$\int_0^{a_d^*} \pi_d \left(q \left(a \right) \right) dG \left(a \right) = f^e, \tag{8}$$

which states that the expected profit of entering the market should be equal to the entry cost f^e. Together with equations (6) and (7), this equation gives the solution to the zero-profit quantity q_d^*. The price index, thus the welfare level, is connected to the zero-profit quantity via the relation

$$P = \left[\frac{B_d \left(1 - \nu_L \right)}{\left(q_d^* \right)^{\nu_R - \nu_L} L^{1-\nu_R} \left(1 - \nu_R \right)} \right]^{\frac{1}{\nu_R}}. \tag{9}$$

2.2 Two Symmetric Countries

Next, we discuss the implications of opening to trade on the welfare in a world with two symmetric countries. We use the subscript d to denote variables related to the domestic market and the subscript x to indicate variables associated with the foreign market. Since countries are symmetric, the market condition parameters, A, are equal in both countries, wages are equalized and normalized to 1. Regarding trade costs, we assume that fixed costs of export are equal to zero. Different from the closed economy scenario, each firm can export to the foreign market subject to an iceberg cost τ, with the domestic iceberg trade cost normalized to 1. Finally, the logistics cost parameter in the foreign market is B_x. We assume that the domestic market faces less friction in logistics, or $B_d < B_x$.

The goal in this subsection is to characterize the welfare changes from trade given any change in the trade costs τ or B_x. Despite the additional complexity associated with the introduction of the logistics costs, the analysis largely remains tractable. In particular, we derive explicit formulas of welfare gains from trade and show that the elasticity of trade with respect to logistics costs is equally informative about the gains from trade as the elasticity of trade with respect to iceberg trade costs.

Using similar argument as in the previous subsection, the first-order conditions of

price has a constant markup over the marginal variable cost. The important difference from the standard model is that the marginal variable cost now depends on the quantity produced.

firm's profit maximization problem in each market define the one-one mappings between the marginal cost and the optimal quantity in each market as

$$a_d\left(q\right) = A\nu_R q^{\nu_R-1} - B_d \nu_L q^{\nu_L-1}, \tag{10}$$

$$a_x\left(q\right) = \frac{A\nu_R q^{\nu_R-1} - B_x \nu_L q^{\nu_L-1}}{\tau}. \tag{11}$$

The inverse functions that define the mappings from the marginal costs to the optimal quantity are denoted as $q_d\left(a\right)$ and $q_x\left(a\right)$. The zero profit conditions for the domestic and the foreign market imply that

$$A = \frac{B_d\left(1-\nu_L\right)}{\left(q_d^*\right)^{\nu_R-\nu_L}\left(1-\nu_R\right)} = \frac{B_x\left(1-\nu_L\right)}{\left(q_x^*\right)^{\nu_R-\nu_L}\left(1-\nu_R\right)}, \tag{12}$$

where q_d^* is the zero-profit cutoff quantity in the domestic market, and q_x^* is the zero-profit cutoff in the foreign market. Plug in this relationship into equations (10), (11) to get

$$a_d^* = \left[\frac{\left(1-\nu_L\right)}{\left(1-\nu_R\right)}\nu_R - \nu_L\right] B_d\left(q_d^*\right)^{\nu_L-1}, \tag{13}$$

$$a_x^* = \frac{\left[\frac{\left(1-\nu_L\right)}{\left(1-\nu_R\right)}\nu_R - \nu_L\right] B_x\left(q_x^*\right)^{\nu_L-1}}{\tau}. \tag{14}$$

The second equality in Equation (12) shows that two cutoff quantities satisfy the relation

$$q_x^* = \left(\frac{B_x}{B_d}\right)^{\frac{1}{\nu_R-\nu_L}} q_d^*, \tag{15}$$

which also shows that the foreign market has a higher entry threshold given Assumption 1 and $B_d < B_x$. Therefore the cutoff marginal costs satisfy the relation

$$a_x^* = \frac{1}{\tau}\left(\frac{B_d}{B_x}\right)^{\left(\frac{1-\nu_R}{\nu_R-\nu_L}\right)} a_d^*. \tag{16}$$

Together with the free entry condition

$$\int_0^{a_d^*} \pi_d\left(q\left(a\right)\right) dG\left(a\right) + \int_0^{a_x^*} \pi_x\left(q\left(a\right)\right) dG\left(a\right) = f^e, \tag{17}$$

we can solve for the zero profit cutoffs a_d^* and a_x^*, and therefore the market condition parameter A. Other aggregated variables of interest can be expressed by the cutoffs. Using Equation (12) and the definition $A = P^{\nu_R} L^{1-\nu_R}$, the real consumption can be derived as

$$W \equiv \frac{1}{P} = \left(\frac{B_d\left(1-\nu_L\right)}{\left(q_d^*\right)^{\nu_R-\nu_L}\left(1-\nu_R\right)}\right)^{-\frac{1}{\nu_R}} L^{\frac{1-\nu_R}{\nu_R}}. \tag{18}$$

Take logarithmic difference to this equation. Since we only consider the effects of changes in τ and B_x on the welfare, it reduces to

$$d\ln W = \left(\frac{\nu_R-\nu_L}{\nu_R}\right) d\ln q_d^* = -\left(\frac{\nu_R-\nu_L}{\nu_R\left(1-\nu_L\right)}\right) d\ln a_d^*. \tag{19}$$

The change in welfare is therefore summarized by the change in the domestic zero profit cutoff. Moreover, when $\nu_L > 0$, the pass-through elasticity of change in the cutoff to the change in welfare is determined by two elasticities ν_R and ν_L.

To build connection between welfare changes and data, we derive expressions for the expenditure share on the domestic goods and the trade elasticity. These two variables form the sufficient statistics to calculate welfare gains for a large class of trade models, as shown by ACR. The expenditure share on the domestic goods is

$$\begin{aligned}\lambda &= \frac{\int_0^{a_d^*} X_d\left(q\left(a\right)\right) dG\left(a\right)}{\int_0^{a_d^*} X_d\left(q\left(a\right)\right) dG\left(a\right) + \int_0^{a_x^*} X_x\left(q\left(a\right)\right) dG\left(a\right)} \\ &= \frac{\int_0^{a_d^*} q_d^{\nu_R}\left(a\right) dG\left(a\right)}{\int_0^{a_d^*} q_d^{\nu_R}\left(a\right) dG\left(a\right) + \int_0^{a_x^*} q_x^{\nu_R}\left(a\right) dG\left(a\right)}.\end{aligned} \tag{20}$$

When $\nu_L > 0$, both the iceberg trade costs and the logistics costs serve as the variable trade costs, therefore we define elasticities of trade to both costs. Moreover, since most papers estimate the elasticities from the gravity equation, which exploits cross sectional variation in the bilateral frictions controlling for the origin and the destination fixed effects, we hold domestic environment, namely a_d^* as constant in our definition of elasticities. To be explicit, we treat the domestic expenditure share $\lambda = \lambda\left(a_d^*, a_x^*, \tau, B_x\right)$ as a function of two cutoff quantities and trade costs parameters, and the foreign market cutoff $a_x^* = a_x^*\left(a_d^*, \tau, B_x\right)$ as a function of the domestic cutoff and trade costs, as defined in Equation (16). Finally, the domestic cutoff $a_d^* = a_d^*\left(\tau, B_x\right)$ is a function of the trade costs parameters, as implicitly defined in the free entry condition. The elasticity with respect to τ is

$$\begin{aligned}
\vartheta_\tau &\equiv -\left.\frac{d\ln\left(\frac{1-\lambda}{\lambda}\right)}{d\ln\tau}\right|_{a_d^*} \\
&= -\left[\frac{\partial\ln\left(\int_0^{a_x^*} q_x^{\nu_R}(a)\,dG(a)\right)}{\partial\ln\tau} + \frac{\partial\ln\left(\int_0^{a_x^*} q_x^{\nu_R}(a)\,dG(a)\right)}{\partial\ln a_x^*}\frac{\partial\ln a_x^*}{\partial\ln\tau}\right] \\
&= -\left[\frac{\partial\ln\left(\int_0^{a_x^*} q_x^{\nu_R}(a)\,dG(a)\right)}{\partial\ln\tau} + \frac{\partial\ln\left(\int_0^{a_x^*} q_x^{\nu_R}(a)\,dG(a)\right)}{\partial\ln a_x^*}(-1)\right], \qquad (21)
\end{aligned}$$

where the first equality results from the restriction of q_d^* being constant, and the second equality uses Equation (16). Similarly, the elasticity with respect to B_x is

$$\begin{aligned}
\vartheta_B &\equiv -\left.\frac{d\ln\left(\frac{1-\lambda}{\lambda}\right)}{d\ln B_x}\right|_{a_d^*} \\
&= -\left[\frac{\partial\ln\left(\int_0^{a_x^*} q_x^{\nu_R}(a)\,dG(a)\right)}{\partial\ln B_x} + \frac{\partial\ln\left(\int_0^{a_x^*} q_x^{\nu_R}(a)\,dG(a)\right)}{\partial\ln a_x^*}\frac{\partial\ln a_x^*}{\partial\ln B_x}\right] \\
&= -\left[\frac{\partial\ln\left(\int_0^{a_x^*} q_x^{\nu_R}(a)\,dG(a)\right)}{\partial\ln B_x} + \frac{\partial\ln\int_0^{a_x^*} q_x^{\nu_R}(a)\,dG(a)}{\partial\ln a_x^*}\left(-\frac{1-\nu_R}{\nu_R-\nu_L}\right)\right], \qquad (22)
\end{aligned}$$

where the second equality uses Equation (16) as well.

Using the definition of price index, we have

$$P^{\frac{-\nu_R}{1-\nu_R}} = N^e A^{\frac{-\nu_R}{1-\nu_R}}\left(\int_0^{a_d^*} q_d^{\nu_R}(a)\,dG(a) + \int_0^{a_x^*} q_x^{\nu_R}(a)\,dG(a)\right), \qquad (23)$$

where N^e is the mass of potential entrants. Using the definition of real consumption, and Equation (20), one can show that the real consumption is given by

$$W = L^{-1}\left[N^e \frac{\int_0^{a_d^*} q_d^{\nu_R}(a)\, dG(a)}{\lambda}\right]^{\frac{1}{\nu_R}}. \tag{24}$$

Together with Equation (19), this shows that the change in real consumption can be expressed as

$$d\ln W = \frac{1}{\nu_R\left(1+\gamma_d\left(a_d^*\right)\left(\frac{1-\nu_L}{\nu_R-\nu_L}\right)\right)}\left(d\ln N^e - d\ln\lambda\right),$$

where $\gamma_d(x) \equiv \frac{d\ln\int_0^{a_d^*} q_d^{\nu_R}(a)dG(a)}{d\ln x}$, $\gamma_x(x) \equiv \frac{d\ln\int_0^{a_x^*} q_x^{\nu_R}(a)dG(a)}{d\ln x}$. Because $\int_0^{a_d^*} q_d^{\nu_R}(a)\, dG(a)$ is proportional to the market share of the domestic firms, $\gamma_d\left(a_d^*\right)$ measures the sensitivity of market share with respect to the domestic zero profit cutoff. Analogous interpretation holds for $\gamma_x\left(a_x^*\right)$.

Using the definitions of the elasticities in equations (21) and (22), the changes in welfare can be further expressed as either

$$d\ln W = \frac{\left(d\ln N^e - d\ln\lambda\right)}{\nu_R\left(1+\left[\gamma_d\left(a_d^*\right)-\gamma_x\left(a_x^*\right)+\vartheta_\tau+\gamma_x(\tau)\right]\left(\frac{1-\nu_L}{\nu_R-\nu_L}\right)\right)}, \tag{25}$$

or

$$d\ln W = \frac{\left(d\ln N^e - d\ln\lambda\right)}{\nu_R\left(1+\left[\gamma_d\left(a_d^*\right)-\gamma_x\left(a_x^*\right)+\left(\frac{\nu_R-\nu_L}{1-\nu_R}\right)\left[\vartheta_B+\gamma_x\left(B_x\right)\right]\right]\left(\frac{1-\nu_L}{\nu_R-\nu_L}\right)\right)}. \tag{26}$$

Similar to the formula derived in MR, equations (25), (26) show that in general, the change in mass of firms could affect welfare, and the difference in the sensitivity $\gamma_d\left(a_d^*\right)-\gamma_x\left(a_x^*\right)$ also matters. Different from MR, we highlight that a different trade cost structure, as modeled through a positive ν_L, could also affect the welfare changes. This effect is mediated via both a different transmission rate of changes in zero profit cutoffs as shown in Equation (19) and a different direct effects contained in the elasticities $\gamma_x(\tau)$, $\gamma_x\left(B_x\right)$. Moreover, the equations show that the elasticity with respect to logistics costs is equally informative about the welfare gains from trade, therefore suggesting a different way of quantifying the effect of trade liberalization.[4]

2.2.1 Solutions Under Pareto Distribution

We derive explicit solutions by imposing the assumption that the inverse of marginal cost follows Pareto distribution given by the cumulative density function

$$G(a) = \theta^{-1}(\kappa_G a)^{\theta}, \tag{27}$$

where $\theta > 0$ and $a \in \left[0, \kappa_G^{-1}\theta^{\frac{1}{\theta}}\right]$. Under this assumption, it can be shown that the aggregated optimal quantity of any power ν in the foreign market, subject to the condition $\frac{\nu+\nu_R\theta-\theta}{\nu_L-\nu_R} > 0$, is given by

$$\int_0^{a_x^*} q_x^{\nu} dG(a) = \kappa_G^{\theta}\tau^{-\theta}(B_x)^{\theta}(q_x^*)^{\nu+\nu_L\theta-\theta}\left(\frac{(1-\nu_L)}{(1-\nu_R)}\right)^{-\frac{\nu+\nu_L\theta-\theta}{\nu_R-\nu_L}} H(\nu,\nu_R,\nu_L,\theta) \tag{28}$$

where $H(\nu,\nu_R,\nu_L,\theta)$ is a positive-valued function that depends only on parameters of the model. The detailed derivation of this formula in any market can be found in Appendix B. In order to simplify exposition, we drop the later three arguments in the $H(\cdot)$ function and write $H(\nu)$ to represent $H(\nu,\nu_R,\nu_L,\theta)$.

Using Equation (28), we see that[5]

$$\int_0^{a_d^*} q_d^{\nu_R}(a)\, dG(a) = \kappa_G^{\theta}(B_d)^{\theta}(q_d^*)^{\nu_R+\theta\nu_L-\theta} H(\nu_R)\left(\frac{(1-\nu_L)}{(1-\nu_R)}\right)^{-\frac{\nu_R+\nu_L\theta-\theta}{\nu_R-\nu_L}},$$

$$\int_0^{a_x^*} q_x^{\nu_R}(a)\, dG(a) = \kappa_G^{\theta}(B_x)^{\theta}\tau^{-\theta}(q_x^*)^{\nu_R+\theta\nu_L-\theta} H(\nu_R)\left(\frac{(1-\nu_L)}{(1-\nu_R)}\right)^{-\frac{\nu_R+\nu_L\theta-\theta}{\nu_R-\nu_L}},$$

from which we can calculate the elasticities as $\vartheta_\tau = \theta$, $\vartheta_B = \frac{\nu_R+\theta\nu_R-\theta}{\nu_L-\nu_R}$. Applying the formula to the labor market clearing condition, as shown in more detail in Appendix A, we show that the aggregate profits are a constant share of the aggregate revenue, and

[4] When $\nu_L = 0$, it is straightforward to verify the the elasticity of trade respect to the fixed costs can also be used to calculate welfare gains from trade.

[5] It is straightforward to apply the formula to the domestic market by replacing the corresponding market specific variables.

therefore $d \ln N^e = 0$. Finally, the welfare changes can be summarized as

$$d \ln W = -\frac{d \ln \lambda}{\nu_R \left(\frac{\nu_L + \theta \nu_L - \theta}{\nu_L - \nu_R} \right)}. \tag{29}$$

The formula clearly illustrates the importance of the microstructure of trade costs in determining the welfare gains from trade. It shows that the trade elasticity ϑ_τ is no longer the sufficient statistics for calculating welfare changes, even under an environment where all three macro restrictions proposed by ACR are satisfied. Finally, the formula collapses to the ACR formula when $\nu_L = 0$.

3 Empirical analysis

3.1 Data

The empirical analysis mainly uses Chinese custom data. The data contains the universe of international trade transactions of Chinese firms for each month from 2000 to 2006. Each transaction is described in details by variables including the year-month when the transaction happens, the import/export dummy, 8-digit harmonized system (HS) code for product classification, 10-digit company identification number, the quantity and the value of the goods, the destination, the mode of transportation, and the mode of trade.[6] For the sake of brevity, we skip detailed data descriptions. Many papers have used this data. For more information about the data, see, for example, Bai *et al.* (2017). To measure the number of firms that sell domestically, we use the annual industrial survey data produced by the National Bureau of Statistics. For more information on this dataset, see Brandt *et al.* (2012).

In our main sample, we use export transactions by manufacturing firms only. We exclude intermediary firms as they do not incur production costs.[7] To reduce the noise from small export destinations, we restrict to the top 100 destinations in terms of export

[6]The mode of trade includes 18 categories, with the top 2 categories being ordinary trade and the processing trade. The other variables include the unit of goods, the port and the route of the trade, the origin city, the zip code, and the type of the firm (with the main categories being state-owned or private).

[7]We use the keywords of firm name provided in Ahn *et al.* (2011) to identify intermediary firms.

value, accounting for more than 99% of the total export value.

3.2 Welfare Gains from Trade

In this subsection, we quantify the gains from trade liberalization using the formula (29) [8], and compare it with the gains derived using the ACR formula. As shown in more detail in Appendix C, using a simple extension of the standard Economic Order Quantity model proposed in Fabinger and Weyl (2018), we can link the logistics costs to the shipment frequency via an inventory management problem. More specifically, the inventory management problem gives us a relation between the optimal shipment frequency F from origin i to destination j and the total quantity q to be shipped as

$$F_{ij}(q) = \frac{1}{1-\nu_L}\kappa_I B_{ij}^{-1} q^{(1-\nu_L)}, \tag{30}$$

where κ_I is the parameter related to inventory costs. Intuitively, in the model, to export a given quantity, the marginal cost of inventory is constant, while the marginal cost of coordination decreases in export quantity. A firm chooses the optimal shipment frequency that equalizes the marginal cost of inventory and the marginal cost of coordination. The elasticity ν_L measures how fast the coordination cost per shipment increases with the total quantity to be shipped.

Equation (30) allows us to estimate ν_L by regressing the logarithm of shipment frequency to the logarithm of traded quantity. Given the detailed definition of a transaction, we use the number of transactions as the measure of the number of shipments. This idea is implemented in Appendix C.2, which gives us a very precise estimate of ν_L close to 0.6.[9] With the estimated ν_L, we can compare gains from trade across models. Table 1 shows the gains from trade that move from the autarky at the observed level of expenditure share on domestic goods for several countries. We compare the gains from trade under the assumption that $\nu_L = 0$ and $\nu_L = 0.6$. The former value is assumed in the standard trade

[8] The formula hold in an environment with asymmetric countries. For details, see Equation (59) in Appendix A.

[9] Fabinger and Weyl (2018) uses the sample of single-product firms and also estimate a value of ν_L about 0.6. In Appendix C.2, we estimate ν_L for different products separately, while the estimates are heterogeneous, the central value is not far from 0.6.

models, while the latter value is supported by the estimation results using the shipment frequency data. We hold ν_R to be 0.8, which is equivalent to the elasticity of substitution equal to 5, consistent with the large literature estimating this parameter. The data of expenditure share comes from the WIOD in 2008 (see Timmer *et al.* 2015). The model under $\nu_L = 0.6$ gives lower welfare gains from trade. The difference is higher for countries like Hungary, where the expenditure on domestic goods is lower. Overall, we observe 11.5% lower welfare gains from trade on average.

3.3 Model Calibration

This section shows how to calibrate other model parameters, particularly those related to trade costs, using trade data. The goal of the calibration exercise is to quantify the significance of logistics costs in terms of rationalizing the observed trade flows.

3.3.1 Target Moments

This subsection presents the data moments that we use to calibrate trade cost parameters. For the calibration exercise, we aggregate the custom data to the firm destination level. For the computational reason, we use firm-level trade data from the top 10 Chinese provinces[10] to the top 8 destinations.[11] Since China has a broad territory, the distance at the country level could be misleading. For example, according to Google Map, while Dalian, a north-east city, is 1,645 km away from Tokyo, Chengdu, a mid-east city, is about 3,353 km from Tokyo. Therefore, to get a more precise distance measure for firms' exports, we split the firms according to their province of origin and calculate the geographic distance between any province and destination using the latitude and gratitude information. More specifically, we calculate the distance between any cities using the haversine formula, then calculate the population-weighted average across all cities within any province-destination pair. The location and population data are from the web-

[10] Provinces include Guangdong, Jiangsu, Shanghai, Zhejiang, Shandong, Fujian, Tianjin, Beijing, Liaoning, Hebei

[11] Destinations include the US, Japan, Korea, Germany, Netherlands, Singapore, UK, and Canada. We exclude Hong Kong since it is subject to a lot of re-export, whose real destinations are not clear.

site Simplemap.[12]

Figure 1 and Figure 2 show the empirical distributions of firm sales and shipment frequency from Guangdong province to its three popular destinations (the US, Japan, and Germany). The panels on the left show the histograms of firm-level sales and shipment frequency. As the export sales decreases, the export shipment frequency decreases as well. The panels on the right show the corresponding cumulative distribution functions (CDFs). The dashed lines are the CDFs of the normal random variables with the same mean and variance as the log export value or log shipment frequency. The log-normal distribution well explains the distribution of export value and has a good fit for the distribution of shipment frequency, despite its discrete nature. The cross-destination variations in the firm distributions conditional on the origin province play a significant role in identifying trade costs. More specifically, conditional on the province and the destination fixed effects, the bilateral shift in export value and shipment frequency must be driven by changes in τ_{ij}, B_{ij}.

Figure 3 shows the share of exporters that export to each destination from Guangdong. Note there is substantial variation across destinations. For example, the figure shows that over 45% of exporters export to the US, but only about 15% of exporters export to South Korea. This variation will allow us to calibrate the relative level of fixed export costs.

Finally, Table 2 shows gravity regressions using all provinces and all destinations in 2006. The regressions put the logarithmic values of total export value X_{ij}, total number of firms N_{ij}, total shipment frequency F_{ij}, and value per firm $\frac{X_{ij}}{N_{ij}}$, shipment per firm $\frac{F_{ij}}{N_{ij}}$, value per shipment $\frac{X_{ij}}{F_{ij}}$ on the left-hand side, the bilateral distance on the right-hand side after taking logarithmic transformation, controlling for the origin plus the destination fixed effects. We see that all the margins decrease significantly with distance, except for the value per shipment, whose coefficient is negative but not statistically significant. As is widely used in the literature, the estimates of gravity equations provide us with information on the magnitude of the underlying trade costs.

[12] We use the basic database from https://simplemaps.com/data/world-cities

3.3.2 Calibration Procedures

To match the targeted empirical patterns, we extend the model such that each firm takes a draw of fixed export cost in each destination independently. The profit function now becomes

$$\pi_{ij}(q) = A_j q^{\nu_R} - w_i B_{ij} q^{\nu_L} - a w_i \tau_{ij} q - w_i \xi_{fj} f_{ij}^x,$$

where $\ln \xi_{fj}$ follows a normal distribution with zero mean and variance σ_ξ^2:

$$P(x) = \Phi\left(\frac{\ln x}{\sigma_\xi}\right). \tag{31}$$

The introduction of heterogeneous fixed costs allows the model to rationalize the coexistence of a decreasing number of exporters and small exporters in distant destinations. Because even the number of exporters decreases as f_{ij}^x increases, small exporters can still survive as long as the firm-destination specific shock ξ_{fj} is low enough. Furthermore, since fixed costs do not affect the optimal quantity either for profit optimization or logistics costs minimization, the firm's choice of quantity q_{fj} or shipment frequency F_{fj} do not change.

We assume that the marginal costs across firms within the same origin follow the log-normal distribution:

$$G_i(a) = \Phi\left(\frac{\ln a - \mu_{a,i}}{\sigma_a}\right), \tag{32}$$

where $\Phi(\cdot)$ is the cumulative distribution function of the standard normal random variable. Although assuming the firm-level productivity follows a Pareto distribution would yield convenient closed-form solutions to the model, as shown in the Appendix D, this assumption implies that the elasticity of the intensive margin $\frac{X_{ij}}{N_{ij}}$ with respect to B_{ij} is positive given that $\nu_R > \nu_L$. Together with a negative distance elasticity of $\frac{X_{ij}}{N_{ij}}$, the model would suggest that the logistics costs are decreasing in the distance, a prediction that we find hard to justify. To avoid this problem, we follow the suggestion in Fernandes *et al.* (2019) and assume that firm-level productivity follows a log-normal distribution.

Since we don't have data on inventory costs, we follow the literature on inventory management (e.g. Alessandria *et al.* 2010) and set κ_I equal to 0.15. Since the inventory costs is equal to the product of the average inventory level and κ_I, this is equivalent to a annual inventory costs of 30% of the stored quantities. The demand side parameter ν_R is set to be 0.8, implying the elasticity of substitution is equal to 5. This value is consistent with the literature that estimates this parameter using different data and approaches (see e.g., Anderson and van Wincoop 2004). Same as previous section, we set $\nu_L = 0.6$. Note that given these values of ν_R and ν_L, we can solve the firm's profit maximization explicitly, which greatly speeds up the numerical calculations[13]. Wages in each province is identified by the GDP per capita that comes from National Statistics Bureau of China. We normalize the mean of wages across all provinces to be 1.

The remaining parameters are $\left(\sigma_a, \sigma_\xi, \mu_{a,i}, A_j, B_{ij}, \tau_{ij}, f^x_{ij}\right)$, so that if there are I origins and J destinations, we have $2 + I + J + 3IJ$ parameters to be calibrated. The parameters σ_a, σ_ξ that determine the variance of the productivity and fixed costs shocks are held to be constant across all origin and destinations. To identify these parameters, we exploit the following moment conditions. Firstly, the average export sales from origin i to destination j, conditional on firms that enter, is

$$\frac{X_{ij}}{N_{ij}} = \int \int_0^{a^*_{ij}(\xi)} A_j q_{ij}^{\nu_R}(a)\, d\frac{G(a)}{G\left(a^*_{ij}(\xi)\right)} dP(\xi), \tag{33}$$

and the variance of firm-level sales is

$$VarX_{ij} = \int \int_0^{a^*_{ij}(\xi)} \left[A_j q_{ij}^{\nu_R}(a) - \frac{X_{ij}}{N_{ij}}\right]^2 d\frac{G(a)}{G\left(a^*_{ij}(\xi)\right)} dP(\xi). \tag{34}$$

Secondly, the mean of shipment frequency conditional on firms that export, is

$$\frac{F_{ij}}{N_{ij}} = \int \int_0^{a^*_{ij}(\xi)} \frac{1}{1-\nu_L} \kappa_I B_{ij}^{-1} q_{ij}^{(1-\nu_L)}(a)\, d\frac{G(a)}{G\left(a^*_{ij}(\xi)\right)} dP(\xi), \tag{35}$$

[13] More specifically, we use Equation (60) in Appendix A

and the variance of firm-level shipment frequency is

$$VarF_{ij} = \int \int_0^{a^*_{ij}(\xi)} \left[\frac{1}{1-\nu_L} \kappa_I B_{ij}^{-1} q_{ij}^{(1-\nu_L)}(a) - \frac{F_{ij}}{N_{ij}} \right]^2 d\frac{G(a)}{G\left(a^*_{ij}(\xi)\right)} dP(\xi). \tag{36}$$

Finally, the number of firms that export from i to j can be expressed as:

$$N_{ij} = N_i^e \int \int_0^{a^*_{ij}(\xi)} dG(a)\, dP(\xi) = N_i^e \int G\left(a^*_{ij}(\xi)\right) dP(\xi),$$

where $\int G\left(a^*_{ij}(\xi)\right) dP(\xi)$ is the share of firms find it profitable to enter. Normalizing it with the number of firms that sell domestically, we get

$$\frac{N_{ij}}{N_{ii}} = \frac{\int G\left(a^*_{ij}(\xi)\right) dP(\xi)}{\int G\left(a^*_{ii}(\xi)\right) dP(\xi)}. \tag{37}$$

Therefore equations (33)-(37) define five moments for each origin-destination pair, and in total we observe $5IJ$ moment conditions from data. As a result, the number of the moment conditions will exceed the number of parameters we need to calibrate as long as the number of origin-destination pairs IJ is large enough.

The intuition of the identification works as follows. As destination-specific effects, A_j can be identified from the average sales and shipment frequency specific to each destination across origins. Similarly, μ_i is identified from province-specific variations across destinations. Given the province-specific and the destination-specific effects, τ_{ij} and B_{ij} can be identified from the bilateral changes in the average sales and shipment frequency. We expect that B_{ij} to have a larger impact on the bilateral shipment frequency, as can be seen in Equation (35). Finally, f^x_{ij} is identified from the condition shown in Equation (37), since the average bilateral fixed costs affect the number of firms enter each market. Importantly, the relative extensive margin only identifies levels of f^x_{ij} relative to the domestic fixed costs, which we normalize to 0. Similarly, we normalize the domestic iceberg trade costs to 1.

The shape of the distributions is informative about the variance of marginal costs, σ_a^2, because within the province-destination, the marginal cost a is an important source of firm heterogeneity in deciding sales or shipment frequency. Moreover, the observed firm-level sales and shipment frequency distribution represent different entrants across different marginal cost levels. Thus the shapes of the distributions are also informative about the variance σ_{ξ}^{2}.

This model does not allow for a big firm in one destination to sell little in another destination. This model also does not allow for idiosyncratic shipment frequency across firms conditional on sales. It predicts a perfect correlation between sales and shipment frequency across firms within the same market. However, introducing more shocks on demand and logistics costs can solve all these problems. Since introducing such features does not contribute to our main goal of inferring province-destination level trade costs, we choose not to complicate the model further.

Simulation is performed and the parameters are chosen to match the simulated moments with the empirical moments. The simulation algorithm is summarized as follows:

- For each province, we simulate 10,000 firms, indexed by s. Each simulated firm takes a productivity draw $a_i(s)$, and for each destination a fixed export cost draw $\xi_{ij}(s)$.
- Given parameter values, solve the export decisions for each firm from each origin, according to the model discussed in the previous section. Shipment frequency is taken as the smallest integer greater or equal to the value given by Equation (30).
- Given other parameters, we solve for f_{ij}^{x} by solving Equation (37).
- In the outer loop, search over σ_{ξ}, σ_a, A_j, B_{ij} , τ_{ij} to match firm level sales and shipment frequency distribution for each origin-destination pair, by minimizing the distance defined by the moment conditions (33)-(37).

3.4 Calibration Results

The calibration result of σ_{ξ} and σ_a is shown in Table 3. The calibrated value of σ_a is comparable to the value estimated in Fernandes *et al.* (2019). The inferred value of σ_{ξ} is higher under our model. It comes from the fact that productive firms have a higher advantage when $\nu_L > 0$, therefore to rationalize the presence of small firms, we need more extreme shocks on fixed costs.

As an illustration of the model fits, Figure 4 and Figure 5 show the model fit of sales distribution and shipment frequency distribution, respectively, for the exports from the two biggest provinces, Guangdong and Jiangsu, to the US and Japan. The fits are good in general, and the fits to the sales distributions are better than the shipment frequency distribution. Figure 6 shows the model fit for the normalized extensive margin is perfect, as all the points of empirical and simulated normalized extensive margin lie on the 45-degree line. This is not surprising given that we solve for f_{ij}^x such that Equation (37) is satisfied exactly.

To check whether the calibrated parameters make sense, we run the following regressions:

$$\ln X_{ij} = \beta_0 + \beta_1 lnB_{ij} + \beta_2 \ln \tau_{ij} + \beta_3 \ln f_{ij}^x + \phi_i + \psi_j + u_{ij}, \tag{38}$$

where X_{ij} is the bilateral trade flow from province i to destination j, and B_{ij}, τ_{ij}, f_{ij}^x are calibrated trade cost parameters. We also replace the outcome with the logarithmic value of the bilateral shipment frequency $\ln F_{ij}$. We expect all parameters to negatively correlate with trade flow and shipment frequency. As shown in Table 4, all calibrated parameters are negatively correlated with bilateral trade flows and shipment frequency when regressed separately. When including all explanatory variables, only $\ln \tau_{ij}$ and $\ln B_{ij}$ significantly impact the bilateral trade flow, while all variables negatively correlate with the bilateral shipment frequency. Interestingly, the estimated elasticity of τ_{ij} with respect to bilateral trade flow is comparable to the estimate of trade elasticity in the literature.

The first three columns of Table 5 report the distance elasticity of calibrated trade costs parameters, controlling for province and destination fixed effects. All parameters are increasing in the distance, consistent with intuition. B_{ij} has the lowest slope, driven by the slow change rate in shipment frequency, and f_{ij}^x has the highest slope, driven by the sharp decrease in the extensive margin of trade.

As measures of trade costs, for each firm with marginal cost a that exports from location i to location j, we normalize logistics costs and iceberg trade costs using export revenue, namely we calculate the ratios $w_i B_{ij} q_{ij}^{\nu_L} / A_j q^{\nu_R}$, and $\left(\tau_{ij} - 1\right) a w_i q_{ij} / A_j q^{\nu_R}$. As shown in Figure 7, the logistics costs account for a larger revenue share for less productive firms. More specifically, for the simulated firms exporting from Guangdong to the US, the logistics costs are 5.7% of revenue for 25th-quantile firms but are 15% of revenue for 75th-quantile firms. On the other hand, the iceberg trade costs play a relatively minor role for the less productive firms. The decreasing revenue share of iceberg costs contrasts with the case when $\nu_L = 0$, under which the ratio of iceberg trade costs and revenue is constant.[14]

3.5 Ad Valorem Rate of The Logistics Costs

The calibrated parameters allow us to assess the significance of the logistics costs for each firm. More specifically, for each firm, we ask the following question: keeping the market conditions unchanged, what is the magnitude of iceberg costs required to generate the same variable profit (i.e., the difference between revenue and variables costs) if we shut down the logistics costs by adding the restriction $\nu_L = 0$, $B_{ij} = 0$. Let $O_{ij}(a)$ denote the variable profit for a firm with marginal cost a that exports from location i to location j, and $\tau_{ij}^{Im}(a)$ denote the iceberg costs required to generate the same variable profit. Since logistics costs are heterogeneous across firms, $\tau_{ij}^{Im}(a)$ depends on firm's productivity. The difference $\tau_{ij}^{Im}(a) - \tau_{ij}$ therefore captures the ad valorem rate of the logistics costs for each firm.

When $\nu_L = 0$, the optimal quantity that maximizes the profit is given by

$$q = \left(\frac{A_j \nu_R}{a w_i \tau_{ij}} \right)^{\frac{1}{1-\nu_R}}. \tag{39}$$

[14] When $\nu_L = 0$, the first-order condition of profit maximization problem is

$$\frac{\partial \pi_{ij}}{\partial q} = A_j \nu_R q^{\nu_R - 1} - a w_i \tau_{ij} = 0,$$

so that $\frac{a w_i \left(\tau_{ij} - 1\right) q}{A_j q^{\nu_R}} = \nu_R \frac{\tau_{ij} - 1}{\tau_{ij}}$.

And $O_{ij}(a)$ is given by

$$O_{ij}(a) = A_j^{\frac{1}{1-\nu_R}} \left(aw_i\tau_{ij}\right)^{-\frac{\nu_R}{1-\nu_R}} (\nu_R)^{\frac{1}{1-\nu_R}} \left[\nu_R^{-1} - 1\right]. \tag{40}$$

So that $\tau_{ij}^{Im}(a)$ is given by

$$\tau_{ij}^{Im}(a) = \frac{O_{ij}(a)^{-\frac{1-\nu_R}{\nu_R}}}{(\nu_R)^{-\frac{1}{\nu_R}} \left[\nu_R^{-1} - 1\right]^{-\frac{1-\nu_R}{\nu_R}} A_j^{-\frac{1}{\nu_R}} (aw_i)}. \tag{41}$$

We take $O_{ij}(a)$ as well as the demand shifter A_j from the simulation in the above section to calculate $\tau_{ij}^{Im}(a)$ for each firm that exports from location i to location j. To calculate the ad valorem rate of logistics costs, $\tau_{ij}^{Im}(a) - \tau_{ij}$, we take τ_{ij} as the bilateral iceberg trade costs calibrated from the previous exercise.

The calculated ad valorem rate of logistics costs across firms that export from Guangdong to the US is plotted in Figure 8. As apparent from the figure, the effects of logistics costs are highly heterogeneous. While the most productive firm incurs the logistics costs that has a ad valorem equivalent rate of 1.3%, the least productive firm pays a ad valorem equivalent rate of 138.9%.

We calculate the average implied iceberg trade costs, τ_{ij}^{Im}, by taking the average across firms for each origin-destination pair. The two columns in Table 6 report the distance elasticity of τ_{ij}^{Im} and the distance elasticity of the difference between the calibrated and the implied iceberg trade costs. The result in column 1 shows that after shutting down the logistics costs, the distance elasticity of iceberg trade costs increases slightly. The result shows that adding the logistics costs helps to understand the distance elasticity of trade. Lastly, the estimate in column 2 shows that the ad valorem equivalent rate of logistics costs differ substantially across space.

Conditional on the same variable profit, does the payment of logistics costs increase the total trade costs? To investigate this, we calculate the ratios between total trade costs and revenue, namely $\left(w_i B_{ij} q_{ij}^{\nu_L} + \left(\tau_{ij} - 1\right) aw_i q_{ij}\right) / A_j q^{\nu_R}$ and $\left(\tau_{ij}^{Im} - 1\right) aw_i q_{ij} / A_j q^{\nu_R}$,for each simulated firm that exports from Guangdong to the US. The results are plotted in

Figure 9. For productive firms, it does not make much difference as the logistics costs are relatively low. But for the less productive firms, the total trade costs are higher when there are logistics costs.

4 Conclusion

This paper analyzes the implications of a more flexible trade cost structure for a heterogeneous firm trade model. Theoretically, we extend the established results by showing the importance of the micro-level assumptions. In particular, we derive the formula for the welfare changes given trade costs changes under the assumption that firm-level productivity follows the Pareto distribution. Empirically, we quantify the significance of the logistics costs exploiting the patterns in the shipment frequency. The impact of logistics costs is highly heterogeneous across firms. Overall, our results show that a more realistic trade cost structure can have significant implications for evaluating trade policy.

References

AHN, J., KHANDELWAL, A. K. and WEI, S. J. (2011). The role of intermediaries in facilitating trade. *Journal of International Economics*, **84** (1), 73–85.

ALESSANDRIA, G., KABOSKI, J. P. and MIDRIGAN, V. (2010). Inventories, lumpy trade, and large devaluations. *American Economic Review*, **100** (5), 2304–2339.

ANDERSON, J. E. and VAN WINCOOP, E. (2004). Trade Costs. *Journal of Economic Literature*, **42** (3), 691–751.

ARKOLAKIS, C., COSTINOT, A. and RODRÍGUEZ-CLARE, A. (2012). New trade models, same old gains? *American Economic Review*, **102** (1), 94–130.

BAI, X., KRISHNA, K. and MA, H. (2017). How you export matters: Export mode, learning and productivity in China. *Journal of International Economics*, **104**, 122–137.

BLUM, B. S., CLARO, S., DASGUPTA, K. and HORSTMANN, I. J. (2019). Inventory management, product quality, and cross country income differences. *American Economic Journal: Macroeconomics*, **11** (1), 338–388.

BRANDT, L., VAN BIESEBROECK, J. and ZHANG, Y. (2012). Creative accounting or creative destruction? Firm-level productivity growth in Chinese manufacturing. *Journal of Development Economics*, **97** (2), 339–351.

FABINGER, M. and WEYL, E. G. (2018). Functional Forms for Tractable Economic Models and the Cost Structure of International Trade. pp. 1–99.

FERNANDES, A., KLENOW, P., MELESHCHUK, S., DENISSE PIEROLA, M. and RODRIGUEZ-CLARE, A. (2019). The Intensive Margin in Trade. *IMF Working Papers*, **18** (259), 1.

HEAD, K., MAYER, T. and THOENIG, M. (2014). Welfare and trade without pareto. *American Economic Review*, **104** (5), 310–316.

HORNOK, C. and KOREN, M. (2015a). Administrative barriers to trade. *Journal of International Economics*, **96**, S110–S122.

— and — (2015b). Per-Shipment Costs and the Lumpiness of International Trade. *Review of Economics and Statistics*, **97** (2), 525–530.

HUMMELS, D. and SKIBA, A. (2004). Shipping the Good Apples Out? An Empirical Confirmation of the Alchian-Allen Conjecture. *Journal of Political Economy*, **112** (6), 1384–1402.

IRARRAZABAL, A., MOXNES, A. and OPROMOLLA, L. D. (2015). The Tip of the Iceberg: A Quantitative Framework for Estimating Trade Costs. *Review of Economics and Statistics*, **97** (4), 777–792.

KROPF, A. and SAURÉ, P. (2014). Fixed costs per shipment. *Journal of International Economics*, **92**, 166–184.

LASHKARIPOUR, A. (2020). Weight-based quality specialization. *Journal of International Economics*, **127**, 103380.

MELITZ, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica*, **71** (6), 1695–1725.

— and REDDING, S. J. (2015). New Trade Models, New Welfare Implications. *American Economic Review*, **105** (3), 1105–1146.

TIMMER, M. P., DIETZENBACHER, E., LOS, B., STEHRER, R. and DE VRIES, G. J. (2015). An Illustrated User Guide to the World Input-Output Database: The Case of Global Automotive Production. *Review of International Economics*, **23** (3), 575–605.

	Gains from Trade, %			Gains from Trade, %	
	$\nu_L = 0$	$\nu_L = 0.6$		$\nu_L = 0$	$\nu_L = 0.6$
Country	(1)	(2)	Country	(1)	(2)
AUS	2.32	2.08	IRL	8.04	7.21
AUT	5.65	5.06	ITA	2.89	2.58
BEL	7.49	6.72	JPN	1.69	1.51
BRA	1.50	1.34	KOR	4.30	3.85
CAN	3.77	3.37	MEX	3.30	2.95
CHN	2.65	2.37	NLD	6.16	5.52
CZE	6.00	5.37	POL	4.36	3.90
DEU	4.47	4.00	PRT	4.40	3.94
DNK	5.75	5.15	ROM	4.46	3.99
ESP	3.10	2.77	RUS	2.41	2.15
FIN	4.40	3.94	SVK	7.63	6.84
FRA	2.99	2.67	SVN	6.83	6.13
GBR	3.23	2.89	SWE	5.06	4.53
GRC	4.20	3.76	TUR	2.87	2.57
HUN	8.08	7.25	TWN	6.11	5.47
IDN	2.90	2.60	USA	1.77	1.58
IND	2.37	2.12	ROW	5.23	4.68
			Average	4.36	3.91

Notes: Average values in the last row are calculated based on the full set of countries.

Table 1: Gains from Trade

	$\ln X_{ij}$	$\ln N_{ij}$	$\ln F_{ij}$	$\ln \frac{X_{ij}}{N_{ij}}$	$\ln \frac{F_{ij}}{N_{ij}}$	$\ln \frac{X_{ij}}{F_{ij}}$
$\ln Dist_{ij}$	-1.249^{***}	-0.759^{***}	-1.113^{***}	-0.490^{***}	-0.354^{***}	-0.137
	(0.128)	(0.049)	(0.081)	(0.105)	(0.052)	(0.089)
No. Obs	2837	2837	2837	2837	2837	2837
Adj. R^2	0.831	0.950	0.903	0.450	0.433	0.319

Note: estimation results from the gravity equation of shipment frequency. Origin and destination fixed effects are controlled. The standard errors are reported in the parenthesis. Statistical significance at 5%, 1% level, based on two-tailed tests, is indicated by $^{**}, ^{***}$.

Table 2: Gravity estimates

σ_ξ	σ_a
4.320	0.779

Note: The table reported calibrated values for σ_ξ and σ_a . Estimates reported are the ones with lowest error from different random initial points.

Table 3: Estimates of σ_ξ, σ_a

	$\ln X_{ij}$	$\ln X_{ij}$	$\ln X_{ij}$	$\ln X_{ij}$	$\ln F_{ij}$	$\ln F_{ij}$	$\ln F_{ij}$	$\ln F_{ij}$
$\ln B_{ij}$			-2.800^{***}	-1.447^{**}			-2.901^{***}	-1.213^{***}
			(0.686)	(0.626)			(0.487)	(0.164)
$\ln \tau_{ij}$		-3.015^{***}		-2.603^{***}		-3.342^{***}		-2.889^{***}
		(0.433)		(0.463)		(0.169)		(0.121)
$\ln f_{ij}^x$	-0.190			0.023	-0.335^{**}			-0.118^{***}
	(0.150)			(0.115)	(0.112)			(0.030)
No. Obs	80	80	80	80	80	80	80	80
Adj. R^2	0.853	0.915	0.881	0.920	0.905	0.985	0.931	0.994

Note: The table reports regression results of Equation (38). Province and destination fixed effects are controlled. The standard errors are reported in the parenthesis. Statistical significance at 1% level, based on two-tailed tests, is indicated by ***.

Table 4: Correlation between calibrated trade costs and trade flows

	(1)	(2)	(3)
	$\ln \tau_{ij}$	$\ln B_{ij}$	$\ln f_{ij}^x$
$\ln Dist_{ij}$	0.333^{***}	0.140^{*}	0.729^{**}
	(0.087)	(0.070)	(0.358)
No. Obs	80	80	80
Adj. R^2	0.786	0.812	0.920

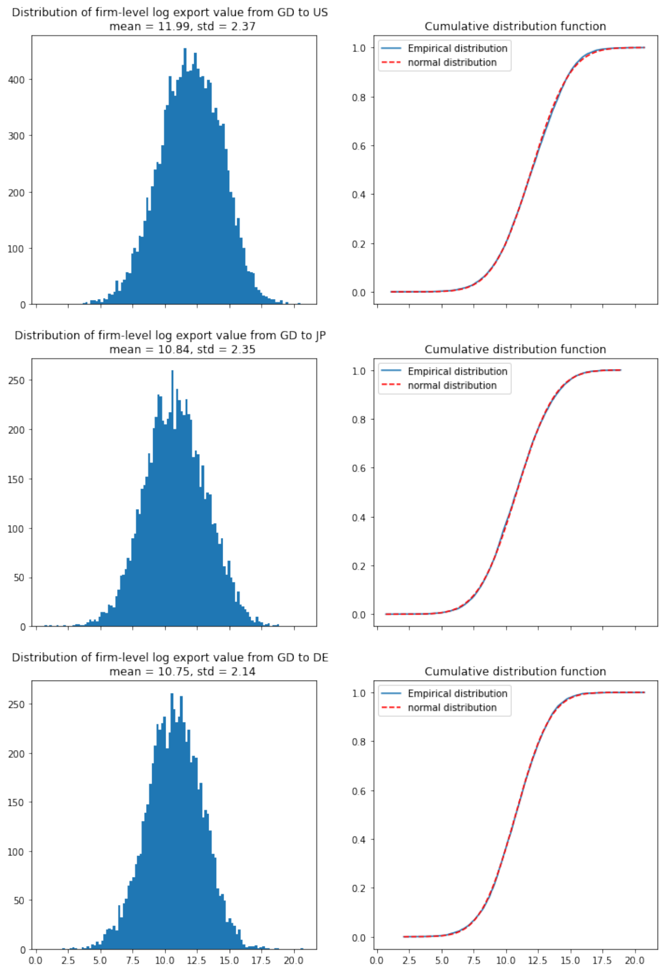
Note: Correlation between estimated trade costs and distance, controlling for province and destination fixed effects. The standard errors are reported in the parenthesis. Statistical significance at 10%, 5%, and 1% level, based on two-tailed tests, are indicated by *, **, ***.

Table 5: Correlation between estimated trade costs and distance

	(1)	(2)
	$\ln \tau_{ij}^{Im}$	$\ln\left(\tau_{ij}^{Im} - \tau_{ij}\right)$
$\ln Dist_{ij}$	0.377^{***}	0.667^{***}
	(0.102)	(0.179)
No. Obs	80	80
Adj. R^2	0.789	0.896

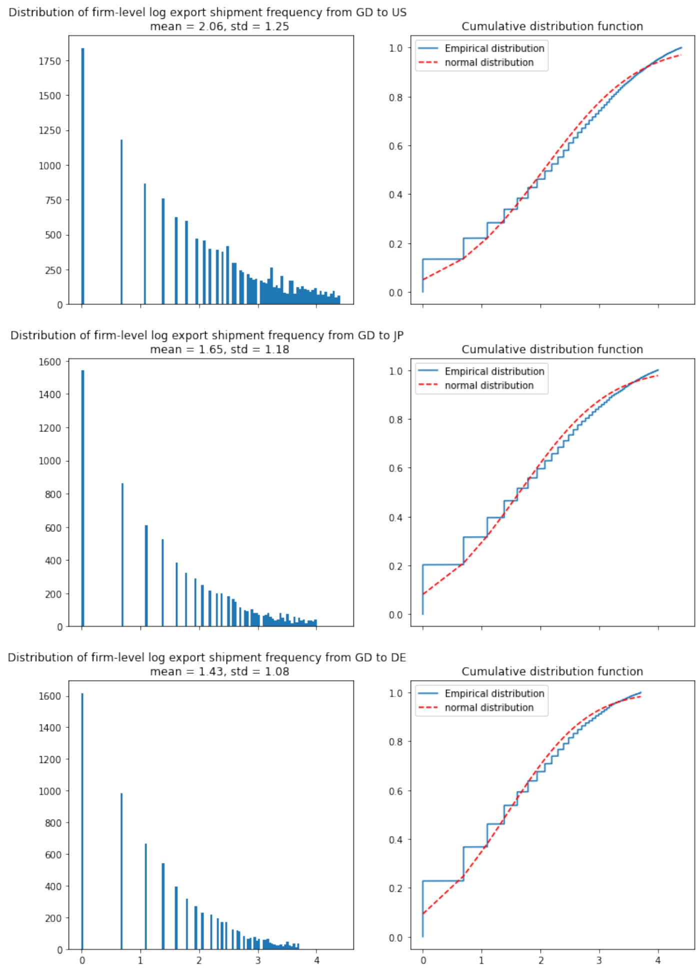
Note: Correlation between the implied iceberg trade costs, the ad-valorem equivalent rate of logistics costs, and distance, controlling for province and destination fixed effects. The standard errors are reported in the parenthesis. Statistical significance at 1% level, based on two-tailed tests, is indicated by ***.

Table 6: Correlation between implied iceberg trade costs and distance



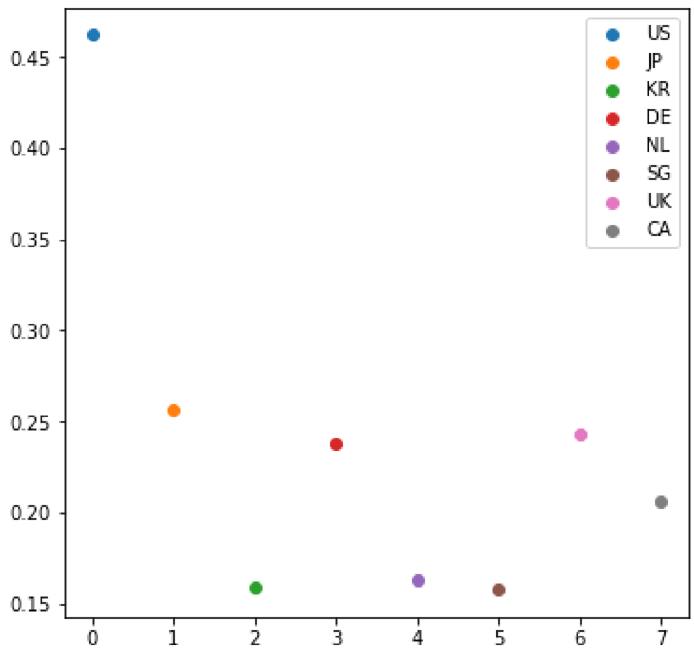
Note: The figures plot the empirical distributions of export sales from Guangdong province to its top three destinations. The dashed line shows the cumulative distribution function of a normal random variables with the same mean and variance as the empirical distribution of the log export value.

Figure 1: Empirical distributions of firm-level export value



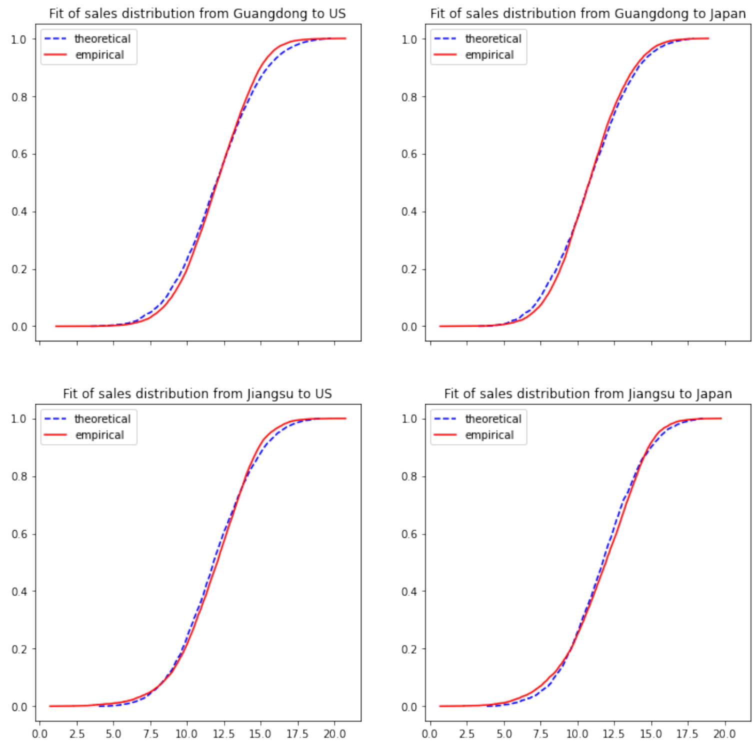
Note: The figures plot the empirical distributions of export shipment frequency from Guangdong province to its top three destinations. The dashed line shows the cumulative distribution function of a normal random variables with the same mean and variance as the empirical distribution of the log export shipment frequency.

Figure 2: Empirical distributions of firm-level export shipment frequency



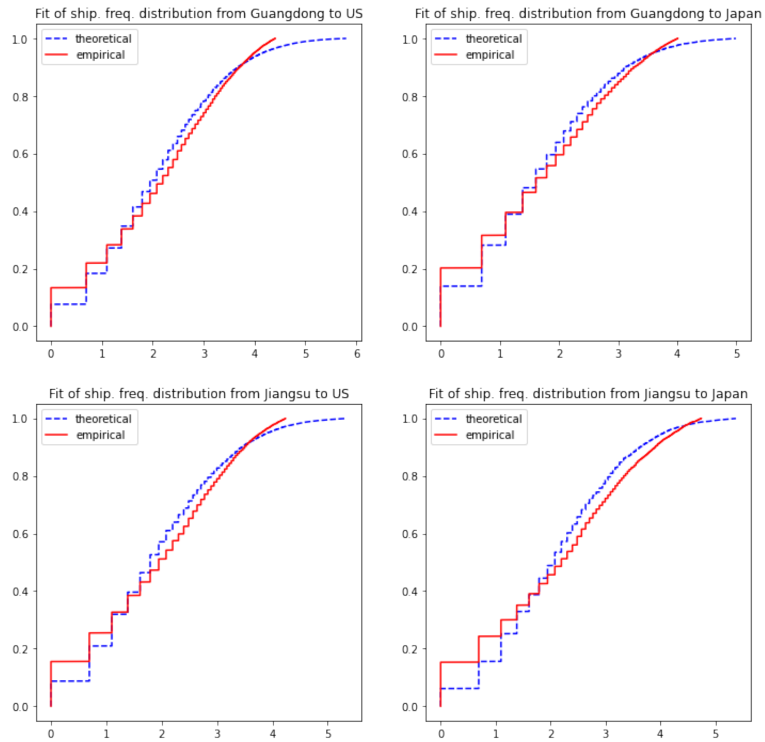
Note: The figure plots the share of firms from Guangdong province that export to each of the eight destinations.

Figure 3: Extensive margins



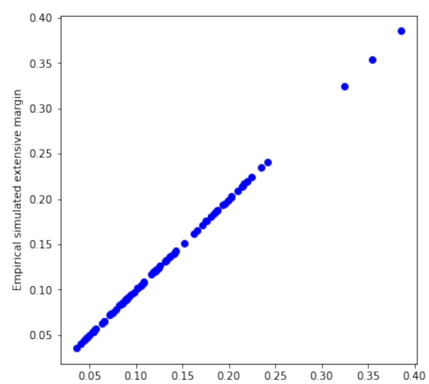
Note: The figures in first row show the fit of the distributions of log export sales from Guangdong Province to the US and Japan. The figures in the second row show the fit of the distributions of log export sales from Jiangsu Province to the US and Japan.

Figure 4: Model fit for sales ditributions



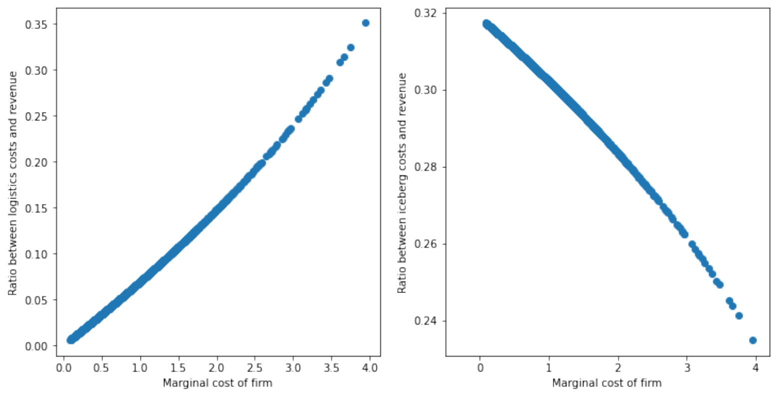
Note: The figures in first row show the fit of the distributions of log shipment frequency from Guangdong Province to the US and Japan. The figures in the second row show the fit of the distributions of log shipment frequency from Jiangsu Province to the US and Japan.

Figure 5: Model fit for sales distributions



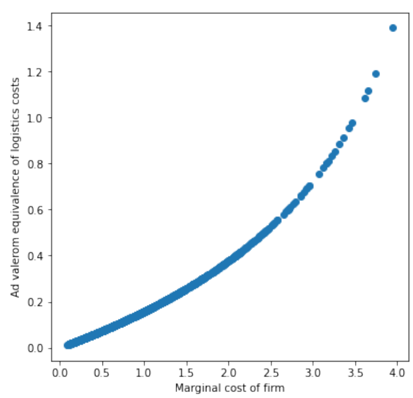
Note: The figure plots the empirical normalized extensive margin on the horizontal axis, and the simulated normalized extensive margin on the vertical axis.

Figure 6: Model fit for normalized extensive margin



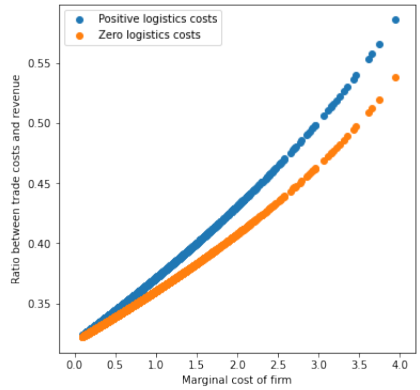
Note: The left figure plots the ratio between logistics costs and export revenue for simulated firms that export from Guangdong Province to the US. The right figure plots the ratio between iceberg costs and export revenue.

Figure 7: Ratios between different components of trade costs and revenue across firms



Note: The figure plots the ad valorem rate of logistics costs across simulated firms that export from Guangdong to the US.

Figure 8: Ad valorem equivalence of logistics costs across firms



Note: The left figure plots the ratio between total costs and export revenue for simulated firms that export from Guangdong Province to the US, with positive and zero logistics costs.

Figure 9: Ratio between total trade costs and revenue across firms

Appendix

A Asymmetric Countries

In this subsection, we extend the model to an environment with multiple asymmetric countries. The economy consists of J countries, indexed by i and j, each endowed with effective labor L_i. Labor is immobile across countries, but perfectly mobile between different uses within a country. Each country i can potentially produce a infinite set of varieties Ω_i indexed by ω. Only an endogenously determined subset Ω_{ij} of Ω_i is available in any destination country j. Utility of the representative consumer in country j is given by

$$U_j = \left(\sum_i \int_{\Omega_{ij}} q_{ij}\left(\omega\right)^{\nu_R} d\omega \right)^{\frac{1}{\nu_R}}, \tag{42}$$

where $q_{ij}\left(\omega\right)$ is the quantity of variety $\omega \in \Omega_{ij}$ from origin i consumed in destination j, and $0 < \nu_R < 1$ is related to the elasticity of substitution between varieties σ through the relation $\nu_R = \frac{\sigma-1}{\sigma}$. Utility maximization gives the inverse demand curve

$$p_{ij}\left(\omega\right) = A_j q_{ij}\left(\omega\right)^{\nu_R - 1}, \tag{43}$$

where the country-specific parameter $A_j = P_j^{\nu_R} I_j^{1-\nu_R}$ summarizes the market condition with I_j and P_j representing the total expenditure and price index in destination j. This gives the relationship between the value and quantity of each firm's export,

$$X_{ij}\left(\omega\right) = A_j q_{ij}\left(\omega\right)^{\nu_R}. \tag{44}$$

In what follows, in order to simplify notation, we also sometimes use the notation q_{fj} instead of $q_{ij}\left(\omega\right)$, with the understanding that firm f from origin i produces variety ω.

Technology of production of varieties features constant return to scale. Each firm in country i has a marginal cost of production $a > 0$ that is drawn from a known distribution

$G_i(a)$. The cost of serving any destination j has three components. The first component is the fixed costs: any firm f from origin i needs pay a cost of f_{ij}^x in terms of country i's labor in order to enter market j. The second component is the usual iceberg trade costs: delivering one unit of any variety from origin i to destination j requires shipping $\tau_{ij} \geq 1$ units of this variety. Finally, the third component constitutes our innovation relative to the standard Melitz model and captures the idea of the "logistic costs": in order to deliver q_{fj} units of its variety, firm f from origin i needs to pay the cost $B_{ij}q_{fj}^{\nu_L}$ measured in units of country i's labor, where $\nu_L > 0$ is the trade costs elasticity with respect to the quantity shipped.

Given the above specifications of technology of production and costs of serving markets, the profit country i's firm with marginal cost a from serving destination j is

$$\pi_{ij}(q) = A_j q^{\nu_R} - w_i B_{ij} q^{\nu_L} - a w_i \tau_{ij} q - w_i f_{ij}^x. \tag{45}$$

For the analytical tractability, we assume that $f_{ij}^x = 0$ in this subsection as well. The first-order condition for the firm's profit maximization problem is

$$\frac{\partial \pi_{ij}}{\partial q} = A_j \nu_R q^{\nu_R - 1} - w_i B_{ij} \nu_L q^{\nu_L - 1} - a w_i \tau_{ij} = 0, \tag{46}$$

which defines a one-one mapping from the optimal quantity to marginal cost for any bilateral country pair as

$$a_{ij}(q) = \frac{A_j \nu_R q^{\nu_R - 1} - w_i B_{ij} \nu_L q^{\nu_L - 1}}{w_i \tau_{ij}}. \tag{47}$$

The inverse mapping from the marginal cost to the optimal quantity is thus $q_{ij}(a)$. The zero profit condition that defines the cutoff q_{ij}^* thus can be written as

$$A_j (1 - \nu_R) \left(q_{ij}^*\right)^{\nu_R} - w_i B_{ij} (1 - \nu_L) \left(q_{ij}^*\right)^{\nu_L} = 0. \tag{48}$$

The free entry condition is any market i is

$$\sum_{j=1}^{J} \int_0^{a_{ij}^*} \pi_{ij} \left(q_{ij} \left(a \right) \right) dG \left(a \right) = f^e. \tag{49}$$

For any market i, equations (48) and (49) therefore define a system of $J+1$ equations that can be used to solve for q_{ij}^* and A_i in terms of wage w_i.

The labor market clearing condition can be used to solve the total mass of potential entrants in country i, which is denoted as N_i^e. Labor is used for the following purposes: entry of firms, logistic costs, and production. The amount of labor used for entry is $L_i^e \equiv N_i^e f_i^e$,where f_i^e is the entry cost. Therefore the labor market clearing condition is

$$L_i = L_i^e + \sum_j L_{ij}^{lm}, \tag{50}$$

where L_{ij}^{lm} represents the amount of labor used in logistics and production for the exports to country j in origin i.

The wages, up to a scale, can be solved using the goods market clearing condition. More specifically, assuming that trade is balanced, the total output in country i is equal to the absorption of country i's production around the world:

$$w_i L_i = \sum_j \lambda_{ij} w_j L_j, \tag{51}$$

where λ_{ij} is the expenditure share of country i in the goods produced by country j. Since λ_{ij} is a function of wages, Equation (51) gives a system of equation that can be used to solve for wages in each country.

A.1 Solutions Under Pareto Distribution: Asymmetric Countries

In this subsection, we show closed form solutions assuming that the marginal cost across firms follows a Pareto distribution given by the cumulative density function

$$G_i \left(a \right) = \theta^{-1} \left(\kappa_{G,i} a \right)^{\theta}, \tag{52}$$

Under this assumption, as shown in Appendix B, we can express the aggregated quantity with any power ν, subject to the condition $\frac{\nu+\nu_R\theta-\theta}{\nu_L-\nu_R}>0$, as

$$\int_0^{a_{ij}^*} q^\nu dG_i\left(a\right) = \kappa_{G,i}^{\theta}\left(w_i\tau_{ij}\right)^{-\theta} A_j^{-\frac{\nu+\nu_L\theta-\theta}{\nu_R-\nu_L}}\left(w_iB_{ij}\right)^{\frac{\nu+\nu_R\theta-\theta}{\nu_R-\nu_L}} H\left(\nu\right), \tag{53}$$

where $H\left(\nu\right)$ is a constant that depends on ν_R, ν_L and θ. Using this formula, we can calculate the aggregate trade flow from country i to country j as

$$\begin{aligned} X_{ij} &= N_i^e A_j \int_0^{a_{ij}^*} q_{ij}^{\nu_R}\left(a\right) dG_i\left(a\right) \\ &= N_i^e\kappa_{G,i}^{\theta}\left(A_j\right)^{\frac{\nu_L+\nu_L\theta-\theta}{\nu_L-\nu_R}}\left(w_i\tau_{ij}\right)^{-\theta}\left(w_iB_{ij}\right)^{-\frac{\nu_R+\nu_R\theta-\theta}{\nu_L-\nu_R}} H\left(\nu_R\right). \end{aligned} \tag{54}$$

The expenditure share of country j on country i's goods is then

$$\lambda_{ij} = \frac{X_{ij}}{\sum_l X_{lj}} = \frac{N_i^e\kappa_{G,i}^{\theta}\left(w_i\tau_{ij}\right)^{-\theta}\left(w_iB_{ij}\right)^{-\frac{\nu_R+\nu_R\theta-\theta}{\nu_L-\nu_R}}}{\sum_l N_l^e\kappa_{G,l}^{\theta}\left(w_l\tau_{lj}\right)^{-\theta}\left(w_lB_{lj}\right)^{-\frac{\nu_R+\nu_R\theta-\theta}{\nu_L-\nu_R}}}. \tag{55}$$

It shows that our model generates a gravity equation under a more flexible trade cost structure. The trade elasticity with respect to τ_{ij}, defined as $\frac{\partial\ln\left(X_{ij}/X_{jj}\right)}{\partial\ln\tau_{ij}}$, is given by the shape parameter of the firm's productivity distribution θ. And the trade elasticity with respect to B_{ij}, defined as $\frac{\partial\ln\left(X_{ij}/X_{jj}\right)}{\partial\ln B_{ij}}$, is determined by the demand elasticity ν_R, the elasticity of the logistics costs ν_L, and the shape parameter θ.

Under the assumption of Pareto distribution, we show that the mass of firms N_i^e in each country is a fixed portion of L_i. Using first order condition (46) and the aggregation formula, L_{ij}^{lm} is equal to

$$L_{ij}^{lm} = N_i^e\int_0^{a_{ij}^*}\left[\left(1-\nu_L\right)B_{ij}q_{ij}^{\nu_L}\left(a\right)+\frac{\nu_RA_jq_{ij}^{\nu_R}\left(a\right)}{w_i}\right]dG_i\left(a\right)$$

$$= \nu_R\left[\left(\frac{1-\nu_L}{\nu_R}\right)\frac{H\left(\nu_L\right)}{H\left(\nu_R\right)}+1\right]\frac{X_{ij}}{w_i}.$$

Then we can solve that

$$N_i^e = \left(1 - \nu_R - (1-\nu_L)\,\frac{H(\nu_L)}{H(\nu_R)}\right)\frac{L_i}{f_i^e}, \tag{56}$$

which shows that N_i^e is a fixed portion of L_i as claimed. From the above calculations, we can also see that the aggregate profit is a constant share of the total revenue:

$$\Pi_i = \left(1 - \nu_R - (1-\nu_L)\,\frac{H(\nu_L)}{H(\nu_R)}\right)\sum_j X_{ij}. \tag{57}$$

Given the gravity equation (55) and the fact that aggregate profit is a constant share of aggregate revenue, as shown in (57), it is clear that the model satisfies all the macro restrictions proposed in ACR. However, we next show that the the welfare gains from trade can not be inferred from the domestic expenditure share λ_{ii} and trade elasticity with respect to τ_{ij} only. Instead, the magnitudes of ν_L and ν_R also play an important role.

Using the aggregation formula (53) and the definition $A_j = P_j^{\nu_R} I_j^{1-\nu_R}$, we can get

$$(P_j)^{\frac{-\nu_R(\nu_L+\theta\nu_L-\theta)}{\nu_L-\nu_R}} = C_P \sum_i N_i^e \kappa_{G,i}^{\theta}\,(w_i\tau_{ij})^{-\theta}\,(w_i B_{ij})^{-\frac{\nu_R+\nu_R\theta-\theta}{\nu_L-\nu_R}}, \tag{58}$$

where

$$C_P = (I_j)^{-\nu_R+\frac{(1-\nu_R)(\theta\nu_L+\nu_R-\theta)}{\nu_L-\nu_R}}\,H(\nu_R),$$

and N_i^e has been solved above. Using (55) and (58), we can write the domestic expenditure share as

$$\lambda_{ii} = C_P N_i^e \kappa_{G,i}^{\theta}\,(w_i)^{-\theta}\,(w_i B_{ii})^{-\frac{\nu_R+\nu_R\theta-\theta}{\nu_L-\nu_R}}\,(P_i)^{\frac{\nu_R(\nu_L+\theta\nu_L-\theta)}{\nu_L-\nu_R}},$$

from which we can derive the expression of the real consumption as

$$W_i \equiv \frac{w_i}{P_i} = \left[\frac{\lambda_{ii}}{C_P N_i^e \kappa_{G,i}^{\theta}\,(B_{ii})^{-\frac{\nu_R+\nu_R\theta-\theta}{\nu_L-\nu_R}}}\right]^{-\frac{\nu_L-\nu_R}{\nu_R(\nu_L+\theta\nu_L-\theta)}}.$$

Because the mass of firms N_i^e is a fixed portion of the labor endowment, and under autarky, $\lambda_{ii}^A = 1$, the welfare gains from opening to trade in autarky is given by

$$\frac{W_i}{W_i^A} = \lambda_{ii}^{-\frac{\nu_L - \nu_R}{\nu_R(\nu_L + \theta\nu_L - \theta)}}. \tag{59}$$

As a widely known formula shown in ACR, the expenditure share on the domestic goods and the trade elasticity are the only two sufficient statistics to calculate welfare gains from opening to trade. In contrast, our model gives a formula that combines trade elasticity, trade cost elasticity and demand elasticity. It is easy to verify that $-\frac{\nu_R(\nu_L+\theta\nu_L-\theta)}{\nu_L-\nu_R}$ is equal to $-\theta$ when $\nu_L = 0$, therefore this formula generalizes the results in ACR. As discussed in the previous section, the trade is balanced, the aggregate profit is a constant share of the total revenue, and the gravity equation is derived. Therefore our only departure from the class of models studied in ACR comes from a different micro structure, in particular the trade costs structure that we are considering.

A.2 Solution of Firm's Profit Maximization Problem

Equation (4) cannot be solved analytically for arbitrary values of ν_R and ν_L. However, an empirically relevant way that gives an explicit solution to the firm's profit maximization problem is to impose $\nu_L = 2\nu_R - 1$. With this assumption, the optimal quantity maximizing firm's profit is

$$q_{ij}(a) = \left[\frac{\left(\nu_R A_j + \sqrt{\left(\nu_R A_j\right)^2 - 4\left(a w_i \tau_{ij}\right)\left(w_i \nu_L B_{ij}\right)}\right)}{2 a w_i \tau_{ij}}\right]^{\frac{1}{1-\nu_R}}. \tag{60}$$

Each firm charges a price given by

$$p_{ij}(a) = \frac{2 a w_i \tau_{ij} A_j}{\left(\nu_R A_j + \sqrt{\left(\nu_R A_j\right)^2 - 4\left(a w_i \tau_{ij}\right)\left(w_i \nu_L B_{ij}\right)}\right)}. \tag{61}$$

From here we see that price depends not only on the marginal cost of production a, but also on the market conditions A_j and logistics costs parameter B_{ij}. As an example that the model has the potential to match the empirical regularities that call for a different cost structure from the standard model, we show that the model can generate Alchian-Allen effect.[15] Suppose that conditional on the marginal cost a, varieties are allowed to differentiate vertically, so that the demand shifter can differ across varieties, we can calculate the relative demand for varieties as

$$\frac{q_{ij}^{H}\left(a\right)}{q_{ij}^{L}\left(a\right)}=\left[\frac{\left(Q^{H}\nu_{R}A_{j}+\sqrt{\left(Q^{H}\nu_{R}A_{j}\right)^{2}-4\left(aw_{i}\tau_{ij}\right)\left(w_{i}\nu_{L}B_{ij}\right)}\right)}{\left(Q^{L}\nu_{R}A_{j}+\sqrt{\left(Q^{L}\nu_{R}A_{j}\right)^{2}-4\left(aw_{i}\tau_{ij}\right)\left(w_{i}\nu_{L}B_{ij}\right)}\right)}\right]^{\frac{1}{1-\nu_{R}}},$$

where $Q^{H}>Q^{L}$ represent high and low level of quality. The Alchian-Allen effect means that relative demand for high quality good is increasing in trade costs, which is true here because $\frac{\partial q_{ij}^{H}/q_{ij}^{L}}{\partial B_{ij}}>0$.

[15]For a definition of Alchian-Allen effect, see, for example, Hummels and Skiba (2004)

B Derivation of aggregation formula

Let us start with calculating the integral $\int_0^{a_{ij}^*} q^\nu dG_i(a)$ for some $\nu > 0$. Using expression (6) for a, and that $G_i(a) = \theta^{-1}(\kappa_{G,i}a)^\theta$, we can derive

$$\begin{aligned}
\int_0^{a_{ij}^*} q^\nu dG_i(a) &= -\int_{q_{ij}^*}^{\infty} q^\nu dG\left(\frac{\nu_R A_j q^{\nu_R-1} - \nu_L w_i B_{ij} q^{\nu_L-1}}{w_i\tau_{ij}}\right) \\
&= \int_{q_{ij}^*}^{\infty}\left\{q^\nu \frac{(1-\nu_R)\,\nu_R A_j q^{\nu_R-2} - (1-\nu_L)\,\nu_L w_i B_{ij} q^{\nu_L-2}}{w_i\tau_{ij}}\right. \\
&\qquad\left.\times\ \kappa_{G,i}^\theta\left(\frac{\nu_R A_j q^{\nu_R-1} - \nu_L w_i B_{ij} q^{\nu_L-1}}{w_i\tau_{ij}}\right)^{\theta-1}\right\} dq \\
&= \kappa_{G,i}^\theta\left(w_i\tau_{ij}\right)^{-\theta}(1-\nu_R)\left(\nu_R A_j\right)^\theta \int_{q_{ij}^*}^{\infty} q^{\nu-1+\nu_R\theta-\theta}\left(1-\frac{\nu_L w_i B_{ij}}{\nu_R A_j}q^{\nu_L-\nu_R}\right)^{\theta-1} dq \\
&\quad -\left\{\kappa_{G,i}^\theta\left(w_i\tau_{ij}\right)^{-\theta}(1-\nu_L)\,\nu_L\left(\nu_R A_j\right)^{\theta-1} w_i B_{ij}\right. \\
&\qquad\left.\times\int_{q_{ij}^*}^{\infty} q^{\nu+\nu_L-2+(\nu_R-1)(\theta-1)}\left(1-\frac{\nu_L w_i B_{ij}}{\nu_R A_j}q^{\nu_L-\nu_R}\right)^{\theta-1} dq\right\}.
\end{aligned}$$

Introduce the change of variables $x = \left(q/q_{ij}^*\right)^{\nu_L-\nu_R}$. Then

$$\begin{aligned}
\int_0^{a_{ij}^*} q^\nu dG_i(a) &= \left\{\frac{1-\nu_R}{\nu_R-\nu_L}\kappa_{G,i}^\theta\left(w_i\tau_{ij}\right)^{-\theta}\left(\nu_R A_j\right)^\theta\left(q_{ij}^*\right)^{\nu+\nu_R\theta-\theta}\right. \\
&\qquad\left.\times\int_0^1 x^{\frac{\nu+\nu_R\theta-\theta}{\nu_L-\nu_R}-1}\left(1-\frac{\nu_L w_i B_{ij}}{\nu_R A_j}\left(q_{ij}^*\right)^{\nu_L-\nu_R}x\right)^{\theta-1} dx\right\} \\
&\quad -\left\{\frac{(1-\nu_L)\,\nu_L}{\nu_R-\nu_L}\kappa_{G,i}^\theta\left(w_i\tau_{ij}\right)^{-\theta}\left(\nu_R A_j\right)^{\theta-1} w_i B_{ij}\left(q_{ij}^*\right)^{\nu+\nu_L-1+(\nu_R-1)(\theta-1)}\right. \\
&\qquad\left.\times\int_0^1 x^{\frac{\nu+\nu_R\theta-\theta}{\nu_L-\nu_R}}\left(1-\frac{\nu_L w_i B_{ij}}{\nu_R A_j}\left(q_{ij}^*\right)^{\nu_L-\nu_R}x\right)^{\theta-1} dx\right\}.
\end{aligned}$$

Using the fact that

$$q_{ij}^{*} = \left[\frac{w_i B_{ij}\left(1-\nu_L\right)}{A_j\left(1-\nu_R\right)}\right]^{\frac{1}{\nu_R-\nu_L}},$$

we get

$$\begin{aligned}
\int_0^{a_{ij}^{*}} q^{\nu} dG_i\left(a\right) = & \left\{\frac{1-\nu_R}{\nu_R-\nu_L}\kappa_{G,i}^{\theta}\left(w_i\tau_{ij}\right)^{-\theta}\left(\nu_R A_j\right)^{\theta}\left[q_{ij}^{*}\right]^{\nu+\nu_R\theta-\theta}\right. \\
& \left.\times \int_0^1 x^{-\frac{\nu+\nu_R\theta-\theta}{\nu_R-\nu_L}-1}\left(1-\frac{\left(1-\nu_R\right)\nu_L}{\left(1-\nu_L\right)\nu_R}x\right)^{\theta-1} dx\right\} \\
& - \left\{\frac{\left(1-\nu_L\right)\nu_L}{\nu_R-\nu_L}\kappa_{G,i}^{\theta}\left(w_i\tau_{ij}\right)^{-\theta}\left(\nu_R A_j\right)^{\theta-1} w_i B_{ij}\left[\frac{w_i B_{ij}\left(1-\nu_L\right)}{A_j\left(1-\nu_R\right)}\right]^{\frac{\nu+\nu_L-1+\left(\nu_R-1\right)\left(\theta-1\right)}{\nu_R-\nu_L}}\right. \\
& \left.\times \int_0^1 x^{-\frac{\nu+\nu_R\theta-\theta}{\nu_R-\nu_L}}\left(1-\frac{\left(1-\nu_R\right)\nu_L}{\left(1-\nu_L\right)\nu_R}x\right)^{\theta-1} dx\right\}.
\end{aligned}$$

At this point we are going to use the hyper-geometric function ${}_2F_1\left(a,b;c;z\right)$ defined by

$${}_2F_1\left(a,b;c;z\right) = \frac{1}{B\left(b,c-b\right)}\int_0^1 x^{b-1}\left(1-x\right)^{c-b-1}\left(1-zx\right)^{-a} dx,$$

where $B\left(b,c-b\right)$ is the beta function. The integral in the expression for $B\left(b,c-b\right){}_2F_1\left(a,b;c;z\right)$ is defined only if $|z|<1$ and $c>b>0$. We have

$$\int_0^1 x^{\frac{\nu+\nu_R\theta-\theta}{\nu_L-\nu_R}-1}\left(1-\frac{\left(1-\nu_R\right)\nu_L}{\left(1-\nu_L\right)\nu_R}x\right)^{\theta-1} dx = B\left(\gamma_1\left(\nu\right),1\right){}_2F_1\left(1-\theta,\gamma_1\left(\nu\right);\gamma_1\left(\nu\right)+1;\gamma_2\right),$$

where

$$\gamma_1\left(\nu\right) \equiv \frac{\theta-\nu-\nu_R\theta}{\nu_R-\nu_L} \quad \text{and} \quad \gamma_2 \equiv \frac{\left(1-\nu_R\right)\nu_L}{\left(1-\nu_L\right)\nu_R},$$

and where we need to have $\gamma_1\left(\nu\right)>0$ and $\gamma_2<1$. The last inequality holds under our assumptions that $0<\nu_L<\nu_R<1$.

We have

$$B\left(\gamma_1\left(\nu\right),1\right) = \int_0^1 t^{\gamma_1\left(\nu\right)-1} dt = \frac{1}{\gamma_1\left(\nu\right)} t^{\gamma_1\left(\nu\right)}\Big|_0^1 = \frac{1}{\gamma_1\left(\nu\right)}.$$

Then

$$\int_0^1 x^{\frac{\nu+\nu_R\theta-\theta}{\nu_L-\nu_R}-1}\left(1-\frac{(1-\nu_R)\,\nu_L}{(1-\nu_L)\,\nu_R}x\right)^{\theta-1}dx=\frac{1}{\gamma_1(\nu)}\times{}_2F_1\left(1-\theta,\gamma_1(\nu);\gamma_1(\nu)+1;\gamma_2\right).$$

Next,

$$\begin{aligned}\int_0^1 x^{\frac{\nu+\nu_R\theta-\theta}{\nu_L-\nu_R}}\left(1-\frac{(1-\nu_R)\,\nu_L}{(1-\nu_L)\,\nu_R}x\right)^{\theta-1}dx&=B\left(\gamma_1(\nu)+1,1\right){}_2F_1\left(1-\theta,\gamma_1(\nu)+1;\gamma_1(\nu)+2;\gamma_2\right)\\&=\frac{1}{\gamma_1(\nu)+1}\times{}_2F_1\left(1-\theta,\gamma_1(\nu)+1;\gamma_1(\nu)+2;\gamma_2\right).\end{aligned}$$

Thus, we get

$$\kappa_{G,i}^{\theta}\left(w_i\tau_{ij}\right)^{-\theta}\left(w_iB_{ij}\right)^{\frac{\nu+\nu_R\theta-\theta}{\nu_R-\nu_L}}A_j^{-\frac{\theta\nu_L+\nu-\theta}{\nu_R-\nu_L}}$$

$$\int_0^{a_{ij}^*}q^{\nu}dG_i(a)=\kappa_{G,i}^{\theta}\left(w_i\tau_{ij}\right)^{-\theta}A_j^{\frac{\theta-\nu-\nu_L\theta}{\nu_R-\nu_L}}\left(w_iB_{ij}\right)^{\frac{\nu+\nu_R\theta-\theta}{\nu_R-\nu_L}}H\left(\nu,\nu_R,\nu_L,\theta\right),$$

where

$$\begin{aligned}H\left(\nu,\nu_R,\nu_L,\theta\right)\equiv{}&\nu_R^{\theta-1}\frac{1-\nu_R}{\nu_R-\nu_L}\left(\frac{1-\nu_R}{1-\nu_L}\right)^{\frac{\theta-\nu-\theta\nu_R}{\nu_R-\nu_L}}\\&\times\left[\frac{\nu_R}{\gamma_1(\nu)}\times{}_2F_1\left(1-\theta,\gamma_1(\nu);\gamma_1(\nu)+1;\gamma_2\right)\right.\\&\qquad\left.-\frac{\nu_L}{\gamma_1(\nu)+1}\times{}_2F_1\left(1-\theta,\gamma_1(\nu)+1;\gamma_1(\nu)+2;\gamma_2\right)\right].\end{aligned}$$

C Using Shipment Frequency to Estimate ν_L

C.1 Micro Foundation of Logistics Costs

In this section, we propose a simple logistics costs minimization problem to micro-found the logistics costs introduced into the profit function of firms. The demand of a variety during a given period of time is predicted without uncertainty. The problem is then how to deliver the required quantity q. The trade-off is to balance inventory cost and cost per shipment: since production is not instantaneous, the producer has to store the products and incur inventory costs.[16] Since the amount of inventory is proportional to the quantity per shipment, in order to save inventory cost, firms tend to ship frequently. But since there is a cost related to each shipment (e.g. paper work and other coordination with trade partner), too frequent shipments will be very costly. Therefore the firm optimally chooses a shipment frequency that balances these two costs.

Formally, we assume that firms choose a constant quantity per each shipment, which is denoted by q_s. The associated inventory cost is assumed to have the form $C_I(q_s) = \kappa_I q_s$, since the amount of goods that need to be stored is proportional to q_s. And for each shipment, firms need to incur coordination cost $C_T(q_s) = \kappa_T q_s^{\alpha}$, where α measures how fast the coordination cost changes with quantity. When $\alpha < 1$, there is a return to scale in coordination: marginal cost of coordination is decreasing in quantity per shipment. And if $\alpha < 0$, the coordination cost $C_T(q_s)$ decreases with quantity per shipment. Finally we add a fixed cost component f^x that does not depend on frequency of shipment. The logistics problem is therefore

$$\min_{q_s} C_I(q_s) + \frac{q}{q_s} C_T(q_s) + f^x.$$

Three special cases are worth mentioning. When $\alpha = 0$, the coordination cost is constant per shipment, the problem becomes the same as the economic order quantity model. When $\alpha = 1$, total coordination cost $\frac{q}{q_s} C_T(q_s)$ will be constant, it is therefore optimal to set q_s as small as possible, and the variable part of logistics cost will be $\kappa_T q$. When $\alpha = -\infty$, coordination cost is zero if q_s is slightly above 1. By choosing q_s near 1, the total logistics cost can be made arbitrarily close to $\kappa_I + f^x$, which is fixed regardless of trade quantity. The first-order condition of the above problem gives

$$q_s^{2-\alpha} = \frac{(1-\alpha)\kappa_T}{\kappa_I} q$$

With $\alpha < 1$, then second-order condition[17] will be positive. Plug in the above solution

[16] As an alternative way to justify inventory cost, if we assume demand is uniformly distributed across time, the goods shipped but not consumed immediately must be stored, and the producer can be assumed to share this inventory costs.

[17] Second-order condition is $q\kappa_T(\alpha-1)(\alpha-2)q_s^{\alpha-3}$

into the cost function, the optimized logistics cost has the form

$$C_{LT}(q) = (1-\alpha)^{-\frac{1-\alpha}{2-\alpha}} (2-\alpha)\, \kappa_I^{\frac{\alpha-1}{\alpha-2}} \kappa_T^{\frac{1}{2-\alpha}} q^{\frac{1}{2-\alpha}} + f^x = Bq^{\nu_L} + f^x, \tag{62}$$

where for the ease of exposition, we let

$$\nu_L = \frac{1}{2-\alpha},$$

$$B = \frac{1}{(\nu_L)^{\nu_L} (1-\nu_L)^{1-\nu_L}} \kappa_I^{1-\nu_L} \kappa_T^{\nu_L}.$$

Since $\lim_{\nu_L \to 0} Bq^{\nu_L} = \kappa_I$, algebraically the variable part of logistic costs reduces to a constant. On the other hand, $\lim_{\nu_L \to 1} Bq^{\nu_L} = \kappa_T q$, in which case the marginal logistics cost is equal to κ_T. The model also gives an explicit expression for the optimal frequency of shipment:

$$F = \left(\frac{1}{\nu_L} - 1\right)^{-\nu_L} \kappa_I^{\nu_L} \kappa_T^{-\nu_L} q^{(1-\nu_L)} = \frac{1}{1-\nu_L} \kappa_I B^{-1} q^{(1-\nu_L)}. \tag{63}$$

It is also worth emphasizing that the logistics problem is separated from other demand or supply side assumptions. The relationship shown in (63) also provides a straightforward way to estimate ν_L using linear regression. The value of ν_L is an easy test to differentiate different models. When $\nu_L = 0$, as is often assumed in the standard heterogeneous firm model, the frequency of shipment is equal to export quantity, namely $F = q$. When the coordination cost per shipment is a constant, $\nu_L = \frac{1}{2}$. Finally, when $\nu_L = 1$, coordination cost is proportional to the export quantity, the current formula does not apply, but the model predicts an infinitely frequent shipment to reduce inventory cost as low as possible.

C.2 Estimation of ν_L

The inventory management problem provides a straightforward way to estimate ν_L. After taking log, the equation (63) becomes:

$$\ln F = \ln \left(\frac{1}{\nu_L} - 1\right)^{-\nu_L} \kappa_I^{\nu_L} \kappa_T^{-\nu_L} + (1-\nu_L) \ln q, \tag{64}$$

therefore we can estimate ν_L by simply regressing log shipment frequency on log quantity. We first estimate ν_L using the whole sample. Since the data contains a 7-year time series, we include quadratic function of the number of years of positive trade for each firm-product-destination to control for experience effect. More specifically, we run the regression

$$\ln F_{fojt} = (1 - \nu_L) \ln q_{fojt} + \phi_{foj} + u_{fojt}, \tag{65}$$

where F_{fojt} is the number of shipment frequency firm f, product o, export to destination j in year t, q_{fojt} is trade volume, and ϕ_{foj} is the firm-product-destination fixed effects. We add the fixed effects in order to control for the potential heterogeneity in $\kappa_I^{\nu_L} \kappa_T^{-\nu_L}$. We select the firm-product pairs with at least 2 years' positive trade, and firm-product-year that has at least a thousand US dollars to run the regression. As shown in Table 7, the estimate of ν_L is close to 0.6. Importantly, the estimated value is significantly difference from either 0 or 1, showing that commonly assumed trade cost structure that imposes $\nu_L = 0$ is not consistent with the data.

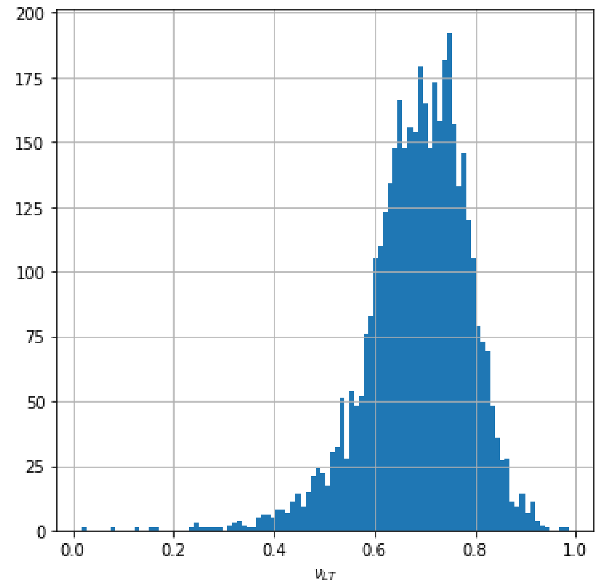
Variable	Estimate
ν_L	0.611***
	(0.001)
No. Obs.	11638122
R^2	0.485

Note: Estimate of ν_L using the whole sample. Firm-product-destination fixed effects are controlled. Standard errors are clustered at firm level and are reported in the brackets. Due to computational reason, we estimate the model by first demeaning $\ln F_{fojt}$ and $\ln q_{fojt}$ at firm-product-destination level, and regress the demeaned variables.

Table 7: Estimation of ν_L

To have a better idea of potential heterogeneity of coordination costs across different sub-samples, using the year 2006 data, we run the frequency regression (64) for each product defined by the HS8 codes, controlling for the destination fixed effects. Figure 10 shows the distribution of estimated ν_L across products, where we exclude products that have less than 30 observations. Note that consistent with the estimate using the whole sample, we clearly rejects the hypothesis that $\nu_L = 0$. While $\nu_L = 0.5$ or $\nu_L = 1$ is closer to the data, the mean of this distribution is 0.66, with a small standard deviation equal to

0.09.[18]

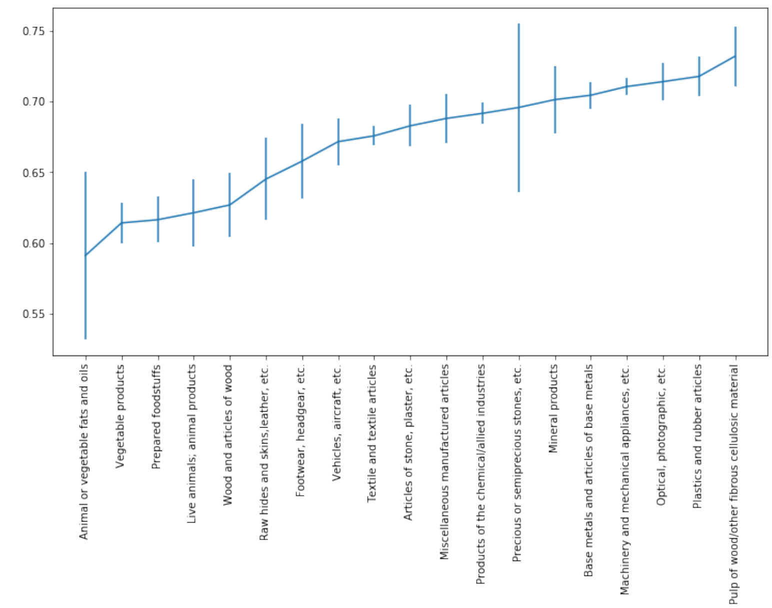


Note: Distribution of estimated ν_L across products. Products that have less than 30 observations are excluded. Mean of the estimates is 0.66, standard deviation is 0.09.

Figure 10: Distribution of estimated ν_L across products

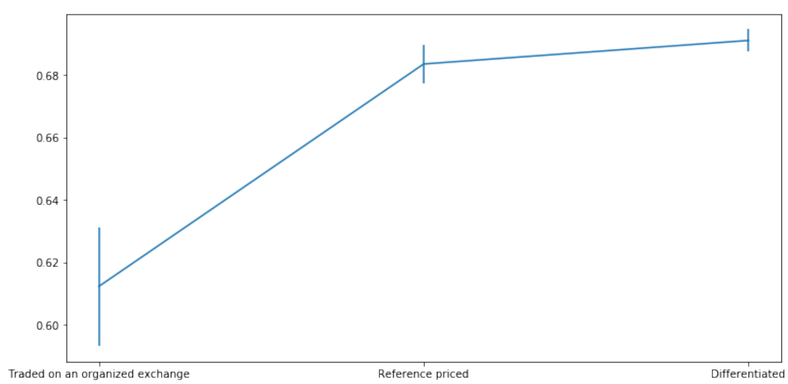
In order to understand what drives the heterogeneity of ν_L across products, we regress the estimated product level ν_L on the sector dummy. Figure 11 shows that the average value of ν_L ranges from slightly above 0.55 to about 0.7. The vertical lines shows the 95 confidence interval of ν_L in each sector. Sectors are ordered by the estimated value of ν_L. Products that seem to be more homogeneous, like animal fat and prepared foodstuffs, tend to have lower ν_L and therefore a lower logistics costs conditional on the quantity shipped. On the other hand, the more complex products like machinery tend to have a higher value of ν_L. Consistent with this intuition, Figure 12 shows that when we regress estimated ν_L across categories defined by the Rauch classification, a clear sorting pattern emerges: the differentiated products have a significantly higher value of ν_L than the products having a reference price, which has ν_L higher than the products traded in the organized exchange.

[18]Note that in contrast with theory, the frequency of shipment is measured as number of transactions, and therefore is a discrete variable in the data. To test whether this issue significantly affects our result, we run a Poisson regression instead of ordinary linear regression, and find that the results only change slightly.



Note: Estimated ν_L across sectors. The vertical lines shows the 95 confidence intervals of estimated ν_L in each sector.

Figure 11: Estimated ν_L across sectors of products



Note: Estimated ν_L across Rauch categories. The vertical lines shows the 95 confidence intervals of estimated ν_L in each category.

Figure 12: Estimated ν_L across Rauch classifications

D Calibration under Pareto

In this section, we illustrate the idea of identifying trade costs parameters using flows under the assumption of $G(a)$ being Pareto distribution and $f_{ij}^x = 0$. Under these assumptions, we can apply the aggregation formula (28) to get the closed form solution for the bilateral trade flows. The number of firms that export from i to j is

$$N_{ij} = N_i^e \int_0^{a_{ij}^*} dG\left(a\right) = N_i^e G\left(a_{ij}^*\right)$$

$$= H\left(0\right)\left(A_j\right)^{\frac{\nu_L\theta-\theta}{\nu_L-\nu_R}} Z_{ij}\left(w_i B_{ij}\right)^{-\frac{\theta\left(1-\nu_R\right)}{\nu_R-\nu_L}}, \tag{66}$$

where $Z_{ij} = N_i^e \kappa_{G,i}^{\theta}\left(w_i \tau_{ij}\right)^{-\theta}$. Therefore together with the expression on bilateral trade flow (54), the intensive margin is

$$\frac{X_{ij}}{N_{ij}} = \frac{H\left(\nu_R\right)}{H\left(0\right)}\left(A_j\right)^{\frac{\nu_L}{\nu_L-\nu_R}}\left(w_i B_{ij}\right)^{\frac{\nu_R}{\nu_R-\nu_L}}. \tag{67}$$

The total frequency of shipments is

$$F_{ij} = N_i^e \int_0^{a_{ij}^*} F_{fj} dG\left(a\right) = N_i^e \int_0^{a_{ij}^*} \frac{1}{1-\nu_L}\kappa_I B_{ij}^{-1} q_{fj}^{\left(1-\nu_L\right)} dG\left(a\right)$$

$$= \frac{H\left(1-\nu_L\right)}{1-\nu_L}\kappa_I\left(A_j\right)^{\frac{\left(1-\nu_L\right)+\nu_L\theta-\theta}{\nu_L-\nu_R}} Z_{ij}\left(w_i B_{ij}\right)^{-\frac{1-\nu_R+\nu_R\theta-\theta}{\nu_L-\nu_R}}.$$

Average shipment frequency is

$$\frac{F_{ij}}{N_{ij}} = \frac{H\left(1-\nu_L\right)}{H\left(0\right)\left(1-\nu_L\right)}\kappa_I\left(A_j\right)^{\frac{\left(1-\nu_L\right)}{\nu_L-\nu_R}}\left(w_i B_{ij}\right)^{\frac{1-\nu_R}{\nu_R-\nu_L}} \tag{68}$$

Given that we observe X_{ij}, N_{ij} and F_{ij} in the data, and ν_L can be estimated separately, we can solve for A_j, B_{ij}, Z_{ij} up to a level of wage and the shape parameter of marginal cost distribution θ. Since we observe firm level sales, we can identify θ from the shape of the sales distribution.

However, despite the transparency in identification, the assumption of Pareto generates peculiar predictions regarding the intensive margins of trade. We could not think of a plausible theoretical reason for this to hold true. Fortunately, as suggested in Fernandes *et al.* (2019), when the marginal costs follow log-normal distribution, the Melitz model is able to match the patterns of intensive margin. Therefore in the next sub-section, we calibrate the model using the same logic but with the assumption that the marginal costs follow log-normal distribution.

E Auxiliary Empirical Analysis

In this subsection we use the sample of Guangdong province to show evidence that supports the idea how firms arrange shipment may reflect their underlying trade costs. Using data from a single province controls for the potential origin effects. Guangdong Province is the largest province in terms of trade value, accounting for about 30% of total trade value in China. We first examine the difference in shipment frequency between intermediaries and other firms. The literature studies intermediaries (e.g. Bai *et al.* (2017)) point out that firms export via intermediaries pay less entry cost, but incur higher variable cost, because producers have to pay a margin to intermediaries, and they also lose the chance of directly interact with buyers , thus are less likely to build long-term trust with buyers. This argument shows that trade via intermediaries is likely to have higher coordination cost and thus lower frequency of shipment. The regression we run to test this is

$$\log F_{foj} = \gamma_0 + (1 - \nu_L) \log q_{foj} + \phi_{oj} + u_{foj},$$

where ϕ_{oj} is product-country fixed effect. The regressions are run for both the sub-sample of intermediary firms and non-intermediary firms. table 8 shows that the sub-sample of intermediaries not only has a lower value of intercept, but also has a higher estimated ν_L. If the inventory costs are product specific and therefore on average the same across intermediaries and non-intermediaries, the lower intercept implies a higher coordination cost parameter κ_T for the intermediaries. Moreover, the higher estimated ν_L shows that the logistics costs increase at a faster speed for the intermediaries.

	Intermediary	Non-intermediary
Intercept	-0.0657^{***}	0.0794^{***}
t-value	-153.959	133.821
ν_L	0.838^{***}	0.787^{***}
t-value	704.982	752.8732
No. Obs	1321772	1022501
Adj. R^2	0.27	0.36

Note: Standard deviation is reported in the bracket, product-country fixed effect is controlled.

Table 8: Shipment frequency and intermediary

As another evidence of the associate between shipment frequency and trade costs, we run a gravity style regression and test whether the usual proxies of trade barriers are good predictors of shipment frequency. In the regression, we put annual number of shipment for each firm-product-destination on the left hand side, controls for value of shipment and gravity variables on the right hand side. For the gravity variables, besides GDP and GDP per ca pita, we also add proxy for trade costs including contiguous or not, sharing common language or not, and the cost of business startup in the destination country. The gravity variables are obtained from CEPII. To use the variation across destinations, firm-product fixed effect is controlled. Inference is clustered at firm level. Table 9 shows that contiguity and common language indeed associate higher frequency of shipment, and a higher business startup costs is associated with lower frequency of shipment.

	Estimation result	t-value
$\log X_{foj}$	0.305	214.057
$\log GDP_j$	0.055	78.143
$\log GDPpca_j$	0.016	14.858
$Contig_{ij}$	0.014	17.181
$Enthno_{ij}$	0.042	27.028
$BusiCost_{ij}$	-0.002	-1.956
No. Obs	2491115	
Adj. R^2	0.56	

Note: Firm-product fixed effect is controlled, standard deviation clustered at firm level.

Table 9: Shipment frequency and gravity variables