Trade Costs and Mark-Ups in Maritime Shipping

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Abstract

Worldwide, delivered prices of traded goods are 15% higher on average than their prices in the country of origin. It is also widely believed that non-competitive pricing behavior in the maritime shipping market raises the cost of freight. Using U.S. import data, this paper estimates the effects of non-competitive behavior on total freight costs, international trade flows, and economic welfare. Estimated short-run pass-through rates of cost to destination prices are used to calculate the freight mark-ups charged on U.S. imports shipped by sea. Freight mark-ups account for approximately one-third of total freight charges in U.S. imports, equivalent to an *ad valorem* tariff of 1.4-2.6 percent. U.S. imports would be 4.2 to 11.6 percent higher if these mark-ups were eliminated. The cost of these mark-ups in terms of economic welfare for U.S. consumers represents a reduction of approximately 0.1-0.2 percent of their real income. Goods imported from developing countries or from countries at greater distances to the U.S. have larger tariff equivalent mark-ups.

Keywords: Maritime Shipping Mark-Ups, Trade Costs, Welfare

JEL Codes: D43, F14, L11, R41

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1 Introduction

Worldwide, delivered prices of traded goods are 15% higher on average than their prices in the country of origin (UNCTAD, 2017). It is also widely believed that non-competitive pricing behavior in the maritime shipping market raises the cost of freight.[1] About that 70% to 80% of international trade flows (in value) move by sea (UNCTAD, 2017). Furthermore, barriers to entry into this market are enormous, given the significant economies of scope and economies of scale exploited by large carriers (Hummels et al., 2009). The market thus tends to be concentrated. [2] Likewise, mergers and alliances among carriers produce an oligopolistic structure (Sys, 2009). So, although previous studies find evidence that market power exists in the maritime shipping industry, the literature still lacks absolute measures of the mark-ups that carriers charge.[3] In this paper I estimate these mark-ups to quantify the magnitude of the market power. I then use these estimates to evaluate how shipping mark-ups affect the cost of freight, trade flows and welfare.

Atkin and Donaldson (2015) develop an innovative methodology for estimating intermediaries' trade costs in a market with variable mark-ups. Using theoretical insights from the Industrial Organization literature, they show that the pass-through rate of costs to prices is a sufficient statistic for quantifying the response of mark-ups to trade cost changes. Furthermore, the pass-through rate permits identification of firms' marginal costs and mark-ups. I apply the methodology to the maritime shipping industry, using U.S. import data for the period 2002-2017. The objective is to quantify the effect of non-competitive pricing behavior on the cost of freight.

The main question that this paper answer is: What share of observed freight charges is attributable to non-competitive conditions in the shipping market? The paper also provides an answer to the following questions: What is the effect of shipping mark-ups on trade flows? What are the welfare costs of these mark-ups? How large are carriers' mark-ups relative to tariffs? Do market conditions in routes to smaller destination ports allow carriers to charge larger mark-ups? Do developing countries pay higher shipping mark-ups? Are mark-ups larger on longer routes?

[1] See Fink (2002), Hummels et al. (2009) and Asturias (2019).

[2] In the liner shipping market, for instance, half of the routes are served by at most three carriers, and almost three-quarters of them by five shipping carriers (UNCTAD, 2017).

[3] See Fink (2002), and Hummels et al. (2009).

This paper is related to three strands of the literature. First, it contributes to the debate over the presence of market power in the maritime shipping industry.[4] The most closely related paper is Hummels et al. (2009), which provides evidence of market power. However, the assumed CES preference structure does not allow that study to calculate shipping mark-ups. It also leads that study to implicitly assume that shipping mark-ups are fixed when marginal cost changes. This paper differs from Hummels et al. (2009), by estimating absolute–rather than relative–shipping mark-ups. It also calculates the effect of shipping mark-ups on trade flows and economic welfare, and it evaluates whether developing and/or distant countries pay higher shipping mark-ups.[5]

Second, this paper contributes to the literature on (1) the underlying mechanisms that determine freight costs, and (2) the effects of freight costs on international trade. Academic research on this topic attempts to understand and quantify determinants of total trade costs.[6] Other studies estimate the impact of freight charges on countries' export performance.[7] Still others document the evolution of freight costs over time, and examine the underlying market conditions that determine these costs.[8] This paper contributes to this literature by (1) decomposing shipping freight rates into marginal cost and mark-up components, and (2) providing quantitative estimates of the degree to which positive freight mark-ups reduce international trade flows and welfare.

Finally, this paper expands the growing literature that uses the pass-through rate of cost to prices to identify the presence of market power. The seminal paper in this strand of the literature is Atkin and Donaldson (2015). That study shows that the pass-through rate is a sufficient statistic for quantifying the response of mark-ups to trade cost changes. Other studies have used the method in other applications.[9] This paper applies the approach to the maritime shipping industry. It also

[4] See e.g. Heaver (1973), Bryan (1974), Devanney III et al. (1975), Davies (1986), Clyde and Reitzes (1998), Fink (2002), Sys (2009) and Hummels et al. (2009).

[5] Recently, Asturias (2019) estimates these mark-ups, aiming to model the importance of the transportation sector for trade. However, Asturias uses data for containerized shipping services for the year 2014, and exploits cross-section variation in that year. The calculated mark-ups correspond to those charged to shipments from U.S. ports to foreign countries. In contrast, in this paper I use panel data, exploit the time variation, and calculate the mark-ups from foreign countries to U.S. customs districts.

[6] See e.g. Limao and Venables (2001), Micco and Pérez (2001), Sánchez et al. (2003), Clark et al. (2004), Wilmsmeier et al. (2006), Martínez-Zarzoso et al. (2008) and Wilmsmeier and Hoffmann (2008).

[7] See e.g. Amjadi and Yeats (1995), Radelet and Sachs (1998), Hummels and Skiba (2004) and Korinek and Sourdin (2009).

[8] See e.g. Hummels and Skiba (2002), Hummels (2007), Hoffmann and Kumar (2013), Brancaccio et al. (2020), Wong (2017), Ardelean and Lugovskyy (2018) and Asturias (2019).

[9] Pless and Van Benthem (2017) applies this method to study the residential market for the installation of solar power systems in California. Bergquist and Dinerstein (2020) uses it to investigate the existence of market power

uses U.S. import data, which allows the direction of the trade flows to be observed rather than inferred, as in Atkin and Donaldson (2015). All results are also robust to the level of aggregation of U.S. imports, finding similar estimates in magnitude at the HS6- and HS10- digit level.

This paper estimates that pass-through rates of cost to freight rates for shipping differentiated products to the U.S. range from 0.4 to 2.7.[10] Given that competitive markets imply a pass-through rate of 1, these estimates imply a latent presence of non-competitive conditions in the market for maritime transport of U.S. imports of these products. The paper also estimates that shipping mark-ups represent a third of freight charges for U.S. imports of differentiated products. The estimated share of mark-ups in freight costs ranges from 34% to 43% on shipments delivered to the U.S. East coast and from 32% to 34% on shipments delivered to the U.S. West coast.

Assuming a trade elasticity of 3 to 5, back-of-the envelope calculations predict that U.S. imports of differentiated products would have been 4.2% to 11.6% higher if the estimated mark-ups were set equal to zero.[11] Using the estimated mark-ups to decompose observed freight charges, shipping mark-ups account for an *ad valorem* tariff equivalent ranging from 1.4% to 2.6%. Taken together, these estimates imply that the cost of maritime shipping mark-ups in terms of welfare for U.S. consumers amounts to an annual reduction of approximately 0.1%-0.2% of real income.

The paper proceeds as follows. Section 2 explains the theoretical framework used to estimate maritime shipping mark-ups. Section 3 describes the data and presents a descriptive statistical analysis. Section 4 describes the estimation strategy used to calculate maritime shipping mark-ups. Section 5 presents results. Section 6 summarizes the main conclusions.

2 Theoretical Framework

In order characterize carriers' behavior in setting their freight rates, I adapt the structural model of Atkin and Donaldson (2015) to this industry. I also make three assumptions that are standard in

among intermediaries in the agricultural sector in sub-Saharan countries.

[10]Shipping mark-ups are only estimated for imports of differentiated products. The identification strategy applied in this paper assumes that all unobservable components of freight charges are carriers' mark-ups. So, it is a reasonable assumption when modelling *Liner Shipping* which mainly carries differentiated products. However, the assumption is overly strong when modelling *Bulk Shipping*. Search costs account for an important unobservable factor for carriers in this segment of the market Brancaccio et al. (2020, 2021).

[11]Recent estimates predict trade elasticities ranging from 3 to 5, and estimates of this elasticity in shipping markets find that it is around to 3 (Simonovska and Waugh, 2014; Wong, 2017).

the literature. First, carriers are rational agents.[12] Second, demand for shipping services is entirely indexed to the demand for imports shipped by sea, and carriers observe it.[13] Third, carriers set freight rates to collect the largest share of consumers' willingness to pay for shipping a product.[14]

The underlying idea of the model is that carriers in international trade charge a price f for shipping products between two places. In a simplistic representation of the world with only one carrier, one product and two countries (A and B), f corresponds to the observed price wedge for this product between A and at B.[15] f also represents the sum of carriers' cost c and mark-ups μ.

$$f = c + \mu \tag{1}$$

If c were observed, μ would be straightforward to estimate using f. Unfortunately, data only allows components of c to be observed. μ is also likely endogenous to c. It might also depend on factors related to demand z and market competition ϕ. If so, a cost shock x may not always be completely passed through to f. The change in f due to x will depend on the pass-through rate of c to f, ρ. That is, it depends on how much carriers pass through to f the change in c due to x.

$$\frac{\partial f}{\partial x} = \rho \frac{\partial c}{\partial x} + \frac{\partial \mu}{\partial \phi}\frac{\partial \phi}{\partial x} + \frac{\partial \mu}{\partial z}\frac{\partial z}{\partial x} \tag{2}$$

A standard CES framework presumes that μ is not endogenous to c. Its multiplicative pricing structure, along with the constant price elasticity of demand, constrains the value of ρ to the range $[1, \infty)$. This leads μ to be overestimated. In order to properly identify it, ρ should be explicitly considered in the modeling. ρ brings two important pieces of information related to market power to the estimation: competitive conditions and demand curvature. ρ is also structurally a function of the slope of the inverse demand curve, which captures the endogenous relationship of μ to c.

In the model below, I use ρ for estimating μ in a world with multiple carriers, shipping routes and products. As explained below, I exploit time variation in U.S. import data to estimate ρ for every combination of product, country of origin and U.S. coast of delivery. Then, I exploit the cross-sectional variation in the data to estimate an specification for carriers freight rates f adjusted by ρ on a set of shipping cost determinants (e.g. shipping distance, oil price, etc) to retrieve an estimate of c. The retrieved c allows μ to be estimated for every product shipped on every route.

[12]See e.g. Fink (2002), Hummels et al. (2009) and Asturias (2019).
[13]See e.g. Fink (2002) and Hummels et al. (2009).
[14]See e.g. Hoffmann and Kumar (2013).
[15]Subscripts are excluded for clarity of exposition.

2.1 Model Set-up

Let the world consist of $o = 1, 2, ..., O$ origin countries exporting $k = 1, 2, ..., K$ products by sea to a destination with $d = 1, 2, ..., D$ arrival ports. Further, $\ell = 1, 2, ..., L$ carriers ship all products, and compete for each shipping route od in an oligopolistic market structure.[16] Carriers also observe the inverse demand for each imported product k, $P^k_{od}(Q^k_{od}, \Theta^k_{od})$, where P^k_{od} is the price of each product k in port d imported from country o, Q^k_{od} is the amount imported of each k in destination d from country o, and Θ^k_{od} are demand shifters from importing this product k in d from o.[17] The inverse demand for shipping a product k through route od is given by $f^k_{od}(Q^k_{od}, \Theta^k_{od})$, where f^k_{od} is the shipping freight rate. Additionally, carriers incur a set of fixed costs, FC^ℓ_{od}, and variable costs, $c^\ell(\chi^k_{od})$, which depend on route conditions and the shipped product k.[18] Each carrier ℓ thus maximizes the following profit function with respect to the shipped amount $q^{\ell,k}_{od}$.[19]

$$\max_{q^{\ell,k}_{od}} \pi^\ell = \sum_{od} \sum_{k} \left[f^k_{od}(Q^k_{od}, \Theta^k_{od}) - c^\ell(\chi^k_{od}) \right] q^{\ell,k}_{od} - FC^\ell_{od} \tag{3}$$

The optimal freight rate $f^{\ell,k}_{od}$ that carrier ℓ charges for shipping product k from o to d is given by:

$$f^{\ell,k}_{od} = c^\ell(\chi^k_{od}) - \frac{\partial f^k_{od}}{\partial Q^k_{od}} \frac{\partial Q^k_{od}}{\partial q^{\ell,k}_{od}} q^{\ell,k}_{od}. \tag{4}$$

Shipping freight rates thus depend on variable costs $c^\ell(\chi^k_{od})$ and carriers' ability to alter the overall shipping capacity for product k on route od, $\frac{\partial Q^k_{od}}{\partial q^{\ell,k}_{od}}$. These rates also depend on the number of carriers L^k_{od} equal to $\frac{Q^k_{od}}{q^{\ell,k}_{od}}$ competing on route od for shipping product k. Thus, in order to model $f^{\ell,k}_{od}$, two additional assumptions are made as in Atkin and Donaldson (2015) and Bergquist and Dinerstein (2020). First, a conduct parameter θ^k_{od} is defined equal to $\frac{\partial Q^k_{od}}{\partial q^{\ell,k}_{od}}$.[20] Second, a competition

[16] For simplicity, carrier heterogeneity is not explicitly modelled in this framework. However, I model the presumable effect on carriers' optimal pricing decision, considering an inverse conduct parameter ϕ to model the competition in the market. I detail this below after deriving the optimal shipping freight charge.

[17] As noted above, this paper focuses on estimating freight mark-ups charged to U.S. imports of differentiated products shipped by sea. This is a simplifying assumption, given that few imported products are shipped to the U.S. by many shipping modes (excluding Mexican and Canadian imports flows, as I do in this paper.) Additionally, differentiated products are mostly shipped by *Liner Shipping*, in which most routes are pre-scheduled and offered based on the demand of trade flows.

[18] These costs are mainly related to shipping distance, fuel prices, volume shipped in a route, the ratio weight-to-value, etc. (Radelet and Sachs, 1998; Micco and Pérez, 2001; Sánchez et al., 2003; Wilmsmeier et al., 2006; Wilmsmeier and Hoffmann, 2008; Martínez-Zarzoso et al., 2008; Hoffmann and Kumar, 2013).

[19] All variables vary over time. The time subscript is suppressed for notational ease.

[20] As is standard in the literature, this conduct parameter takes the following values according to the market structure (1) $\theta^k_{od} \to 0$ in perfect competition; (2) $\theta^k_{od} \to 1$ in a *Cournot* competition and monopoly, and (3) $\theta^k_{od} \to L^k_{od}$ in the case of collusion (Weyl and Fabinger, 2013; Atkin and Donaldson, 2015).

index ϕ^k_{od} is defined equal to $\frac{L^k_{od}}{\theta^k_{od}}$ for each route od. ϕ allows the problem of identifying L^k_{od}, separately from the structure of market competition θ^k_{od} to be circumvented.[21]

2.2 Identification of Shipping Costs and Mark-ups

A problem in the measurement of $f^{\ell,k}_{od}$ is how to separately identify costs and mark-ups. Atkin and Donaldson (2015) show that the pass-through rate of cost to prices ρ is a sufficient statistic to identify firms' marginal costs and mark-ups. ρ measures firms' ability to pass through a cost shock to final prices. Carriers might find it optimal to transmit a change in costs to freight rates partially ($\rho < 1$), completely ($\rho = 1$), or more than completely ($\rho > 1$). ρ also structurally captures information on two unobservable drivers of mark-ups: (1) consumer preferences, and (2) competition in the market.[22] Furthermore, ρ allows any change in freight rates due to a cost shock to be decomposed into an observed portion related to costs and an unobserved portion related to mark-ups. ρ thus allows considering that carriers' mark-ups are endogenous to costs.[23]

ρ is derived by taking the partial derivative of the optimal pricing rule (4) with respect to costs.[24] As in Atkin and Donaldson (2015), this yields ρ as a function of the curvature of the inverse demand in the market, $E^k_{od}(f^k_{od})$, and (2) the competition index in route od, ϕ^k_{od} (see expression (5)).[25] ρ is also a flexible parameter that can take any positive value, depending on the market structure. For instance, ρ tends to 1 as the market becomes more competitive. (i.e. $\phi^k_{od} \to \infty$).

$$\rho^k_{od} = \left[1 + \frac{1 + E^k_{od}(f^k_{od})}{\phi^k_{od}}\right]^{-1} \tag{5}$$

Atkin and Donaldson (2015) explain that all is needed to operationalize ρ is a parsimonious demand system. In this paper, the demand for maritime shipping services is modelled as a derived

[21] For simplicity, this competition index is assumed to only vary across shipping routes od (i.e. $\phi^k_{od} \to \phi_{od}$). In liner shipping service carriers often ship different products in the same vessel. Competition among carriers is thus at the route level than at the route-product level.

[22] As is shown below in expression (5), ρ structurally depends on the demand curvature and the market competition conditions. ρ thus permits modelling the differential effect of the demand curvature on the transmission of cost shock to prices (See Figure 1a and Figure 1b).

[23] When shipping carriers partially (more than completely) pass-through a cost shock to shipping freight rates, they reduce (raise) their mark-ups when there is a cost shock. Additionally, when carriers completely pass-through a cost shock to freight rates prices ($\rho = 1$), they are able to keep constant their mark-ups (Fabinger and Weyl, 2012).

[24] See Appendix A

[25] The elasticity of the slope of the inverse demand, $E^k_{od}(f^k_{od})$, is equal to $\left(\frac{Q^k_{od}}{\frac{\partial f^k_{od}}{\partial Q^k_{od}}}\right)\left(\frac{\partial\left(\frac{\partial f^k_{od}}{\partial Q^k_{od}}\right)}{\partial Q^k_{od}}\right)$.

demand tied directly to import demand, as is standard in the literature (Hummels et al., 2009; Hummels and Schaur, 2013).[26] Carriers are assumed to observe this demand, which is represented as a Bulow and Pfleiderer (1983) demand system as in Atkin and Donaldson (2015). Products are also assumed to be unique to their origin country, as in the standard Armington (1969) assumption. Thus, the demand for importing a product k from country o to d, $P^k_{od}(Q^k_{od}, \Theta^k_{od})$, which underlies the shipping demand of that product k through that route od is given by:

$$P^k_{od}(Q^k_{od}, \Theta^k_{od}) = \begin{cases} a^k_{od} - b^k_{od}(Q^k_{od})^{\delta^k_{od}}, \text{if } \delta^k_{od} > 0 \text{ and } a^k_{od} > P^k_{od} > 0, b^k_{od} > 0, 0 < Q^k_{od} < \left(\frac{a^k_{od}}{b^k_{od}}\right)^{\frac{1}{\delta^k_{od}}} \\ a^k_{od} - b^k_{od}\ln(Q^k_{od}), \text{if } \delta^k_{od} = 0 \text{ and } a^k_{od} > P^k_{od} > 0, b^k_{od} > 0, 0 < Q^k_{od} < e^{\left(\frac{a^k_{od}}{b^k_{od}}\right)} \\ a^k_{od} - b^k_{od}(Q^k_{od})^{\delta^k_{od}}, \text{if } \delta^k_{od} < 0 \text{ and } P^k_{od} > a^k_{od} \geq 0, b^k_{od} < 0, 0 < Q^k_{od} < \infty \end{cases} \tag{6}$$

This inverse demand system is very flexible, embedding multiple demand functional forms (linear, quadratic, and isoelastic demands) (Bergquist and Dinerstein, 2020). It is also structurally tractable, yielding a constant elasticity of the slope of the inverse demand curve $E^k_{od}(f^k_{od})$. Likewise, this demand system allows consideration of the three different types of pass-through rates in the calculation of maritime shipping mark-ups.[27] Furthermore, it permits using b^k_{od} as a free parameter in the estimation, in order to capture any omitted variables.[28] More importantly, it allows the optimal pricing-rule derived in (4) to be written as follows, by taking carriers' FOC with respect to this demand system. Then, denoting the shipping freight rate $f^{\ell,k}_{od}$ equal as the price gap of product k between the price in the destination country P^k_{od} and the price in the origin P^k_o.

$$f^{\ell,k}_{od} = \rho^k_{od} c^\ell(\chi^k_{od}) + (1 - \rho^k_{od})(a^k_{od} - P^k_o) \tag{7}$$

[26] Shipping services are demanded because of the utility for delivered products. There is no independent demand for the transportation service itself. The demand for imports is commonly used in the literature to proxy shipping demand (Hummels et al., 2009; Hummels and Schaur, 2013).

[27] When δ^k_{od} is positive, this demand system permits modelling the case when ρ is partial. A cost shifter x thus is partially transmitted to shipping freight rates (i.e. Δ c is less than Δ p) (see Figure 1a. Consequently, carriers reduce their shipping mark-ups when that occurs. In contrast, when δ^k_{od} is negative, this demand system permits modelling when ρ is more than complete. A cost shifter x thus is more than completely transmitted to shipping freight rates (i.e. Δ c is greater than Δ p) (see Figure 1b. Hence, carriers raise their shipping mark-ups when that happens. Additionally, when δ^k_{od} is equal to zero, this demand system permits modelling the case in which a cost shifter is completely transmitted to freight rates (i.e. ρ is equal to one). So, carriers are able to keep constant their mark-ups.

[28] Atkin and Donaldson (2015) explain that these omitted variables are mainly related to: (1) unobserved preferences (e.g. the quality of the shipping service in this context of maritime shipping); and (2) market structure (e.g. number of shipping carriers per route).

This expression separates shipping costs and shipping mark-ups.[29] Consistently with Atkin and Donaldson (2015), all observable cost' shifters for intermediaries (i.e. carriers) are captured in the first term, while all unobservable factors (e.g. competitive and demand conditions, which are related to mark-ups) are captured in the second. Thus, if shipping costs are measured and ρ estimated, shipping mark-ups can be calculated by applying a standard Lerner (1934) index to (7).

3 Data

This paper employs data from the U.S. Import Merchandise trade files of the U.S. Census Bureau.[30] Specifically, I use annual U.S. import flows moved by sea during the period 2002-2017.[31] I pool these flows at the HS6-digit level following Hummels and Schaur (2013).[32] Each observation compiles information disaggregated by HS6-digit product k, origin country o, U.S. customs district of arrival d and year t for (1) general value of imports, calculated in FOB terms, (2) shipping charges, and (3) imported quantities shipped per mode of transportation (in kg.).

In order to control for geography in the estimation, shipping distances were merged to this data. I calculated all distances using the GPS coordinates from each origin country o and U.S. customs district d and applying the great-circle distance formula.[33] The Rauch (1999) classification is used to distinguish between bulk commodities and differentiated products.[34] All variables also are adjusted for inflation, using the U.S. Consumer Price Index (CPI) of 2017 as the base year.

[29] See Appendix A.

[30] All U.S. import data files were retrieved from Peter Schott's web page `https://sompks4.github.io/sub_data.html`. The variable layout in each of these files corresponds to the *IMP_DETL* layout at which the U.S. Census Bureau releases the U.S. imports.

[31] For further details about how I build this database, see Appendix B.

[32] That approach allows avoiding the aggregation of products with dissimilar quality or shipping characteristics within the same HS6-digit product code.

[33] GPS coordinates were retrieved from `https://simplemaps.com/data/world-cities`.

[34] The Rauch (1999) classification relies on SITC codes to classify the products. So, I use the U.S. census concordances to this aim. However, the Revision number of the SITC codes in the concordances for the years 2002 to 2015 is unknown. Revision 4 is only attributed to the concordances of 2016 and 2017. Thus, in order to circumvent this issue, all SITC codes are assumed to be at Revision 2. This solves the methodological problem of classifying products as differentiated and homogeneous. This problem arises when a set of SITC codes at Revision 4–accounting for approximately 2% to 3% of U.S. imports (in value)–are converted to Revision 2 for applying the Rauch classification. More importantly, this approach does not significant affect the results. The classification for most U.S. imports in value (94% to 96%) as homogeneous and differentiated products is the same regardless of the SITC classification. Either way, I evaluate the robustness of the estimates to this assumption in Appendix G.

4 Estimation Strategy

This section describes the two-step estimation strategy followed to estimate carriers' shipping mark-ups. Following Atkin and Donaldson (2015), the first step is the estimation of ρ. The second step is the estimation of carriers' marginal cost, using $\widehat{\rho}$ to purge endogenous responses of mark-ups to changes in cost.

4.1 Short-run Pass-through Rate

Expression (7) shows that ρ can be estimated using variation in levels of $c^{\ell}(\dot{})$. The problem for estimation is that its functional form, and the structure of the demand shifters, a^k_{od}, are unknown. Thus, in order to solve this issue, I write the shipping freight rates $f^{\ell,k}_{od}$ in terms of the price of product k in destination market d, P^k_{od}, and the price of the same product in origin market o, P^k_o, using the definition $f^{\ell,k}_{od}$ denoted above (consistent with Hummels and Skiba (2004)).[35] This allows writing the optimal pricing-rule (7) in terms of observed prices, as in Atkin and Donaldson (2015):

$$P^k_{od} = \rho^k_{od} P^k_o + \rho^k_{od} c^{\ell}(\chi^k_{od}) + (1 - \rho^k_{od}) a^k_{od}. \tag{8}$$

This expression shows that ρ is the same structural coefficient as is applied to P^k_o. ρ can thus be estimated by exploiting the variation of P^k_o. Additionally, the cost function, $c^{\ell}(\dot{})$ and the minimum/maximum willingness to pay for shipping k, a^k_{od}, can be modelled with fixed effects as in Atkin and Donaldson (2015).[36] Hence, the final specification estimated to predict ρ is given by:[37]

$$P^k_{od} = \rho^{k,c}_o P^k_o + \sum_d (\gamma^{k,c}_{od} + \gamma^{k,c}_{od} t) + \epsilon^k_{od}. \tag{9}$$

[35] P^k_{od} is calculated for every combination of origin-destination-product-time (i.e. $odkt$) as the ratio of the FOB value of the U.S. imports shipped by sea $M^{k\,FOB}_o$ plus the freight charges for shipping these imports ShF^k_{od} to the physical weight W^k_o (i.e. $P^k_{od} = (M^{k\,FOB}_o + ShF^k_{od})/W^k_o$). Similarly, P^k_o is calculated for every combination as well as the ratio of the FOB value of the U.S. imports shipped by sea to the weight (i.e. $P^k_o = M^{k\,FOB}_o / W^k_o$). This yields the CIF and the FOB price for each combination, respectively, in terms of US$ per Kg.

[36] This strategy generates structural forms involving two components. First, a time-invariant component, which in this context captures (1) inherent costs for shipping a product k through a shipping route od; and (2) long-run preferences for importing and so shipping product k from country o to a particular destination d. Second, a time-variant component, which captures (1) variable shipping costs over time due to changes in economic conditions for shipping a product k via a shipping route od, and (2) changes in consumer preferences over time for importing and so shipping product k from country o to destination market d.

[37] It is implausible to estimate ρ for every route od. I thus pool destinations for each U.S. coast. The estimation of ρ is restricted for every combination product-(k) – origin (o) – U.S. coast (c) to ensure more degrees of freedom in the econometric estimation.

A condition for ensuring econometric identification of $\rho_o^{k,c}$ is that P_o^k must be orthogonal to demand forces captured by ϵ_{od}^k. Atkin and Donaldson (2015) assumes that P_o^k is exogenous in their context, given that prices in Ethiopia, Nigeria and the U.S. are plausibly set on world markets. This is a strong assumption in the case of U.S. imports. FOB prices might be endogenous to U.S. trade flows. In order to address this endogeneity issue, I estimate ρ in two ways. First, I use a 2SLS model. Then, I estimate ρ using a instrument-free technique. Section 4.4 describes each approach.

ρ is estimated for every combination of product k (at the HS6-digit product code), origin country o and U.S. coast c.[38] The uniqueness of each product k from a particular origin country o through each U.S. coast c permits the estimation of separate regression models for every combination to retrieve the corresponding $\rho_o^{k,c}$. Every model is also estimated by exploiting the time variation of the data within each route od and the average variation across destinations in every U.S. coast.

4.2 Adjusted Shipping Freight Rates

Following Atkin and Donaldson (2015), the second step of the estimation strategy is to estimate carriers' marginal cost. Carriers' pricing rule derived in (8) is rearranged, yielding the following expression for carriers' freight rates as a function of carriers' *ad valorem* shipping costs $T^\ell(\chi_{od}^{k,c})$ and consumers' maximum/minimum willingness to pay for shipping a product $a_{od}^{k,c}$.[39]

$$\frac{P_{od}^k - \widehat{\rho_o^{k,c}} P_o^k}{\widehat{\rho_o^{k,c}} P_o^k} = T^\ell(\chi_{od}^{k,c}) + \frac{(1 - \widehat{\rho_o^{k,c}})}{\widehat{\rho_o^{k,c}} P_o^k} a_{od}^{k,c} \tag{10}$$

The key feature of this expression is that both sides are divided by ρ. The endogenous relationship between shipping costs and shipping mark-ups is thus removed from the model. ρ also enters as a factor determining carriers' freight rates (i.e. the LHS variable in this expression). Additionally, the linear and an additive structure of this expression allows carriers' marginal cost to be predicted via regressions of this adjusted shipping freight rate variable on variables explaining $T^\ell(\chi_{od}^{k,c})$.

[38] Given that P_{od}^k and P_o^k are in U.S.$/ kg., ρ corresponds to the marginal effect in U.S. per kg. This implies that any difference in terms of quality within a HS6-digit product code is unlikely to have a significant effect on the estimated ρ. The rationale is simple. The cost, for instance, for shipping a kilogram of high quality shirts is very likely similar to the cost for shipping a kilogram of low quality shirts. Thus, the short-run pass-through rate ρ should be also quite similar, regardless to the quality of a product. In the section of results, I provide evidence of this statement, showing that the estimated short-run pass-through rates ρ at HS6-digit product code are robust when I calculated them at HS10-digit product codes.

[39] $c^\ell(\chi_{od}^{k,c})$ incurred for shipping product k is assumed to be here a function of its price. This implies that $c^\ell(\chi_{od}^{k,c})$ equals to $P_o^k T^\ell(\chi_{od}^{k,c})$; where $T()$ corresponds to the *ad valorem* shipping cost function. This approach is different with respect to Atkin and Donaldson (2015) which assumes that intermediate costs are specific.

This expression is equivalent to (14) in Atkin and Donaldson (2015). The difference is that $\tau()$ in that paper, denoted here by $c^{\ell}(\chi_{od}^{k,c})$, is assumed to be equal to $P_o^k T^{\ell}(\chi_{od}^{k,c})$. I also divide both sides by P_o^k, yielding the previous expression for the shipping freight rates in *ad valorem* terms. The rationale is treating freight costs as *ad valorem* following (Hummels, 2007; Hummels et al., 2009, 2014; Asturias, 2019). Furthermore, this approach permits considering into the model that shipping costs and mark-ups affect the demand for shipping services according to products' prices.[40]

Once again, a key problem is that the functional form of $T^{\ell}(\chi_{od}^{k,c})$, and the minimum/maximum willingness to pay for shipping a product, $a_{od}^{k,c}$, are unknown. I adopt a similar strategy to Atkin and Donaldson (2015) to identify these parameters. $T^{\ell}(\chi_{od}^{k,c})$ is assumed linear based on the literature about transportation costs for seaborne freight.[41] Specifically, $T^{\ell}(\chi_{od}^{k,c})$ is assumed to be a function of: (1) shipping distance along route od, $DIST_{od}$; (2) fuel expenses on a route od, $DIST_{od} \times POil_t$; (3) aggregate volume shipped in route od during year t, V_{odt}^{c}; (4) the weight-to-value ratio of product k shipped via route od in year t, $WV_{odt}^{k,c}$; and (5) the volume of cargo handled in a destination d during year t, VH_{dt}^{c}. A fixed effect $\kappa_o^{s,c}$ is also included for each combination of origin country o and sector s to model unobservable idiosyncratic efficiency factors explaining shipping costs at the port level in the origin country o for shipping products within the same HS2-sector, s.

$$\begin{aligned} T^{\ell}(\chi_{od}^{k,c}) = \kappa_o^{s,c} + \gamma_1 ln(DIST_{od}) + \gamma_2 ln(POil_t) + \gamma_3 \big[ln(DIST_{od}) \times ln(POil_t)\big] + \\ + \gamma_4 ln(V_{odt}^{c}) + \gamma_5 ln(WV_{odt}^{k,c}) + \gamma_6 ln(VH_{dt}^{c}) + \epsilon_{od}^{k,c} \end{aligned} \tag{11}$$

As in Atkin and Donaldson (2015), the willingness to pay for shipping a product $a_{od}^{k,c}$ is modeled as the sum of a time-product fixed effect, $\alpha_t^{k,c}$, a destination-product fixed effect, $\alpha_d^{k,c}$, and an origin-product fixed effect $\alpha_o^{k,c}$. The difference is that I also account for the preference in destination d for imported product k from country o in the manner of Armington (1969).[42]

$$a_{od}^{k,c} = \alpha_t^{k,c} + \alpha_d^{k,c} + \alpha_o^{k,c} + \upsilon_{od}^{k,c} \tag{12}$$

[40] This expression structurally differs from the *ad valorem* version in Atkin and Donaldson (2015), which they acknowledge likely overestimates intermediaries' mark-ups. This specification merely corresponds to a rearranged version of the optimal pricing rule derived above in expression (8) divided by the price of product k in the origin country o, P_o^k.

[41] See e.g. Radelet and Sachs (1998), Micco and Pérez (2001), Sánchez et al. (2003), Wilmsmeier et al. (2006), Wilmsmeier and Hoffmann (2008), Martínez-Zarzoso et al. (2008), and Hoffmann and Kumar (2013).

[42] Other fixed effects structures could be potentially plausible for estimating this model (e.g. including fixed effects for combinations of product-destination-time or product-destination-time). However, the costs in terms of exploitable variation would be very high.

Substituting (11) and (12) into equation (10) yields the final expression used to separately identifying shipping costs and shipping mark-ups.[43]

$$\frac{P_{od}^k - \widehat{\rho_o^{k,c}}P_o^k}{\widehat{\rho_o^{k,c}}P_o^k} = \kappa_o^{s,c} + \gamma_1 ln(DIST_{od}) + \gamma_2 ln(POil_t) + \gamma_3\left[ln(DIST_{od}) \times ln(POil_t)\right] + \gamma_4 ln(V_{odt}^c) +$$
$$+ \gamma_5 ln(WV_{odt}^{k,c}) + \gamma_6 ln(VH_{dt}^c) + \frac{(1-\widehat{\rho_o^{k,c}})}{\widehat{\rho_o^{k,c}}P_o^k}\alpha_t^{k,c} + \frac{(1-\widehat{\rho_o^{k,c}})}{\widehat{\rho_o^{k,c}}P_o^k}\alpha_d^{k,c} + \frac{(1-\widehat{\rho_o^{k,c}})}{\widehat{\rho_o^{k,c}}P_o^k}\alpha_o^{k,c} + \epsilon_{od}^{k,c} \tag{13}$$

4.3 Maritime Shipping Mark-Ups

The estimated pass-through rates $\widehat{\rho_o^{k,c}}$ and willingness to pay $\widehat{a_{od}^{k,c}}$ are used to calculate shipping mark-ups, $\mu_{od}^{\ell,k,c}$. The standard Lerner (1934) index generates the following expression.[44]

$$\mu_{od}^{\ell,k,c} = \frac{(1-\widehat{\rho_o^{k,c}})(\widehat{a_{od}^{k,c}} - (1+\widehat{T^{\ell}(\chi_{od}^{k,c})})P_o^k)}{P_{od}^k - P_o^k} \tag{14}$$

By rearranging terms in this expression, shipping mark-ups can also be defined in terms of the demand curvature δ and the elasticity of the inverse demand for shipping η.

$$\mu_{od}^{\ell,k,c} = -\left(\frac{1-\widehat{\rho_o^{k,c}}}{\widehat{\rho_o^{k,c}}}\right)\left(\frac{\eta_r^{k,c}}{\delta_{od}^{k,c}}\right)\left(\frac{P_{od}^k}{P_{od}^k - P_o^k}\right) \tag{15}$$

Shipping mark-ups increase when market conditions are less competitive in a route (i.e. $\rho \rightarrow 0$ or $\rho \rightarrow \infty$). Likewise, mark-ups are higher for high-value products, products with a higher elasticity of the inverse demand for shipping η or with a lower curvature of shipping demand δ.

4.4 Econometric Strategy for Estimating Short-run Pass-Through Rates

One challenge facing identification of ρ is that these rates are potentially endogenous to freight charges. In order to investigate this possibility, three sets of ρ are estimated.

The first set of estimates retrieves $\widehat{\rho}$ from equation (9), using OLS as in Atkin and Donaldson (2015). ρ is thus predicted assuming complete exogeneity of P_o^k to the residuals of the estimation.

[43] All γ terms along with the sector fixed effect at the origin-country κ capture variation in shipping costs. Mark-ups are embedded in the α fixed effects.

[44] Using expression (14), it is straightforward to show that maritime shipping mark-ups are positive when the short-run pass-through rate ρ is different from 1. This also occurs when the underlying conditions from each schedule of the Bulow and Pfleiderer (1983) demand system are satisfied. That is, P_{od}^k is greater or equal than $a_{od}^{k,c}$ when $\rho_o^{k,c}$ is more than complete, and P_{od}^k is lower or equal than $a_{od}^{k,c}$ when $\rho_o^{k,c}$ is partial.

The second set of estimates retrieves $\widehat{\rho}$, using 2SLS. In the first stage, each P_o^k is regressed on: (1) the GDP per-capita from each origin country o; (2) the U.S. tariff for every k over time; (3) the Revealed Comparative Advantage (RCA) from each country o producing k; and (4) the World Export Supply (WES) of each k, here excluding the U.S. flows.[45] In the second stage, equation (9) is estimated using $\widehat{P_o^k}$ from the first stage. Then, ρ are retrieved as the coefficient this price.

While 2SLS is the most common approach to solve this type of endogeneity issue, strong and valid instruments are critical inputs. Otherwise, the bias on the estimates could be even greater (Park and Gupta, 2012). This is an issue in the 2SLS estimates for $\widehat{\rho}$. The instruments are not strong and valid in all cases. Thus, a third set of estimates is estimated, using an instrument-free technique.

This third set of estimates uses the Gaussian Copula (hereafter GC) method to control for the endogeneity of P_o^k (Park and Gupta, 2012).[46] This instrument-free technique specifically uses information from the joint distribution between an endogenous variable and the residuals on the estimation (i.e. $F(P_o^k, \epsilon_{od}^k)$) to remove the endogeneity bias. Using non-parametric techniques and applying Gaussian copula, this joint distribution is retrieved as a standard bivariate standard normal distribution Ψ with correlation ϱ. $F(P_o^k, \epsilon_{od}^k)$ thus can be written as $\Psi({P_o^k}^*, {\epsilon_{od}^k}^*)$, where ${P_o^k}^*$ and ${\epsilon_{od}^k}^*$ corresponds to each variable that is assumed to be normally distributed.[47] Then, the likelihood function calculated for this joint distribution is maximized, in order to retrieve $\widehat{\rho}$.

The identification strategy in the GC method relies on the orthogonality between the shocks ω affecting ${P_o^k}^*$ and ϵ_{od}^{k,c^*} (similar to Feenstra (1994)). This can be seen by writing the recovered bivariate normal joint distribution $F(P_o^{k,c^*}, \epsilon_{od}^{k,c^*})$ with the GC method in matrix form.

[45]The GDP per capita variable is taken from CEPII database. U.S. tariffs are taken from USITC. Revealed Comparative Advantage (RCA) and World Export Supply (WES) estimates are calculated at the country-product-time level, using the BACI dataset (Balassa, 1965). The GDP per-capita and the U.S. tariff are only used in the estimations for which BACI dataset does not report data to calculate the RCA and the WES.

[46]The GC method exploits the variation in the data in a manner similar to Feenstra (1994). That study introduced an instrument-free method to estimate trade elasticities that is widely used in the international trade literature.

[47]Specifically, the joint distribution $F(P_o^k, \epsilon_{od}^k)$ is retrieved, applying a Gaussian copula to the univariate marginal distribution of the FOB price (U_p) and the univariate marginal distribution of the residuals (U_ϵ) (i.e $F(P_o^k, \epsilon_{od}^k) = \mathcal{C}(U_p, U_\epsilon)$). $F(P_o^k, \epsilon_{od}^k)$ thus is equal to $\Psi(\phi^{-1}(U_p), \phi^{-1}(U_\epsilon))$ and so to $\Psi({P_o^k}^*, {\epsilon_{od}^k}^*)$ once the Gaussian Copula is applied, where ϕ corresponds to a univariate standard normal distribution. The only previous step consists of using non-parametric techniques to retrieve the univariate marginal distribution of the FOB prices U_p, and to assume that it is normally distributed for the residuals U_ϵ. Park and Gupta (2012) show that estimates are robust to misspecification in the assumed distribution for the residuals.

$$\begin{pmatrix} P_o^{k*} \\ \epsilon_{od}^{k\ *} \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ \varrho & \sqrt{1-\varrho^2} \end{pmatrix} \begin{pmatrix} \omega_{p^*} \\ \omega_{\epsilon^*} \end{pmatrix}, \begin{pmatrix} \omega_{p^*} \\ \omega_{\epsilon^*} \end{pmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \right)$$

Assuming that the residuals of the estimation are normally distributed with mean equal to zero and variance equal to σ_ϵ, the solution of this system of equations yields that the residuals ϵ_{od}^k of expression (9) are equal to $\sigma_\epsilon \epsilon_{od}^{k\ *}$ and so to $\sigma_\epsilon \varrho P_o^{k*} + \sigma_\epsilon \sqrt{1-\varrho^2}\omega_\epsilon$. Thus, the GC method ends up essentially estimating the following modified version of expression (9).

$$P_{od}^k = \rho_o^{k,c} P_o^k + \sum_d (\gamma_{od}^{k,c} + \gamma_{od}^{k,c} t) + \sigma_\epsilon \varrho P_o^{k*} + \sigma_\epsilon \sqrt{1-\varrho^2}\omega_\epsilon \tag{16}$$

where the identification of ρ comes from the fact that P_o^{k*} captures the variation of the FOB prices initially compiled in the residuals, and ω_{ϵ^*} is orthogonal to all terms in the expression. All parameters $\Omega : \{\rho_o^{k,c}, \gamma_{od}^{k,c}, \gamma_{od}^{k,c}, \sigma_\epsilon, \varrho\}$ are estimable by maximizing the log-likelihood function of the joint distribution of the FOB prices and the residuals.

4.5 Explaining variation in estimated Shipping Mark-ups

Does distance affect the size of shipping mark-ups? Do shipping mark-ups lead U.S. importers to incur higher transportation costs when shipping products from lower-income countries? The estimation strategy explained above generates a rich distribution of estimated mark-ups across origin countries, U.S. customs districts, products at HS6 digit-code, U.S. coasts and years. In order to better understand how these mark-ups are distributed per route and product, reduced form regressions are estimated with predicted mark-ups on the LHS. Specifically, the reduced form models regress the *ad valorem* shipping mark-ups $\mu_{od}^{\ell,k,c}$ and the tariff equivalent mark-ups $\tau_{\mu_{od}}^{\ell,k,c}$, respectively, on (1) the shipping distance in a route, $DIST_{od}$; (2) origin countries' GDP per capita, $GDPpc_o$; and (3) substitution elasticities estimated by Soderbery (2015). Shipping distances and GDP per capita allow an understanding of how shipping mark-ups vary with distance and exporter per capita income. The substitution elasticity offers first-order information on cross-product variation in the predicted mark-ups. In an extension, similar reduced-form regression models are estimated to link the *ad valorem* freight rates $f_{od}^{\ell,k\,adv}$ to the same independent variables.[48]

[48] *Ad valorem* freight rates $f_{od}^{\ell,k\,adv}$ are calculated as the ratio cost of freight to the FOB value of the imports (i.e $f_{od}^{\ell,k\,adv} = ShF_{od}/M_o^{k\,FOB}$). *Ad valorem* mark-ups $\mu_{od}^{\ell,k,c}$ corresponds to those retrieved from applying expression (14). The equivalent tariffs to the estimated mark-ups $\tau_{\mu_{od}}^{\ell,k,c}$ are calculated as the product between the *Ad valorem* freight

5 Results

The estimation strategy is applied to the U.S. imports of differentiated products shipped by sea for periods that pre-date (2002-2007) and post-date (2013-2017) the global financial crisis (GFC). This strategy removes the noise from the 2008-2012 period, which is necessary given the approach's maintained hypothesis of parameter stability over a short panel.[49] I also control for presumably different market conditions, splitting the sample data into shipments to the U.S. East coast and shipments to the U.S. West coast.[50]

Section 5.1 reports statistics on the distributions of $\widehat{\rho}$ estimated with OLS, the 2SLS model, and the GC method. All subsequent results rely on the GC method estimates, given that those are better grounded in statistical terms. Section 5.2 describes estimates from the model of *ad valorem* adjusted freights. Section 5.3 discusses the estimated shipping mark-ups.

5.1 Short-run Pass-through Rates in Maritime Shipping

5.1.1 Distribution of the estimated Short-run Pass-through Rates

Table 1 shows statistics on the distributions of $\widehat{\rho}$.[51] All econometric techniques produce similar estimates for the median and average $\widehat{\rho}$. For the periods before and after the GFC, all methods predict a median $\widehat{\rho}$ that ranges from 1.00 to 1.02, and an average $\widehat{\rho}$ ranging from 1.06 to 1.42.[52] All methods also predict that $\widehat{\rho}$ ranges in most cases from 0.4 to 2.7. Hence, this reveals that carriers' ability to pass through a cost shock to freight rates varies a lot across combinations of product, country of origin and U.S. delivered coast. In about half of the combinations, a cost shock is more than passed through to freight rates, while the other half sees only partial pass-through.

rate $f_{od}^{\ell,k^{adv}}$ and the *Ad valorem* mark-ups $\mu_{od}^{\ell,k,c}$ (i.e. $\tau_{\mu_{od}}^{\ell,k,c} = f_{od}^{\ell,k^{adv}} \times \mu_{od}^{\ell,k,c}$).

[49] Despite the challenges of estimation, the GFC is a period of significant interest. I thus apply all methods to that period.

[50] Section C presents summary statistics for U.S. shipping freight rates and other variables used in the analysis.

[51] A problem with some estimates is that there are few data points to produce them. So, the estimation of ρ is not possible for all combinations. Some are negative and others are equal to zero. Yet, the cost of this issue is relatively low. Table F1 shows that the value of U.S. imports through those missing combinations only account for less than 1% of the total. Table F2 and Table F3 also shows the same analysis per number of products and number of countries excluded from the sample.

[52] Table 2 shows the correlation among the estimated short-run pass-through rate retrieved from all techniques. The estimates are very similar. Most similarities occur among the estimated short-run pass-through rates using OLS and the GC method.

The robustness of $\widehat{\rho}$ across techniques is heartening. Yet, the remainder of this paper relies on the GC estimates. The OLS estimates might suffer from endogeneity bias.[53] The 2SLS estimates reveal evidence of weak instruments.[54] Thus, the GC estimates are better grounded in statistical terms.[55]

Estimates of $\widehat{\rho}$ show that, on average, carriers pass-through an increase of costs more-than-completely to freight charges (i.e. $\bar{\rho} > 1$). Specifically, columns (3) and (9) in Table 1 show that an increase of $1 in shipping costs implies a median increase in freight charges of about $1.01 and an average increase of $1.11-$1.42. Likewise, the distribution of the estimates–ranging from 0.4 to 2.7–shows that carriers' ability to pass-through a cost shock to freight charges varies a lot across products.

These estimates of $\widehat{\rho}$ are bounded by others in the literature. Atkin and Donaldson (2015) estimate an average $\widehat{\rho}$ of 0.5 for intermediaries in the intra-national trade markets of Nigeria, Ethiopia, and the U.S. Bergquist and Dinerstein (2020) estimate an average $\widehat{\rho}$ of 0.2 for intermediaries in the agricultural markets of sub-Saharan Africa. Likewise, Pless and Van Benthem (2017) estimate an average $\widehat{\rho}$ of 1.6 for intermediaries in the market of residential solar power systems in California.

5.1.2 Bullow and Pfeiderer ρ estimates vs. CES ρ estimates

In this paper, ρ is estimated assuming a Bulow and Pfleiderer (1983) demand system. This is a very flexible demand system, nesting different demand schedules such as the CES. One key question is how these estimates are related to those that I would have predicted if I had assumed a CES. As detailed in Appendix D, all $\widehat{\rho}$ would have been overestimated. The rationale is simple. A CES framework assigns σ to capture much information. The super-elasticity of demand (or price elasticity of the demand elasticity) is also assumed to be equal to zero, despite being an important channel for determining firms' market power for passing through a cost to prices.

[53] The GC method predicts that the correlation (ϱ) between the FOB price and the residual estimates is higher than 40% for half of the combinations in the U.S. East coast and higher than 25% of them in the U.S. West coast when the pass-through rates are estimated using OLS.

[54] The first-stage f-test is not statistically significant (at 10%) for more than 90% of the combinations. This test thus indicates that the instruments in the 2SLS approach are weak in most cases.

[55] The GC method reports Confidence Intervals (CI) at 95% level to test the statistical significance of the estimators. All upper bounds are positive for all $\widehat{\rho}$ estimates. Only, about 25% of the lower bounds are negative (See Figure 2, 3 and 4). Thus, the hypothesis that $\widehat{\rho} = 0$ cannot be rejected in this percent of the cases. In order to evaluate whether multicolinearity in the estimation of these ρ led to the overestimation of the standard errors, the Shapiro–Wilk normality test is applied to the FOB prices. This test reveals that the FOB price is normally distributed for two-thirds out of the estimated $\widehat{\rho}$ with CI including zero. So, the estimated standard error for these $\widehat{\rho}$ might be overestimated. Additionally, an evaluation of the remaining third of the estimated $\widehat{\rho}$ reveals that those $\widehat{\rho}$ correspond to combinations $k - c - o$ that only account for 1.4% to 3% of the value of U.S. imports.

5.2 The Adjusted Shipping Freight Rate Function

After estimating $\widehat{\rho}$, the next step in the two-step strategy of Atkin and Donaldson (2015) is the estimation of (13). This section reports the results of doing so for each U.S. coast and period of analysis.[56] All estimates indicate that volatility in shipping freight rates is related to shipping freight mark-ups. The shipping cost function is not very responsive to individual cost shocks.

Table 3 show the results of estimating (13) among shipments bound to each U.S. coast during 2002-2007. Columns (1) and (4) indicate three main conclusions. First,*ad valorem* freight rates responded differently to distance in each market.[57] While freight rates increased by 0.21 percentage points when distance increased by 10% among shipments bound to the U.S. East coast, freight rates fell 0.11 percentage points among shipments bound to the U.S. West coast when distance increased in that magnitude. Second, freight rates are not sensitive to oil prices. Freight rates only increased by 0.03-0.04 percentage points in shipments bound to both U.S. coasts, when oil prices increased by 10%.[58] In addition, freight rates only decreased 0.01 and 0.03 percentage points, respectively, when the volume shipped in a route or handled at the destination d increased by 10%.

Columns (3) and (6) in Table 3 show the results of estimating (13) among shipments of U.S. imports bound to each U.S. coast during 2013-2017. Specifically, Column (3) indicates that freight rates charged to shipments bound to the U.S. East coast were more sensitive to cost shocks. Freight rates charged to these shipments increased by 0.15 percentage points when distance increased by 10%. These also increased by 0.02 percentage points when oil prices increased by 10%. Likewise, they fell 0.01 and 0.03 percentage points, respectively, when volume shipped in a route or in the cargo handled at destination d increased by 10%. By contrast, freight rates charged to shipments bound to the U.S. West coast only responded to the scale of shipping in the destination port. These freight rates decreased by 0.03 percentage points when volume handled in destination d increased by 10%. All the above thus indicates that freight rates responded slightly to cost shifters during 2002-2007 and 2013-2017. Freight rate volatility was more related to shipping mark-ups.

[56] As explained above, U.S. imports of oil and related products are excluded from these estimates. These flows might generate an endogeneity problem in the estimation, given the role of oil as input for carriers.

[57] An increase of 10% is approximately 1,200 kilometers when it is evaluated at the mean shipping distance.

[58] In order to estimate the expected change in the *ad valorem* freight rates due to an increase of X% in one of the cost shifters, I use the fact that this change is equal to $\widehat{\gamma} \times \ln\left(\frac{100+X}{100}\right)$. In all cases, $\widehat{\gamma}$ corresponds to the estimated coefficients to each variable in the estimation.

5.3 Maritime Shipping Mark-ups

Having estimated $\rho_o^{k,c}$ in Section 5.1 and *ad valorem* shipping costs ($T^\ell(\chi_{od}^{k,c})$) and the maximum/minimum willingness to pay for shipping product ($a_{od}^{k,c}$) in Section 5.2, shipping mark-ups ($\mu_{od}^{k,c}$) are calculated for every combination $o - d - k - c - t$. In order to characterize the central tendency of these estimates, the median per shipping route (od) and then per year (t) is calculated. This section reports the results of these estimates. It then shows results from estimating how shipping mark-ups vary with product and route characteristics. Finally, it shows back-of-the-envelope calculations conducted to estimate the U.S. reduction in welfare due to shipping mark-ups.

5.3.1 The size of Maritime Shipping Mark-ups

Table 4 shows the median shipping mark-up as a share of freight charges. The first row shows that the median $\widehat{\mu_{od}^{k,c}}$ ranges from 34% to 43% on U.S. import shipments bound to the U.S. East coast. The second row indicates that the median $\widehat{\mu_{od}^{k,c}}$ ranges from about 32% to 34% on U.S. import shipments bound to the U.S. West coast.[59] Additionally, Table 4 shows that carriers reduced the rents that they could extract from the market along with the observed reduction in freight rates after the GFC. Prior to the crisis, the median $\widehat{\mu_{od}^{k,c}}$ accounted for 43.4% of the freight rates charged for shipping products to the U.S. East coast, and 34.2% of the freight rates charged for shipping products to the U.S. West coast. During the post-crisis period, the median $\widehat{\mu_{od}^{k,c}}$ only accounted for 34.1% and 32.7% of the freight rates, respectively. Thus, this reduction in the shipping mark-ups just confirms the tougher market conditions that carriers faced after the GFC.[60]

At the country level, Table 5 does not show an overall pattern during 2002-2017. The median $\widehat{\mu_{od}^{k,c}}$

[59] As noted, shipping mark-ups are estimated as a Lerner (1934) index. These mark-ups thus are positive when the elasticity of the inverse demand elasticity (η) is negative (See expression (15)). Estimates from this sample though produce a puzzle. About 20% to 25% of the estimated mark-ups on shipments to the U.S. East coast and 30% to 36% of those charged on shipments to the U.S. West coast are negative. One explanation is that mode switching in the transportation market may lead freight markets to have a positive elasticity for a single mode. Given that shipping a product by air is very sensitive to fuel prices (Hummels et al., 2014), the price demand elasticity can be positive for products that more often switch among modes of transportation. The rationale is simple. A negative (positive) shock in fuel prices tends to more drastically increase (decrease) the cost of freight by air than the costs of shipping via other modes of transportation. Hence, this may encourage mode switching and expands the demand for other shipping modes, despite the cost of freight via those modes could have also increased (decreased). I mainly attribute the estimated negative mark-ups to this phenomenon. However, I acknowledge that these negative mark-ups might be also explained by excessive shipping capacity, subventions for shipping products or even insufficient observations for estimating the mark-ups for some combinations of origin, destination, product, and year.

[60] See GSF Global Shippers Forum (2017), ICS International Chamber of Shipping (2017), and Samunderu (2018).

depends on the U.S. coast to which carriers ship the products. Columns (1) to (3) show that carriers serving the U.S. East coast reduced more their mark-ups during 2013-2017 on shipments from Asian countries (such as Japan and Vietnam) than on shipments from European countries (such as Germany and the United Kingdom). In contrast, columns (4) to (6) show that carriers serving the U.S. West coast reduced the mark-ups charged on shipments from Asian countries (such as China, Taiwan and Vietnam) during this period, but they raised the mark-ups on shipments from European countries (such as Germany, the United Kingdom and Italy). Additionally, Table 6 and Table 7 show that carriers charge higher mark-ups when shipping products to larger U.S. customs districts. These estimates thus offer evidence that larger mark-ups are charged on routes to bigger destination ports. The intuition behind this is that carriers can exploit significant economies of scale when shipping products to these ports. The resulting lower shipping costs end up leading their mark-ups to account for a larger share of the freight rates. Additionally, freight rates are set off of the demand curve. Carriers thus can leverage the greater preference for shipping products to these ports by charging higher mark-ups.

5.3.2 Evaluating the Predicted Shipping Mark-ups

In order to investigate whether non-competitive behavior in the maritime shipping market disproportionately affects developing and distant countries, I estimate reduced-form models of the *ad valorem* shipping freight rates ${f_{od}^{\ell,k}}^{adv}$, *ad valorem* shipping mark-ups $\widehat{\mu_{od}^{\ell,k}}$, and the tariff equivalent of these mark-ups $\widehat{\tau_{\mu_{od}}^{\ell,k}}$ on the following variables: (1) the shipping distance on a route, $DIST_{od}$; (2) the origin country's GDP per capita, $GDPpc_{ot}$; and (3) the substitution elasticity of each product σ^k (estimated by Soderbery (2015)).[61]

Table 8 shows the results of this estimation. All estimates are very robust and predict the same conclusions in all periods.[62] First, *ad valorem* freight rates are higher for products shipped from developing and distant countries to the U.S. (See Columns 1-2, 7-8 and 13-14). Doubling GDP per capita reduces shipping freight rates by 9 to 11 percent.[63] Shipping freight rates also increase about

[61] The estimated negative mark-ups are excluded from this estimation. These product-country pair might add noise and some endogeneity to the estimation.

[62] To estimate the expected change in the *ad valorem* freight rates and shipping mark-ups due to an increase of X% in the shipping distance or the GDP per capita, I applied $\exp(\widehat{\gamma} \times \ln(\frac{100+X}{100})) - 1$. In all cases, $\widehat{\gamma}$ corresponds to the predicted coefficients in the estimation.

[63] Approximately, this accounts for 0.6 percentage points of the freight rates, assuming an ad valorem freight rate

1.8 to 2.2 percent (i.e. about 0.12 percentage points) for every 1,200 kilometers of extra shipping distance.[64] Second, mark-ups are higher relative to freight rates, when shipping from developed countries, and countries closer to the U.S (See Columns 3-4, 9-10 and 15 - 16). Doubling GDP per capita increases the share of *ad valorem* mark-ups in freight charges by 2 to 3 percent. Likewise, reducing the shipping distance by 10% increases *ad valorem* mark-ups by 0.6 to 0.7 percent. Finally, shipping mark-ups represent a higher tariff equivalent on products shipped from developing and distant countries (See columns 5-6, 11-12 and 17-18). Specifically, these estimates show that halving GDP per capita increases the tariff equivalent of mark-ups approximately by 8 to 11 percent (equivalent to 0.1 to 0.3 percentage points). Likewise, doubling the shipping distance raises this equivalent tariff by 8 to 13 percent (equivalent to 0.1 to 0.3 percentage points).[65]

5.3.3 Counterfactual Calculations

To investigate how shipping mark-ups affect import prices, the estimated mark-ups are used to decompose freight rates into shipping costs and shipping mark-ups. This exercise yields that for each U.S.$6 paid for shipping U.S.$100 of differentiated products during 2002-2007, shipping mark-ups account for U.S.$2.1 to $2.6 (See Figure 5).[66] Likewise, for each U.S.$4.1 to U.S.$4.3 paid for shipping the same amount of merchandise during 2013-2017, shipping mark-ups were about U.S.$1.4. Thus, shipping mark-ups represented an equivalent *ad valorem* tariff of 2.1% to 2.6% during 2002-2007 and of 1.4% during 2013-2017. These estimates are roughly one to two-thirds of the average U.S. tariff during this period, which ranged from 2.8% to 4.0% (World-Bank, 2021).

5.3.4 The Effects of Shipping Mark-ups on International Trade Flows and Welfare

In order to estimate the quantitative implications of non-competitive pricing behavior on trade and welfare, I conduct two additional exercises. First, I apply a standard value for the trade

of about 6%.

[64] 1,200 kilometers is equivalent to an increase of 10% in the average shipping distance.

[65] An intuitive way to understand these results is that freight rates are lower when shipping products from developed countries or nearby countries to the U.S. Then, shipping mark-ups account for a greater share with respect to the freight charges on shipments from those countries. However, shipping mark-ups account for a larger share relative to the value of the products shipped from developing countries, given that developing countries mostly produce lower unit-value products. This implies that the share on shipping mark-ups in the unit value of the produced manufacturers in these countries is higher than the share in developed countries.

[66] Approximately, 6% corresponds to the median *ad valorem* freight rate during 2002-2007. About 4.1% to 4.3% corresponds to the median *ad valorem* freight rates charged for shipping a product to the U.S. during 2013-2017.

elasticity to quantify the response of U.S. imports to the implicit costs of the estimated mark-ups. Second, I conduct back-of-the envelope calculations, applying the trade elasticity to calculate the welfare loss attributable to maritime shipping mark-ups.

The response of trade flows to trade costs largely depends on the assumed trade elasticity.[67] Many studies estimate trade elasticities ranging from 5 to 10.[68] Recent estimates predict smaller elasticities, ranging from 3 to 5, and estimates in shipping markets find that it equals to 3 (Simonovska and Waugh, 2014; Wong, 2017). Using these estimates for the trade elasticity, and that shipping mark-ups accounted for an equivalent *ad valorem* tariff of 2.1% to 2.6% during 2002-2007 and of 1.4% during 2013-2017, I estimate that U.S. imports would have been 7.0% to 11.6% greater in 2002-2007 and 4.2% to 6.1% in 2013-2017 if mark-ups had been set to zero (See Table 9).

In terms of welfare, the loss attributed to non-competitive behavior in the shipping industry can be estimated by applying the approach of Arkolakis et al. (2012). That paper shows that the percentage change in welfare ($\widehat{W}$) due to a shock can be computed as $\widehat{\lambda}^{-1/\epsilon}$; where $\widehat{\lambda}$ is the percentage change in the share of domestic expenditure and ϵ is the trade elasticity. Costinot and Rodríguez-Clare (2014) also show that this formula is robust to the micro-level structure of a model. I thus calculate the welfare loss of shipping mark-ups this way.

$$\widehat{W} = \lambda_{NOmark-ups}^{-1/\epsilon} - \lambda_{mark-ups}^{-1/\epsilon} \tag{17}$$

Using the fact that U.S. import penetration ranged from 12.5% to 16.6% during 2002-2017 and predicting that it would have been 13.1% to 17.2% in a scenario without mark-ups for differentiated products, $\lambda_{mark-ups}$ would average 83.4%-87.5%, and $\lambda_{NOmark-ups}$ would average 82.8%-86.9%. Using a trade elasticity of 3 to 5, equation (17) yields that U.S. consumers perceived an average loss of about 0.1%-0.2% in their real income during 2002-2017 due to shipping mark-ups (See Table 10). As a point of reference, this loss would be about two-thirds of the 0.3% estimated cost to consumers of the U.S.-China trade war (Fajgelbaum et al., 2019).

[67] Simonovska and Waugh (2014) survey most of these studies.
[68] See Anderson and van Wincoop (2004).

5.3.5 Did the 2008-2012 Global Financial Crisis (GFC) Affect Carriers' Ability to Exert Market Power?

The estimation strategy employed in this paper assumes parameter stability within the period of study. Assuming stability during the GFC period (2008-2012) is questionable. Global aggregate demand for goods and services was seriously distorted. Some costs for carriers (e.g. oil prices) reached atypical levels, and unused capacity in the market significantly increased (UNCTAD, 2017).[69] However, this is a period of significant interest. I thus apply the same estimation strategy to the period 2008-2012, in order to inform our understanding of the effects of the GFC.

All estimates reveal two lessons. First, shipping costs were volatile during 2008-2012. Second, carriers reduced their μ during this period. Appendix E shows a detailed analysis of these results.

5.3.6 Robustness to disaggregation

All previous results were estimated using the U.S. imports at HS6-digit product code. Atkin and Donaldson (2015) apply this estimation strategy using product barcode level data. One concern thus is whether all estimates are robust to the data aggregation. Alchian-Allen effects may undermine the identification of $\widehat{\rho}$ and so of $\widehat{\mu}$.[70] In order to test the robustness of the previous estimates, all models were re-estimated using U.S. imports at HS10-digit product level.

This exercise shows that $\widehat{\rho}$ are robust to disaggregation of the U.S. import data to the HS10 level.[71] The correlation between the $\widehat{\rho}$ using data at HS6-digit product code versus the average of those estimated using data at HS10-digit code ranges between 66% to 78%. Likewise, a graphical analysis, in which both sets of $\widehat{\rho}$ are plotted along with a solid 45-degree line, indicates that most $\widehat{\rho}$ are

[69] Table C1 shows that, during the crisis period, *ad valorem* freight rates ($f^k_{\ell,r}$) decreased to 6.2%-6.7%, 1.5 percentage points lower than in the period 2002-2007. The average volume of goods shipped also fell by 10.2% in routes to the U.S. East coast and by 5.6% in routes to the U.S. West coast. Likewise, important cost shifters for shipping carriers such as oil prices were very volatile. Oil prices decreased to almost US$40 per barrel in 2009. Then, these prices reversed their trend and touched the barrier of US$120 in 2011 and oscillated around US$90 to US$100 afterwards.

[70] Hummels and Skiba (2004) show that transport costs affect the quality-composition of the traded products. So, if the quality of the products pooled within each HS6-digit level is sufficiently large, a transportation cost shock would affect the quality-composition within each HS6-digit product. Hence, the FOB price would be endogenous to transportation costs within each HS6 digit product code.

[71] To conduct this exercise, I previously removed every outlier estimated for ρ. To do so, every $\widehat{\rho}$ higher than 30 (which is roughly 10 times the percentile 90 of $\widehat{\rho}$) was excluded from this exercise. That is, I excluded about 40 observations out of approximately 50,000 observations in the subsample for the U.S. East coast, and 30 observations out of the 28,000 in the subsample of the West coast.

stable surrounding this solid line; regardless the level of aggregation of the U.S. imports data (See Figure 6 and Figure 7). Most discrepancies appear to be related to some extremely high values for ρ for a relatively small number of HS10-digit products. The HS10 data have fewer observations per product-category, and thus are subject to more measurement error in the estimates of ρ.

Table 11 shows that all estimates for ρ are robust to the aggregation level. The distribution of both sets of estimates is quite similar. The median ρ in both distributions is 1.01. The mean only differs by 0.2 points. Likewise, both distributions have their minimum values around 0.4.

Another concern is whether the estimated $\widehat{\mu}$ are robust to the aggregation level of the data. To evaluate this issue, shipping mark-ups are calculated using $\widehat{\rho}$ for HS10-digit product codes. Table 12 shows that $\widehat{\mu}$ are robust in terms of magnitude. Regardless of the level of product disaggregation, the median $\widehat{\mu}$ is about one-third of the shipping freight charges. Likewise, estimates at HS10-digit product code reaffirms that carriers charged higher mark-ups before the GFC. I therefore conclude that aggregation of the data does not generate any quantitatively important bias.

6 Conclusion

This paper quantifies the effect of non-competitive pricing behavior in the maritime shipping industry on (1) total freight costs, (2) the volume of international trade, and (3) economic welfare. The method of Atkin and Donaldson (2015) is applied to maritime shipments of U.S. imports. Shipping mark-ups charged on freight charges for periods 2002-2007, 2008-2012, and 2013-2017 are estimated. The method allows quantifying the magnitude and implications for trade and welfare of the problem of market power in the maritime shipping industry.

The method of Atkin and Donaldson (2015) solves the theoretical problem of separately identifying firms' marginal costs and mark-ups. Using the pass-through rates ρ of marginal costs to freight rates to purge endogenous responses of mark-ups to changes in cost on an estimated model for shipping freight rates, carriers' marginal costs are retrieved. Then, shipping mark-ups are calculated as a standard Lerner (1934) index.

The estimated pass-through rates reaffirm previous empirical evidence of imperfect competition in the maritime shipping industry. Furthermore, the distribution of the pass-through rates reveals that carriers do not exert their market power uniformly across routes, products, and over time. Carriers extract larger rents when shipping products for which they can more-than-completely pass through a cost shock to their freight (about half of the products). Likewise, they do the same when shipping products with partial pass-through rates. The difference, in this second case, is that carriers are forced to reduce their mark-ups whenever there is a positive cost shock.

This paper also estimates that maritime shipping mark-ups represent approximately one third of shipping freight charges on U.S. imports. Specifically, these estimated margins range from 34% to 43% of freight charges on shipments delivered to the U.S. East coast and from 32% to 34% on those delivered to the U.S. West coast. Likewise, the estimates imply that shipping carriers charge higher mark-ups on shipments delivered to U.S. ports that handle large flows of imports.

Putting these results in context, this paper estimates that maritime shipping mark-ups represent an *ad valorem* tariff for differentiated products that ranges from 1.4% to 2.6%. These are similar in magnitude to average *ad valorem* tariffs in the U.S. from the last two decades. Using trade elasticities from the literature, the estimates imply that U.S. imports would have been approximately 4.2% to 11.6% higher if mark-ups were set equal to zero. The implied welfare costs of mark-ups for U.S. consumers is an annual reduction of approximately 0.1%-0.2% of their real income. In addition, estimated mark-ups are larger for shipments from poorer and more distant countries.

References

Amjadi, A. and A. Yeats (1995). Have Transport Costs Contributed to the Relative Decline of Sub-Saharan African Exports? Policy Research, Working Paper 1558, World Bank, Washington, D.C.

Anderson, J. E. and E. van Wincoop (2004). Trade Costs. *Journal of Economic Literature 42*(3), 691–751.

Ardelean, A. and V. Lugovskyy (2018). Firm-level heterogeneity in International Transport Costs: Evidence from Chile. *Mimeo.*

Arkolakis, C., A. Costinot, and A. Rodriguez-Clare (2012). New Trade Models, Same Old Gains? *American Economic Review 102*(1), 94–130.

Armington, P. S. (1969). A Theory of Demand for Products Distinguished by Place of Production. *Staff Papers 16*(1), 159–178.

Asturias, J. (2019). Endogenous transportation costs. [Revise and Resubmit, *European Economic Review*].

Atkin, D. and D. Donaldson (2015). Who's Getting Globalized? The Size and Implications of Intra-National Trade Costs. [Revise and Resubmit, *Econometrica*].

Balassa, B. (1965). Trade Liberalisation and "Revealed" Comparative Advantage. *The Manchester School 33*(2), 99–123.

Bergquist, L. F. and M. Dinerstein (2020). Competition and entry in agricultural markets: Experimental evidence from kenya. *American Economic Review 110*(12), 3705–47.

Brancaccio, G., M. Kalouptsidi, and T. Papageorgiou (2020). Geography, transportation, and endogenous trade costs. *Econometrica 88*(2), 657–691.

Brancaccio, G., M. Kalouptsidi, T. Papageorgiou, and N. Rosaia (2021). Search frictions and efficiency in decentralized transportation markets. Technical report, National Bureau of Economic Research.

Broda, C. and D. E. Weinstein (2006). Globalization and the Gains from Variety. *The Quarterly Journal of Economics 121*(2), 541–585.

Bryan, I. (1974). Regression Analysis of Ocean Liner Freight Rates on some Canadian Export Routes. *Journal of Transport Economics and Policy 8*(2), 161–173.

Bulow, J. I. . and P. Pfleiderer (1983). A Note on the Effect of Cost Changes on Prices. *Journal of Political Economy 91*(1), 182–185.

Clark, X., D. Dollar, and A. Micco (2004). Port Efficiency, Maritime Transport Costs, and Bilateral Trade. *Journal of Development Economics 75*(2), 417–450.

Clyde, P. S. and J. D. Reitzes (1998). Market Power and Collusion in the Ocean Shipping Industry: Is a Bigger Cartel a Better Cartel? *Economic Inquiry 36*(2), 292–304.

Costinot, A. and A. Rodríguez-Clare (2014). Trade theory with numbers: Quantifying the consequences of globalization. In *Handbook of international economics*, Volume 4, pp. 197–261. Elsevier.

Davies, J. (1986). *The Theory of Contestable Markets and its Application to the Liner Shipping Industry*. Canadian Transport Commission, Research Branch, Transport Industries Analysis.

Devanney III, J. W., V. Livanos, and R. Stewart (1975). Conference Ratemaking and the West Coast of South America. *Journal of Transport Economics and Policy 9*(2), 154–177.

Fabinger, M. and E. G. Weyl (2012). Pass-Through and Demand Forms. University of Chicago. *Mimeo*.

Fajgelbaum, P. D., P. K. Goldberg, P. J. Kennedy, and A. K. Khandelwal (2019). The Return to Protectionism. National Bureau of Economic Research - NBER, Working Paper 25638, Cambridge, MA.

Feenstra, R. C. (1994). New Product Varieties and the Measurement of International Prices. *The American Economic Review*, 157–177.

Fink, C. (2002). Trade in International Maritime Services: How Much Does Policy Matter? *The World Bank Economic Review 16*(1), 81–108.

GSF Global Shippers Forum (2017). 6th Annual Report. Technical Report October, Global Shippers' Forum, Kent, UK.

Heaver, T. D. (1973). The Structure of Liner Conference Rates. *The Journal of Industrial Economics 21*(3), 257–265.

Hoffmann, J. and S. Kumar (2013). Globalisation–The Maritime Nexus. In *The Handbook of Maritime Economics and Business*, pp. 65–94. Informa Law from Routledge.

Hummels, D. (2007). Transportation Costs and International Trade in the Second Era of Globalization. *Journal of Economic Perspectives 21*(3), 131–154.

Hummels, D., R. Jørgensen, J. Munch, and C. Xiang (2014). The Wage Effects of Offshoring: Evidence from Danish Matched Worker-Firm Data. *American Economic Review 104*(6), 1597–1629.

Hummels, D., V. Lugovskyy, and A. Skiba (2009). The Trade Reducing Effects of Market Power in International Shipping. *Journal of Development Economics 89*(1), 84–97.

Hummels, D. and A. Skiba (2002). A Virtuous Circle? Regional Tariff Liberalization and Scale Economies in Transport. Purdue University. *Mimeo*.

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

Hummels, D. L. and G. Schaur (2013). Time as a Trade Barrier. *American Economic Review 103*(7), 2935–59.

ICS International Chamber of Shipping (2017). 2017 Annual Review. Technical report, Global Shipping Industry, London.

Korinek, J. and P. Sourdin (2009). Maritime Transport Costs and Their Impact on Trade. Organization for Economic Co-operation and Development TAD/TC/WP (2009)7.

Lai, H. and D. Trefler (2002). The gains from trade with monopolistic competition: specification, estimation, and mis-specification.

Lerner, A. P. (1934). The Concept of Monopoly and the Measurement of Monopoly Power. *The Review of Economic Studies 1*(3), 157–175.

Limao, N. and A. J. Venables (2001). Infrastructure, Geographical Disadvantage, Transport Costs, and Trade. *The World Bank Economic Review 15*(3), 451–479.

Martínez-Zarzoso, I., E. M. Pérez-García, and C. Suárez-Burguet (2008). Do Transport Costs have a Differential Effect on Trade at the Sectoral Level? *Applied Economics 40*(24), 3145–3157.

Micco, A. and N. Pérez (2001). Maritime Transport Costs and Port Efficiency. In *Seminar "Towards Competitiveness: The Institutional Path". Santiago, Chile: IDB*. Citeseer.

Park, S. and S. Gupta (2012). Handling endogenous regressors by joint estimation using copulas. *Marketing Science 31*(4), 567–586.

Pless, J. and A. A. Van Benthem (2017). The Surprising Pass-Through of Solar Subsidies. National Bureau of Economic Research - NBER, Working Paper 23260, Cambridge, MA.

Radelet, S. and J. D. Sachs (1998). Shipping Costs, Manufactured Exports, and Economic Growth. Harvard Institute for Economic Development. *Mimeo*.

Rauch, J. E. (1999). Networks Versus Markets in International Trade. *Journal of International Economics 48*(1), 7–35.

Samunderu, E. (2018). The Maritime Container Transportation Chain (MCTC). In R. Neise (Ed.), *Container Logistics: The Role of the Container in the Supply Chain*, Chapter ONE, pp. 11–30.

Sánchez, R. J., J. Hoffmann, A. Micco, G. V. Pizzolitto, M. Sgut, and G. Wilmsmeier (2003). Port Efficiency and International Trade: Port Efficiency as a Determinant of Maritime Transport Costs. *Maritime Economics & Logistics 5*(2), 199–218.

Simonovska, I. and M. E. Waugh (2014). The elasticity of trade: Estimates and evidence. *Journal of international Economics 92*(1), 34–50.

Soderbery, A. (2015). Estimating import supply and demand elasticities: Analysis and implications. *Journal of International Economics 96*(1), 1–17.

Sys, C. (2009). Is the container liner shipping industry an oligopoly? *Transport Policy 16*(5), 259–270.

UNCTAD (2017). *Review of Maritime Transport 2017*. New York and Geneva: UNITED NATIONS PUBLICATION.

Weyl, E. G. and M. Fabinger (2013). Pass-Through as an Economic Tool: Principles of Incidence under Imperfect Competition. *Journal of Political Economy 121*(3), 528–583.

Wilmsmeier, G. and J. Hoffmann (2008). Liner Shipping Connectivity and Port Infrastructure as Determinants of Freight Rates in the Caribbean. *Maritime Economics & Logistics 10*(1-2), 130–151.

Wilmsmeier, G., J. Hoffmann, and R. J. Sanchez (2006). The Impact of Port Characteristics on International Maritime Transport Costs. *Research in Transportation Economics 16*, 117–140.

Wong, W. F. (2017). The Round Trip Effect : Endogenous Transport Costs and International Trade. World Trade Organization, Geneva, Switzerland.

World-Bank (2021). Database, Statistics, World Development Indicators - WB-WDI.

7 Tables

Table 1: Summary Statistics - Short Run Pass Through-Rate ρ

	U.S. East Coast								
	2002-2007			2008-2012			2013-2017		
	OLS	2SLS	GC	OLS	2SLS	GC	OLS	2SLS	GC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Mean	1.09	1.10	1.42	1.07	1.14	1.10	1.06	1.10	1.16
Median	1.02	1.02	1.01	1.02	1.01	1.01	1.01	1.01	1.01
Std Deviation	1.30	2.04	31.98	1.22	4.23	2.73	0.77	3.55	9.78
Percentile 1%	0.59	0.49	0.43	0.60	0.49	0.44	0.62	0.51	0.46
Percentile 99%	2.00	2.26	2.71	1.94	2.36	2.54	1.91	2.26	2.47
Number Obs.	44,555	42,966	55,212	39,642	37,474	48,578	42,914	41,400	52,277

	U.S. West Coast								
	2002-2007			2008-2012			2013-2017		
	OLS	2SLS	GC	OLS	2SLS	GC	OLS	2SLS	GC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Mean	1.09	1.10	1.11	1.06	1.36	1.06	1.12	1.14	1.13
Median	1.02	1.02	1.01	1.01	1.01	1.00	1.01	1.01	1.00
Std Deviation	1.77	1.85	3.14	1.73	41.62	1.73	8.86	9.09	8.61
Percentile 1%	0.58	0.51	0.46	0.58	0.52	0.44	0.61	0.51	0.46
Percentile 99%	1.90	2.11	2.30	1.78	2.07	2.09	1.81	2.11	2.14
Number Obs.	27,971	26,992	31,823	24,398	23,112	27,520	25,603	24,673	28,819

Table 2: Correlation of the estimated Short-run Pass Through-Rates among econometric techniques

	U.S. East Coast				U.S. West Coast		
2002-2007		OLS	2SLS	GC		OLS	2SLS	GC
	OLS	1.000			OLS	1.000		
	2SLS	0.695	1.000		2SLS	0.972	1.000	
	GC	0.996	0.691	1.000	GC	0.998	0.970	1.000
2008-2012		OLS	2SLS	GC		OLS	2SLS	GC
	OLS	1.000			OLS	1.000		
	2SLS	0.308	1.000		2SLS	0.043	1.000	
	GC	0.996	0.307	1.000	GC	0.998	0.042	1.000
2013-2017		OLS	2SLS	GC		OLS	2SLS	GC
	OLS	1.000			OLS	1.000		
	2SLS	0.486	1.000		2SLS	0.997	1.000	
	GC	0.991	0.477	1.000	GC	1.000	0.997	1.000

Table 3: Adjusted *Ad-Valorem* Freight Rates Function

	U.S. East Coast			U.S. West Coast		
	2002-2007	2008-2012	2013-2017	2002-2007	2008-2012	2013-2017
	(1)	(2)	(3)	(4)	(5)	(6)
log (Distance)	0.0342***	-0.00438	-0.00248	-0.0365**	-0.00633	0.0363
	(0.00446)	(0.00861)	(0.00421)	(0.0152)	(0.0244)	(0.0313)
log (Oil Price)	0.0325***	-0.0219	-0.0327***	-0.0545*	0.0300	0.117
	(0.00837)	(0.0179)	(0.00766)	(0.0315)	(0.0490)	(0.0764)
log (Distance) × log (Oil Price)	-0.00299***	0.00385**	0.00366***	0.00614*	-0.00210	-0.0123
	(0.000899)	(0.00189)	(0.000826)	(0.00338)	(0.00526)	(0.00816)
log (Weight/Value)	0.0120***	0.00817***	0.00827***	0.0111***	0.0112***	0.00976***
	(0.000743)	(0.00103)	(0.000689)	(0.000933)	(0.000901)	(0.00124)
log (Vol. Route)	-0.00135***	-0.00113***	-0.000934***	-0.000996**	-0.00161***	-0.000151
	(0.000249)	(0.000230)	(0.000228)	(0.000387)	(0.000471)	(0.00118)
log (Vol. Destination Port)	-0.00356***	-0.00304***	-0.00289***	-0.00356***	-0.00201***	-0.00385***
	(0.000369)	(0.000374)	(0.000296)	(0.000429)	(0.000524)	(0.000965)
constant	-0.0871**	0.187**	0.226***	0.630***	0.243	-0.0897
	(0.0404)	(0.0798)	(0.0388)	(0.141)	(0.228)	(0.277)
N	873,922	700,917	778,280	296,375	231,678	244,074
R-sq	0.996	0.993	1.000	1.000	0.999	0.995

Standard errors in parenthesis are clustered by product-origin country, product-year and product-U.S. customs district of entry.
*p $<$ 0.1, **p $<$ 0.05, ***p $<$ 0.01
Note: these model excludes imports of oil and related products, pooled at the HS2 digit-code sector 27. The dependent variable is the adjusted freight rate derived in expression (13).

Table 4: Median Maritime Shipping Mark-ups
(% of Maritime Shipping Freight Charges)

	2002-2007	2008-2012	2013-2017
	(1)	(2)	(3)
U.S. East Coast	43.4	38.2	34.1
U.S. West Coast	34.2	27.5	32.7

Note: columns (1)-(6) report the median *ad valorem* mark-ups to maritime shipping freight rates across HS6-digit products and shipping routes.

Table 5: Median Maritime Shipping Mark-ups per Origin Country
(% of Maritime Shipping Freight Charges)

		U.S. East Coast			U.S. West Coast		
	Avg. Share Imports	2002-2007	2008-2012	2013-2017	2002-2007	2008-2012	2013-2017
	2002-2017	(1)	(2)	(3)	(4)	(5)	(6)
China	36.4%	45.4	43.5	40.1	34.7	18.9	4.8
Japan	15.1%	45.3	32.4	31.6	18.4	6.3	23.1
Germany	8.5%	34.9	34.9	34.9	20.8	16.4	31.0
South Korea	5.0%	41.0	38.6	35.0	28.6	24.4	28.6
Taiwan	2.9%	43.2	37.7	35.7	23.7	17.1	10.9
United Kingdom	2.4%	41.5	40.0	45.9	27.3	26.2	51.3
Italy	2.4%	44.4	35.9	39.0	27.8	21.6	38.8
Vietnam	2.0%	67.3	52.6	39.6	43.6	30.9	16.1

Note: columns (1)-(6) report the median *ad valorem* mark-ups to maritime shipping freight rates across HS6-digit products and shipping routes from the main U.S trade partners.
All shipping mark-ups reported in this table are estimated using the estimated short-run pass-through rate $\widehat{\rho}$ with the GC method.

Table 6: Median Maritime Shipping Mark-ups per U.S. Customs District - U.S. East Coast (% of Maritime Shipping Freight Charges, Vol in tons.)

U.S. Customs District	U.S. State	Average Volume of Imports (2002-2017)	2002-2007 (1)	2008-2012 (2)	2013-2017 (3)
New York	New York	12,279,871	51.8	46.1	39.0
Houston	Texas	9,039,294	45.0	43.0	36.6
Savannah	Georgia	6,843,465	43.1	42.2	34.6
New Orleans	Louisiana	4,690,192	43.9	40.5	32.8
Norfolk	Virginia	3,683,120	44.8	38.7	35.6
Charleston	South Carolina	3,639,882	41.6	37.1	34.7
Miami	Florida	3,182,187	47.3	41.2	36.1
Baltimore	Maryland	2,983,977	40.8	33.5	34.4
Philadelphia	Pennsylvania	2,922,930	43.6	36.2	33.2
Mobile	Alabama	2,105,040	36.9	34.6	34.3
Tampa	Florida	1,954,416	42.9	36.5	30.1
Charlotte	North Carolina	1,181,784	39.7	32.3	30.0
Boston	Massachusetts	766,603	42.8	33.3	30.8
Port Arthur	Texas	303,223	23.6	25.7	29.1
Providence	Rhode Island	279,663	29.6	23.4	28.7
Portland	Maine	89,718	32.4	27.3	11.3
Washington	District of Columbia	12,902	28.2	17.7	17.5

Note: columns (1)-(3) report the median *ad valorem* mark-ups to maritime shipping freight rates across HS6-digit products and shipping routes to U.S. Customs Districts located geographically in the U.S. East coast.
All shipping mark-ups reported in this table are estimated using the estimated short-run pass-through rate $\widehat{\rho}$ with the GC method.

Table 7: Median Maritime Shipping Mark-ups per U.S. Customs District - U.S. West Coast (% of Maritime Shipping Freight Charges, Vol in tons.)

U.S. Customs District	U.S. State	Average Volume of Imports (2002-2017)	2002-2007 (1)	2008-2012 (2)	2013-2017 (3)
Los Angeles	California	26,182,706	37.7	38.4	43.1
Seattle	Washington	3,748,008	34.2	24.3	27.0
San Francisco	California	3,739,735	32.9	27.1	34.1
Columbia-Snake	Oregon	1,683,939	37.0	22.7	22.3
San Diego	California	416,418	27.9	9.6	24.3
Anchorage	Alaska	16,333	19.3	36.9	40.5

Note: columns (1)-(3) report the median *ad valorem* mark-ups to maritime shipping freight rates across HS6-digit products and shipping routes to U.S. Customs Districts located geographically in the U.S. West coast.
All shipping mark-ups reported in this table are estimated using the estimated short-run pass-through rate $\widehat{\rho}$ with the GC method.

Table 8: Determinants of Maritime Shipping Mark-Ups

	2002-2007					
	Freight Rate		Mark-ups			
	Ad Valorem		*Ad Valorem*		Equivalent Tariff	
	(1)	(2)	(3)	(4)	(5)	(6)
log GDP per capita	-0.154***		0.00341		-0.151***	
	(0.00165)		(0.00209)		(0.00235)	
log Distance	0.231***		-0.0607***		0.170***	
	(0.00461)		(0.00589)		(0.00635)	
log σ		-0.0586***		-0.00162		-0.0603***
		(0.0124)		(0.00625)		(0.0146)
constant	0.881***	1.591***	4.622***	4.095***	0.897***	1.081***
	(0.0484)	(0.00973)	(0.0630)	(0.00347)	(0.0675)	(0.0128)
N	896,701	668,898	896,701	668,898	896,701	668,898
R-sq	0.313	0.073	0.136	0.018	0.329	0.071

	2008-2012					
	Freight Rate		Mark-ups			
	Ad Valorem		*Ad Valorem*		Equivalent Tariff	
	(7)	(8)	(9)	(10)	(11)	(12)
log GDP per capita	-0.161***		0.0272***		-0.134***	
	(0.00236)		(0.00283)		(0.00308)	
log Distance	0.192***		-0.0479***		0.144***	
	(0.00581)		(0.00716)		(0.00745)	
log σ		-0.0484**		0.00602		-0.0424**
		(0.0128)		(0.00843)		(0.0127)
constant	1.100***	1.342***	4.265***	4.074***	0.760***	0.811***
	(0.0649)	(0.00945)	(0.0804)	(0.00606)	(0.0820)	(0.00967)
N	683,896	491,701	683,893	491,698	683,893	491,698
R-sq	0.285	0.054	0.141	0.021	0.316	0.059

	2013-2017					
	Freight Rate		Mark-ups			
	Ad Valorem		*Ad Valorem*		Equivalent Tariff	
	(13)	(14)	(15)	(16)	(17)	(18)
log GDP per capita	-0.148***		0.0388***		-0.110***	
	(0.00273)		(0.00326)		(0.00339)	
log Distance	0.190***		-0.0763***		0.114***	
	(0.00619)		(0.00834)		(0.00737)	
log σ		-0.0635***		-0.00323		-0.0667**
		(0.0130)		(0.00972)		(0.0151)
constant	0.902***	1.246***	4.469***	4.127***	0.765***	0.768***
	(0.0701)	(0.00974)	(0.0930)	(0.00641)	(0.0837)	(0.0124)
N	717,818	524,225	717,810	524,224	717,810	524,224
R-sq	0.258	0.040	0.136	0.019	0.298	0.040
FE: Destination	N	Y	N	Y	N	Y
FE: Year	N	Y	N	Y	N	Y
FE: Origin	N	Y	N	Y	N	Y
FE: Product & Destination	Y	N	Y	N	Y	N
FE: Product & Year	Y	N	Y	N	Y	N

Standard errors in parenthesis are clustered by product-year and product-U.S customs district of entry in columns with an odd number. Standard errors clustered by origin country, U.S. customs district of entry and year in columns with an even number.

*p < 0.1, **p < 0.05, ***p < 0.01

Note: *Ad valorem* freight rates $f_{od}^{\ell,k^{adv}}$ are calculated as the ratio cost of freight to imports FOB value (i.e $f_{od}^{\ell,k^{adv}} = ShF_{od}/M_o^{k^{FOB}}$). *Ad valorem* mark-ups $\mu_{od}^{\ell,k}$ corresponds to those retrieved from applying expression (14). The equivalent tariffs to the estimated mark-ups $\tau_{\mu_{od}}^{\ell,k}$ are calculated as the product between the *Ad valorem* freight rate $f_{od}^{\ell,k^{adv}}$ and the *Ad valorem* mark-ups $\mu_{od}^{\ell,k}$ (i.e. $\tau_{\mu_{od}}^{\ell,k} = f_{od}^{\ell,k^{adv}} \times \mu_{od}^{\ell,k}$). All dependent variables are regressed in natural logarithms.

Table 9: Potential U.S. Import Growth without Shipping Mark-Ups for Differentiated Products

Assumed Trade Elasticity (σ)	2002-2007	2008-2012	2013-2017
$\sigma = 3$	7.0%	4.7%	4.2%
$\sigma = 5$	11.6%	7.8%	7.0%

Note: These estimates show how much U.S. imports would be higher in a scenario were maritime shipping mark-ups were set equal to zero.

Table 10: Welfare Change due to Maritime Shipping Mark-ups (% of GDP)

Assumed Trade Elasticity (σ)	2002-2007	2008-2012	2013-2017
$\sigma = 3$	-0.20%	-0.13%	-0.14%
$\sigma = 5$	-0.20%	-0.13%	-0.14%

Note: These estimates show welfare costs of maritime shipping mark-ups for U.S. consumers relative to their real income.

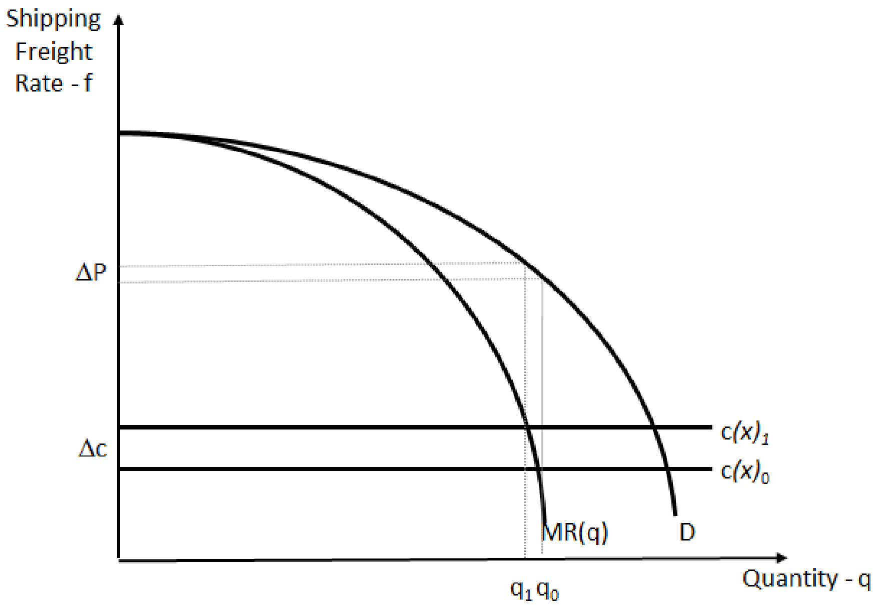
Table 11: Summary Statistics - Short Run Pass Through-Rate ρ
(HS6 digit-code vs HS10 digit-code, Gaussian Copula Estimates)

	U.S. East Coast			
	2002-2007		2013-2017	
	HS6	HS10	HS6	HS10
	(1)	(2)	(5)	(6)
Mean	1.42	1.56	1.16	1.38
Median	1.01	1.01	1.01	1.01
Std Deviation	31.98	53.42	9.78	31.79
Percentile 1%	0.43	0.39	0.46	0.40
Percentile 99%	2.71	2.98	2.47	2.71
Number Obs.	55,212	107,719	52,277	103,990
	U.S. West Coast			
	2002-2007		2013-2017	
	HS6	HS10	HS6	HS10
	(1)	(2)	(5)	(6)
Mean	1.11	1.36	1.13	1.13
Median	1.01	1.01	1.00	1.00
Std Deviation	3.14	47.99	8.61	8.27
Percentile 1%	0.46	0.43	0.46	0.44
Percentile 99%	2.30	2.36	2.14	2.36
Number Obs.	31,823	60,813	28,819	55,637

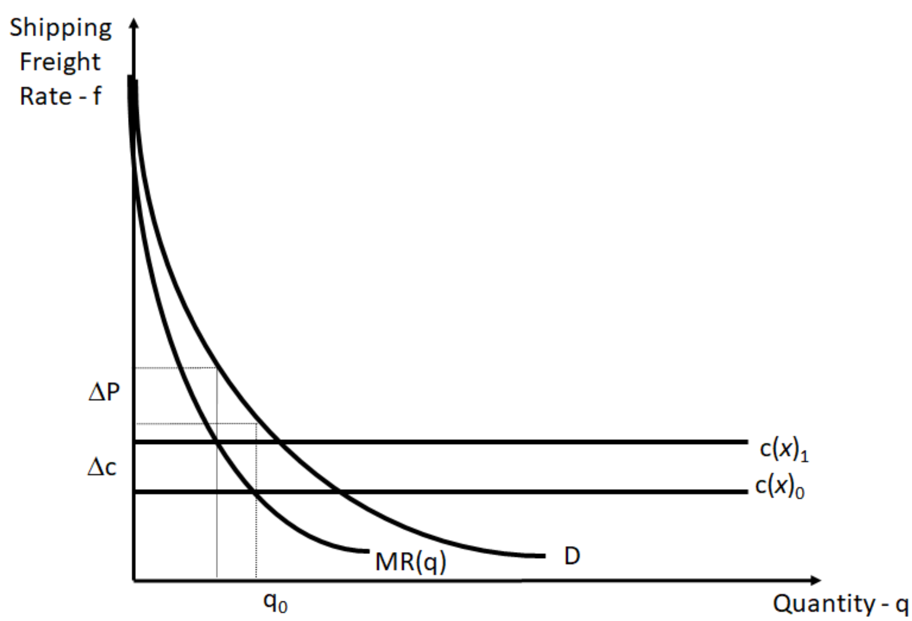
Table 12: Median Maritime Shipping Mark-up - % of Maritime Shipping Freight Freight
(HS6 digit-code vs HS10 digit-code, Gaussian Copula Estimates)

	U.S. East Coast		U.S. West Coast	
	2002-2007	2013-2017	2002-2007	2013-2017
	(1)	(2)	(3)	(4)
HS6 digit-code	43.4	34.1	34.2	32.7
HS10 digit-code	38.0	28.2	37.9	30.1

8 Figures



(a) Concave Demand ($\delta > 0$)
Partial Short-Run Pass-Through Rate ($\rho < 1$)



(b) Convex Demand ($\delta < 0$)
More than complete Short-Run Pass-Through Rate ($\rho > 1$)

Figure 1: Types of Shipping Demand

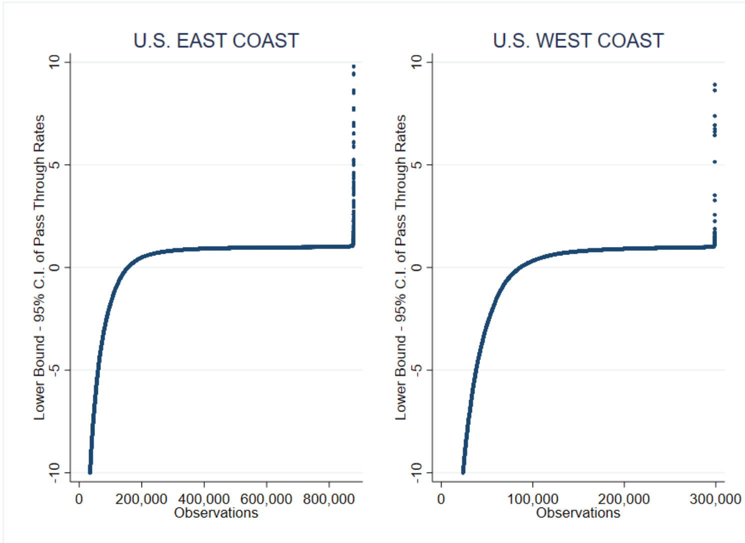


Figure 2: Lower Bound - 95% Confidence Interval of the Estimated Pass-Through Routes 2002-2007

Note: For visual clarity, this figure only shows the lower bound of the 95% Confidence Interval of estimated pass-through rates with the GC method, ranging from -10 to +10. Approximately, this range compiles the values from percentile 10% to percentile 100%.

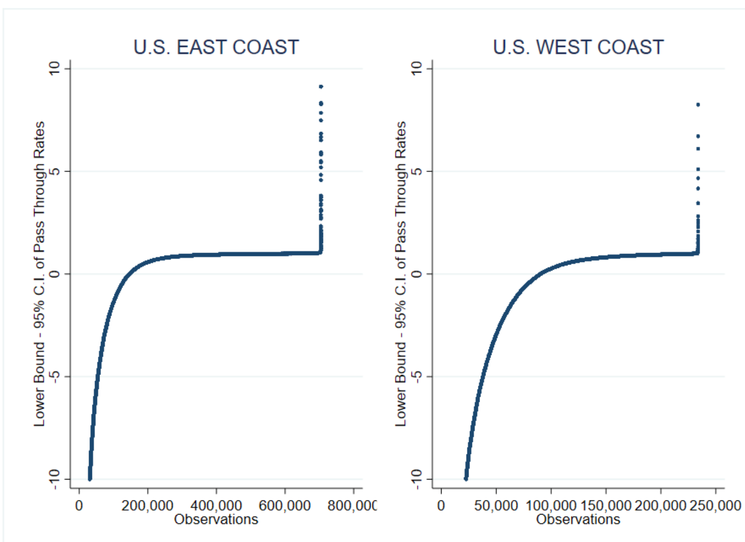


Figure 3: Lower Bound - 95% Confidence Interval of the Estimated Pass-Through Routes - 2008-2012

Note: For visual clarity, this figure only shows the lower bound of the 95% Confidence Interval of estimated pass-through rates with the GC method, ranging from -10 to +10. Approximately, this range compiles the values from percentile 10% to percentile 100%.

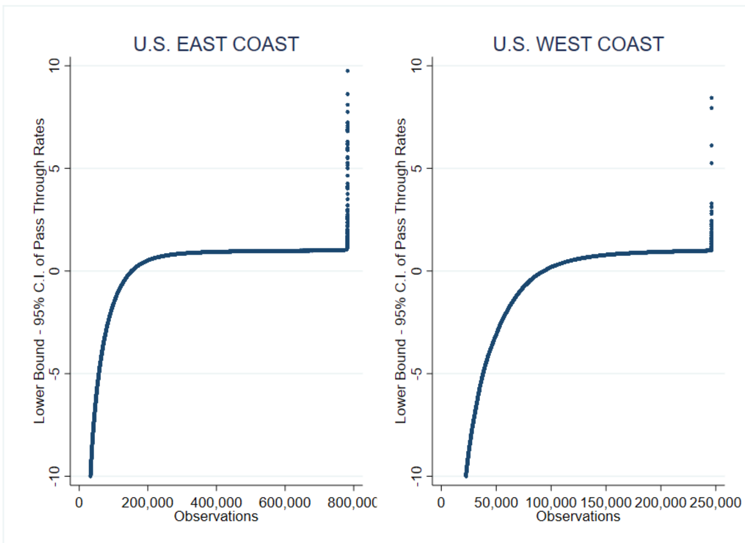


Figure 4: Lower Bound - 95% Confidence Interval of the Estimated Pass-Through Routes - 2013-2017

Note: For visual clarity, this figure only shows the lower bound of the 95% Confidence Interval of estimated pass-through rates with the GC method, ranging from -10 to +10. Approximately, this range compiles the values from percentile 10% to percentile 100%.

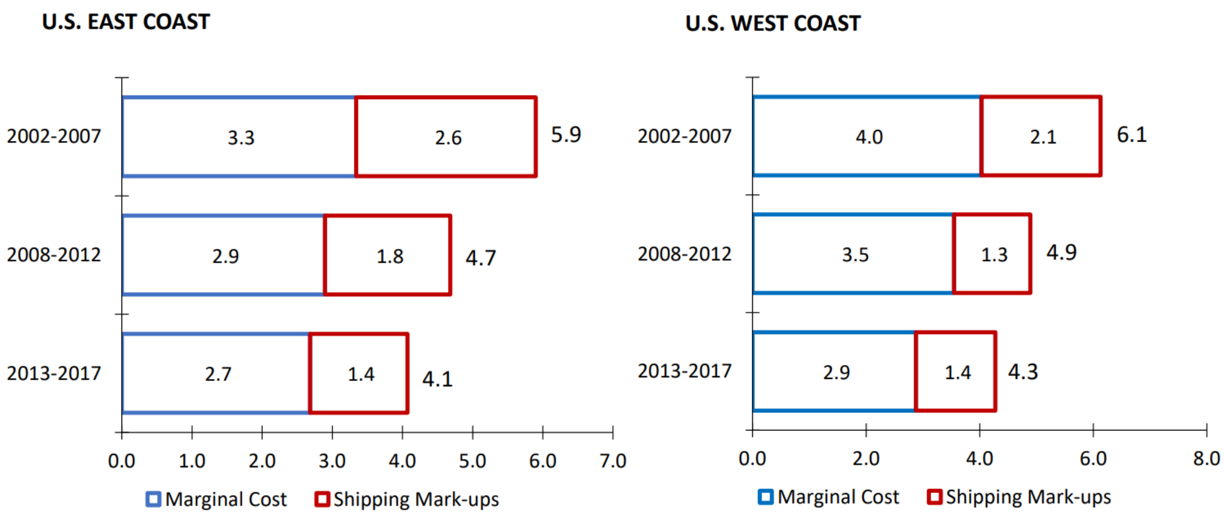


Figure 5: Composition of the median *Ad-Valorem* Shipping Freight Rates, %

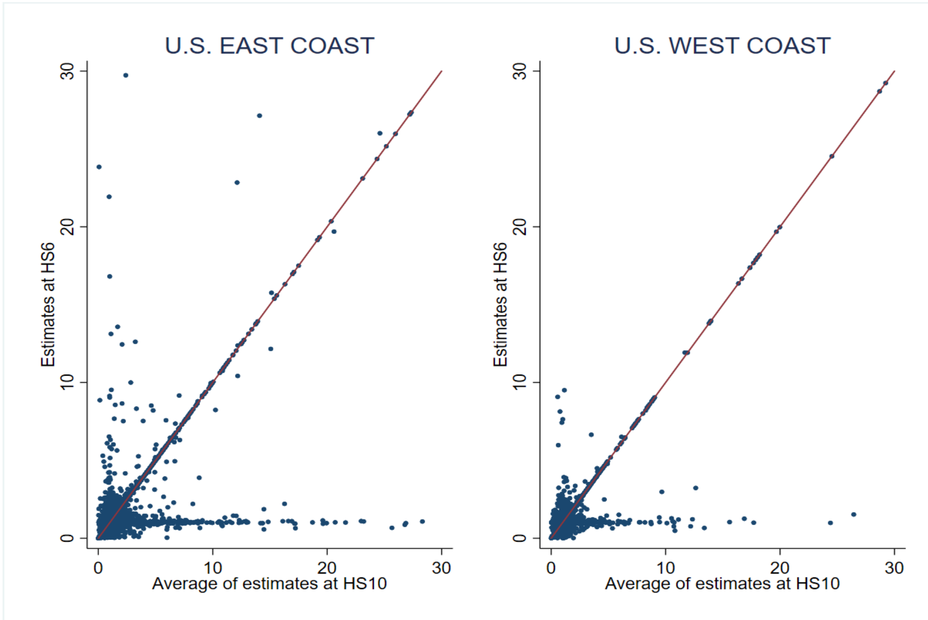


Figure 6: Comparison Estimated Short-Run Pass-Through Rates at HS6 vs at HS10 - Period 2002-2007

Note: For visual purposes, this figure excludes short-run pass-through rates higher than 30. Those observations account for less than 1% of the total.

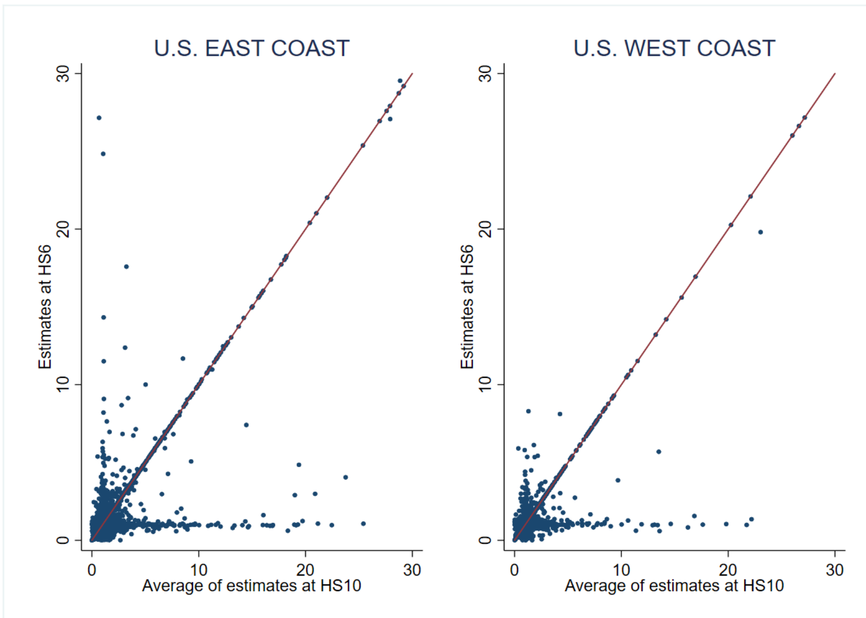


Figure 7: Comparison Estimated Short-Run Pass-Through Rates at HS6 vs at HS10 - Period 2013-2017

Note: For visual purposes, this figure excludes short-run pass-through rates higher than 30. Those observations account for less than 1% of the total.

Appendixes

A Mathematical Derivations

Derivation Eq. (5)
To decompose the short-run pass-through rate ρ^k_{od}, equation (4) shows that the first-order condition of carriers' maximization problem is given by:

$$f^{\ell,k}_{od} = c^{\ell}(\chi^k_{od}) - \frac{\partial f^k_{od}}{\partial Q^k_{od}} \frac{\partial Q^k_{od}}{\partial q^{\ell,k}_{od}} q^{\ell,k}_{od} \tag{A.1}$$

Now, defining a standard conduct parameter $\theta^k_{od} = \frac{\partial Q^k_{od}}{\partial q^{\ell,k}_{od}}$, and differentiating this expression with respect to the shipping cost $c(\chi^k_{od})$, the short-run pass-through rate ρ^k_{od} is equal to:

$$\rho^k_{od} = \frac{\partial f^k_{od}}{\partial c(\chi^k_{od})} = \left[1 + \frac{1 + E^k_{od}(f^k_{od})}{\phi^k_{od}}\right]^{-1} \tag{A.2}$$

Derivation Eq. (7)
To derive the optimal pricing-rule for maritime shipping carriers, I know from equation (4) that the first-order condition of carriers maximization problem is given by:

$$f^{\ell,k}_{od} = c^{\ell}(\chi^k_{od}) - \frac{\partial f^k_{od}}{\partial Q^k_{od}} \frac{\partial Q^k_{od}}{\partial q^{\ell,k}_{od}} q^{\ell,k}_{od} \tag{A.3}$$

Writing the shipping freight rate $f^{\ell,k}_{od}$ as the price gap of product k between the price in the origin P^k_o and the price in the destination country P^k_{od} yields:

$$P^k_{od} = P^k_o + c^{\ell}(\chi^k_{od}) - \frac{\partial (P^k_{od} - P^k_o)}{\partial Q^k_{od}} \frac{\partial Q^k_{od}}{\partial q^{\ell,k}_{od}} q^{\ell,k}_{od} \tag{A.4}$$

Now, defining and substituting a standard conduct parameter $\theta^k_{od} = \frac{\partial Q^k_{od}}{\partial q^{\ell,k}_{od}}$, and assuming that demand for importing product k in market d does not affect the price in the origin market o, yields

$$\begin{aligned} P^k_{od} &= P^k_o + c^{\ell}(\chi^k_{od}) - \frac{\partial P^k_{od}}{\partial Q^k_{od}} \theta^k_{od} \frac{Q^{\ell,k}_{od}}{L^{\ell,k}_{od}} \\ &= P^k_o + c^{\ell}(\chi^k_{od}) - \frac{\partial P^k_{od}}{\partial Q^k_{od}} \frac{Q^k_{od}}{\phi^k_{od}} \end{aligned} \tag{A.5}$$

In parallel, differentiating the assumed Bulow and Pfleiderer (1983) inverse demand for maritime shipping services with respect to the aggregate quantity of product k, that it is shipped per route od, yields:

$$\frac{\partial P^k_{od}}{\partial Q^k_{od}} = -b^k_{od}\delta^k_{od}{Q^k_{od}}^{\delta^k_{od}-1} \tag{A.6}$$

which given the structure on this demand function is equivalent to:

$$\frac{\partial P^k_{od}}{\partial Q^k_{od}} Q^k_{od} = -\delta^k_{od}(a^k_{od} - P^k_{od}) \tag{A.7}$$

Then, substituting this expression into the optimal pricing-rule defined above yields:

$$P^k_{od} = P^k_o + c^\ell(\chi^k_{od}) + \frac{\delta^k_{od}(a^k_{od} - P^k_{od})}{\phi^k_{od}} \tag{A.8}$$

Finally, substituting the definition of the short-run pass-through rate, $\rho^k_{od} = \left[1+\frac{\delta^k_{od}}{\phi^k_{od}}\right]^{-1}$ and writing the spatial price gap, as the shipping freight rate, $f^{\ell,k}_{od} = P^k_{od} = P^k_o$, yields:

$$f^{\ell,k}_{od} = \rho^k_{od}c^\ell(\chi^k_{od}) + (1-\rho^k_{od})(a^k_{od} - P^k_o) \tag{A.9}$$

Derivation Eq. (9)

To derive this expression, I substitute in expression (8) the additive structural forms for $c^\ell(\chi^k_{od})$ and a^k_{od} similar to Atkin and Donaldson (2015), one for each shipping route od in each shipping U.S. coast c, yielding:

$$\begin{aligned} P^{k,c}_{od} &= \rho^k_{od}P^{k,c}_o + \rho^k_{od}c^\ell(\chi^{k,c}_{od}) + (1-\rho^k_{od})a^{k,c}_{od} \\ &= \rho^k_{od}P^{k,c}_o + \rho^k_{od}\big[\sum_d(\beta^{k,c}_{1,od} + \beta^{k,c}_{2,od}t + \xi^{k,c}_{od})\big] + (1-\rho^k_{od})\big[\sum_d(\alpha^{k,c}_{1,od} + \alpha^{k,c}_{2,od}t\big] + \upsilon^{k,c}_{od}) \end{aligned} \tag{A.10}$$

Rearranging terms and approximating ρ^k_{od} with $\rho^{k,c}_o$ yields:

$$P^{k,c}_{od} = \rho^{k,c}_o P^k_o + \sum_d\big(\big[\rho^{k,c}_o\beta^{k,c}_{1,od} + (1-\rho^{k,c}_o)\alpha^{k,c}_{1,od}\big] + \big[\rho^{k,c}_o\beta^{k,c}_{2,od} + (1-\rho^{k,c}_o)\alpha^{k,c}_{2,od}\big]t\big) + \big[\rho^{k,c}_o\xi^k_{od} + (1-\rho^{k,c}_o)\upsilon^k_{od}\big] \tag{A.11}$$

which can be written as:

$$P^{k,c}_{od} = \rho^{k,c}_o P^{k,o}_o + \sum_d(\gamma^{k,c}_{od} + \gamma^{k,c}_{od}t) + \epsilon^k_{od} \tag{A.12}$$

Derivation Eq. (14)
To derive the expression for calculating maritime shipping mark-ups, I know that the optimal pricing-rule can be written as:

$$f_{od}^{\ell,k,c} = \widehat{\rho_o^{k,c}} P_o^{k,c} \widehat{T^{\ell}(\chi_{od}^{k,c})} + (1 - \widehat{\rho_o^{k,c}})(\widehat{a_{od}^{k,c}} - P_o^{k,c}) \tag{A.13}$$

Subtracting the shipping costs function in both sides yields:

$$f_{od}^{\ell,k,c} - P_o^{k,c} \widehat{T^{\ell}(\chi_{od}^{k,c})} = (1 - \widehat{\rho_o^{k,c}})(\widehat{a_{od}^{k,c}} - P_o^{k,c} \widehat{T^{\ell}(\chi_{od}^{k,c})} - P_o^{k,c}) \tag{A.14}$$

Finally, calculating the ratio of this expression to the shipping freight rates yields:

$$\mu_{od}^{\ell,k,c} = \frac{(1 - \widehat{\rho_o^{k,c}})(\widehat{a_{od}^{k,c}} - (1 + \widehat{T^{\ell}(\chi_{od}^{k,c})}) P_o^{k,c})}{P_{od}^{k,c} - P_o^{k,c}} \tag{A.15}$$

Derivation Eq. (15)
To derive this equivalent expression for calculating maritime shipping mark-ups, I know that the mark-ups are given as follows from expression (14):

$$\mu_{od}^{\ell,k,c} = \frac{(1 - \widehat{\rho_o^{k,c}})(\widehat{a_{od}^{k,c}} - (1 + \widehat{T^{\ell}(\chi_{od}^{k,c})}) P_o^{k,c})}{P_{od}^{k,c} - P_o^{k,c}} \tag{A.16}$$

Now, substituting the spatial price gap definition of the shipping freight rates, the mark-ups can be written as:

$$\mu_{od}^{\ell,k,c} = \left(\frac{1 - \widehat{\rho_o^{k,c}}}{\widehat{\rho_o^{k,c}}} \right) \left(\frac{\widehat{a_{od}^{k,c}} - P_{od}^{k,c}}{P_{od}^{k,c} - P_o^{k,c}} \right) \tag{A.17}$$

In parallel, calculating the elasticity of the shipping inverse demand yields:

$$\eta_{od}^{k,c} = -\left(\frac{\widehat{a_{od}^{k,c}} - P_{od}^{k,c}}{P_{od}^{k,c}} \right) \delta_{or}^{k,c} \tag{A.18}$$

Finally, solving for the difference between $a_{od}^{k,c}$ and $P_{od}^{k,c}$ and substituting in the derived expression for mark-ups yields:

$$\mu_{od}^{\ell,k,c} = -\left(\frac{1 - \widehat{\rho_o^{k,c}}}{\widehat{\rho_o^{k,c}}} \right) \left(\frac{\eta_{od}^{k,c}}{\delta_{od}^{k,c}} \right) \left(\frac{P_{od}^{k,c}}{P_{od}^{k,c} - P_o^{k,c}} \right) \tag{A.19}$$

B Data Description

As noted above, I use in this paper data from the U.S. Imports Merchandise trade files of the U.S. Census Bureau. Specifically, I use a data sample which I built exclusively for U.S. imports shipped by sea for the period 2002-2017. To do so, I applied the following step-wise procedure to all U.S. imports files downloaded from Peter Schott' web page `https://sompks4.github.io/sub_data.html`, which are annual at HS10-digit product code k, origin country o, U.S. customs district of arrival d and year t.

First, I kept only those import flows shipped by sea. To do so, I dropped all observations for which imports value and/or imports weight moved by sea were equal to zero. Second, I kept in the database those import flows that certainly were shipped to the U.S. by sea. For this purpose, I trimmed all import flows that entered into the U.S. via any inland customs district following Hummels and Schaur (2013). These imports flows might have originally arrived to the U.S. by sea but presumably were only recorded in these inland regions. This is an issue, given that they must have arrived to these regions via others mode of transportation (e.g. air or ground) for which I ignore the transportation costs information. So, I excluded these shipments to abstract the estimations from this potential noise. Along with these U.S. customs districts, I drop all imports flows shipped to Hawaii, Puerto Rico and the U.S. Virgin Islands as Hummels and Schaur (2013). These flows might not be reliable for estimating the costs and mark-ups of shipping, given that these flows might be distorted by the Jones Act. Third, I dropped from the database all import flows coming from Canada and Mexico. Those flows might not be reliable for estimating the maritime shipping costs and maritime shipping mark-ups from shipments coming from these countries, given that a large portion of these flows is moved by ground. Forth, I trimmed all imports flows within each HS6-digit product group in a year t imported from a particular origin country o with either unit prices or *ad-valorem* freight charges below the 1st percentile or above the 99th percentile. The rationale is that I develop this paper at the HS6-digit product k level. Thus, to avoid the potential problem of combining imports flows from products within the same HS6-digit product group and imported from the same country with different shipping characteristics, I trimmed these observations following consistently to Hummels and Schaur (2013). Fifth, I dropped all import flows for which it is unknown the SITC code, using as reference the annual U.S. Census Concordance. This code is key for determining whether a product is homogeneous or differentiated according to the Rauch (1999) product classification. Thus, it provides a good idea of the shipping technology used for shipping a products. Sixth, I merged the conservative Rauch (1999) product classification, trimming all observations for which it is unknown the correlation in the U.S. database. As explained above, I used this classification to infer the most presumable technology for shipping the products (i.e. bulk or liner shipping). Finally, I dropped all HS6-digit product codes pooling products considered homogeneous and other differentiated at the HS10 digit product level. I assumed this is a clear signal of heterogeneity within a HS6 digit product group.

Thus, the database I ended up using in this paper considers approximately 91% to 94% of the total value of the U.S. imports moved by sea over the period 2002-2017. Each observation compiles information disaggregated by HS6-digit product k, origin country o, U.S. customs district of arrival d and year t for (1) the imports' FOB value (in current U.S.$), (2) the imports' CIF value (in current U.S.$), (3) imported quantities (in kg.), and (4) the cost of insurances and freight.

The maritime shipping distance I use in all estimations is calculated using the World Cities Database retrieved from https://simplemaps.com/data/world-cities. This database provides the GPS coordinates (i.e. longitude and latitude) from all cities worldwide, relying on gathered data from NGIA, U.S. Geological Survey, U.S. Census Bureau and NASA. So, to calculate the shipping distance for all shipping routes in the US imports database, I applied the great-circle distance formula to the GPS coordinates of each route. A problem that surged was how to merge this database of shipping distances to the U.S. imports database. As explained, the U.S. imports database reports each import flow by origin country o and U.S. customs district of arrival d. In contrast, the database built for the distances was at the city level in each origin country to each U.S. customs district. Thus, to circumvent this problem, I adjusted the database of distances as follows. First, I calculated a weighted average distance from every origin country o to every U.S. customs district d, using (1) all shipping distances previously calculated from each city in a particular origin country o to each U.S. customs district d; and (2) the population shares of each city in an origin country o as shares for this calculation. Exceptionally, I calculated these distances as a simple average in those cases in which it lacked these population shares. Second, I considered some geographical restrictions in these calculations. For the sake of simplicity, I assumed that all shipments coming to the U.S. East coast from Europe and Africa occurs point-to-point, whereas those coming from Asia and Australia arrive via the Panama Canal. Similarly, I assume that all shipments coming to the U.S. West coast from Asia and Australia occurs point-to-point, while those coming from Europa and Africa arrive via the Panama Canal. In addition, I assumed that all shipments coming from Latin America are point-to point or via the Panama Canal, depending on the ocean over each country has located its main maritime port. To define these regions, I used the World Bank geographical classification. That is, Europe compiles all countries in the World Bank's regions Europe & Central Asia; Africa compiles all countries in regions Middle East & North Africa and Sub-Saharan Africa; Asia compiles all countries in regions East Asia & Pacific and South Asia; and Latin America compiles all countries in region Latin America and the Caribbean.

Other sources used to build this database are CEPII and BACI. From CEPII, I pulled the GDP per capita and from BACI the data to calculate the Revealed Comparative Advantage (RCA) (as a standard Balassa Index) and the World Export Supply (WES) (Balassa (1965) and Hummels et al. (2014)). I also employ the U.S. Tariffs database from the USITC. Additionally, I used the substitution elasticities calculated by Soderbery (2015), using the hybrid Feenstra (1994)/Broda and Weinstein (2006) methodology. Finally, I deflated all figures with the annual average of the U.S. Consumer Price Index (CPI), setting as the basis year 2017.

C Descriptive Statistics

This section reports summary statistics for freight rates and other variables used in the regression models. These statistics reveal three main lessons regarding shipping freight rates. First, *ad valorem* freight rates are higher for shipments to the U.S. East coast than to the U.S. West coast. Table C1 shows that *ad valorem* freight rates for shipped products to the U.S. East coast averaged 8.1% in 2002-2007, 6.7% in 2008-2012 and 6.1% in 2013-2017, compared to 7.6%, 6.2% and 5.8% for products delivered to the U.S. West coast. Second, the distribution of *ad valorem* freight rates charged on U.S. imports is right skewed. The median *ad valorem* freight rate is 2 to 3 percentage points lower than the mean in all periods. Third, *ad valorem* freight rates fell over the sample. *Ad-valorem* freight rates were 1.5 percentage points lower during the GFC than during the previous period, and another 0.4 to 0.6 percentage points lower during the post-crisis period.

The summary statistics for the variables used to estimate the adjusted freight rate function (expression (13)) indicate that the average shipping distance is approximately 12,000 kilometers for all shipped products to either U.S. coast (see Table C1).[72] Furthermore, this distance is very similar across East and West coast subsamples. The shipping distances do vary more across routes serving the U.S. East coast than the West coast.

The thickness of the shipping routes (measured in terms of shipping volume) also affect shipping freight rates. Table C1 reports heterogeneity among the shipping routes serving the U.S. Specifically, the average thickness of routes serving the U.S. West coast is 1,500 million kilograms, which is more than twice the 650 million kilograms in shipments to the U.S. East coast. Likewise, the thickness of routes serving the U.S. West coast varies substantially more than among routes serving the U.S. East coast.

Fuel prices remained at low levels in the last decades, and even fell during the GFC period. Table C1 reports that the median oil price fell from U.S.$71.1 per barrel in 2002-2007 to U.S.$50.8 per barrel in 2013-2017. Yet, the high oil price volatility would have been an issue for carriers. The range in which these prices fluctuated grew from US$50 (U.S.$35.7 to U.S.$85.5) in 2002-2007 up to nearly U.S.$60 (U.S.$44.2 to U.S.$103.1) in 2013-2017.

Finally, the average weight-to-value ratio of U.S. imports per shipment averaged 0.2 to 0.3 kilograms per dollar on most shipments delivered to the U.S. regardless of the destination coast. This ratio also decreased slightly after the global crisis from 0.25-0.27 in 2002-2007 to 0.21-0.22.

[72] Just to bear in mind a benchmark, this average shipping distance is equivalent to the distance between Long Beach in Los Angeles, CA, and Hong Kong.

Table C1: Summary Statistics - Key Variables in U.S. Maritime Shipping Market - Differentiated Products

2002-2007	U.S. East Coast						U.S. West Coast					
	Obs.	Mean	Median	Std. Dev.	Perc. 1%	Perc. 99%	Obs.	Mean	Median	Std. Dev.	Perc. 1%	Perc. 99%
Ad Valorem Freight Rate†	931,501	8.1	5.1	11.9	0.0	49.5	334,177	7.6	4.8	11.1	0.0	46.0
Shipping Distance‡	931,501	12,089	9,028	6,023	1,733	21,832	334,177	12,020	12,167	2,558	5,048	17,855
Shipping Volume - Route*	931,501	703	234	1,438	0	5,843	334,177	1,444	294	3,616	0	20,945
Oil Price*	931,501	61.6	71.1	18.9	35.7	85.5	334,177	61.7	71.1	18.9	35.7	85.5
Ratio Weight-to-Value$^{\mp}$	931,501	0.25	0.09	3.02	0.00	2.06	334,177	0.27	0.09	18.34	0.00	1.94

2008-2012	U.S. East Coast						U.S. West Coast					
	Obs.	Mean	Median	Std. Dev.	Perc. 1%	Perc. 99%	Obs.	Mean	Median	Std. Dev.	Perc. 1%	Perc. 99%
Ad Valorem Freight Rate†	749,548	6.7	4.1	11.2	0.0	42.9	263,635	6.2	3.8	10.0	0.0	39.3
Shipping Distance‡	749,548	12,238	9,093	5,999	1,733	21,832	263,635	12,015	12,167	2,513	5,463	17,481
Shipping Volume - Route*	749,548	631	201	1,231	0	5,790	263,635	1,363	256	3,482	0	16,835
Oil Price*	749,548	95.8	100.4	14.5	70.8	113.5	263,635	95.9	100.4	14.5	70.8	113.5
Ratio Weight-to-Value$^{\mp}$	749,548	0.21	0.08	2.57	0.00	1.78	263,635	0.20	0.08	0.68	0.00	1.69

2013-2017	U.S. East Coast						U.S. West Coast					
	Obs.	Mean	Median	Std. Dev.	Perc. 1%	Perc. 99%	Obs.	Mean	Median	Std. Dev.	Perc. 1%	Perc. 99%
Ad Valorem Freight Rate†	829,324	6.1	3.7	9.7	0.0	40.3	277,467	5.8	3.6	9.0	0.0	38.1
Shipping Distance‡	829,324	12,046	8,832	5,925	1,782	21,832	277,467	12,120	12,551	2,529	5,394	17,481
Shipping Volume - Route*	829,324	687	252	1,231	0	6,724	277,467	1,565	296	3,998	0	19,741
Oil Price*	829,324	68.1	50.8	25.1	44.2	103.1	277,467	68.6	50.8	25.3	44.2	103.1
Ratio Weight-to-Value$^{\mp}$	829,324	0.21	0.08	1.48	0.00	1.88	277,467	0.22	0.09	1.97	0.00	1.80

†: *ad valorem* freight rate charged in the origin country o for shipping product k to the U.S. Customs district d in year t.

‡: maritime shipping distance (in kilometers) for delivering product k from country o to the U.S. Customs district d.

$*$: total shipping volume (in million of kilograms) from origin country o to the U.S. Customs district d in year t.

$\star$: WTI oil price (in U.S.$ prices of 2017) in year t.

$\mp$: ratio weight-to-value of product k shipped from country o to the U.S. Customs district d in year t (in kg/U.S.$ prices of 2017).

D Bullow and Pfeiderer ρ estimates vs. CES ρ estimates

In the Bulow and Pfleiderer (1983) system, ρ can be written in terms of the demand elasticity σ and the demand super-elasticity φ (i.e. change in the demand elasticity to changes in prices).[73]

$$\rho = \frac{\sigma}{\sigma - 1 + \varphi} \tag{D.1}$$

A CES framework thus is a special case of the Bulow and Pfleiderer (1983) demand system, in which φ equals zero. More importantly, it is restrictive for estimating carriers' shipping mark-ups, given that it does not allow considering that changes in freight charges may affect the demand elasticity, φ, and thus shipping mark-ups. This is a critical channel when modeling carriers' mark-ups, given the inverse relationship between the demand elasticity and mark-ups (Lerner, 1934).

In order to quantify how assuming CES framework would have affected the previous $\widehat{\rho}$, I conduct three simple exercises. First, I calculate the average and median ρ on a CES framework, substituing the average and median $\widehat{\sigma}$ (2.1 and 4.7, respectively) estimated by Soderbery (2015) on expression (D.1). This exercise yields that $\widehat{\rho}$ would have ranged between 1.27 and 1.91 rather than between 1.01 and 1.42 as I estimate above. All $\widehat{\rho}$ thus would have been biased upwards if I had assumed a CES framework. Then, given that ρ is only a function of σ in a CES framework, I estimate–in a second exercise–how strong is the relationship between these variables. To this aim, a reduced-form model of $\widehat{\rho}$ is estimated on σ.[74] This model predicts a weak and nonexistent relationship between both variables in the shipping market carrying U.S. imports, against the CES assumption (See Table D1). This result reinforces the idea that σ is assigned to capture much information in a CES framework (Lai and Trefler, 2002). Finally, I evaluate–in a third exercise–how strong is the CES assumption that the demand super-elasticity φ is equal to zero in the U.S. shipping market carrying U.S. imports. To this aim, I substitute the average $widehat\rho$ (around 1) assuming a Bulow and Pfleiderer (1983) demand system to model U.S. imports demand in (D.1). Then, I solve for φ. This exercise yields that φ is around 1 in the shipping market. This means that changes in shipping freight rates affect the demand elasticity almost in the same magnitude, and so do carriers' mark-ups. Hence, carriers' mark-ups are not constant as would be the CES prediction assuming φ equal to 0.

[73] The super-elasticity of the demand φ is equal to $\frac{\partial \sigma}{\partial P}\frac{P}{\sigma} = -\left[1 + \sigma + \left(\frac{\partial\left(\frac{\partial Q}{\partial P}\right)}{\partial P}\frac{P}{\left(\frac{\partial Q}{\partial P}\right)}\right)\right]$

[74] As explained above, δ is positive in a Bulow and Pfleiderer (1983) demand system when ρ is greater than 1, and negative otherwise. So, I estimate this model, splitting the sample between all observations for which ρ is less than 1 and those for which ρ is greater than 1.

Table D1: Short-run Pass-Through Rates vs. Price Demand Elasticities

	$\rho > 1$			ρ <1		
	2002-2007	2008-2012	2013-2017	2002-2007	2008-2012	2013-2017
	(1)	(2)	(3)	(4)	(5)	(6)
σ	-0.00195**	0.000136	0.00248	0.0000785	0.0000850*	0.0000919*
	(0.000844)	(0.000279)	(0.00231)	(0.0000714)	(0.0000491)	(0.0000477)
constant	1.217***	1.095***	1.115***	0.938***	0.940***	0.941***
	(0.00395)	(0.00129)	(0.0107)	(0.000337)	(0.000236)	(0.000239)
N	513,176	384,910	421,103	353,937	283,996	305,137
R-sq	0.000	0.003	0.001	0.046	0.041	0.041

Standard errors in parenthesis are clustered by origin country.
*p < 0.1, **p < 0.05, ***p < 0.01
Note: the dependent variables is the estimated pass-through rates, ρ. All regressions include origin country fixed effects.

E Did the 2008-2012 Global Financial Crisis (GFC) Affect Carriers' Ability to Exert Market Power?

The estimation strategy employed in this paper assumes parameter stability within the period of study. Assuming stability during the GFC period (2008-2012) is questionable. Global aggregate demand for goods and services was seriously distorted. Some costs for carriers (e.g. oil prices) reached atypical levels, and unused capacity in the market significantly increased (UNCTAD, 2017).[75] However, this is a period of significant interest. In order to inform our understanding of the effects of the GFC, I apply the same estimation strategy to the period 2008-2012.

This exercise indicates that carriers' ability to transfer a cost shock to freight rates slightly decreased during 2008-2012 period. Columns (3) and (6) in Table 1 show that the average pass-through rate ρ decreased from 1.42 in 2002-2007 to 1.10 in 2008-2012 on shipments to the U.S. East coast, and from 1.11 in 2002-2007 to 1.06 in 2008-2012 on those to the U.S. West coast. Carriers thus were unable to continue transferring the same share of costs to freight charged on the products to which they transferred the most in 2002-2007. Moreover, this result reinforces the thesis that shipping carriers faced tougher conditions during this period (GSF Global Shippers Forum, 2017; ICS International Chamber of Shipping, 2017; Samunderu, 2018).

Column (2) in Table 3 also shows that oil price volatility significantly affected shipping freight rates charged for products during this period, especially to those charged for products shipped to the U.S. East coast. Specifically, an increase of 10% in the oil price during 2008-2012 led to an increase of 0.35 percentage points in the *ad valorem* shipping freight rates. That is, it implied an increase approximately 10 times larger than during 2002-2007. In contrast, Column (2) and (5) in Table 3 show that an increase of 10% in the shipping volume in a route or the volume handled in a destination port continued to lead to a reduction in freight rates of 0.1-0.3 percentage points.

Estimates in Table 4 indicate that carriers significantly reduced their mark-ups during the crisis. Specifically, *ad valorem* shipping mark-ups ($\mu_{od}^{\ell,k}$) fell from 43.4% on average in 2002-2007 to 38.2% in 2008-2012 for differentiated products shipped to the U.S. East coast, and from 34.2% to 27.5% for products shipped to the U.S. West coast. That is, the equivalent *ad valorem* tariff decreased from 2.1%-2.6% to 1.3%-1.8%. In the post-crisis period, mark-ups of shipments to the U.S. East coast fell even further (to 34.1%), and rose slightly (to 32.7%) on shipments to the U.S. West coast.

All these results reveal two main lessons for the period of GFC (2008-2012). Shipping costs were volatile, and carriers reduced their market power. Two outcomes that my estimates show persisted during the post-crisis period, as explained above.

[75] Table C1 shows that, during the crisis period, *ad valorem* freight rates ($f_{\ell,r}^{k}$) decreased to 6.2%-6.7%, 1.5 percentage points lower than in the period 2002-2007. The average volume of goods shipped also fell by 10.2% in routes to the U.S. East coast and by 5.6% in routes to the U.S. West coast. Likewise, important cost shifters for shipping carriers such as oil prices were very volatile. Oil prices decreased to almost US$40 per barrel in 2009. Then, these prices reversed their trend and touched the barrier of US$120 in 2011 and oscillated around US$90 to US$100 afterwards.

F Analysis of the Data

Table F1: Value of U.S. Imports (U.S. \$billions) (constant prices of 2017)

	U.S. East Coast						U.S. West Coast					
	2002-2007						2002-2007					
	OLS	%	2SLS	%	GC	%	OLS	%	2SLS	%	GC	%
Included in the analysis†	1,567	97.8%	1,554	96.9%	1,592	99.3%	1,450	96.1%	1,444	95.7%	1,501	99.5%
Excluded from the analysis‡	36	2.3%	49	3.1%	11	0.7%	59	3.9%	65	4.3%	8	0.5%
TOTAL	1,603	100.0%	1,603	100.0%	1,603	100.0%	1,509	100.0%	1,509	100.0%	1,509	100.0%
	2008-2012						2008-2012					
	OLS	%	2SLS	%	GC	%	OLS	%	2SLS	%	GC	%
Included in the analysis†	1,368	98.6%	1,348	97.2%	1,379	99.4%	1,282	98.9%	1,275	98.4%	1,290	99.5%
Excluded from the analysis‡	19	1.4%	39	2.8%	8	0.6%	13	1.0%	21	1.6%	5	0.4%
TOTAL	1,387	100.0%	1,387	100.0%	1,387	100.0%	1,296	100.0%	1,296	100.0%	1,296	100.0%
	2013-2017						2013-2017					
	OLS	%	2SLS	%	GC	%	OLS	%	2SLS	%	GC	%
Included in the analysis†	1,692	98.5%	1,675	97.5%	1,711	99.6%	1,379	98.9%	1,357	97.3%	1,390	99.6%
Excluded from the analysis‡	26	1.5%	43	2.5%	7	0.4%	17	1.2%	38	2.7%	5	0.4%
TOTAL	1,718	100.0%	1,718	100.0%	1,718	100.0%	1,395	100.0%	1,395	100.0%	1,395	100.0%

†: all pairs product k - origin country o for which it is feasible estimating a short-run pass-through rate (i.e. $\rho > 0$).
‡: all pairs (product k - origin country o) for which it is not possible or is unfeasible estimating a short-run pass-through rate (i.e. $\rho \leq 0$).

Table F2: HS6-digit Products in Sampling Data

	U.S. East Coast						U.S. West Coast					
	2002-2007						2002-2007					
	OLS	%	2SLS	%	GC	%	OLS	%	2SLS	%	GC	%
Included in the analysis†	2,942	89.9%	2,910	88.9%	3,141	95.9%	2,820	87.5%	2,785	86.4%	2,967	92.0%
Excluded from the analysis‡	332	10.1%	364	11.1%	133	4.1%	404	12.5%	439	13.6%	257	8.0%
TOTAL	3,274	100.0%	3,274	100.0%	3,274	100.0%	3,224	100.0%	3,224	100.0%	3,224	100.0%

	2008-2012						2008-2012					
	OLS	%	2SLS	%	GC	%	OLS	%	2SLS	%	GC	%
Included in the analysis†	2,823	93.6%	2,783	92.3%	2,903	96.3%	2,722	91.7%	2,678	90.2%	2,782	93.7%
Excluded from the analysis‡	192	6.4%	232	7.7%	112	3.7%	246	8.3%	290	9.8%	186	6.3%
TOTAL	3,015	100.0%	3,015	100.0%	3,015	100.0%	2,968	100.0%	2,968	100.0%	2,968	100.0%

	2013-2017						2013-2017					
	OLS	%	2SLS	%	GC	%	OLS	%	2SLS	%	GC	%
Included in the analysis†	2,827	93.1%	2,797	92.1%	2,935	96.6%	2,730	91.2%	2,698	90.2%	2,819	94.2%
Excluded from the analysis‡	211	6.9%	241	7.9%	103	3.4%	262	8.8%	294	9.8%	173	5.8%
TOTAL	3,038	100.0%	3,038	100.0%	3,038	100.0%	2,992	100.0%	2,992	100.0%	2,992	100.0%

†: all pairs product k - origin country o for which it is feasible estimating a short-run pass-through rate (i.e. $\rho >0$).
‡: all pairs (product k - origin country o) for which it is not possible or is unfeasible estimating a short-run pass-through rate (i.e. $\rho \leq 0$).

Table F3: Countries in Sampling Data

	U.S. East Coast						U.S. West Coast					
	2002-2007						2002-2007					
	OLS	%	2SLS	%	GC	%	OLS	%	2SLS	%	GC	%
Included in the analysis†	192	84.6%	171	75.3%	205	90.3%	151	69.9%	138	63.9%	161	74.5%
Excluded from the analysis‡	35	15.4%	56	24.7%	22	9.7%	65	30.1%	78	36.1%	55	25.5%
TOTAL	227	100.0%	227	100.0%	227	100.0%	216	100.0%	216	100.0%	216	100.0%

	2008-2012						2008-2012					
	OLS	%	2SLS	%	GC	%	OLS	%	2SLS	%	GC	%
Included in the analysis†	180	79.6%	158	69.9%	196	86.7%	146	69.5%	127	60.5%	154	73.3%
Excluded from the analysis‡	46	20.4%	68	30.1%	30	13.3%	64	30.5%	83	39.5%	56	26.7%
TOTAL	226	100.0%	226	100.0%	226	100.0%	210	100.0%	210	100.0%	210	100.0%

	2013-2017						2013-2017					
	OLS	%	2SLS	%	GC	%	OLS	%	2SLS	%	GC	%
Included in the analysis†	188	82.1%	161	70.3%	202	88.2%	151	69.3%	132	60.6%	156	71.6%
Excluded from the analysis‡	41	17.9%	68	29.7%	27	11.8%	67	30.7%	86	39.4%	62	28.4%
TOTAL	229	100.0%	229	100.0%	229	100.0%	218	100.0%	218	100.0%	218	100.0%

†: all pairs product k - origin country o for which it is feasible estimating a short-run pass-through rate (i.e. $\rho > 0$).

‡: all pairs (product k - origin country o) for which it is not possible or is unfeasible estimating a short-run pass-through rate (i.e. $\rho \leq 0$).

G Robustness Exercises

As noted, the revision of the SITC codes in the U.S. census concordances–used to merge the Rauch product classification–is unclear for the years 2002-2015.[76] So, I assume that all SITC codes were at Revision 2, in order to circumvent the methodological problem of having SITC codes classified as both differentiated and homogeneous, when some codes were converted from Revision 4 to Revision 2. Thus, in order to evaluate the robustness of all estimates to this assumption, all estimates were calculated again assuming that all SITC codes were at Revision 4. This exercise shows that all estimates are very robust to the assumed revisions for the SITC codes. For instance, Table G1 shows that the median pass-through rate ranges continue to center around 1.01, and the average ranges from 1.1 to 1.6. Similarly, Table G2 indicates that the maritime shipping mark-ups are also very similar, assuming Revision 4 for the SITC codes. Specifically, shipping mark-ups continue to account for approximately one-third of the freight charges.

[76] See Section 3, footnote 34.

Table G1: Summary Statistics - Short-Run Pass-Through Rates
(SITC Rev. 2 versus SITC Rev. 4 to classify U.S. Imports)

	U.S. East Coast					
	2002-2007		2008-2012		2013-2017	
	HS10 SITC Rev. 2	HS10 SITC Rev. 4	HS10 SITC Rev. 2	HS10 SITC Rev. 4	HS10 SITC Rev. 2	HS10 SITC Rev. 4
	(1)	(2)	(3)	(4)	(5)	(6)
Mean	1.56	1.60	1.62	1.64	1.38	1.37
Median	1.01	1.01	1.01	1.01	1.01	1.01
Std Deviation	53.42	55.29	117.54	119.59	31.79	32.04
Percentile 1%	0.39	0.39	0.41	0.42	0.40	0.41
Percentile 99%	2.98	2.97	2.71	2.69	2.71	2.67
Number Obs.	107,718	103,474	93,031	89,867	103,990	100,707

	U.S. West Coast					
	2002-2007		2008-2012		2013-2017	
	HS10 SITC Rev. 2	HS10 SITC Rev. 4	HS10 SITC Rev. 2	HS10 SITC Rev. 4	HS10 SITC Rev. 2	HS10 SITC Rev. 4
	(1)	(2)	(3)	(4)	(5)	(6)
Mean	1.36	1.37	1.21	1.22	1.13	1.13
Median	1.01	1.01	1.00	1.00	1.00	1.00
Std Deviation	47.99	48.92	28.75	29.22	8.27	8.38
Percentile 1%	0.43	0.44	0.43	0.44	0.44	0.45
Percentile 99%	2.36	2.38	2.27	2.24	2.36	2.35
Number Obs.	60,812	58,513	51,617	49,959	55,637	53,956

Table G2: Median Maritime Shipping Mark-up
(SITC Rev. 2 versus SITC Rev. 4 to classify U.S. Imports)

	U.S. East Coast			U.S. West Coast		
	2002-2007	2008-2012	2013-2017	2002-2007	2008-2012	2013-2017
	(1)	(2)	(3)	(4)	(5)	(6)
HS10 - SITC Rev. 2	38.0	29.2	28.2	37.9	-60.2	30.1
HS10 - SITC Rev. 4	38.7	29.0	28.8	37.9	-45.6	30.3