Trade Costs and Mark-Ups in Maritime Shipping

Manuel I. Jimenez*

April 19, 2021

Abstract

Transportation costs represent about 15% of global import value. Non-competitive pricing behavior is the maritime shipping market is also widely believed to raise the cost of freight. Using U.S. import data, this paper estimates the effects of this presumably non-competitive behavior on (1) total freight costs, (2) international trade flows, and (3) economic welfare. It also evaluates whether such behavior disproportionately affects shipments from developing and/or countries distant from the U.S. To this aim, short-run pass-through rates of cost to freight rates are estimated and used to calculate the freight mark-ups charged on U.S. imports shipped by sea during 2002-2007, 2008-2012 and 2013-2017. The estimates show that 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

*Department of Agricultural Economics, Purdue University, 403 W State Street, Krannert Building Rm 610, West Lafayette IN, 47907; e-mail: jimene19@purdue.edu. This research was financed by USDA NIFA grant #2020-67023-30963. I thank Russell Hillberry, David Hummels, Anson Soderbery, Farid Farrokhi, Joseph Balagtas, Dominique van der Mensbrugghe, and Dave Donaldson for helpful advice and comments. All errors are my own.

1 Introduction

Maritime shipping is the most important mode of transportation used in international trade. About 70% to 80% of international trade flows (in value) move by sea (UNCTAD, 2017). International trade is thus highly dependent on an industry in which suppliers are widely believed to exert market power. Empirical research finds that two main reasons underlie carriers' market power in international shipping. First, excessive shipping capacity supplied in the market by larger carriers companies, along with the significant economies of scope they exploit, lead to the concentration of the market in fewer companies (Hummels et al., 2009).[1] Second, the lack of anti-trust enforcement policies allows carriers to make price-fixing agreements (Fink, 2002).[2] 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] Such estimates would allow: (1) a decomposition of the freight cost into shipping costs and shipping mark-ups; (2) a comparison with other trade costs, including tariffs; (3) a quantification of the effects of market power in the maritime shipping industry on trade flows and economic welfare; and (4) an evaluation of whether non-competitive behavior in the maritime shipping industry disproportionately affects developing and/or countries that are geographically distant from destination markets.

Atkin and Donaldson (2015) developed 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 short-run pass-through rate of costs to prices is a sufficient statistic for quantifying the response of mark-ups to trade cost changes (Weyl and Fabinger, 2013). Furthermore, the short-run pass-through rate in the two-stage method proposed theoretical identification of firms' marginal costs and mark-ups. I apply thus this methodology in this paper 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 questions that this paper answers are: How much higher are freight rates than they would be without non-competitive pricing behavior? What is the effect of shipping mark-ups on

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

[2] Many countries, arguing economic and national security interests, have also domestically kept in place Cargo Reservation Schemes (e.g. The Jones Act in the USA) to protect this industry (Fink, 2002). Consequently, competition is widely believed is limited in their shipping markets.

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

trade flows? What are the welfare costs of these mark-ups? To the extent it provides an answer to these questions, this paper also answers further questions, such as: How large are shipping carriers' mark-ups relative to tariffs? Do market conditions in shipping routes to smaller destination ports allow carriers to charge larger mark-ups? Do developing pay higher shipping mark-ups? Are mark-ups larger on longer routes?

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). However, this paper differs from that study by (1) estimating absolute, rather than relative, measures of maritime shipping mark-ups; (2) calculating their implied effect on trade flows and economic welfare; and (3) evaluating 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 sources of freight costs.[6] Other studies estimate the impact of freight charges on countries' export performance.[7] Other works 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 total 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 also expands the growing literature that operationalizes the short-run pass-through rates of cost to prices for identifying the presence of market power. The seminal paper in this strand of the literature is Atkin and Donaldson (2015). As noted, that study shows that the short-run pass-through rate is a sufficient statistic for quantifying the response of mark-ups to

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

[5]The underlying CES preference structure assumed by Hummels et al. (2009) does not allow that study to calculate the shipping mark-ups. 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 the cross-section variation in that year. In this paper, I use panel data and exploit the time variation.

[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).

trade cost changes. Other recent studies have also successfully used the method in other applications, including a study of the agricultural sector in sub-Saharan countries (Bergquist, 2017) and of the residential market for installation of solar-power systems in California (Pless and Van Benthem, 2017). This paper extends this approach to the maritime shipping industry, and does so in a context with multiple products and origin countries.[9]

This paper estimates that short-run pass-through rates of cost to freight rates for shipping products to the U.S. range from 0.4 to 2.7. That is, it finds evidence of the latent presence of non-competitive market conditions in the market for maritime transport of U.S. imports. This paper estimates that shipping mark-ups represent a third of total 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. Additionally, the paper finds evidence that shipping carriers charge higher mark-ups on shipments delivered to U.S. ports that handle larger imports flows.

Assuming a trade elasticity lying between 3 and 5, U.S. import quantities of differentiated products would have been approximately 4.2% to 11.6% higher if the estimated mark-ups were set equal to zero. Using the estimated mark-ups to decompose the freight charges, I estimate that maritime shipping mark-ups account for an *ad valorem* tariff equivalent ranging from 1.4% to 2.6% of U.S. imports value of differentiated products. The implied cost of the shipping mark-ups in terms of welfare for U.S. consumers amounts to an annual reduction of approximately 0.1%-0.2% of their real income. Additionally, estimates show that U.S. consumers importing products from developing and distant countries pay higher mark-ups.

This 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.

[9] Atkin and Donaldson (2015) develop this method for a single origin country and multiple intranational destinations. Several challenges arise when applying this method to multiple origin and destination countries.

2 Theoretical Framework

U.S. import data show notable differences in the CIF price of products imported from the same country but delivered to different U.S. customs districts. Differences in the shipping freight charge certainly explain this result. For instance, Panel A in Table 1 shows that freight charges for shipping cell phones, televisions, bicycles, and car tires from China to the U.S. are higher when shipped to Los Angeles and San Francisco than to Seattle. Panel B shows that these first two U.S. customs districts are larger. Geographically, Seattle is also closer to China than Los Angeles and San Francisco. The question thus is whether it is really more costly for carriers to ship these products to Los Angeles and San Francisco than to Seattle, or whether market conditions on routes to these U.S. customs districts allow carriers to charge larger shipping mark-ups.

To answer this question, I adapt the theoretical framework of Atkin and Donaldson (2015) to the maritime shipping industry. The objective is to characterize shipping carriers' behavior in setting their shipping freight rates. To do so, I develop a structural model, making three standard assumptions in the literature. First, shipping carriers are rational agents and thus maximize their profits.[10] Second, demand for maritime shipping services is entirely indexed to the demand for imports shipped by sea, and shipping carriers observe this demand.[11] Third, shipping carriers set shipping freight rates, aiming to collect the largest share of consumers' willingness to pay for shipping a product.[12]

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 unique destination country with $d = 1, 2, ..., D$ arrival ports. The shipping network nests a structure of $O \times D$ shipping routes r, in which each route r corresponds to a pair o-d. Further, $\ell = 1, 2, ..., L$ carriers ship all products, and compete for each shipping route in an oligopolistic market structure. Carriers also observe the inverse demand for each imported product k by sea $P^k_{od}(Q^k_{od}, \Theta^k_{od})$, where P^k_{od} is the price of each product k in maritime shipping port d imported from origin country o, Q^k_{od} is the amount imported of each product k in destination market d from origin country o, and Θ^k_{od} are demand shifters from importing this product k in d from o. Additionally,

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

[11] See e.g. Fink (2002) and Hummels et al. (2009).

[12] See e.g. Hoffmann and Kumar (2013).

carriers incur a set of per-route fixed costs for shipping the products, FC_r^ℓ, and a set of variable costs, $c^\ell(\chi_r^k)$, that depend on the shipping route conditions and/or the shipped product k.[13] Thus, each shipping carrier ℓ maximizes the following profit function with respect to the amount $q_r^{\ell,k}$ it ships of product k through route r.[14]

$$\max_{q_r^{\ell,k}} \pi^\ell = \sum_r \sum_k \left[f_r^k(Q_r^k, \Theta_r^k) - c^\ell(\chi_r^k)\right] q_r^{\ell,k} - FC_r^\ell \tag{1}$$

This implies that the optimal shipping freight rate $f_r^{\ell,k}$ that carrier ℓ charges for shipping product k through route r is given by:[15]

$$f_r^{\ell,k} = c^\ell(\chi_r^k) - \frac{\partial f_r^k}{\partial Q_r^k} \frac{\partial Q_r^k}{\partial q_r^{\ell,k}} q_r^{\ell,k} \tag{2}$$

such that shipping freight costs depend on variable costs $c^\ell(\chi_r^k)$ and carriers' ability to alter the overall shipping capacity supply for product k in route r, $\frac{\partial Q_r^k}{\partial q_r^{\ell,k}}$. Shipping freight rates also depend on the number of carriers competing on a route r for shipping product k, defining L_r^k equal to $\frac{Q_r^k}{q_r^{\ell,k}}$. So, in order to consider these two features into the model, I make three additional assumptions as in Atkin and Donaldson (2015) and Bergquist (2017). First, I define a standard conduct parameter θ_r^k equal to $\frac{\partial Q_r^k}{\partial q_r^{\ell,k}}$.[16] Second, I define a competition index ϕ_r^k equal to $\frac{L_r^k}{\theta_r^k}$ for each shipping route r, in order to circumvent the potential problem of identification of the number of carriers L_r^k shipping product k via route r, and the structure of the market competition θ_r^k.[17]

A theoretical problem in the measurement of the optimal freight charges is how to separately identify shipping costs and shipping mark-ups. So, in order to circumvent this theoretical puzzle, I apply the identification strategy of Atkin and Donaldson (2015) as detailed below.

[13] 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).

[14] All variables vary over time, for which the time subscript is suppressed for notational ease.

[15] All carriers' decision variables are indexed to r, because they make decisions per route. However, they could have also be indexed equivalently per combination *od*, given that the shipping demand in indexed to the imports demand and carriers observed it.

[16] As standard in the literature, this conduct parameter takes the following values according to the market structure (1) $\theta_r^k \to 0$ in perfect competition; (2) $\theta_r^k \to 1$ in a *Cournot* competition and monopoly, and (3) $\theta_r^k \to L_r^k$ in the case of collusion (Weyl and Fabinger, 2013; Atkin and Donaldson, 2015).

[17] For simplicity, this competition index is assumed to only vary across shipping routes r. In liner shipping service, for instance, carriers often ship different products in the same vessel. Then, competition for carriers is more at the route level than at the route-product level.

2.2 Theoretical Identification of the Shipping Costs and Mark-ups

Atkin and Donaldson (2015) show that firms' marginal costs and mark-ups are theoretically identifiable, when the transmission of cost shocks to prices is considered for modelling their optimal price decisions. Defining this rate of transmission as the short-run pass-through rate ρ, they demonstrate that two unobservable drivers for firms' mark-ups are captured when is operationalized in firms' optimal pricing rule: (1) consumers preferences, and (2) competition in the market. The key feature of ρ is that it structurally depends on the demand curvature and the market competition conditions, as detailed below.[18] An estimate of ρ permits the identification of the residual effect of a cost shifter onto freight rates due to changes to either of these two factors. Additionally, it allows the possibility that carriers may adjust their shipping mark-ups differently due to a cost shock (Fabinger and Weyl, 2012; Atkin and Donaldson, 2015).[19]

In this context, the short-run pass-through rate ρ is easily derivable, by taking the partial derivative of the optimal pricing rule with respect to the costs as in Atkin and Donaldson (2015). As noted, this yields that ρ is a function of the curvature of the inverse demand in the market, $E_r^k(f_r^k)$, and (2) the competition index in route r, ϕ_r^k.[20] Furthermore, ρ only takes positive values, and, for instance, tends to 1 as competition conditions in the market grow more fierce (i.e. $\phi_r^k \to \infty$).

$$\rho_r^k = \left[1 + \frac{1 + E_r^k(f_r^k)}{\phi_r^k}\right]^{-1} \tag{3}$$

Atkin and Donaldson (2015) explain that this result indicates that all is needed to operationalize the short-run pass-through rate ρ is a parsimonious demand system. In order to model the demand for maritime shipping services in this paper, I assume it is a derived demand that is tied to import demand. Shipping services are demanded because of the utility for delivered products; there is not 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

[18] The short-run pass-though rate captures, for instance, the differential effect of the demand curvature on the transmission of cost shock to prices (See Figure 1a and Figure 1b). Some carriers might find optimal to transmit partially, completely, or more than completely a change in shipping costs to shipping freight rates. Each pass-through rate type is defined as follows: (1) partial pass-through, if $\rho < 1$, (2) complete pass-through, if $\rho = 1$, and (3) more than complete pass-through, if $\rho > 1$.

[19] When shipping carries are able to partially (more than completely) pass-through a cost shifter to the shipping freight rates, they reduce (raise) their mark-ups when there is a cost shock. Carriers also keep their mark-ups constant only when they completely pass-through a cost shifter to freight rates prices ($\rho = 1$).

[20] The elasticity of the slope of the inverse demand, $E_r^k(f_r^k)$, is equal to $\left\{\frac{Q_r^k}{\frac{\partial f_r^k}{\partial Q_r^k}}\right\}\left\{\frac{\partial\left(\frac{\partial f_r^k}{\partial Q_r^k}\right)}{\partial Q_r^k}\right\}$.

Schaur, 2013). Additionally, I assume that carriers observe this demand, and that demand can be represented as a Bulow and Pfleiderer (1983) demand system as in Atkin and Donaldson (2015). I also assume that products are unique per origin country, as the standard Armington (1969) assumption. Then, the demand for importing a product k from country o to d, which corresponds to the shipping demand of that product k through that route r is given by:

$$P_{od}^{k}(Q_{od}^{k},\Theta_{od}^{k}) = \begin{cases} a_{od}^{k} - b_{od}^{k}(Q_{od}^{k})^{\delta_{od}^{k}}, \text{if } \delta_{od}^{k} > 0 \text{ and } a_{od}^{k} > P_{od}^{k} > 0, b_{od}^{k} > 0, 0 < Q_{od}^{k} < \left(\frac{a_{od}^{k}}{b_{od}^{k}}\right)^{\frac{1}{\delta_{od}^{k}}} \\ a_{od}^{k} - b_{od}^{k}\ln(Q_{od}^{k}), \text{if } \delta_{od}^{k} = 0 \text{ and } a_{od}^{k} > P_{od}^{k} > 0, b_{od}^{k} > 0, 0 < Q_{od}^{k} < e^{\left(\frac{a_{od}^{k}}{b_{od}^{k}}\right)} \\ a_{od}^{k} - b_{od}^{k}(Q_{od}^{k})^{\delta_{od}^{k}}, \text{if } \delta_{od}^{k} < 0 \text{ and } P_{od}^{k} > a_{od}^{k} \geq 0, b_{od}^{k} < 0, 0 < Q_{od}^{k} < \infty \end{cases} \tag{4}$$

This inverse demand system is very flexible, embedding multiple demand functional forms (linear, quadratic, and isoelastic demands) (Bergquist, 2017). It is also structurally tractable, yielding a constant elasticity of the slope of the inverse demand $E_r^k(f_r^k)$. Likewise, it permits the use of b_{od}^k as a free parameter in the estimation, in order to capture any omitted variables.[21] Furthermore, the Bulow and Pfleiderer (1983) demand system allows consideration of the three different types of pass-through rates in the calculation of maritime shipping mark-ups.[22] More importantly, it allows the optimal pricing-rule derived above in equation (2) to be written as:

$$f_r^{\ell,k} = \rho_r^k c^{\ell}(\chi_r^k) + (1-\rho_r^k)(a_{od}^k - P_o^k) \tag{5}$$

This expression theoretically separately shipping costs and shipping mark-ups following Atkin and Donaldson (2015).[23] Carriers' marginal costs are compiled in the first term of this expression, while carriers' mark-up determinant in the second. This allows mark-ups to be calculated with a standard Lerner (1934) index.

[21] 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).

[22] When this inverse demand is concave (convex) to the origin –that is, when δ_r^k is positive (negative)– the short-run pass-through rate ρ is lower (higher) than one. This implies that a cost shifter x is partially (more than completely) transmitted to the shipping freight rates (i.e. $\Delta\, c$ is less (greater) than $\Delta\, p$) (see Figure 1a and Figure 1b, respectively), and consequently carriers reduce (raise) their shipping mark-ups when there is a cost shock.

[23] See Appendix A.

3 Data

3.1 Data Description

This paper employs data from the U.S. Merchandise Imports database for the period 2002-2017.[24] Specifically, the data sample consists, exclusively, of U.S. imports moved by sea.[25] 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 shipping charges (in current U.S.$).

These data also include the maritime shipping distance for all shipping routes used for delivering U.S. imports. I calculated these distances, using the GPS coordinates from each origin country o and each U.S. customs district d and applying the great-circle distance formula to those coordinates.[26] Likewise, Revealed Comparative Advantage (RCA) and the World Export Supply (WES) are calculated at the country-product-time level using the BACI dataset (Balassa, 1965; Hummels et al., 2014). A GDP per capita variable from CEPII database is employed, as the Rauch (1999) classification of products that distinguishes between bulk commodities and differentiated products.[27] Additionally, U.S. tariffs from 2002 to 2017 released by the USITC enter as another variable. The U.S. Consumer Price Index (CPI) is used to adjust all variables for inflation, using 2017 as the base year.

[24] All U.S. import data files used in this paper were retrieved from Peter Schott' web page.

[25] Appendix B describes in detail the construction of this dataset.

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

[27] U.S. census concordances were used to merge the Rauch product classification. However, the revision of the SITC codes –key for this merge– is unknown for the years 2002 to 2015. Revision 4 is only explicitly attributed to SITC codes in the concordances of 2016 and 2017. Thus, I assume that all SITC codes are at Revision 2, in order to circumvent the methodological problem of having SITC codes classified as differentiated and homogeneous. This problem arises when a set of SITC codes at Revision 4, which accounts for approximately 2% to 3% of U.S. imports (in value), are converted to Revision 2 for applying the Rauch classification. This is a weak assumption to significantly affect the results, given that the classification for most U.S. imports in value (94% to 96%) as homogeneous and differentiated products would be the same regardless of the SITC classification. In either way, I evaluate the robustness of the estimates to this assumption in Section 5.5.

4 Estimation Strategy

This section describes the two-step estimation strategy used to estimate shipping mark-ups. Specifically, it details the modified version of Atkin and Donaldson (2015) applied here. The first step is the estimation of the short-run pass-through rates of shipping costs to freight rates, ρ. The second step uses those estimated pass-through rates (1) to infer the strategic behavior of shipping carriers, and (2) to quantify the maritime shipping mark-ups charged for shipping differentiated products. The section also details the econometric approach followed to adjust for endogeneity in the econometric estimation of the short-run pass-through rates.

4.1 Short-run Pass-through Rate

The optimal pricing-rule derived above shows that the short-run pass-through rates ρ can be estimated using variation in levels of shipping costs. The key problem is that the functional form of the maritime shipping cost function, $c^\ell(\dot{})$, and the structure of the demand shifters for shipping a product k from o to d, a^k_{od}, are unknown. Data is only available for maritime shipping freight rates $f^{\ell,k}_r$ and many cost shifters (e.g. maritime shipping distance, oil price, volume shipped via a route, etc.). To solve this issue, I define the shipping freight rates as the price gap between the price of product k in destination market d imported from market o, P^k_{od}, and the price of the same product k in origin market, o, P^k_o (consistent with Hummels and Skiba (2004)). This permits writing the optimal pricing-rule in terms of observed prices as in Atkin and Donaldson (2015):

$$P^k_{od} = \rho^k_r P^k_o + \rho^k_r c^\ell(\chi^k_r) + (1 - \rho^k_r) a^k_{od} \tag{6}$$

which shows that the short-run pass-through rate ρ on marginal cost is structurally the same coefficient that is applied to the price of product k in the origin country o, P^k_o. Thus, it is econometrically estimable, using the variation of the price of each product k in an origin market o, P^k_o, across all destination markets d and overtime t within each U.S. coast c.[28] The cost function, $c^\ell(\dot{})$ and the minimum/maximum willingness to pay for shipping a product, a^k_{od} can be controlled using

[28]This identification strategy does not change with the assumed cost structure. When an *ad valorem* cost structure is assumed as I do it in this paper, the only difference is that the second term on the LHS of this expression is equal to $P^k_o T^\ell(\chi^k_r)$; defining $T()$ as the *ad valorem* shipping cost function. Thus, the structure of the first term does not change, which is the key for retrieving the short-run pass-through rate, ρ.

a fixed effects approach as in Atkin and Donaldson (2015).[29] Hence, the final specification that I econometrically estimate to predict the short-run pass-through rates is given by:[30]

$$P_{od}^{k,c} = \rho_o^{k,c} P_o^{k,c} + \sum_d (\gamma_{od}^{k,c} + \gamma_{od}^{k,c} t) + \epsilon_{od}^{k,c} \tag{7}$$

A serious econometric issue estimating this expression is that the price of a product k in origin country o ($P_o^{k,c}$) might be related to cost or demand shocks captured in the residuals of the estimation ($\epsilon_{od}^{k,c}$). Atkin and Donaldson (2015) assume this relationship to be completely exogenous in the context of intra-national trade. This assumption is, however, very strong in the context of maritime shipping. FOB prices might be endogenous, especially when considering U.S. import demand. Accordingly, this paper estimates the short-run pass-through rates, using a two stage-model approach and a recent instrument-free technique. Section **4.4** describes each approach in detail. The short-run pass-through rates are also estimated as Atkin and Donaldson (2015) to illustrate the impact of the endogeneity of the FOB prices on these estimates.

In all cases, the short-run pass-through rates are estimated for every combination of product k (defined as a HS6-digit product), origin country o and U.S. coast c. 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 each combination to retrieve the corresponding short-run pass-through rate, $\rho_o^{k,c}$. Additionally, the fixed effect ($\gamma_{od}^{k,c}$) and linear time trend ($\gamma_{od}^{k,c} t$) permit capturing the intra-route variation in each shipping route route r.

[29] This strategy generates structural forms involving two components. On the one hand, a time-invariant component, which in the context of maritime shipping captures (1) inherent costs for shipping a product k through a shipping route r; and (2) long-run preferences for shipping product k from country o to a particular destination d. On the other hand, 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 r, and (2) changes in consumer preferences over time due to economic conditions for shipping a product from country o to destination market d.

[30] Given the structure of the U.S. imports data used in this paper, it is implausible to estimate the short-run pass-through rate for every route r. The cost in terms of data variability is high. Thus, the estimation of the short-run pass-through rates is restricted for every combination $k - o - c$ to ensure more variability and degrees of freedom in the econometric estimation. This implies that ρ_r^k is approximated with the data as an average, per U.S. coast with the estimation of $\rho_o^{k,c}$.

4.2 Adjusted Shipping Freight Rates

Following Atkin and Donaldson (2015), the second step of this strategy is the estimation of determinants of the shipping freight rates. To this aim, carriers' optimal pricing-rule is rearranged such that the LHS variable becomes in an adjusted version of the *ad valorem* shipping freight rates for carriers' pass-through rates.[31]

$$\frac{P_{od}^{k,c} - \widehat{\rho_o^{k,c}} P_o^{k,c}}{\widehat{\rho_o^{k,c}} P_o^{k,c}} = T^{\ell}(\chi_r^{k,c}) + \frac{(1-\widehat{\rho_o^{k,c}})}{\widehat{\rho_o^{k,c}} P_o^{k,c}} a_{od}^{k,c} \tag{8}$$

The main difference with respect to Atkin and Donaldson (2015) is that carriers' shipping-cost structure is assumed here to be *ad valorem*. Empirical evidence has widely found that transportation costs are *ad valorem* rather than specific (Hummels and Skiba, 2004; Hummels, 2007; Hummels et al., 2009, 2014). That is, shipping costs and thus shipping mark-ups affect consumers' implicit demand for shipping services, according to products' FOB price as in Hummels (2007). Thus, I assume that carriers' cost function $c^{\ell}(\chi_r^{k,c})$ is equal to $P_o^{k,c}T^{\ell}(\chi_r^{k,c})$, where $T()$ corresponds to the *ad valorem* shipping cost function.[32]

The problem again is that the functional form of the shipping costs, $T^{\ell}(\chi_r^{k,c})$, and the minimum-maximum willingness to pay for shipping a product, $a_{od}^{k,c}$, are unknown. To circumvent this issue, I adopt a similar strategy as in Atkin and Donaldson (2015). Specifically, the cost function is assumed to be a parametric function of standard variables in the literature. Likewise, the minimum/maximum willingness to pay for shipping a product is modeled using a fixed-effects approach.

The maritime shipping cost function $T^{\ell}(\chi_r^{k,c})$ is modeled parametrically, and builds upon the literature about transportation costs for seaborne freight.[33] It is assumed to be linear in parameters and mainly explained by: (1) shipping distance along route r, $DIST_r^c$; (2) fuel expenses on a

[31]This structure of the LHS variable allows consideration of the strategic behavior of shipping carriers to manage a potential cost shock, charging (1) a higher shipping freight rate for shipping a product when the short-run pass-through rate ρ_r^k for product k delivered on route r is partial, or (2) a lower shipping freight rate when this pass-through rate is more than complete (Fabinger and Weyl, 2012; Weyl and Fabinger, 2013).

[32]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 rearranged version of the optimal pricing rule derived above divided by the price of product k in the origin country o, $P_o^{k,c}$.

[33]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).

route r, $DIST^c_r \times POil_t$; (3) aggregate volume shipped in route r during year t, V^c_{rt}; (4) the weight-to-value ratio of product k shipped via route r in year t, $WV^{k,c}_{rt}$; and (5) the volume of cargo handled in a destination d during year t, VH^c_{dt}, to capture the net cost (or gain) for a vessel to dock in a port according to the congestion of cargo. Additionally, a fixed effect $\kappa^{s,c}_o$ is included for each combination of origin country o and sector s, in order 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.

$$\begin{aligned} T^{\ell}(\chi^{k,c}_r) = {} & \kappa^{s,c}_o + \theta_1 ln(DIST^c_r) + \theta_2 ln(POil_t) + \\ & + \theta_3 \big[ln(DIST^c_r) \times ln(POil_t)\big] + \theta_4 ln(WV^{k,c}_{rt}) + \theta_5 ln(V^c_{rt}) + \theta_6 ln(VH^c_{dt}) + \epsilon^{k,c}_r \end{aligned} \tag{9}$$

As in Atkin and Donaldson (2015), the maximum/minimum willingness to pay for shipping a product $a^{k,c}_{od}$ is modeled as the sum of a time-product fixed effect, $\alpha^{k,c}_t$, a destination-product fixed effect, $\alpha^{k,c}_d$, and an origin-product fixed effect for a particular product k, $\alpha^{k,c}_o$. The difference here is that this fixed-effects structure controls for the preference in a destination market d for an imported product k from an origin country o. So, this structure allows consideration in the estimation of the Armington (1969) assumption.

$$a^{k,c}_{od} = \alpha^{k,c}_t + \alpha^{k,c}_d + \alpha^{k,c}_o + \upsilon^{k,c}_{od} \tag{10}$$

Substituting these expressions into equation (8) yields the final estimating equation that is used to separately identifying shipping costs and shipping mark-ups.[34] To this aim, I exploit the variation across time and products within shipping markets.

$$\begin{aligned} \frac{P^{k,c}_{od} - \widehat{\rho^{k,c}_o} P^{k,c}_o}{\widehat{\rho^{k,c}_o} P^{k,c}_o} = {} & \kappa^{s,c}_o + \theta_1 ln(DIST^c_r) + \theta_2 ln(POil_t) + \\ & + \theta_3 \big[ln(DIST^c_r) \times ln(POil_t)\big] + \theta_4 ln(WV^{k,c}_{rt}) + \theta_5 ln(V^c_{rt}) + \theta_6 ln(VH^c_{dt}) + \\ & + \frac{(1 - \widehat{\rho^{k,c}_o})}{\widehat{\rho^{k,c}_o} P^{k,c}_o} \alpha^{k,c}_t + \frac{(1 - \widehat{\rho^{k,c}_o})}{\widehat{\rho^{k,c}_o} P^{k,c}_o} \alpha^{k,c}_d + \frac{(1 - \widehat{\rho^{k,c}_o})}{\widehat{\rho^{k,c}_o} P^{k,c}_o} \alpha^{k,c}_o + \epsilon^{k,c}_r \end{aligned} \tag{11}$$

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

4.3 Maritime Shipping Mark-Ups

The estimated short-run pass-through rates $\widehat{\rho_o^{k,c}}$ and the maximum/minimum willingness to pay $\widehat{a_{od}^{k,c}}$ are used to calculate maritime shipping mark-ups, $\mu_r^{\ell,k}$.[35] The standard Lerner (1934) index generates the following expression.[36]

$$\mu_r^{\ell,k,c} = \frac{(1-\widehat{\rho_o^{k,c}})(\widehat{a_{od}^{k,c}} - (1+\widehat{T^{\ell}(\chi_r^{k,c}}))P_o^{k,c})}{P_{od}^{k,c} - P_o^{k,c}} \tag{12}$$

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.

$$\mu_r^{\ell,k,c} = -\left(\frac{1-\widehat{\rho_o^{k,c}}}{\widehat{\rho_o^{k,c}}}\right)\left(\frac{\eta_r^{k,c}}{\delta_r^{k,c}}\right)\left(\frac{P_{od}^{k,c}}{P_{od}^{k,c} - P_o^{k,c}}\right) \tag{13}$$

This expression shows that mark-ups increase when market conditions are less competitive in a maritime shipping route (i.e. $\rho \to 0$ or $\rho \to \infty$). Moreover, mark-ups are higher for high-value products, products with a higher elasticity of the inverse demand for shipping η or with a higher curvature of shipping demand δ. Additionally, mark-ups are sensitive to short-run pass-through rates, such as their elasticity relative to the short-run pass-through rates ($\varepsilon_{r,(\rho,\mu)}^{\ell,k,c}$) is shown below.

$$\varepsilon_{r,(\rho,\mu)}^{\ell,k,c} = \left(\frac{\widehat{\rho_o^{k,c}} - 1}{\widehat{\rho_o^{k,c}}}\right)^{-1}(1-\widehat{\mu_r^{\ell,k,c}}) \tag{14}$$

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

The FOB prices used to estimate short-run pass-through rates in the context of shipping are likely endogenous to the freight charges. In order to investigate this possibility, three sets of short-run pass-through rates are estimated for each period of analysis.

[35] Given the structure of the U.S. import data used in this paper, these mark-ups correspond exclusively to the portion charged by shipping carriers with respect to the observe shipping freight charges.

[36] Using expression (12), 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, $P_{od}^{k,c}$ is greater or equal than $a_{od}^{k,c}$ when $\rho_o^{k,c}$ is more than complete, and $P_{od}^{k,c}$ is lower or equal than $a_{od}^{k,c}$ when $\rho_o^{k,c}$ is partial.

The first set of estimates retrieves $\widehat{\rho}$ from equation (7) using OLS as in Atkin and Donaldson (2015). That is, ρ is predicted assuming complete exogeneity of the price of each product k in origin market o ($P_o^{k,c}$) to the residuals of the estimation. To this aim, the estimation also considers the aforementioned fixed effects, and exploits the variation in the data over time within destinations markets and across the average variation over destinations.

The second approach estimates ρ, using instruments the FOB price of each product k in country o to absorb the endogenous component related to the freight charges. Assuming that this endogeneity is mainly due to heterogeneous comparative advantage conditions, differences in domestic and global production efficiencies, macroeconomic conditions, and even important differences in the size of the origin countries, the FOB prices are regressed in a first stage on: (1) the GDP per-capita from each origin country o; (2) the U.S. tariff for every product k over time; (3) the Revealed Comparative Advantage (RCA) from each origin country o producing product k; and (4) the World Export Supply (WES) of each product k, here excluding the U.S. trade flows.[37] Then, equation (7) is estimated as a second stage, using the predicted FOB price from the first stage. Finally, the short-run pass-through rates are retrieved as the coefficient of this FOB price.

The third set of $\widehat{\rho}$ estimates relies on the Gaussian Copula (hereafter GC) method to control for the endogeneity of $P_o^{k,c}$ (Park and Gupta, 2012).[38] This instrument free technique controls and corrects for endogeneity bias, by constructing and then applying a Gaussian copula to the joint distribution between an endogenous variable and the residuals of the estimation. In this context the GC method models explicitly the joint distribution between the FOB prices and the residuals of the estimation $f(P_o^{k,c}, \epsilon_{od}^{k,c})$. Using non-parametric techniques and applying Gaussian copulas, the GC method retrieves this distribution as a standard bivariate normal $f(P_o^{k,c^*}, \epsilon_{od}^{k,c^*})$ with correlation ϱ; where P_o^{k,c^*} and ϵ_{od}^{k,c^*} correspond to the version of each variable normally distributed.[39] Exploiting the orthogonality between the variation of these variables ω (similar to Feenstra (1994)),

[37] Exceptionally, the GDP per-capita and the U.S. tariff are used in those estimations for which BACI dataset does not report data to calculate the RCA and the WES.

[38] This method avoids the hard task of finding strong and exogenous instruments for the FOB prices. It exploits the variation in the data as Feenstra (1994). That study introduced an instrument free method that that it is widely used in the international trade literature.

[39] Specifically, the joint distribution is retrieved, applying a Gaussian copula to the univariate marginal distribution of $P_o^{k,c}$ and $\epsilon_{od}^{k,c}$. Non-parametric techniques are used to retrieved the univariate marginal distribution of $P_o^{k,c}$. A normal marginal distribution is assumed for $\epsilon_{od}^{k,c}$, given the robustness of the estimated to misspecification in the distribution for the residuals Park and Gupta (2012).

the endogeneity bias is removed from the estimation.[40] The joint distribution can be written as:

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

Assuming that the residuals of the estimation are normally distributed with mean equal to zero and variance equal to σ_ϵ, and solving this system of equations, yields that the residuals $\epsilon_{od}^{k,c}$ of expression (7) are equal to $\sigma_\epsilon \epsilon_{od}^{k,c*}$ and then to $\sigma_\epsilon \varrho P_o^{k,c*} + \sigma_\epsilon \sqrt{1-\varrho^2}\omega_\epsilon$. This implies that the GC method actually estimates the following modified version of expression (7).

$$P_{od}^{k,c} = \rho_o^{k,c} P_o^{k,c} + \sum_d (\gamma_{od}^{k,c} + \gamma_{od}^{k,c} t) + \sigma_\epsilon \varrho P_{od}^{k,c*} + \sigma_\epsilon \sqrt{1-\varrho^2}\omega_\epsilon \quad (15)$$

Conditional on the orthogonality between ω_{p^*} and ω_{ϵ^*} the GC method removes the endogeneity bias from the model. The identification of ρ comes from the fact that $P_o^{k,c*}$ captures the endogenous variation of the FOB prices initially compiled in the residuals, and ω_{ϵ^*} is also orthogonal to all terms in the expression by assumption. Therefore, all parameters $\Theta : \{\rho_o^{k,c}, \gamma_{od}^{k,c}, \gamma_{od}^{k,c}, \sigma_\epsilon, \varrho\}$ are estimable, by maximizing the log-likelihood function of the joint distribution of the FOB prices and the residuals.[41]

4.5 Explaining variation in estimated Shipping Mark-ups

Do shipping carriers charge larger mark-ups to freight rates on longer shipping routes to the U.S.? 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 shipping mark-ups across origin countries, U.S. customs districts, products at HS6 digit-code, U.S. coasts and years. So, in order to better understand how these mark-ups vary with route and product, reduced form regressions of the estimated mark-ups across these characteristics allow a better understanding of how these estimated mark-ups are distributed. Specifically,

[40] The approach of Feenstra (1994) is similar, assuming that variation on supply and demand shocks is orthogonal. So, the supply variation allows identifying demand and vice versa.

[41] To ensure model identification, the endogenous variable (in this case the FOB price, $P_o^{k,c*}$) has to be non-normally distributed. Otherwise, multicollinearity might arise in the estimation. As explained, $P_o^{k,c*}$ is modeled as a univariate normal distribution. Then, $P_o^{k,c*}$ might be a linear transformation of $P_o^{k,c}$. The positive thing, though, is that multicollinearity does not affect the properties of the estimated parameters, as well known. It mainly leads an overestimation of the parameters' standard errors. Then, it may mislead the statistical inference based on the predicted estimates.

the reduced form models regress the *ad valorem* shipping mark-ups $\mu_r^{\ell,k}$ and the tariff equivalent mark-ups $\tau_{\mu_r}^{\ell,k}$, respectively, on (1) the shipping distance in a route $DIST_r$; (2) the origin countries' GDP per capita $GDPpc_{ot}$; and (3) the 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 regressions models are estimated to link the *ad valorem* freight rates $f_{\ell,r}^k$ to the same independent variables.

5 Results

The estimation strategy is applied to the sample of U.S. imports of differentiated products shipped by sea for periods that pre-date and post-date the global financial crisis: 2002-2007 and 2013-2017. This strategy removes the noise from the global financial crisis 2008-2012, which is necessary given the approach's maintained hypothesis of parameter stability over a short panel.[42] In an effort to evaluate how the global financial crisis affected non-competitive pricing behavior in the shipping industry, I also apply this strategy to that period, acknowledging the volatility of that period. Throughout the exercises, the sample data is split into shipments to the U.S. East coast and shipments to the U.S. West coast, in order to control for presumably different market conditions.

The results of all estimates are presented in the following sections. Section 5.1 presents summary statistics for U.S. shipping freight rates and for the other variables used in the analysis. Section 5.2 reports the summary statistics of the estimated short-run pass-through rates for each combination $k-o-c$ retrieved using OLS, 2SLS model and the GC method. From then, most shown results rely on the GC method estimates for ρ, given that these are better grounded in statistical terms. Section 5.3 describes estimates from the model of *ad valorem* adjusted freights. Section 5.4 discusses the estimated maritime shipping mark-ups. Section 5.5 shows results of robustness exercises.

[42]The global financial crisis of 2008-2012 pushed some costs of maritime shipping carriers (e.g. oil prices) to atypical levels. It also generated a significant increase in the unused capacity in the market, which presumably distorted shipping carriers' power in the market.

5.1 Descriptive Statistics

Before turning to the results, this section reports summary statistics for freight rates and for the other variables used in the regression models. The objective is to investigate underlying patterns in the data that permit a better interpretation of the estimates.

The summary statistics reveal three main lessons regarding the shipping freight rate. First, *ad valorem* shipping freight rates are somewhat higher for import shipments to the U.S. East coast than to the U.S. West coast. Table 2 shows that *ad valorem* freight charges for products shipped 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, *ad valorem* freight rates charged to most U.S. imports are right skewed. The median *ad valorem* freight rate is 2 to 3 percentage points lower than the average in all periods. Third, *ad valorem* freight rates fell thrpugh out the sample. On average, *ad-valorem* shipping freight rates were about 1.5 percentage points lower during the crisis than during the previous period, and another 0.4 to 0.6 percentage points lower during the post-crisis period.

Shipping distance is one of the main drivers of shipping freight rates. Table 2 shows that the average shipping distance is approximately 12,000 kilometers for shipping products to either U.S. coast.[43] 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) is also key for carriers to set the shipping freight rates. Table 2 reports considerable 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 expenses, an important cost shifter for carriers, remained apparently at low levels in the last decades, and even might have fallen during the post-crisis period. Table 2 reports that the median WTI oil price fell from U.S.$71.1 per barrel in 2002-2007 to U.S.$50.8 per barrel during 2013-2017.

[43] 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.

Yet, the higher 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.

5.2 Short-run Pass-through Rates in Maritime Shipping

As explained, carriers' rate of pass-through of costs to freight rates are key for the measurement of shipping mark-ups. This section reports the summary statistics of the estimated short-run pass-through rates for U.S. imports moved by sea from 2002 to 2017. It then shows estimates of how the estimated pass-through rates are related to determinants of shipping mark-ups, such as shipping distance and the origin country's GDP per capita.

5.2.1 Summary Statistics of Short-run Pass-through Rates

Table 3 shows the summary statistics of the estimated short-run pass-through rates ρ.[44] All econometric techniques predict quite similar estimates for the median (average) pass-through rate among all combinations $k - c - o$. For the periods before and after the crisis, all methods predict a median pass-through rate ranging from 1.00 to 1.02, and an average rate ranging from 1.06 to 1.42.[45] All three techniques thus suggest that carriers exert market power. These estimates clearly show evidence of carriers' ability to either pass through partially or more than completely a cost shock to freight rates. Furthermore, they reveal that carriers' ability mainly depends on: (1) the product shipped; (2) the origin country, and (3) the U.S. coast of delivery.

[44] A problem with many estimates is that there are few data points to produce them. That is, 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 C1 shows that the value of U.S. imports through those missing combinations only account less than 1% of the total. Table C2 also shows that the number of products related to those combinations only represents 3% to 4% of the total for the U.S. East coast and 6% to 8% of the total for the U.S. West coast. In addition, Table C3 shows that the number of countries excluded from the analysis due to this issue represents 10% to 13% of the total in the U.S. East coast and 25% to 28% of the total in the U.S. West coast.

[45] Table 4 shows the correlation among the estimated short-run pass-through rate retrieved from all techniques. Overall, it reaffirms that are very similar among them. Most discrepancies, though, it indicates occur among the estimated short-run pass-through rates using 2SLS versus those retrieved using OLS or the GC method.

Yet, the estimated short-run pass-through rates with the GC method are better grounded in statistical terms. The OLS estimates potentially suffer from endogeneity bias.[46] The 2SLS estimates reveal evidence of a weak instruments problem. The remainder of the paper relies on the GC estimates of the short-run pass-through rates.[47]

The estimated pass-though rates show that, on average, carriers pass-through an increase of costs more than completely to shipping freight charges (i.e. $\bar{\rho} > 1$). Specifically, columns (3) and (9) in Table 3 show that an increase of \$1 in shipping costs imply a median (average) increase in shipping freight charges of about \$1.01 (\$1.11-\$1.42).[48] Likewise, the distribution of these estimates, historically ranging from 0.4 to 2.7 reaffirms that carriers ability to pass-through a cost shock to freight charges varies significantly across products, origin country and the U.S. coast of delivery. Hence, these estimates show that carriers have the ability to differently respond to a cost shock, which is evidence of non-competitive conditions.[49]

The estimated short-run pass-through rates in this context of maritime shipping are somewhat larger than estimates from other markets. For instance, Atkin and Donaldson (2015) estimate an average short-run pass-through rate of 0.5 for intermediaries within the intra-national trade markets of Nigeria, Ethiopia, and the U.S. Likewise, Bergquist (2017) estimates a pass-through rate of 0.2 for intermediaries in the agricultural markets of sub-Saharan Africa. The average short-run pass-through rate in the U.S. maritime shipping market is lower than the 1.6 estimated for intermediaries in the market of residential solar power systems in California, as discussed by Pless and Van Benthem (2017).

[46]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.

[47]The GC method reports Confidence Intervals (CI) at 95% level to test the statistical significance. All upper bounds are positive for all $\widehat{\rho}$ estimates. However, about 25% of the lower bounds are negative (See Figure 2, 3 and 4). Then, the hypothesis that $\widehat{\rho} = 1$ cannot be rejected. In order to evaluate whether this is due to overestimated standard errors resulted from inherent multicolinearity in the estimation, I apply the Shapiro–Wilk normality test to the FOB prices. This test reveals that two-thirds of the $\widehat{\rho}$ estimates with negative CI were affected because of this problem. Consequently, the statistical inference might be misleading in these cases. These $\widehat{\rho}$ estimates might be statistically significant. Additionally, an evaluation of the remaining third of $\widehat{\rho}$ estimates shows that it only account for 1.4% to 3% of the value of U.S. imports.

[48]This median pass-through rates near to 1 shows the identification problem when evaluating the presence of market power in this industry. When studies ignore carriers' ability to pass-though a cost shock to shipping freight rates depending upon the shipped product and the route such as Jeon (2020), the data implicitly leads to assuming that this pass-through rate is equal to 1 (i.e. the average). Then, it is mistakenly claimed that conditions in this market are competitive. However, once one considers carriers' ability to pass through a cost shock to freight rates as I do it in this paper, all estimates indicate that conditions in the maritime shipping market are not competitive.

[49]As explained above, an estimated short-run pass-through equal to one implies a competitive market. Any pass-through rate below and above this mark, thus, implies that carriers extract rents from the market.

5.2.2 Short-run Pass-through Rates and Market Conditions

The previous section shows evidence that conditions are non-competitive in the U.S. shipping market. Shipping carriers exert market power in this market. Given that their ability to do so depends on product features and/or on the market conditions in each shipping route, this section investigates under what market conditions carriers are more able to do so. Specifically, it evaluates whether the estimated short-run pass-through rates are related to shipping distance and origin countries' GDP per capita. For the sake of simplicity, each relationship is estimated non-parametrically, assuming an Epanechnikov kernel with bandwidth optimally defined by a cross-validation process.

Figures 5 and 6 show the results of estimating the relationship between shipping distance and short-run pass-through rates. Both figures show higher short-run pass-through rates on products shipped on very short routes or on medium to long shipping routes during the pre-date and post-date period to the global recession (2008-2012). Likewise, they reveal a rough positive relationship between carriers' pass-through rates and shipping distance during these periods (except for products shipped to the U.S. East coast during 2013-2017 where the relationship is much weaker). Hence, both figures reveal two lessons. First, shipping competition is fiercer on short to medium length shipping routes, given carriers' lower ability to pass-though a costs shock to freight charges. Second, this carriers' ability increases with the shipping distance.

Figures 7 and 8 show the results of estimating the relationship between the estimated short-run pass-through rates and origin countries' GDP per capita. Both figures show higher pass-through rates on products shipped from countries with lower GDP per capita to both U.S. coast. Furthermore, both depict a rough negative relationship between these variables, except again by the increasing relationship of the pass-through rates and the GDP per capita of the products shipped to the U.S. East coast during 2013-2017. Hence, these estimates reveal that carriers passed through a higher portion of costs to freight rates when shipping from poorer countries to the U.S.

5.3 Adjusted Shipping Freight Rates Function

In order to quantify the magnitude of non-competitive behaviour in this industry identified above, the estimation of the shipping mark-ups is the next step. Thus, I estimate the adjusted freight rates expression on cost shifters, using the estimated short-run pass-through rates. As explained, this estimation predicts the cost component explaining the shipping freight charges. It then generates the input to estimate the shipping mark-ups. Before turning to those estimates, this section reports the results of estimating each adjusted freight rate expression for each U.S. coast and period of analysis.[50]

5.3.1 U.S. East Coast

Table 5 shows the results of estimating the adjusted freight expression among shipments bound to the U.S. East Coast. Specifically, column 1 shows *ad valorem* freight rates tended to increase by 0.21 percentage points when shipping distance increased by 10% (approximately 1,200 kilometers at the mean) during the period 2002-2007. These freight rates were also not very sensitive to oil prices, increasing only by 0.04 percentage points when the oil price increased by 10% over this period.[51] Additionally, freight rates tended to decrease by about 0.01 and 0.03 percentage points, when the volume shipped in a route or handled on the destination port increased by 10%. Hence, *ad valorem* shipping freight rates responded only slightly to cost shifters during 2002-2017. Additional volatility seems to have been more related to shipping freight mark-ups.

Column 3 in Table 5 shows the same pattern during 2013-2017. An increase of 10% only led *ad valorem* freight rates to increase by 0.15 percentage points. An increase of 10% in the oil prices implied an increase of 0.02 percentage points. Additionally, an increase of 10% in the volume shipped in a route or in the cargo handled on the destination port led the shipping freight rates to fall by about 0.01 and 0.03 percentage points, respectively. The main difference with respect to the period 2002-2007 is that *ad valorem* freight rates decreased by 2 percentage points on average to 6.1% in this period, as shown in Table 2. Although shipping freight rates remained not very responsive to costs shifters, it appears that carriers reduced the mark-ups shown in Section 5.4.

[50] 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 shipping carriers.

[51] To estimate the expected change in the freight rates due to an increase of X% in one of the cost shifters, it is applied that this change is equal to $\widehat{\Theta} \times \ln\left(\frac{100+X\%}{100}\right)$. In all cases, $\widehat{\Theta}$ corresponds to the coefficients component predicted in the estimation.

5.3.2 U.S. West Coast

Table 5 shows the results of estimating the adjusted freight expression for shipments delivered to the U.S. West Coast. Column 4 reports that *ad valorem* freight rates charged to shipments bound for the West coast were also not very responsive to cost shifters prior to the crisis. *Ad valorem* freight rates only increased by 0.03 percentage points when oil prices increased by 10%. These freight rates also decreased by 0.01 and 0.03 percentage points when the volume shipped in a route or handled in the destination port increased by 10%. Interestingly, this column also reports that *Ad valorem* freight rates could have even reduced by 0.11 percentage points when the shipping distance increased by 10%. Therefore, these estimates suggest that nearly any increase in the freight rates should be primarily attributed to changes in shipping mark-ups.

Column 6 in Table 5 shows a similar pattern during 2013-2017. *Ad valorem* freight rates charged for shipments bound for the West coast remained not very responsive to cost shifters. For instance, neither shipping distance nor the oil price can explain these freight rates. The coefficients on these variables are not statistically significant. *Ad valorem* freight rates only responded to the scale of shipping in the destination port. Column 6 shows that freight rates decreased by 0.03 percentage points when the volume handled in the destination port increased by 10%. Thus, the main difference with respect to the period 2002-2007 was also that *ad valorem* freight fell by 1.8 percentage point on average to 5.8%. Additionally, carriers serving this U.S. coast also reduced their mark-ups.

5.4 Maritime Shipping Mark-ups

Having estimated the short-run pass-through rates ($\rho_o^{k,c}$) in Section 5.2 and *ad valorem* shipping costs ($T^\ell(\chi_r^{k,c})$) and the maximum/minimum willingness to pay for shipping product k ($a_{od}^{k,c}$) in Section 5.3, maritime shipping mark-ups ($\mu_r^{k,c}$) are calculated for every combination $r-k-c-t$. In order to characterize the central tendency of these estimates, the median per shipping route (r) and then per year (t) is calculated. This section reports the results of these estimates. Then, it reports the results from estimating how shipping mark-ups vary with product and route characteristics. Finally, it shows estimates from back-of-the-envelope calculations conducted to estimate the U.S. reduction in welfare due to shipping mark-ups.

5.4.1 The size of Maritime Shipping Mark-ups

Table 6 shows the median shipping mark-up charged to U.S. imports of differentiated products. Estimating all mark-ups as a share of freights charges, the first row in this table reports that the median mark-up ranges from 34% to 43% for shipments to the U.S. East coast and from about 32% to 34% for shipments to the U.S. West coast.[52] The second and third rows also show evidence of how sensitive mark-ups are to the short-run pass-through rates. Using the estimated short-run pass-through rates with OLS and 2SLS models, the median mark-up ranges from 60% to 90% for products shipped to the U.S. East coast and from almost 50% to 80% for those shipped to the U.S. West coast.[53] Thus, these estimates of the shipping mark-ups clearly show evidence of the strong dependency of the mark-up estimates on the short-run pass-through rates. These results also reaffirm the importance to properly econometric identification of these rates. Accordingly, the remainder of this paper relies upon the estimated mark-ups, using the predicted short-run pass-through rates with the GC method. As noted, the OLS estimates for ρ are subject to endogeneity bias. The 2SLS approach does not solve the endogeneity problem, as the instruments are weak.

Examining in detail the estimated shipping mark-ups, Table 6 shows they decreased after the global financial crisis 2008-2012. Prior to the global financial crisis, the median mark-up 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, though, the median mark-up only accounted for 34.1% and 32.7% of the freight rates, respectively. This reduction in the mark-ups confirms the tough market conditions that carriers faced

[52] As noted, shipping mark-ups are estimated as a Lerner (1934) index. Accordingly, these mark-ups are always positive, assuming a negative inverse demand elasticity (η) (See expression (13)). However, this is a puzzle in the shipping industry. 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. It appears that mode switching in the transportation market may lead freight markets to have a positive elasticity for a single mode. Given that shipping products by air is very sensitive to fuel prices (Hummels et al., 2014), this elasticity can be positive for products that more often switch among modes of transportation. The rationale is simple. A negative (positive) shock in the fuel prices tends to more drastically increase (decrease) the cost of freight by air than the costs of shipping via other modes of transportation. Thus, the demand for other modes of shipping services may increase (decreases), despite the cost of freight via those modes also increases (decreases). I mainly attribute to this puzzle the estimated negative mark-ups. However, I acknowledge that these 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 (origin-destination-product-year).

[53] Preliminary versions of this paper predicted a median maritime shipping mark-up of about 30% to 38% when estimating the short-run pass-through rates with OLS and 2SLS. The difference with respect to these updated estimates is due to the fact that in the estimation of adjusted freight function considers: (1) the volume handled in a destination port, and (2) the consumers preferences for products from a particular origin country. Two modification incorporated to the adjusted freight function aimed to improve the identification of the shipping costs, and so of the shipping mark-ups.

after the crisis (GSF Global Shippers Forum, 2017; ICS International Chamber of Shipping, 2017; Samunderu, 2018). It clearly show that carriers reduced the rents extracted from the market, given that freight charges also decreased. These estimates also show that the difference between the median mark-up charged for shipping products to both U.S. coasts diminished from 9 percentage points of the freight rates prior to the global financial crisis to 1.5 percentage point during the post-crisis period.[54]

At the country level, Table 7 does not show an overall pattern during the period 2002-2017. Average shipping mark-ups per country tended to be apparently conditional on the U.S. coast to which carriers ship the products. For instance, columns 1-3 show that carriers serving the U.S. East coast reduced relatively 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 United Kingdom). In contrast, columns 4-6 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-up on shipments from European countries (such as Germany United Kingdom and Italy). Additionally, Table 8 and Table 9 show that carriers charge higher mark-ups when delivering products to larger U.S. customs districts such as New York, NY, and Houston, TX, in the U.S. East coast and Los Angeles, CA, Seattle, WA and San Francisco, CA, in the U.S. West coast. These estimates thus offer anecdotal evidence that larger mark-ups are charged on routes with bigger destination ports.

5.4.2 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 $f^k_{\ell,r}$, *ad valorem* shipping mark-ups $\widehat{\mu^{\ell,k}_r}$, and the tariff equivalent of these mark-ups $\widehat{\tau^{\ell,k}_{\mu r}}$ on the following variables: (1) the shipping distance on a route, $DIST_r$; (2) the origin country's GDP per capita, $GDPpc_{ot}$; and (3) the substitution elasticity of each product σ^k (estimated by Soderbery (2015)).[55]

[54] As explained, these shipping mark-ups estimates merely correspond to median mark-up charged within a route in a particular year. Thus, this does not imply that carriers charge these mark-ups to all products. These are just point estimates, calculated as an median, from the estimated shipping mark-ups at the product and route level over time.

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

Table 10 shows the results of this estimation. As shown, all estimates are very robust and predict the same conclusions in all periods.[56] 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.[57] Shipping freight rates also increase about 1.8 to 2.2 percent (i.e. about 0.12 percentage points) for every 1,200 kilometers of extra shipping distance.[58] Second, freight mark-ups are higher relative to freight rates charged when shipping products from developed and closer countries to the U.S (See Columns 3-4, 9-10 and 15-16). Doubling GDP per capita increases *ad valorem* mark-ups to freight charges by 2 to 3 percent (i.e. almost one percentage point). 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).

5.4.3 Counterfactual Calculations

To investigate how shipping mark-ups affect import prices, I apply the estimated mark-ups to the freight rates in order to decompose it between marginal shipping costs and shipping mark-ups. This exercise yields that for each U.S.$5.5 to U.S.$6.3 paid at the median for shipping U.S.$100 of differentiated products to the U.S. during 2002-2007, U.S.$2.1 to $2.6 corresponded to shipping mark-ups (See Figure 9). Likewise, for each U.S.$3.9 to U.S.$4.5 paid for shipping the same amount of merchandise during 2013-2017, about U.S.$1.4 of this constituted mark-ups. Thus, maritime shipping mark-ups represented an equivalent *ad valorem* tariff ranging from 2.1% to 2.6% during 2002-2007 and of 1.4% during 2013-2017. These estimates are roughly equivalent to one to two-thirds of the average U.S. tariff during this period, which ranged from 2.8% to 4.0% (World-Bank, 2021).

[56] To estimate the expected change in the freight rates and shipping mark-ups due to an increase of X% in the shipping distance or the GDP per capita, it is applied that this change is equal to $\exp(\widehat{\Theta} \times \ln(\frac{100+X\%}{100})) - 1$. In all cases, $\widehat{\Theta}$ corresponds to the coefficients component predicted on the estimation.

[57] Approximately, this accounts for 0.6 percentage points of the freight rates, assuming an ad valorem freight rate of about 6%.

[58] 1,200 kilometers is equivalent to an increase of 10% in the average shipping distance.

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

In order to determine what the non-competitive pricing behavior in the maritime shipping industry implies for trade and welfare, I conduct two additional exercises. First, the trade elasticity is used to determine the response of U.S. imports to the implicit costs of the estimated mark-ups. Second, back-to-the envelope calculations apply the trade elasticity in order to estimate the welfare loss resulting from the maritime shipping mark-ups.

Most structural gravity models show that the response of trade flows to trade costs largely depends on the assumed trade elasticity.[59] Many gravity studies thus estimate trade elasticities ranging from 5 to 10 Anderson and van Wincoop (2004). Recent estimates also imply a smaller elasticity, ranging from 3 to 5, and estimates of this elasticity in shipping markets find that it is equal to 3 (Simonovska and Waugh, 2014; Wong, 2017).[60] Using the previous result that shipping mark-ups accounted for an equivalent *ad valorem* tariff ranging from 2.1% to 2.6% during 2002-2007 and of 1.4% during 2013-2017, this paper estimates 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 were set to zero (See Table 11).

In terms of welfare, the loss attributed to non-competitive behavior in the maritime shipping industry can be estimated by applying the approach of Arkolakis et al. (2012). That paper shows that the change in welfare ($\widehat{W}$) due to a foreign shock can be computed as $\widehat{\lambda}^{-1/\epsilon}$, regardless of the micro-level implications of a model; where $\widehat{\lambda}$ is the change in the share of domestic expenditure and ϵ is the trade elasticity. Thus, the welfare loss of shipping mark-ups for U.S. can be easily calculated as follows, comparing trade flows with and without shipping mark-ups.

$$\widehat{W} = \lambda_{mark-ups}^{-1/\epsilon} - \lambda_{NOmark-ups}^{-1/\epsilon} \tag{16}$$

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%. Equation (16) implies that U.S. consumers perceived an average loss of about 0.1%-0.2% in their real income during 2002-2017 due to the shipping mark-ups, assuming a trade elasticity ϵ between

[59] Simonovska and Waugh (2014) survey most of these studies.

[60] These studies though do not consider the non-competitive behavior in the shipping market on these estimates.

3 and 5 (See Table 12). 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).

5.4.5 Did the 2008-2012 Global Financial Crisis 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 global financial crisis period (2008-2012) is questionable. Global aggregate demand for goods and services was seriously distorted. Some shipping costs for carriers (e.g. oil prices) reached atypical levels, and unused capacity in the market significantly increased during this period (UNCTAD, 2017).[61] This is, however, a period of significant interest. Thus, in order to inform our understanding of the effects of the crisis, I apply the same estimation strategy to the period 2008-2012.

Applying the same estimation strategy to 2008-2012 indicates that carriers' ability to transfer a cost shock to freight rates slightly decreased during 2008-2012 period. Columns (3) and (6) in Table 3 show that the average pass-through rate 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. So, carriers were unable to keep transferring the same proportion of costs to freight charged on the products to which they transferred the most in 2002-2007. This result reinforces the thesis that shipping carriers faced tough conditions during this period (GSF Global Shippers Forum, 2017; ICS International Chamber of Shipping, 2017; Samunderu, 2018).

Column (2) in Table 5 also shows that oil price volatility slightly affected shipping carriers during this period, especially to those serving the U.S. East coast. An increase of 10% in the oil price during 2008-2012 implied an increase of 0.35 percentage pointsin the shipping freight rates. That is, the response in ad valorem freight rates of changes to prices was approximately 10 times larger than during 2002-2007. In contrast, Column (2) and (5) in Table 5 show that an increase of 10% in the shipping volume in a route or the volume handled in a destination port continued to lead a reduction in freight rates of 0.1-0.3 percentage points.

[61] Table 2 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, reversing their course these prices touched the barrier of US$120 in 2011 and oscillated around US$90 to US$100 afterwards.

Estimates in Table 6 indicate that carriers significantly reduced their mark-ups during the crisis. Specifically, *ad valorem* shipping mark-ups ($\mu_r^{\ell,k}$) 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 for the U.S. West coast.

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

5.5 Robustness exercises

In order to quantify the effect of non-competitive pricing behavior in the maritime shipping industry, this paper applies a modified version of Atkin and Donaldson (2015). To this aim, it uses U.S. import data at HS6-digit code level, as is standard most trade studies. One concern regarding this level of product aggregation is whether the Alchian-Allen effect undermines the identification of the estimated short-run pass-through rates and so of the shipping mark-ups. Hummels and Skiba (2004) show that transport costs affect the quality-composition of the traded good. So, if the quality variation across the products within each HS6-digit level is sufficiently large, estimates at HS6 level could be biased. In order to test the robustness of the previous estimates for the short-run pass-through rates and the shipping mark-ups, all models are also estimated using U.S. imports at HS10-digit product level.

This robustness exercise shows that estimated short-run pass-through rates (ρ) are robust to disaggregation of the U.S. import data to the HS10 level.[62] The correlation between the estimated short-run pass-through rates using data at HS6 digit-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 short-run pass-through rates are plotted along with a solid 45-degree line, also indicates that the estimated short-run pass-through rates are stable surrounding this solid line; regardless the level of aggregation of the U.S. imports data (See Figure D1 and Figure D2). Most

[62] To this particular exercise, I previously removed outlier estimates for ρ in order to reduce the noise in this estimation. To so so, I set 30 as the highest feasible level, which is roughly 10 times the percentile 90 of the estimated ρ. This exercise implied dropping about 40 observations out of approximately 50,000 observation in the subsample for the U.S. East coast, and 30 observations out of the 28,000 in the subsample of the West coast.

discrepancies appear to be related to some extremely high short-run pass-through rates estimated for HS10 digit products. Larger variance in the HS10-digit level data is expected, given the smaller number of observations used to estimate the HS10 level short-run pass-through rates.

Table D1 also reinforces this result, showing that the distribution of both sets of short-run pass-through rates is similar. The median short-run pass-through rate in both distributions is 1.01. Both distributions also have their minimum values around 0.4. The main difference between both distributions is that the average short-run pass-through rate is higher in about 0.2 points when estimated at HS10 than at HS6. Thus, the Alchian-Allen effect would be leading to underestimating carriers' ability to pass-through a cost shock to freight rates.

Another important concern is whether the estimated maritime shipping mark-ups μ are also robust. To evaluate this issue, the maritime shipping mark-ups are calculated using the estimated short-run pass-through rates for HS10 product codes. Table D2 shows that the estimated mark-ups are very robust overall in terms of magnitude. Regardless of the level of product disaggregation, the median shipping mark-up is about one third of the shipping freight charges. Likewise, the HS10 estimates confirm that mark-ups were higher before the global financial crisis. Nevertheless, columns (1)-(2) show that the median shipping mark-up on shipments to the U.S. East coast is about 5 to 6 percentage points lower, when is calculated using data at HS10 product-code than with data at HS6 product-code. Likewise, columns (3)-(4) show that the median mark-ups on shipments to the U.S. West coast differ in about 3 percentage points, when is calculated using data at HS10 product-code than with data at HS6 product-code.

Finally, 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.[63] 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 D3 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 D4 indicates that the maritime shipping mark-ups are also very similar, assuming Revision 4 for the SITC codes. Specifically, shipping mark-ups continue to

[63] See Section 3, footnote 27.

account for approximately one-third of the freight charges.

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. It also evaluates whether non-competitive behavior disproportionately affects developing and/or distant countries. Using U.S. import data, the method of Atkin and Donaldson (2015) is applied to the maritime shipping industry. This permits estimating the shipping mark-ups charged on freight charges for periods 2002-2007, 2008-2012, and 2013-2017.

The method of Atkin and Donaldson (2015) solves the theoretical problem of separately identifying firms' marginal costs and mark-ups. Following a two-step procedure, the pass-through rate of marginal costs to freight rates is first estimated for most imported products to the U.S. Then, an adjusted expression for shipping freight rates is estimated using the estimated short-run pass-through rates from the first stage. Finally, shipping mark-ups are calculated as a standard Lerner (1934) index, using previous estimates.

The estimated short-run pass-through rates of shipping cost to freight rates reaffirm previous empirical evidence of imperfect competition in the maritime shipping industry. Furthermore, the distribution of these pass-though rates reveals that carriers do not exert market power evenly. Carriers extract larger rents when shipping products for which they can pass through more than completely 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, it shows that these 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, it finds evidence 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 ranging 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 these 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. (2017). Pass-through, Competition, and Entry in Agricultural Markets: Experimental Evidence from Kenya. [Revise and Resubmit, *American Economic Review*].

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

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.

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.

Jeon, J. (2020). Learning and investment under demand uncertainty in container shipping. *Manuscript, Department of Economics, Boston University*.

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.

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.

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: *Ad-Valorem* Freight Charges from China and Loading Cargo of U.S. Imports to U.S. Ports located in U.S. West Coast - 2017

	Seattle	**Los Angeles**	**San Francisco**
Panel A.			
Ad-Valorem Freight Charges			
Cell Phones	0.7%	0.8%	5.2%
Televisions	1.9%	2.3%	2.8%
Bicycles	5.4%	6.5%	8.1%
Car Tires	14.0%	13.5%	14.0%
Panel B.			
Number of Transactions (Millions)	15	107	19
Total Volume Imported (Million tons)	154	995	425
Total Value Imported - FOB (US$ Billion)	508	3,116	566

Note: HS6 digit-codes used for these calculations are: cellphones, 85.17.12; televisions, 85.28.72; bicycles, 82.12.00; and car tires; 40.11.10. *Ad Valorem* freight rates are calculated using U.S. Merchandise Imports Database. The number of transactions corresponds to the number of cards reported in the U.S. Merchandise Imports Database

Table 2: 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

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

$\ddagger$: 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).

Table 3: 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 4: 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			1.000		
	2SLS	0.695	1.000		0.972	1.000	
	GC	0.996	0.691	1.000	0.998	0.970	1.000
2008-2012		OLS	2SLS	GC	OLS	2SLS	GC
	OLS	1.000			1.000		
	2SLS	0.308	1.000		0.043	1.000	
	GC	0.996	0.307	1.000	0.998	0.042	1.000
2013-2017		OLS	2SLS	GC	OLS	2SLS	GC
	OLS	1.000			1.000		
	2SLS	0.486	1.000		0.997	1.000	
	GC	0.991	0.477	1.000	1.000	0.997	1.000

Table 5: 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) $\times$ 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 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 the imports of oil and related products, pooled on the HS2 digit-code sector 27.

Table 6: Median Maritime Shipping Mark-ups
(% of Maritime Shipping Freight Charges)

	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)
Gaussian Copula	43.4	38.2	34.1	34.2	27.5	32.7
OLS	86.6	71.0	71.5	74.7	77.7	74.5
2SLS	83.0	67.6	61.3	48.9	65.0	65.9

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

Table 7: 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 ρ with the GC method.

Table 8: 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 ρ with the GC method.

Table 9: 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 ρ with the GC method.

Table 10: 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)
_cons	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 & Time	Y	N	Y	N	Y	N

Standard errors in parenthesis clustered by product-time and product-U.S customs district of entry in columns with an odd number. Standard errors clustered by origin, 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 rate is calculated as the ratio cost of freight to imports FOB value. *Ad valorem* mark-ups is calculated as the ratio estimated mark-ups to cost of freight. The equivalent tariff to the estimated mark-ups is calculated to the ratio estimated mark-ups to imports FOB value.

Table 11: 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%

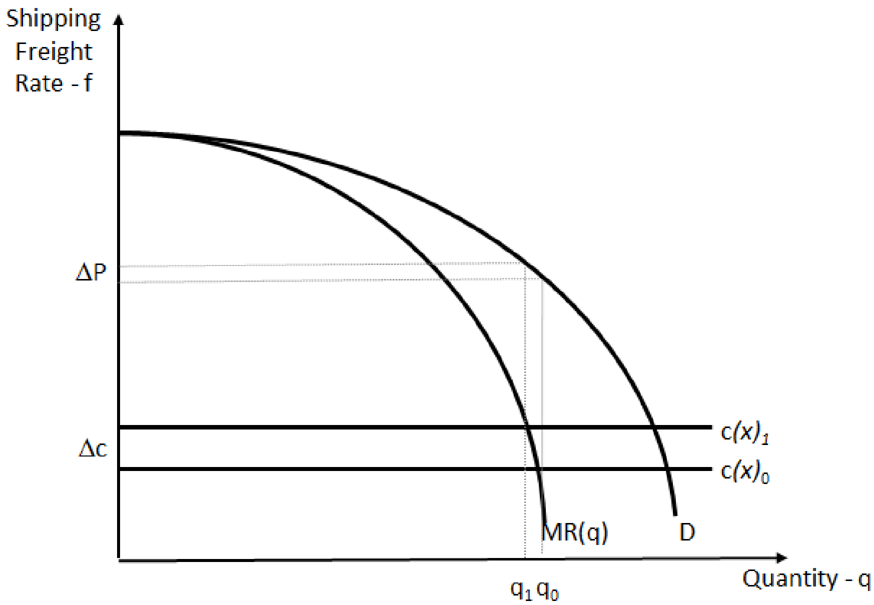
Note: These estimates show how much U.S. imports would be higher in a scenario were maritime shipping mark-ups were set equal to zero.

Table 12: Cost of Maritime Shipping Mark-ups for Welfare (% of GDP)

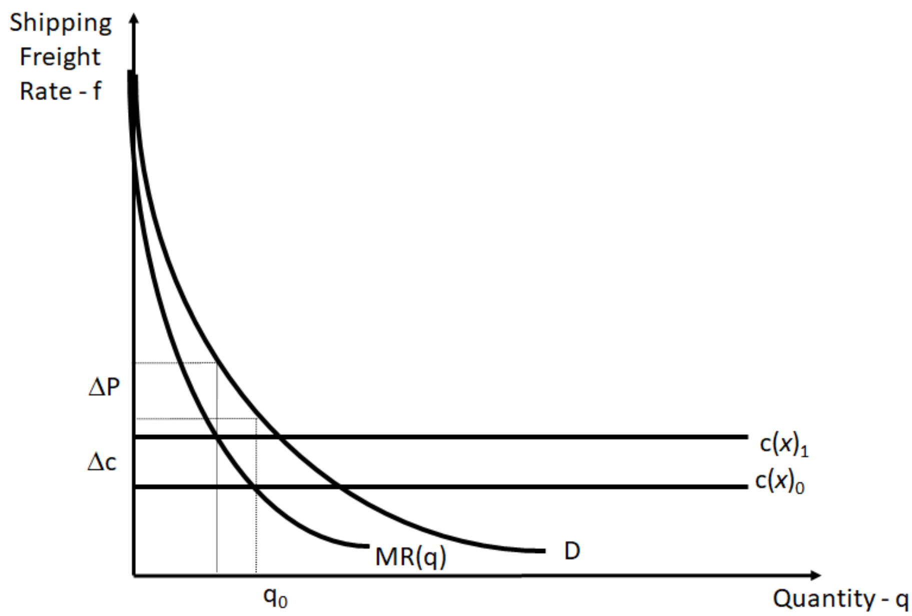
Assumed Trade Elasticity (σ)	2002-2007	2008-2012	2013-2017
$\sigma = 3$	0.20%	0.13%	0.14%
$\sigma = 5$	0.20%	0.13%	0.14%

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

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

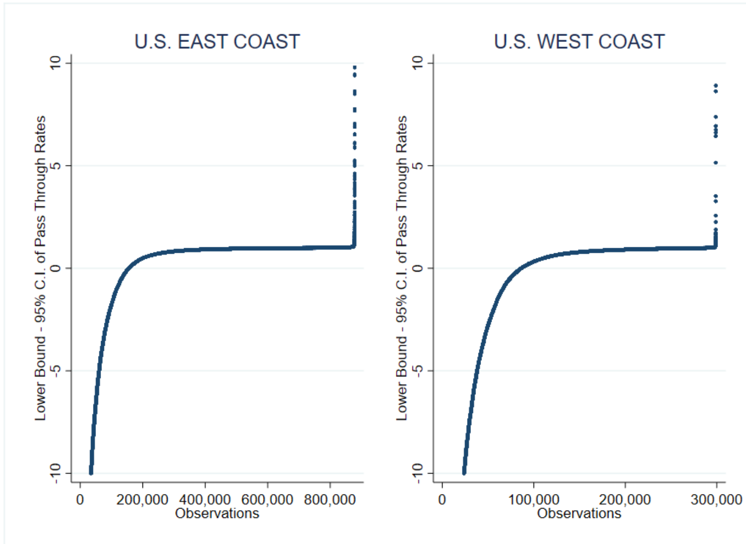


Figure 2: Lower Bound - 95% Confidence Interval of the Estimated Pass-Through Routes 2002-2007

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%.

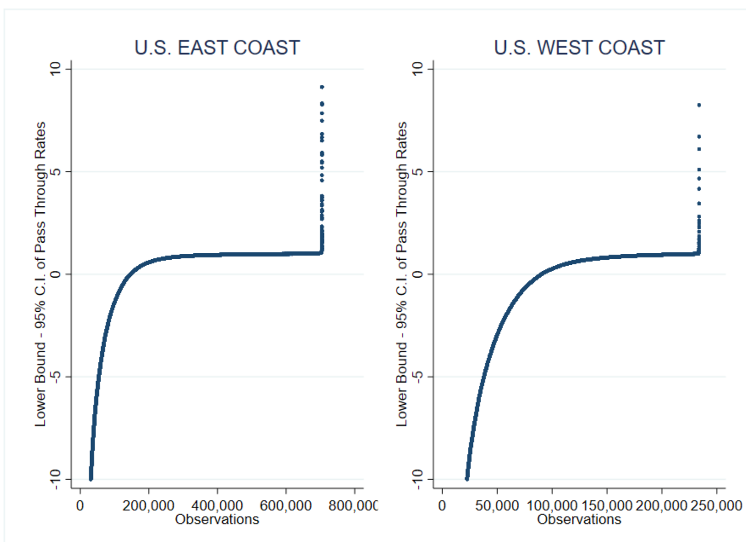


Figure 3: Lower Bound - 95% Confidence Interval of the Estimated Pass-Through Routes - 2008-2012

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%.

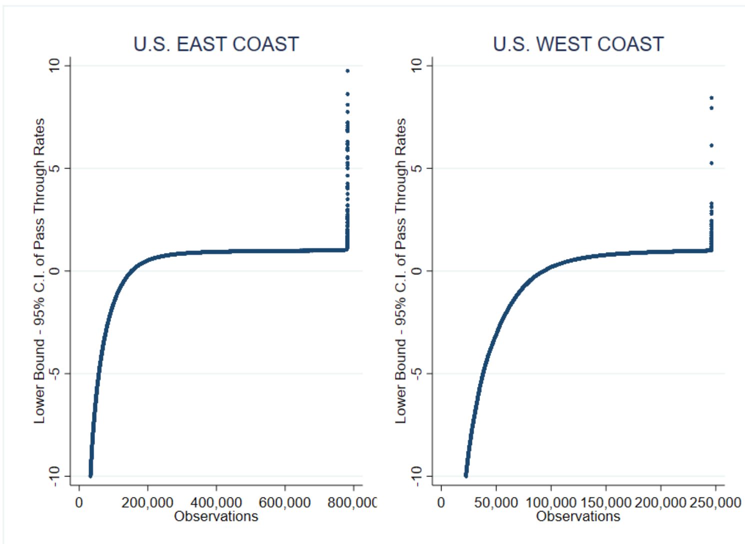


Figure 4: Lower Bound - 95% Confidence Interval of the Estimated Pass-Through Routes - 2013-2017

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%.

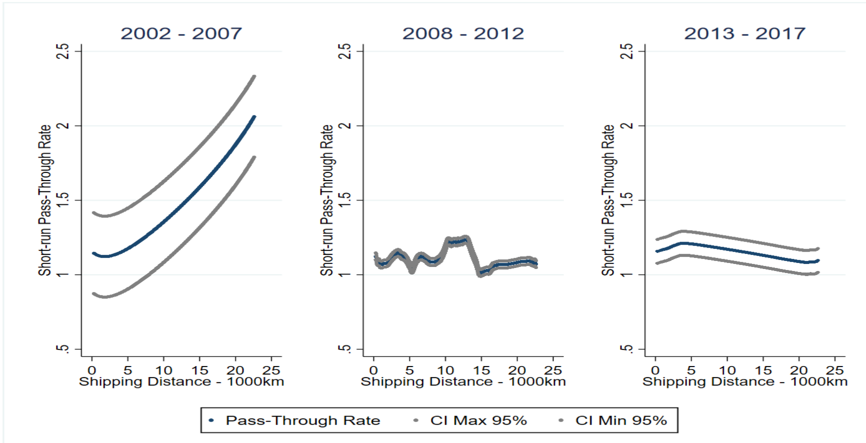


Figure 5: U.S. East Coast: Short Run Pass-Through Rate vs. Shipping Distance

Note: these figures show non-parametric predictions for the short-run pass through rates, assuming an Epanechnikov kernel with bandwidth optimally defined by cross-validation.

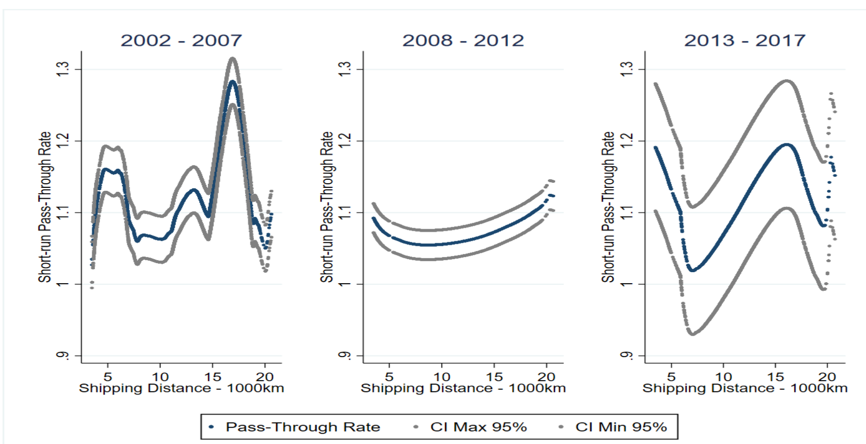


Figure 6: U.S. West Coast: Short Run Pass-Through Rate vs. Shipping Distance

Note: these figures show non-parametric predictions for the short-run pass through rates, assuming an Epanechnikov kernel with bandwidth optimally defined by cross-validation.

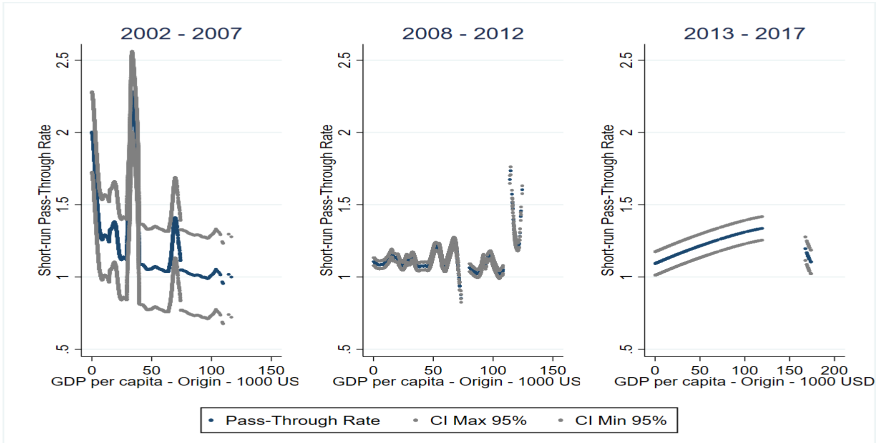


Figure 7: U.S. East Coast: Short Run Pass-Through Rate vs. Origin Country GDP per capita

Note: these figures show non-parametric predictions for the short-run pass through rates, assuming an Epanechnikov kernel with bandwidth optimally defined by cross-validation.

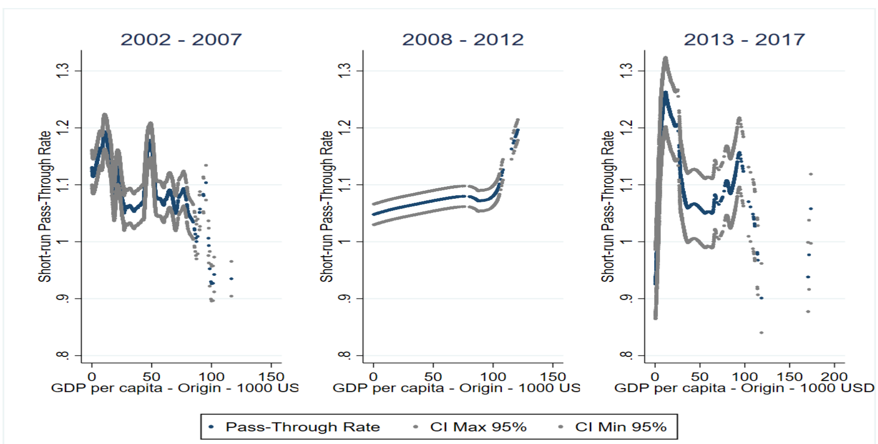


Figure 8: U.S. West Coast: Short Run Pass-Through Rate vs. Origin Country GDP per capita

Note: these figures show non-parametric predictions for the short-run pass through rates, assuming an Epanechnikov kernel with bandwidth optimally defined by cross-validation.

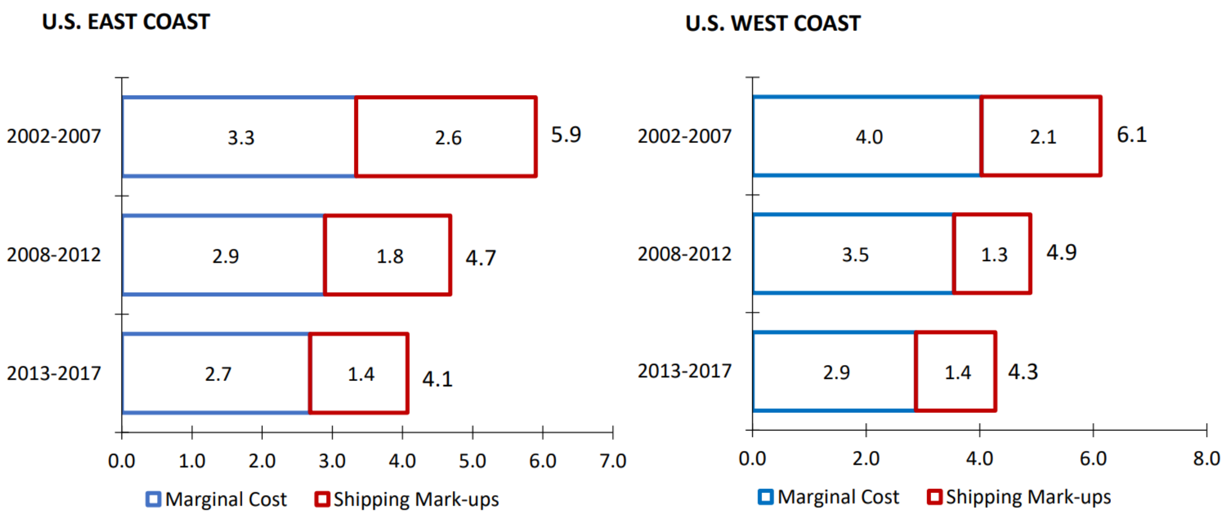


Figure 9: Composition of *Ad-Valorem* % Maritime Shipping Freights

Appendixes

A Mathematical Derivations

Derivation Eq. (3)
To decompose the short-run pass-through rate ρ_r^k, equation (2) shows that the first-order condition of carriers' maximization problem is given by:

$$f_r^{\ell,k} = c^\ell(\chi_r^k) - \frac{\partial f_r^k}{\partial Q_r^k}\frac{\partial Q_r^k}{\partial q_{\ell,r}^k} q_{\ell,r}^k \tag{A.1}$$

Now, defining a standard conduct parameter $\theta_r^k = \frac{\partial Q_r^k}{\partial q_{l,r}^k}$, and differentiating this expression with respect to the shipping cost $c(\chi_r^k)$, the short-run pass-through rate ρ_r^k is equal to:

$$\rho_r^k = \frac{\partial f_r^k}{\partial c(\chi_r^k)} = \left[1 + \frac{1 + E_r^k(f_r^k)}{\phi_r^k}\right]^{-1} \tag{A.2}$$

Derivation Eq. (5)
To derive the optimal pricing-rule for maritime shipping carriers, I know from equation (2) that the first-order condition of carriers maximization problem is given by:

$$f_r^{\ell,k} = c^\ell(\chi_r^k) - \frac{\partial f_r^k}{\partial Q_r^k}\frac{\partial Q_r^k}{\partial q_{\ell,r}^k} q_{\ell,r}^k \tag{A.3}$$

Writing the shipping freight rate $f_r^{\ell,k}$ as the wedge between the price of product k in the origin P_o^k and in the destination country P_d^k yields:

$$P_d^k = P_o^k + c^\ell(\chi_r^k) - \frac{\partial (P_d^k - P_o^k)}{\partial Q_r^k}\frac{\partial Q_r^k}{\partial q_{l,r}^k} q_{l,r}^k \tag{A.4}$$

Now, defining and substituting a standard conduct parameter $\theta_r^k = \frac{\partial Q_r^k}{\partial q_{l,r}^k}$, and invoking the assumption that demand for importing product k in market d does not affect the price in the origin market o, yields

$$\begin{aligned} P_d^k &= P_o^k + c^\ell(\chi_r^k) - \frac{\partial P_d^k}{\partial Q_r^k}\theta_r^k \frac{Q_{l,r}^k}{L_{l,r}^k} \\ &= P_o^k + c^\ell(\chi_r^k) - \frac{\partial P_d^k}{\partial Q_r^k}\frac{Q_r^k}{\phi_r^k} \end{aligned} \tag{A.5}$$

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 r, yields:

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

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

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

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

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

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

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

Derivation Eq. (7)

To derive this expression, I substitute in expression (6) the additive structural forms for $c^\ell(\chi^k_r)$ and a^k_{od} similar to Atkin and Donaldson (2015), one for each shipping route r in each shipping U.S. coast c, yielding:

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

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

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

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. (12)
To derive the expression for calculating maritime shipping mark-ups, I know that the optimal pricing-rule can be written as:

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

Subtracting the shipping costs function in both sides yields:

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

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

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

Derivation Eq. (13)
To derive this equivalent expression for calculating maritime shipping mark-ups, I know that the mark-ups are given as follows from expression (12):

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

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

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

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

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

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

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

Derivation Eq. (14)
To derive this expression, I differentiate the structural specification of the maritime shipping mark-ups defined in expression (12) with respect the short-run pass-through rate.

$$\frac{\partial \mu_r^{\ell,k,c}}{\partial \rho_o^{k,c}} = (1-\widehat{\rho_o^{k,c}})\left[-\frac{\widehat{a_{od}^{k,c}} - \widehat{T^\ell(\chi_r^{k,c})}P_o^{k,c} - P_o^{kc}}{(P_{od}^{k,c}-P_o^{k,c})^2}\right]\frac{\partial P_{od}^{k,c}}{\partial \rho_o^{k,c}} - \left[\frac{\widehat{a_{od}^{k,c}} - \widehat{T^\ell(\chi_r^{k,c})}P_o^{k,c} - P_o^{k,c}}{P_{od}^{k,c}-P_o^{k,c}}\right] \tag{A.20}$$

Substituting the expression derived above for the maritime shipping mark-ups yields:

$$\frac{\partial \mu_r^{\ell,k,c}}{\partial \rho_o^{k,c}} = -\widehat{\mu_r^{\ell,k,c}}\left[\frac{\partial P_{od}^{k,c}}{\partial \rho_o^{k,c}}\frac{1}{(P_{od}^{k,c}-P_o^{k,c})} + \frac{1}{1-\widehat{\rho_o^{k,c}}}\right] \tag{A.21}$$

Differentiating expression (13) specified in unit prices, with respect the short-run pass-through rate, and rearranging terms yields:

$$\frac{\partial \mu_r^{\ell,k,c}}{\partial \rho_o^{k,c}} = \frac{\widehat{\mu_r^{\ell,k,c}}(1-\widehat{\mu_r^{\ell,k,c}})}{\widehat{\rho_o^{k,c}}-1} \tag{A.22}$$

which permits to define the elasticity of the maritime shipping mark-ups to the short-run pass-through rates ($\varepsilon_{r,(\rho,\mu)}^{\ell,k,c}$) as:

$$\begin{aligned}\varepsilon_{r,(\rho,\mu)}^{\ell,k,c} &= \frac{\partial \mu_r^{\ell,k,c}}{\partial \rho_o^{k,c}}\frac{\rho_o^{k,c}}{\mu_r^{\ell,k,c}} \\ &= \left(\frac{\widehat{\rho_o^{k,c}}-1}{\widehat{\rho_o^{k,c}}}\right)^{-1}(1-\widehat{\mu_r^{\ell,k,c}}) \end{aligned} \tag{A.23}$$

B Data Description

As noted above, I use in this paper data from the U.S. Merchandise Imports for the period 2002-2017. Specifically, I use a data sample which I built exclusively for U.S. imports shipped by sea. To do so, I started off working with the complete U.S. Merchandise Imports database for the period 2002-2017 pulled from the U.S. Census Bureau, which compiles annual U.S. imports by HS10-digit product k, origin country o, U.S. customs district of arrival d and year t. Then, I applied the following step-wise procedure, which generated the final database that I used for all estimations in this paper.

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. 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 in this database 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, US Geographical Survey, US 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 Analysis of the Data

Table C1: 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 C2: 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 C3: 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. $\rho \leq 0$).

D Robustness Exercises

Table D1: 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 D2: 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

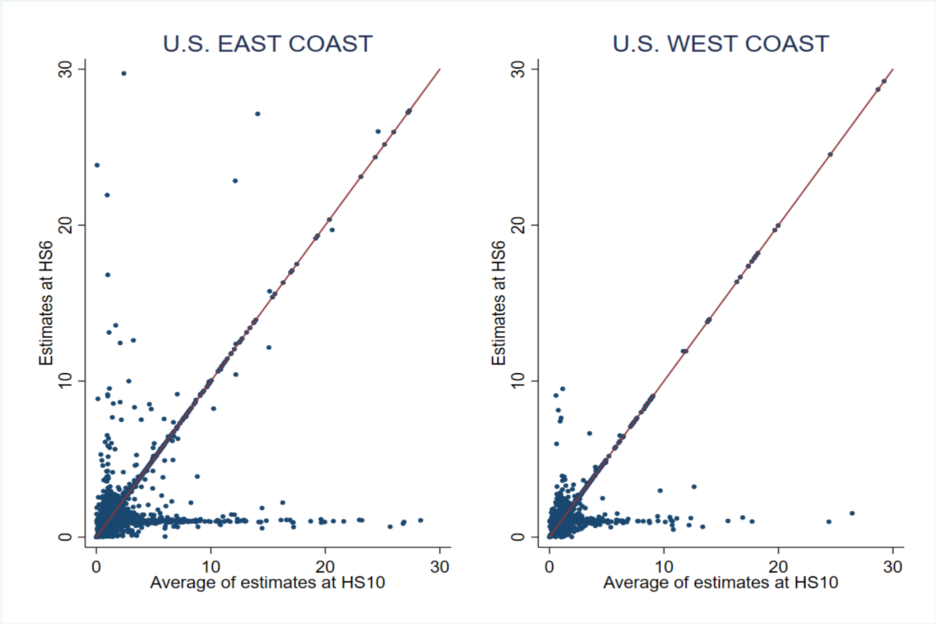


Figure D1: Comparison Estimated Short-Run Pass-Through Rates at HS6 vs at HS10 - Period 2002-2007

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.

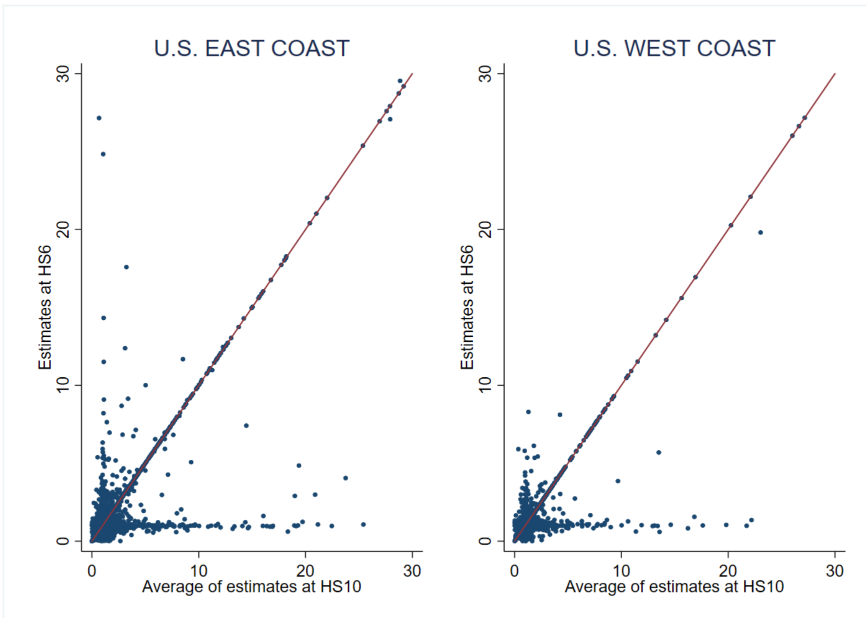


Figure D2: Comparison Estimated Short-Run Pass-Through Rates at HS6 vs at HS10 - Period 2013-2017

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.

Table D3: 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 D4: 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