The Value of De Minimis Imports*

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Abstract

Section 321 of the 1930 Trade Act allows up to $800 in imports per person per day to enter the US duty-free and with minimal customs requirements. Fueled by rising direct-to-consumer trade, these "de minimis" shipments have exploded yet are not recorded in Census trade data. Who benefits from this type of trade, and what are the policy implications? We analyze international shipment data, including de minimis shipments, from three global carriers and US Customs and Border Protection. Lower-income zip codes are more likely to import de minimis shipments, particularly from China, suggesting that the tariff and administrative fee incidence in direct-to-consumer trade is pro-poor. Theoretically, imposing tariffs above a threshold leads to terms-of-trade gains through bunching, even in a setting with complete pass-through to linear tariffs. Empirically, bunching pins down the demand elasticity for direct shipments. Eliminating §321 would reduce aggregate welfare by $11.8-$14.3 billion and disproportionately hurt lower-income and minority consumers.

JEL: F1

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1 Introduction

Since 2018, the US has sharply raised tariffs, with their incidence falling predominantly on US consumers (Fajgelbaum and Khandelwal, 2021). However, §321 of the 1930 Trade Act allows up to $800 goods per day per person to be imported free of tariffs and much of the administrative fees of clearing customs. Whether or not consumers incur these extra costs depends on whether imported shipments enter through this "de minimis" channel. In recent years, de minimis imports have exploded, fueled by streamlined customs processing, high tariffs, and an emergent type of international trade that ships directly to consumers purchasing through online retail platforms. For such transactions, online orders bypass domestic warehousing via shipments directly to consumers (often referred to as "direct-to-consumer" or "drop ship" shipments).

To get a sense of de minimis' rising importance, in 2023 these imports totaled $54.5 billion over 1 billion shipments, up from just $0.05 billion over 110 million shipments in 2012. Scaled against natural benchmarks, de minimis imports are currently 7.2% of US imports of consumer goods and 19.2% of e-commerce sales, a substantial increase from just 0.7% and 3.9%, respectively, from before the trade war. De minimis is an integral logistics strategy of some of the world's largest and fastest-growing retailers, such as Shein and Temu, that ship directly to consumers.[1] Two proposals in Congress consider modifying §321, and other countries are also actively debating the role of de minimis imports as direct-to-consumer trade continues to grow.[2]

Who benefits from direct-to-consumer and de minimis trade? What are the aggregate and distributional welfare consequences of potential changes to §321 trade policy? Research on these questions has been limited since Census data exclude de minimis shipments. We rely on a novel dataset encompassing the universe of shipments into the US handled by three global carriers. In 2021, the data account for 36.1% of total value and 17.0% of total US de minimis shipments. A key feature of the data is the destination address or zip code, allowing us to link shipments to income and demographic characteristics of buyers. We complement these data with a sample of shipments from the universe of carriers obtained from U.S. Customs and Border Protection (CBP) via FOIA.

A standard trade framework with heterogeneous exporters operating under monopolistic competition guides the analysis. Exporters operate subject to de minimis rules and sell to heterogeneous consumer groups who vary in their preferences for direct-to-consumer imports and their preferences across sellers of these goods. When a shipment's value exceeds the de minimis threshold, it is subject to an (ad-valorem) tariff and (per shipment) administrative fee. The latter

[1] In 2022, Shein represented 50% of the US fast-fashion retail market, larger than Zara and H&M combined (Bloomberg Second Measure 2023-01-04. Temu, whose product offerings extend beyond apparel, surpassed Shein's sales in June 2023 (WSJ 2023-07-30. In January 2024, Shein and Temu had 26 million and 51.4 million active users, compared to Amazon's 67 million active users (WSJ 2024-03-01). Both companies' iPhone apps have ranked in the top 10 in the recent past, with Temu #1 in June 2024. Congress has found that Shein and Temu account for 30% of total de minimis imports (Select Committee on the CCP, 2023).

[2] The "Import Security and Fairness Act" would prevent "non-market" economies from using the de minimis channel, and the "De Minimis Reciprocity Act of 2023" would bar some countries, including China, from accessing §321 and impose the reciprocal de minimis threshold that US shipments face in other countries. In May 2024, Brazil modified its de minimis rules to include Temu (Reuters 2024-05-24). As of July 2024, South Africa is effectively rescinding its de minimis threshold of ZAF 500 (about $27) (Sourcing Journal 2024-06-12).

acts like a specific tariff, except its revenue is allocated to finance administrative costs of processing above-threshold shipments rather than being rebated to consumers. We show that the de minimis tax notch is a source of terms-of-trade gains: a range of exporters who, in the absence of tariffs, would have set prices above the threshold now lower them and bunch at the threshold. This policy is preferred to free trade when the distribution of imported shipments is biased to low values.

The framework guides the empirical analysis of §321 and the direct shipments to final consumers to which this policy is intimately linked. The density of shipments over package values by consumer groups–defined across zip codes by median income or share of non-white residents–informs the relative preferences for direct and de minimis shipments. This information suffices to compute, to a first order approximation, the consumer losses from eliminating de minimis under the assumption of complete pass-through. For exact welfare calculations using the model, we need a demand substitution elasticity across shipments from each origin, defined in our implementation as China and Rest of the World (RW). To estimate these parameters, we exploit shifts in bunching around the de minimis threshold due to policy changes, analogous to approaches in public economics that identify labor supply elasticities from notches along the tax schedule (Kleven and Waseem, 2013).

The densities reveal that direct-to-consumer shipments (defined as shipments below $5,000 in our data), their cheaper de minimis subset (below $800), and the de minimis share originating from China are relatively more important for low-income households. 74% of direct shipments imported by the poorest zip codes are de minimis compared to 52% for the richest zip codes. Furthermore, the share of de minimis shipments from China declines with income: 48% for the poorest zip codes compared to 23% for the richest.

These patterns, along with the exemptions from fees and the much higher tariffs on imports from China, determine that §321 is a pro-poor trade policy: the average tariff on direct shipments to the poorest zip codes–0.5%–is lower than to the richest zip codes–1.5%.[3] If §321 were eliminated, the tariff schedule would *flip* from pro-poor to pro-rich: the poorest zip codes would face average tariffs of 12.1% compared with 6.7% for the richest zip codes. Moreover, without §321, all shipments would incur an administrative fee. Eliminating §321 would disproportionately raise the fee burden of low-income households, given their higher de minimis spending shares. We document similar spending patterns in the CBP sample. Credit card transaction data from a different proprietary dataset further confirm that low-income disproportionately shop at three platforms–AliExpress, Shein, and Temu–whose business model leverages §321.

We consider a policy counterfactual that eliminates the $800 minimum threshold exemption codified in §321. In this counterfactual scenario, the tariffs on all shipments below $800 would rise from zero to roughly 15% for China and 2.1% for RW, and the per-shipment administrative fee would rise from zero to $23.19.[4] A first-order approximation of the policy change, which

[3] These averages tariffs are low since we only include imports up to $5,000, a large portion of which are de minimis.

[4] CBP levies a merchandise processing fee and requires shipments to use a licensed broker on shipments above $800. The fee for brokerage services varies by logistics provider, range of services offered, and quantity discounts, making it difficult to pin down the broker fee. The carriers' per-package broker fee for informal shipments is $30. The Postal

assumes complete pass-through and uses only the carrier (or CBP) spending shares, tariffs, and administrative fees, yields a consumer loss of $11.1b or $35 per person. With the CBP data, the loss is larger–$22.2b, or $69 per person–since these data report a greater share of shipments from China than the carrier data. Given the large differences in spending shares across groups, consumer costs in the poorest zip codes would rise 24.8% more than the aggregate (or 9.1% more using CBP data). We also leverage information on the destination zip code to examine impacts across demographics beyond income, such as the share of minority households, to gauge broader distributional effects of trade (USTR 2023, ITC 2023). We find the least white zip codes would experience a cost increase of 39.4% (or 17.3% with CBP data) more than the representative consumer.

As mentioned, computing the exact welfare changes from the model incorporates the price responses through bunching and tariff revenues. We use the observed changes in bunching to pin down the within-origin demand elasticity across shipments from China and RW. Specifically, using the carrier data, we estimate densities of shipments across value bins in four categories: shipments to the US and OECD, before and after March 2016. This period marks a threshold change in the US from $200 to $800, while the OECD countries maintain lower thresholds. We observe bunching at the thresholds, particularly in the post period at $800. When expressed as a difference-in-differences, we observe a rise in the relative density of shipments right below $800 and then a 27.0% drop in shipments above the notch. The drop in shipments from China is starker. The CBP sample also shows evidence of bunching below the notch and a subsequent decline in shipments above $800, suggesting that shipments above $800 are not simply re-routed to other logistics companies. The observed changes in bunching are matched by elasticities of substitution across shipments from China of 4.42 and from RW of 1.81. We also identify a cross-origin demand elasticity through indirect inference that leverages differences in tariffs across origins and de minimis expenditure exposure across consumer groups and origins, finding an elasticity of 18.92.

Incorporating these demand elasticities and assuming that tariffs are rebated back to consumers, we find that eliminating §321 reduces aggregate welfare by $11.8 billion. In the CBP sample, we estimate a larger decline of $14.3 billion. To put these numbers in perspective, Fajgelbaum et al. (2020) estimate the sum of consumer cost and tariff revenue gain of the 2018 US tariffs at $16.1 billion and the tariffs through 2019 at $48.2 billion.

The per capita welfare losses across income groups are inverted U-shaped: median incomes below $40k would lose $46 per capita per year compared to a $39 loss for zip codes with $100k incomes and a $95 per capita loss for the richest zip codes. When expressed as a share of family income, the corresponding declines are biased against the poor. Across zip codes with different racial composition, we find that welfare in zip codes with 5% white households would experience a per capita decline of $54, compared with declines of $44 for zip codes with 45% white share and $18 in 95% white share. As a share of income, the corresponding declines for low, median, and

Service's fee for handling international shipments is $8.55 (United States Postal Service, 2024). The National Foreign Trade Council estimates a broker fee of $20.00. In 2023, express carriers handled 19% of de minimis shipments, the Postal Service handled 8%, and other logistics providers handled the remaining 73%. Using these weights, we arrive at an average broker fee of $20.97. We then apply the CBP's lowest merchandise process fee on informal shipments–$2.22–to arrive at the total administrative fee of $23.19 per shipment.

high white shares are 0.10%, 0.06%, and 0.02%. The lowest-income and non-white households would bear the brunt of eliminating §321.[5]

Our paper contributes to studies of the importance of trade for consumption, with a distinct focus on trade policy. Acosta and Cox (2019) study the distributional bias of US tariffs through consumer exposure. They digitized historical US tariff lines and showed that high unit-value commodities–presumably more important in the consumption basket of the rich–are subject to lower tariffs, implying that trade policy for consumption goods is regressive. In our setup, we can directly link direct-to-consumer imported shipments to the demographics and income of the receiving zip code. We demonstrate that the tariff incidence has a pro-poor bias among this type of trade because of the §321 exemption. Without this exemption, tariffs would be regressive just as Acosta and Cox (2019) uncover from statutory tariff lines.

Several papers have studied the distributional effects of trade through consumption in response to shocks other than tariffs. A key challenge in this literature is that households' consumption of imports is rarely directly observed. Using cross-country and cross-industry data, Fajgelbaum and Khandelwal (2016) develop a trade framework with non-homothetic demand to measure unequal gains from trade across consumers, finding that since the poor consumers concentrate more spending on traded goods, trade is pro-poor. Recent papers have leveraged additional micro evidence on consumption exposure. Cravino and Levchenko (2017) and Auer et al. (2023) use consumer surveys and scanner data to measure differential consumer exposure to large devaluations in Mexico and Switzerland. Hottman and Monarch (2020) and Borusyak and Jaravel (2021) match consumer expenditure surveys to trade data and do not find substantial differences in import shares across US households, suggesting weak distributional impacts. In Mexico, Atkin et al. (2018) find that the entry of foreign retailers favored richer households. In relation to these papers, we can observe imports directly shipped to consumers and study the distributional consequences of a trade policy affecting these shipments.

Several papers have found evidence of complete pass-through of US tariffs on China to US import prices; see Amiti et al. (2019), Fajgelbaum et al. (2020), Flaaen et al. (2020), and Cavallo et al. (2021). However, analyses of public trade data or Census' Longitudinal Firm Trade Transactions Database are unable to assess the importance of de minimis imports because they only compile import transactions above $2000.[6] In contrast, our finding of bunching implies that the de minimis threshold leads to a form of terms-of-trade manipulation: bunching occurs because firms that would have otherwise priced above the threshold lower their prices to avoid the tariff.[7] Our paper

[5]These calculations require assumptions about how the government rebates the revenue. We assume that each group is rebated the tariff revenue generated by its own imports. The per capita losses, excluding tariff rebates, for median incomes <$40k, $100k, and >$150k are $48, $41, and $103. For zip codes with white household shares of 5%, 55%, and 95%, the per capita tariff-exclusive losses are $57, $47, and $19.

[6]Public and confidential Census trade data are compiled from CBP Form 7501 (Kamal and Ouyang, 2020). These data capture all formal entries and a subset of informal entries but exclude de minimis shipments.

[7]Flaaen et al. (2020) study washing machines, which are unlikely to be shipped through the de minimis channel. Cavallo et al. (2021) use data from the BLS Import Price Program, which samples entries directly from CBP's Automated Commercial Environment (ACE), the system for processing imports. It is unclear how the IPP sampling applies to de minimis import entries, which, as discussed in Section 2, often do not clear through ACE.

also relates to the work studying non-tariff barriers, specifically customs facilitation.[8] We find that the minimal customs requirements for de minimis shipments, which include cost savings from using brokers—agents responsible for preparing and submitting import documentation, assigning product codes, ensuring regulatory compliance, and facilitating the entry of goods through ports—significantly benefit low-value shipments.

Section 321 has received little attention due to the data limitations we have described, and it has become economically relevant only in recent years. Recent papers have studied how e-commerce platforms affect consumption patterns, but do not differentiate between domestic and international shipments via these platforms, either through de minimis or through formal imports distributed via domestic warehouses. Dolfen et al. (2023) find that higher-income households in the US benefit more from online platforms, Jo et al. (2022) find that e-commerce lowered price dispersion across locations in Japan, and Couture et al. (2021) implement a randomized trial that connects an e-commerce platform with 100 villages in China, finding that e-commerce reduces the cost of retail consumption for younger and richer households. Our paper focuses on the role of low-value international shipments for welfare, studying how this emergent direct-to-consumer trade benefits different consumer groups and how these benefits are affected by trade policy currently under debate.

Methodologically, our approach to estimating the tariff elasticity exploits bunching in the shipment density around a tax notch. A tax notch is a defining feature of de minimis trade policies worldwide, with large heterogeneity in the threshold value.[9] Estimation based on kinks or notches is commonly used in the public economics literature to estimate, for instance, labor supply elasticities.[10] In our setting, we exploit two control shipment densities over values not subject to the $800 threshold (shipments to the US before March 2016 and to OECD). This allows us to identify bunching induced by the threshold through a difference-in-differences specification.

The remainder of the paper is organized as follows. Section 2 describes the details of §321 trade policy and de minimis imports. Section 3 provides a framework for analyzing imports subject to a minimum threshold for tariffs. Section 4 describes the data and provides summary statistics. Section 5 examines the density of shipments around the threshold. Section 6 implements the model and provides a welfare analysis of §321.

2 §321 Trade Policy and De Minimis Imports

The process of importing shipments involves paying applicable duties and taxes, meeting regulatory standards, and filing paperwork. In the US, most import transactions require filing at least two forms: CBP Form 7501, which is used to assess tariff duties, processing fees, and compliance; and CBP Form 3461, which secures the release of imported merchandise. Most

[8] See Anderson and van Wincoop (2004), Volpe Martincus et al. (2015), and Ederington and Ruta (2016).

[9] The average threshold across countries is $145 (sd $139). Amongst OECD countries (excluding USA), the average is $180 (sd of $157) Global Express Association (2021).

[10] See Saez (2010), Chetty et al. (2011), Kleven and Waseem (2013), and the review by Kleven (2016).

countries have a "de minimis" policy to reduce the customs burden for low-value shipments.

The US has streamlined procedures for importing two types of low-value shipments: §321 entries ($0-$800) and informal entries ($801-$2500), with the former referred to as de minimis entries. §321 was codified in 1938 by amending the 1930 Trade Act to allow low-value imports to enter the country free of tariff duties and (most) customs processing fees and with minimal paperwork. In March 2016, the US raised the threshold from $200 to $800 per buyer per day, the current threshold, as part of the Trade Facilitation and Trade Enforcement Act of 2015 to reduce transaction costs associated with imported shipments for consumers. §321 prohibits breaking a single order over shipments that span multiple days. Additionally, attempts to undervalue packages are subject to fines, the shipment being withheld by CBP, future shipments from the shipper or importer being flagged, and potential criminal smuggling violations. §321 does not extend to shipments subject to antidumping or countervailing duties, alcohol, perfume, cigarettes, or certain goods regulated by Partner Government Agencies (e.g., FDA, USDA).

Entry through §321 occurs by physically or electronically presenting a manifest to CBP. De minimis shipments are handled by express air carriers, postal service, or non-express carriers (via air, land, and sea); in 2023, their respective shares in the number of de minimis shipments were 19%, 8%, and 73%, respectively. Before 2018, only express air and land carriers could file shipments electronically through the Automated Manifest System, with the remaining carriers limited to physically presenting the manifest. In 2018, CBP expanded the electronic registry of de minimis entries to all carriers and brokers through the so-called "Type 86" pilot clearance; in 2023, Type 86 entries were 62% of de minimis shipments, up from 19% in 2020. CBP does not require HS codes to be declared for de minimis shipments through AMS but does require HS codes for de minimis shipments through the Type 86 pilot.

Regardless of how they are physically registered, de minimis shipments are exempt from tariff duties, do not require a broker, and are not subject to a processing fee (except for express carriers, which are subject to a $1.27 per-package fee). In contrast, informal entries between $801-$2500 are subject to duties and taxes (if applicable) and require filing CBP Form 7501, just like formal entries (shipments above $2500). Unlike formal entries, informal entries do not require a surety bond and can be immediately released by CBP upon payment of duties and taxes. Informal shipments are also subject to two types of administrative costs: a merchandise processing fee ranging from $2.22 to $9.99 per package, and a broker fee is required to clear customs. As noted in footnote 4, our benchmark analysis assumes a per-package administrative fee–inclusive of both the processing and the broker fees–of $23.19 on informal shipments.

De minimis shipments have only become quantitatively important in recent years. The left panel of Table 1 reports the total shipments and value under §321. Aggregate de minimis imports increased from just $0.05 billion in 2012 to $54.5 billion in 2023, peaking at $67.0 billion during the 2020 pandemic lockdowns. Column 2 reports the volume of shipments. In 2012, 110.5 million de minimis shipments entered the US, roughly doubling to 224.0 million in 2016, when the threshold increased. 503.1 million shipments entered in 2019, coinciding with the Type 86 expansion and the

Table 1: §321 Import Statistics

	CBP Official Statistics		US Consumer Spending	
year	value ($b) (1)	entries (m) (2)	consumer imports (%) (3)	e-commerce (%) (4)
2012	0.05	110.5	0.01%	0.1%
2013	0.07	117.9	0.01%	0.1%
2014	0.7	122.8	0.1%	0.9%
2015	1.6	138.9	0.3%	1.8%
2016	9.2	224.0	1.6%	9.2%
2017	13.0	332.3	2.1%	11.1%
2018	29.2	410.6	4.4%	22.2%
2019	56.2	503.1	8.9%	36.8%
2020	67.0	636.7	9.4%	30.4%
2021	43.5	771.5	5.3%	17.8%
2022	46.5	685.4	6.0%	18.1%
2023	54.5	1,000.0	7.2%	19.2%
2024*	32.8	705.1		

Notes: Table reports official §321 statistics obtained through a FOIA request for pre-2018 data, CBP Publication 2036-1022, and CBP E-Commerce Statistics. The de minimis import threshold was $200 before March 2016, and increased to $800 afterwards. Column 3 reports the share of §321 import values to aggregate US imports of consumer goods (excluding autos and food; series A652RC1Q027SBEA from FRED), and column 4 reports the share relative to aggregate E-commerce sales (series ECOMSA from FRED). * denotes data through May 2024.

rising tariffs. By 2023, 1 billion shipments entered through §321, and 705 million packages have already entered through May 2024. In 2023, CBP processed 39.1 million formal entries (although a single formal entry may contain many items).

De minimis shipments contain relatively more consumer goods than overall imports, which are dominated by intermediate products. Below, we document that in the carrier data, the types of products in these shipments reflect final consumer goods. In addition, individuals and small companies often purchased them through online platforms. Thus, two natural benchmarks that gauge the growth and importance of de minimis imports are its share of imports of consumer goods (excluding food and autos, series A652RC1Q027SBEA on FRED) and its share of total e-commerce sales (series ECOMSA on FRED). In 2012, de minimis imports as a share of consumer imports was just 0.01%; by 2023, this share was 7.2%. Column 4 benchmarks de minimis imports relative to US e-commerce sales: in 2012, this share was just 0.1%, but by 2023 it was 19.2%.

Finally, we can also benchmark de minimis' relevance by the duties avoided. Through a FOIA request, CBP provided the universe of de minimis shipments for the first week of December from 2017 to 2021. We estimate that in 2021, consumers avoided paying $7.8 billion in duties on de minimis shipments, or 9.2% of total duties according to 2021 Census data (this calculation omits demand and supply responses, which we incorporate in the quantification).

3 Framework

This section introduces a framework to analyze the impact of a de minimis threshold on imports. The threshold acts as a tax notch and induces bunching that identifies demand elasticities. We also study the welfare implications of de minimis and derive conditions under which a de minimis trade policy is optimal relative to free trade.

3.1 Consumers

We model an importing economy (the US) populated by heterogeneous consumer groups ω, with L_ω consumers in each group. Because direct-to-consumer imports are a small share of the economy, we use a partial-equilibrium setup. Specifically, each type-ω consumer has preferences over a bundle of imported direct-to-consumer goods and an outside good representing money spent in other commodities. Utility of consumer ω is

$$u^\omega(x) = \kappa_0^\omega x^{\frac{\kappa}{1+\kappa}} - P^\omega x + y^\omega + tr^\omega, \tag{1}$$

where x is consumption of direct-to-consumer goods, P^ω is the price index of a bundle of these goods, and y^ω is the consumer's income, and tr^ω is the tariff revenue rebated to each consumer of group ω. The parameter $\kappa_0^\omega \equiv \frac{1+\kappa}{\kappa}(A^\omega)^{\frac{1}{1+\kappa}}$ is a preference shifter for directly imported consumer goods, and κ measures the substitution between these goods and all other consumption.

The basket of direct-to-consumer goods aggregates shipments from different origins o according to a CES aggregator with elasticity of substitution γ across origins. The associated price index is

$$P^\omega = \left(\sum_o A_o^\omega (P_o^\omega)^{1-\gamma}\right)^{\frac{1}{1-\gamma}}, \tag{2}$$

where A_o^ω is an origin-group specific demand shifter. From each origin o, each type ω consumers buys heterogeneous varieties i with price index

$$P_o^\omega = \left(\int_{i\in\Omega_o} a_i^\omega v_i^{1-\sigma_o} di\right)^{\frac{1}{1-\sigma_o}}, \tag{3}$$

where v_i^ω is the value per package of variety i, Ω_o is the set of varieties available from i, and a_i^ω is a consumer-group specific demand shifter for variety i. The parameter σ_o is the substitution elasticity across shipments from a given origin.

We assume throughout that all consumer groups face the same prices. That is, foreign exporters cannot price-discriminate across groups. As a result, demand shifters alone determine differences in welfare of direct-to-consumer shipments and de minimis policy across consumer groups. Consumers buying more goods that are priced below the threshold will lose more from eliminating the policy, and even more so from origins with higher tariffs.

3.2 Firms

Each origin o is populated by heterogeneous exporters. Exporters vary in per-shipment marginal costs z (inclusive of shipping costs) and group-specific demand shocks $\{a^\omega\}$. They face a de minimis trade policy: shipments with values $v > v_{DM}$, the de minimis threshold, are subject to an origin-specific ad-valorem tariff τ_o and to an administrative processing fee T that is common across origins.

The profits of a firm i with unit cost z exporting from o and setting value per package v are:

$$\pi_i\left(v; z\right) = \left[\left(1 - \tau_o\left(v\right)\right) v - z - T\left(v\right)\right] N_i\left(v\right), \tag{4}$$

where

$$\tau_o\left(v\right) \equiv 1_{v > v_{DM}} \tau_o \text{ and } T\left(v\right) \equiv 1_{v > v_{DM}} T \tag{5}$$

are the tariff and the administrative fee as function of the value per package . The total demand faced by the firm is:

$$N_i\left(v\right) = \underbrace{\left[\sum_{\omega} L^{\omega} A^{\omega} A_o^{\omega} a_i^{\omega} \left(P^{\omega}\right)^{\gamma - \kappa - 1} \left(P_o^{\omega}\right)^{\sigma - \gamma}\right]}_{\equiv d_i} v^{-\sigma_o}, \tag{6}$$

where, from the CES demand structure, d_i is an endogenous firm-level demand shifter that includes the aggregate exogenous demand shocks A^{ω} and A_o^{ω}, the firm-level demand shocks a_i^{ω}, and the distribution of competitor's prices as captured in the aggregate and origin-specific price indexes, P^{ω} and P_o^{ω}.

Across firms from o, we allow for a general joint distribution of unit costs z and demand shocks a^{ω} across groups. To aggregate firm decisions, this joint distribution matters only through the following "quality-adjusted" measure of firms with unit cost equal to z from country o:

$$h_o^{\omega}\left(z\right) \equiv \mathbb{E}_o\left[a^{\omega} | z\right] M_o\left(z\right), \tag{7}$$

where $M_o\left(z\right)$ is the mass of firms with unit cost equal to z from origin o. The quality-adjusted measures captures the importance of firms with unit cost z from origin o for consumer group ω, either because of their number (entering through $M_o\left(z\right)$) or because of the preferences that ω has over these firms (entering through $\mathbb{E}_o\left[a^{\omega}|z\right]$).

3.3 Optimal Pricing with Bunching

Each firm i can choose between two shipping modes. It can send shipments through the de minimis channel, pricing at or below the threshold v_{DM} under zero tariffs and fees, or it can send shipments through the standard channel at prices above v_{DM}, and face tariffs and the administrative fee. To characterize the optimal pricing strategy, it is useful to define three profit functions as function of unit costs:

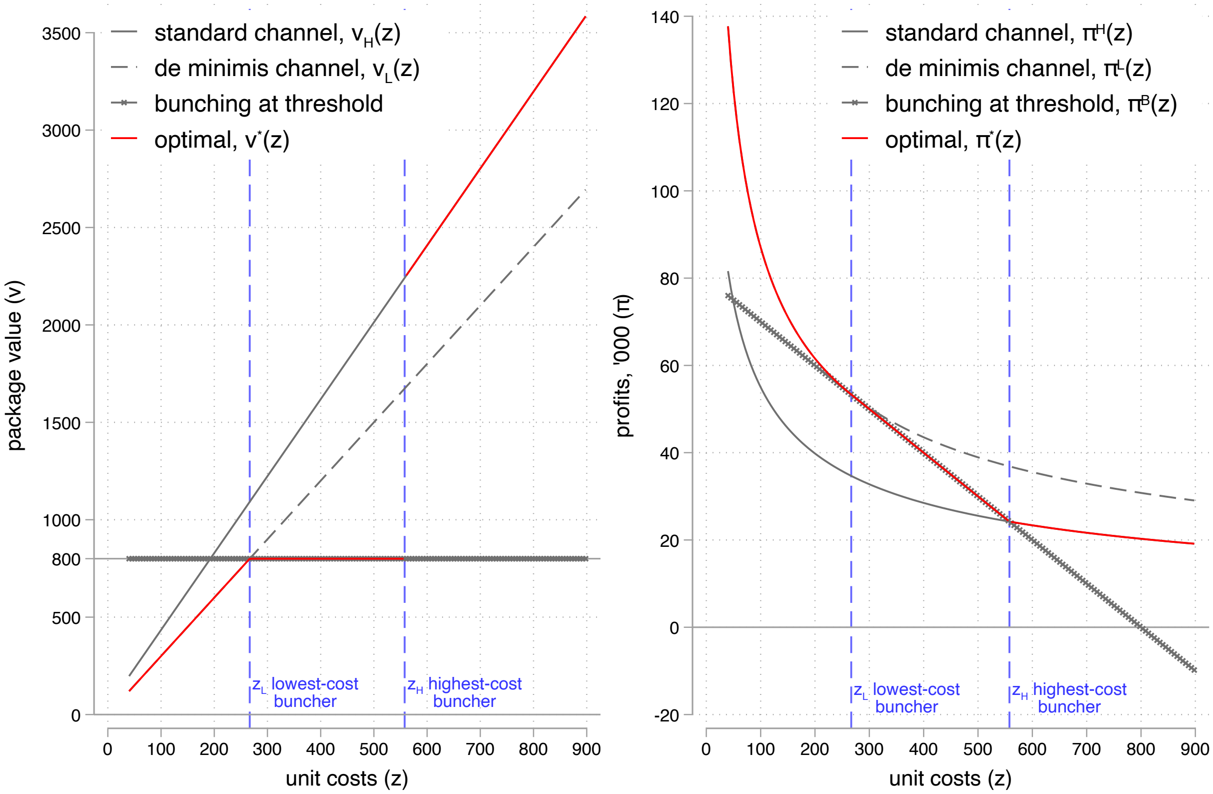
$$\pi_i^L\left(z\right) \equiv \max_v \left(v - z\right) N_i\left(v\right), \tag{8}$$

$$\pi_i^B\left(z\right) = \left(v_{DM} - z\right) N_i\left(v_{DM}\right), \tag{9}$$

$$\pi_i^H\left(z\right) \equiv \max_v \left[\left(1 - \tau_o\right) v - z - T\right] N_i\left(v\right). \tag{10}$$

The profits $\pi_i^L\left(z\right)$ and $\pi_i^H\left(z\right)$ correspond to a firm i with unit cost z shipping through the de minimis and standard channel, respectively. These functions are depicted in dashed and solid lines in the right panel of Figure 1. For these firms, optimal prices are the standard constant markup

FIGURE 1: PROFITS AND PRICING



Notes: The figure illustrates optimal package values (left panel) and profits (right panel) as function of firm's unit cost. The "dm channel" and the 'standard channel" schedules correspond to firms pricing unedr zero tariffs and fees or under positive tariffs and fees, respectively. The "bunching at threshold" schedule corresponds to firms pricing at the $800 threshold.

over marginal cost, i.e.,

$$v_{L,o}(z) = \frac{\sigma_o}{\sigma_o - 1} z \tag{11}$$

and

$$v_{H,o}(z) \equiv \frac{\sigma_o}{\sigma_o - 1} \frac{z + T_o}{1 - \tau_o}. \tag{12}$$

These pricing functions are depicted in the left panel of Figure 1.

The intermediate case, $\pi_i^B(z)$, are the profits of firm i if it bunches at the threshold, setting price v_{DM}. The profits and corresponding price as function of unit cost are shown in the hashed lines in Figure 1. Conditional on bunching, profits are linearly decreasing in unit cost; otherwise, profits are convex in unit costs because a firm optimally adjusts prices when unit costs change.

The optimal profit, $\pi_i^*(v) \equiv \max_v \pi_i(v; z)$ for $\pi_i(v; z)$ defined in (4) is shown in red in the right panel of Figure 1, with associated prices in the left panel. Firms whose products are cheap to produce, with low enough z, naturally select into de minimis shipments. They can do no better than $\pi_i^L(z)$: since their optimal price is below the threshold v_{DM}, they are not liable to pay tariffs. Starting from z close to zero, as we move towards higher-unit cost firms we eventually find a firm with unit cost $z_{L,o}$ such that its zero-tariff price equals the de minimis threshold. At this unit cost, where $v_{L,o}(z_{L,o}) = v_{DM}$, the profits of de minimis shippers and bunchers are tangent.

Imagine now a firm i whose cost increases slightly from $z_{L,o}$ to z'. If this firm were to price optimally with no tariffs, it would choose a value above v_{DM}. The firm will therefore choose between two strategies: setting the optimal price $v_{H,o}(z') > v_{DM}$, export through the standard channel and obtain a profit $\pi_i^H(z)$; or bunch at the threshold by setting the price v_{DM}, export through the de minimis channel and obtain a profit $\pi_i^{DM}(z)$. Compared to its profits at $z_{L,o}$, the firm at z' would face a discrete profit loss if it shipped through the standard channel (equal the difference between the standard and the de minimis profit schedules), but a continuous loss of profits if it bunches (because $\pi_i^L(z_{L,o}) = \pi_i^B(z_{L,o})$). So at $z_{L,o}$ bunching must be preferred to using high tariffs, $\pi_i^B(z_{L,o}) > \pi_i^H(z_{L,o})$. Because both $\pi_i^B(z)$ and $\pi_i^H(z)$ are continuous in z, there must a be an interval with bunchers above $z_{L,o}$.

However, bunching cannot be optimal for all unit costs above $z_{L,o}$: the profits of a buncher hit zero when $z = v^{DM}$; while the profits $\pi_i^H(z)$ of a firm using the standard channel decrease with z at a decreasing rate, as the firm adjust prices, monotonically converging to zero. Therefore, there must be a high enough unit cost $z_{H,o}$ such that the profits of bunchers and standard exporters intersect, $\pi_i^H(z_{H,o}) = \pi_i^{DM}(z_{H,o})$, with firms not bunching above $z_{H,o}$.

In sum, the optimal package value set by firms with unit cost z from origin o, shown in red in the left panel, is such that firms with unit cost below the threshold $z_{L,o}$ set a constant markup in the absence of tariffs or fees. Firms with sufficiently high per-unit cost, above the threshold $z_{H,o}$, also set the standard markup taking into account the ad-valorem tariff (τ_o) and the per-unit administrative cost (T). Firms with unit cost z, in between these thresholds, are bunchers. The following proposition summarizes these results.

Proposition 1. *The optimal pricing strategy from o is given by*

$$v_o^*(z) = \begin{cases} v_{L,o}(z) & z < z_{L,o} \\ v_{DM} & z \in [z_{L,o}, z_{H,o}), \\ v_{H,o}(z) & z \geq z_{H,o}, \end{cases} \tag{13}$$

where the lowest-unit cost buncher is $z_{L,o}$ such that $v_{L,o}(z_{L,o}) = v_{DM}$, or:

$$z_{L,o} = \frac{\sigma_o - 1}{\sigma_o} v_{DM}; \tag{14}$$

while the highest-unit cost buncher is $z_{H,o}$ such that $\pi_i^B(z_{H,o}) = \pi_i^H(z_{H,o})$, or:

$$\frac{1}{\sigma_o}\left(\frac{v_{DM}}{v_{H,o}(z_{H,o})}\right)^{\sigma_o} + \frac{\sigma_o - 1}{\sigma_o} = \frac{1 + T/v_{DM}}{1 - \tau_o}\left(\frac{v_{DM}}{v_{H,o}(z_{H,o})}\right). \tag{15}$$

A convenient feature is that both thresholds, $z_{L,o}$ and $z_{H,o}$, are independent from the firm-level demand shocks d_i entering in $N_i(v)$. This feature is important, as it allows to aggregate heterogeneous demand across consumer groups and define bunching thresholds that are independent from the identities of the likely buyers from each supplier.

3.4 Identification

Analogous to Kleven and Waseem (2013) who estimate labor supply elasticities from income tax notches, condition (15) provides a basis to identify the elasticity σ_o. Given σ_o, this condition depends on directly observable policy parameters (the threshold v_{DM}, the tariff τ_o, and the administrative fee T) and on the relative size of "hole" in the density of unit values, $v_{DM}/v_{H,o}$. That is, the pricing function (13) implies that no firm should price in this range, with the size of this hole being decreasing in σ. Our quantitative implementation deals with the fact that, as shown below, there is no pure hole in the observed density; we do this by including a second type of "naive" firms following Kleven and Waseem (2013). However, our parametrization of σ_o in Section (6) still relies on the logic of matching model-predicted changes in density to its empirical counterpart in response to changes in tariffs and in the de minimis threshold.

3.5 Optimal De Minimis Trade Policy

Standard trade policies typically impose a uniform ad-valorem tariff across all shippers from a given origin. We now discuss potential gains from a more flexible tariff schedule with a threshold, and in Section 6 we match the model to our shipment data to quantify the aggregate and distributional welfare impacts of alternative policies.

To simplify the exposition, we proceed in a special case consisting of a single consumer group importing from a single origin. In this context, a representative agent's indirect utility is

$$u = \frac{1}{\kappa} e + y + tr, \tag{16}$$

where the expenditures in direct-to-consumer imports, price index, and tariff revenue are

$$e = AP^{-\kappa}, \tag{17}$$

$$P = \left(\int_0^{z_L} v_L(z)^{1-\sigma} h(z)\, dz + v_{DM}^{1-\sigma} \int_{z_L}^{z_H} h(z)\, dz + \int_{z_H}^{\infty} v_H(z;\tau)^{1-\sigma} h(z)\, dz \right)^{\frac{1}{1-\sigma}}, \tag{18}$$

$$tr = \tau e \int_{z_H}^{\infty} \left(\frac{v(z;\tau)}{P} \right)^{1-\sigma} h(z)\, dz, \tag{19}$$

with conditions (14) and (15) determining the thresholds z_L and z_H as function of the policies (v_{DM}, τ). In these expressions, $v_L(z)$ and $v_H(z;\tau)$ are the pricing functions below and above the threshold defined in (11) and (12).

We summarize the welfare properties of de minimis in the following proposition.

Proposition 2. *Given a marginal change in tariffs $d\tau$ or in the threshold dv_{DM}, the welfare change of the* *representative consumer relative to initial expenditures is*

$$\frac{du}{e} = \left[\underbrace{\frac{1}{\sigma-1}\left(\left(\frac{v_{DM}}{P}\right)^{1-\sigma} - \left(\frac{v_H\left(z_H;\tau\right)}{P}\right)^{1-\sigma}\right)}_{\text{terms-of-trade change at the threshold}} - \underbrace{\tau\left(\frac{v_H\left(z_H;\tau\right)}{P}\right)^{1-\sigma}}_{\text{tariff change}} \right] h\left(z_H\right) dz_H - \underbrace{\frac{dv_{DM}}{v_{DM}} \int_{z_L}^{z_H} \lambda\left(z\right) dz}_{\text{bunchers' price change}}$$
$$- \underbrace{\left[\tau\left(1+\kappa-\sigma\right)\frac{dP}{P} + \sigma\frac{\tau}{1-\tau} d\tau\right]}_{\text{"standard" welfare impact}} \int_{z_H}^{\infty} \lambda\left(z\right) dz \tag{20}$$

where $\lambda\left(z\right) \equiv \left(v\left(z\right)/P\right)^{1-\sigma} h\left(z\right)$ is the share of firms with unit cost z in total expenditures. These tradeoffs imply that:

(i) in the absence of a de minimis threshold ($v_{DM} = 0$), the optimal policy is free trade ($\tau^* = 0$); and,

(ii) a combination of a positive de minimis threshold with a tariff ($\tau^* > 0$ and $v_{DM}^* > 0$) is preferred to free trade if the distribution of unit costs $h\left(z\right)$ has sufficient mass below the highest-cost buncher z_H.

Expression (20) summarizes the welfare effects from de minimis policy. In the absence of de minimis ($v_{DM} = z_L = z_H = 0$), the terms in the first line vanish and only the "standard welfare impact" from the second line remains. This term captures changes in tariff-inclusive consumer prices (through dP) and in tariff revenue. Through this term, with $v_{DM} = 0$, as stated in part (i), the optimal policy would be free trade ($\tau^* = 0$). That is, with monopolistic exporters operating with constant pass-through, tariffs result in higher consumer prices without terms-of-trade gains. So the model is equivalent to one without terms-of-trade effects. Moreover, the lack of domestic competitors means no profit shifting, and hence no reason to impose tariffs.

Compared to this benchmark, a threshold potentially generates welfare-enhancing terms-of-trade effects. The potential gains of a higher threshold are shown in the first line of (20). Starting from a threshold v_{DM} with associated highest-cost buncher z_H, increasing the threshold generates a first-order reduction in prices by marginally increasing the threshold z_H; the price reduction is equal to the size of the discontinuity in the schedule labeled "optimal" that is seen in the left panel of Figure 1. In other words, when the threshold increases, firms with unit costs just an epsilon above the original highest-cost buncher z_H –who were initially pricing much above v_{DM}– now find it profitable to bunch and lower their prices to the new value of the threshold. This gain comes at the expense of two costs from raising the threshold: the cost of lost tariff revenue (the "tariff change" term in the first line of (20)); and the cost of higher prices set by infra-marginal bunchers (the "buncher's price change" term in the first line of (20)). The latter would be visually represented by a shift up in the horizontal segment of the pricing schedule in Figure 1.

These price effects hold marginally, and whether a positive threshold with a tariff is desirable compared to free trade depends on the shape of the quality-adjusted distribution of firm unit costs $h\left(z\right)$ and the various demand elasticities. However, it can be shown that the combination of the tariff with a threshold can indeed be preferable to free trade, as mentioned in part (ii) of the proposition.

To see why, consider the price schedules in the left panel of Figure 1. In the "optimal" schedule chosen by exporters, corresponding to $v_{DM} > 0$, a density $h(z)$ with enough relative mass on bunchers (i.e., below z_H) would imply a lower price index than under free trade. This would be the case, for instance, if the support of $h(z)$ was bounded at z_H (i.e., the vertical segment). In that case, the "optimal" import price schedule chosen by foreign exporters would be uniformly below the "dm channel" schedule –corresponding to free trade– for all firms with positive mass. In this example, the policy bundle with $v_{DM} > 0$ and $\tau > 0$ would be preferred to free trade, because it leads to both a lower (tariff inclusive) consumer price index and to the same (zero) amount of tariff revenue. Moreover, such an equilibrium can always be constructed for any bounded exporter unit-cost distribution $h(z)$ by raising the value of the threshold v_{DM} and thus the location of the highest-cost buncher.

Why does a non-linear tariff policy with a threshold do better than a linear tariff? A natural analogy is second-degree price discrimination by a monopsonist (i.e., a nonlinear pricing scheme). The perhaps unexpected feature here is that the result holds in a context where a standard ad-valorem tariff is useless to exert market power: with constant-elasticity demand and monopolistic competition, an ad-valorem tariff does not affect the demand elasticity, so marginal cost increases are fully passed through back to the importing country. In contrast, a de minimis threshold distorts the demand faced by exporters over a range of tariff-exclusive prices by effectively making it infinitely elastic, implying that marginal price increases are discontinuously costly. As a result, firms perceive weaker market power and lower their price.

The proposition drives home that, with constant markups and marginal costs (i.e., a benchmark without terms-of-trade effects), a minimum threshold for tariffs can improve the terms of trade, but standard linear tariffs cannot. Of course, this lack of terms-of-trade effects using only linear tariffs depends on our assumptions. Besides being useful to highlight the differential impact of the threshold, these assumptions are consistent with the complete pass-through of import prices to US tariffs that has been identified by recent empirical evidence using datasets that exclude de minimis shipments (Fajgelbaum and Khandelwal, 2021). If an additional margin that can be targeted with tariffs was introduced (e.g., upward sloping marginal costs, wage effects, or variable markups), the result suggests that the threshold structure may still do better than the tariff alone.

4 Data & Summary Statistics

4.1 Carrier Shipments Data

We use proprietary data from three express carriers–hereafter referred to as carriers A, B, and C–obtained through confidential non-disclosure agreements. The data contain the universe of air shipments from overseas origins to the USA handled by each of the three carriers. The data include the shipment date, declared value, origin country postal code, CBP entry type, and destination zip code (or address, for carrier A). For carriers A and B, we observe a text description of the items in the package, and for their shipments above the de minimis threshold the ten-digit HS code is provided.[11] The temporal coverage varies by source: carrier A spans 2014-2021, and carriers B and C have data from 2020-2022. We have all twelve months of the three carriers' shipments for 2021; that year, the carriers handled $292 billion worth of air shipments into the US through 145 million shipments.

A concern with the declared value field is the potential for misreporting –shippers may declare a value that is inconsistent with the true value of the package. However, a few institutional features make us confident about this data field. First, CBP audits the §321 channel, and undervaluation is subject to penalties–fines, delays, seizures, and potential flagging of future shipments. Second, the carriers offer insurance up to $100 per package, and additional insurance is tied to the declared value of the shipment, giving both parties an incentive not to underreport the declared value. Third, carriers reserve the right to inspect packages, as they are concerned with undervaluations because of potential auditing.

A second challenge with the carrier data is determining whether the importers are final consumers instead of commercial businesses. This distinction carries no weight for our analysis of aggregate impacts. For distributional impacts, this distinction is also not relevant if businesses operating in a zip code within a given group of income or demographics mostly sell to residents from zip codes in the same group. The carriers do not carry a flag for whether the consignee is a household or a business. For our analysis, we therefore define direct-to-consumer shipments as shipments below $5,000 and remove shipments above this cutoff. This restriction removes 3.8% of the observations in the data.

We assess this cutoff threshold using the street addresses provided by carrier A, which can be overlaid with a land-use classification raster file developed by McShane et al. (2022). Of the 81% of shipments (77% of value) that match to a specified land use, 76% went to households (68% of value), with the rest going to commercial, industrial, recreational, or agricultural land use. In contrast, including shipments above $5,000, the share of shipments that go to households does not change much–76%–but its value share falls to 59%. We do not utilize this zoning flag to trim shipments further since we cannot perform the exercise for carriers B and C, for whom we only observe the destination zip code.

Table 2 reports statistics from the carrier data. The first column reports the coverage by carrier, with "*" denoting that at least one month from that carrier is missing that year. In 2021, we have complete data across the three carriers and months. Column 2 reports aggregate values. In 2021, the underlying transactions aggregate to 130.9 million shipments (17.0% of aggregate §321 shipments) worth $15.7 billion (36.1% of aggregate de minimis imports).[12] Across all years, we analyze 373m de minimis shipments.

Columns 4-5 report value and entry statistics for imports between $801 and $5,000. Columns

[11] For de minimis entries in these data, the field for the HS code is empty except for a fraction entering through the Type 86 pilot, representing just 0.12% of the 2021 shipments.

[12] In 2021, all express carriers (including those not in our data) handled 30% of de minimis shipments, so the three carriers in our dataset account for more than half of the express segment. Moreover, the vast majority of de minimis shipments, regardless of carrier type, arrived by air–86%. So, the air shipments in our data reflect the dominant mode of §321 imports.

6-7 report samples of shipments to OECD destinations below $5,000. These shipments are included in the carrier data (for carriers A and B) because they fall into CBP entry type 62 ("Transportation and Exportation") or 63 ("Immediate Exportation"). They do not clear US customs and therefore are not subject to US trade policy, but are transshipped through the USA, presumably given the carrier's network of air routes. As explained below, these shipments can serve as an additional counterfactual density. We restrict attention to OECD destinations, as their demand would resemble US demand given similar income levels.

We also obtained, via a FOIA request, CBP shipment-level data on transactions below $1500.[13] CBP initially denied this request on the grounds that the volume of data was too large and eventually provided us with one week per year from 2017 to 2022 (the first week of December). These data contain, for this week in each year, the universe of shipments under $1500 into the US, across *all* carriers. We observe the date, declared value, origin, and destination zip code for each imported transaction. Across all years, we have 5.1 million shipments collectively valued at $263m.

4.2 Product Descriptions

What types of products are shipped directly to consumers? Common product offerings include clothing, accessories, home goods, electronics, and small durable items in the two large platforms (Shein and Temu) accounting for 30% of all de minimis shipments. However, we can inspect the types of products systematically using product descriptions in the data, and by analyzing HS codes in shipments just above the threshold.

As mentioned earlier, almost all the carrier shipments in our data are cleared through the Automated Manifest System, which does not require HS codes to be reported; however, data from two carriers contain a field with item descriptions. Figure A.1 provides a visual representation of the common words that appear in the item descriptions in direct-to-consumer shipments. The items appear to be products that consumers would purchase at retail shops, such as women's clothing (dresses, blouses), men's clothing (pants, suits), fabric types (polyester, cotton), accessories (necklace, decor, nails), and electronics. Second, we do observe HS codes for shipments above the de minimis threshold (and, as mentioned, for two carriers we observe a small number of Type-86 de minimis entries that have HS codes). Up to $50 above the threshold, 81.6% of shipments contain HS codes in the following two-digit HS chapters: 90-99 (miscellaneous), 84-85 (machinery and electrical), 50-63 (textiles), 64-67 (footwear and headgear), and 41-43 (hides, skins, leather, furs). These chapters reflect consumer goods and are consistent with the item descriptions.

[13] A FOIA request for shipments handled by the US Postal Service (USPS) was rejected on the grounds of "FOIA Exemption 3," under the argument that the transactions are of commercial nature and protected as trade secrets. Requests to USPS for aggregated counts by bins of values were also denied on the same grounds.

Table 2: Carrier Data

		shipments to USA ≤$800		shipments to USA [$801,$5000]		shipments to OECD ≤$5000		CBP shipments ≤$1500	
year	carrier (1)	value ($b) (2)	entries (m) (3)	value ($b) (4)	entries (m) (5)	value ($b) (6)	entries (m) (7)	value ($b) (8)	entries (m) (9)
2014	A	0.2	7.0	1.2	1.1	0.2	0.4		
2015	A	0.6	16.1	2.7	2.6	0.5	3.3		
2016	A	1.4	18.3	2.4	1.4	0.5	3.4		
2017	A	2.8	30.0	3.5	1.7	0.8	5.3	0.057	0.99
2018	A	3.6	34.3	4.3	2.0	1.0	6.2	0.074	1.02
2019	A	4.2	36.5	4.6	2.1	1.1	6.5	0.048	1.03
2020	A B* C	7.9	68.5	8.5	3.9	2.2	11.1	0.043	1.04
2021	A B C	15.7	130.9	17.3	8.0	2.8	11.0	0.042	1.04
2022	B* C*	3.6	31.3	5.1	2.4	0.01	0.01		
total		40.0	373.0	49.7	25.4	9.58	47.6	0.263	5.12

Notes: Table reports summary statistics from the carrier data (columns 1-7) and CBP data (columns 8-9). Column 1 reports the source carrier; "*" denotes incomplete data that year. Columns 2-3 report total value and shipments for §321 imports. Columns 4-5 report imports of direct shipments valued between $801-$5,000. Columns 6-7 report statistics of transshippments to OECD under $5,000 handled by carriers A and B. Columns 8-9 report statistics from the CBP sample that contains the universe of shipments entering into the USA under $1500 for the first week of December 2017-2021.

4.3 Demographics

We use a combination of street addresses and zip codes to link demographic characteristics to shipment destinations. Carrier A provided street addresses and states, but not zip codes; for this carrier we infer zip codes from ArcGIS and achieve a match rate of 87%. Carriers B and C provided zip codes, but not addresses.

We match the zip codes to ZIP Code Tabulation Areas (ZCTA), and merge family income and socio-economic characteristics from University of Michigan's ICPSR. Across zip codes, the average median family income is $76k, and the average share of (non-Hispanic) white households is 77%.

4.4 Direct-to-Consumer Imports and De Minimis Spending Across Groups

We document expenditures on direct-to-consumer shipments across zip codes for 2021, the year of full data coverage. We construct per capita measures by aggregating shipments to the zip code and dividing by zip code population. The official aggregates from CBP in Table 1 imply de minimis expenditures in 2021 of $131 per person. The carrier data are about one-third of total de minimis in that year, and average per capita expenditures on de minimis imports across zip codes is $32.6.

The top panel of Figure 2 reports zip code per capita expenditures as a share of median family income, on direct-to-consumer and de minimis shipments. (Figure A.2 shows the expenditures in dollars: richer zip codes naturally spend more, but the lowest-income zip codes spend more than moderately richer zip codes.) There is a U-shaped pattern against income for both total direct shipments and de minimis shipments, with the lowest zip codes spending roughly the same as a share of income as the richest zip codes, and both spending intensities more than twice that of a $70k zip code. The right panel of Figure 2 shows expenditures by zip code white household share. We find that zip codes with the lowest white share spend the most, which suggests that non-homothetic preferences are in incomplete description and group-specific preferences also play a role in the demand for direct shipments.

The bottom panel of Figure 2 reports the share of direct shipments that are de minimis (blue series). Lower-income zip codes report a much larger fraction of spending on de minimis: the lowest-income zip codes spend 74% of direct purchases on de minimis imports, compared to 52% for the wealthiest zip codes. The right panel shows that the de minimis share of expenditures is U-shaped with respect to white household share, with a de minimis share of 74% in the direct spending of the zip codes with the least share of white households.

The red series shows the share shipments from China within de minimis. There is a negative relationship between China's import share and zip code income: 48% of the lowest income zip codes' purchases of de minimis shipments are from China, compared to 23% for the richest zip codes. The patterns decrease by white share, though not as sharply as with income.

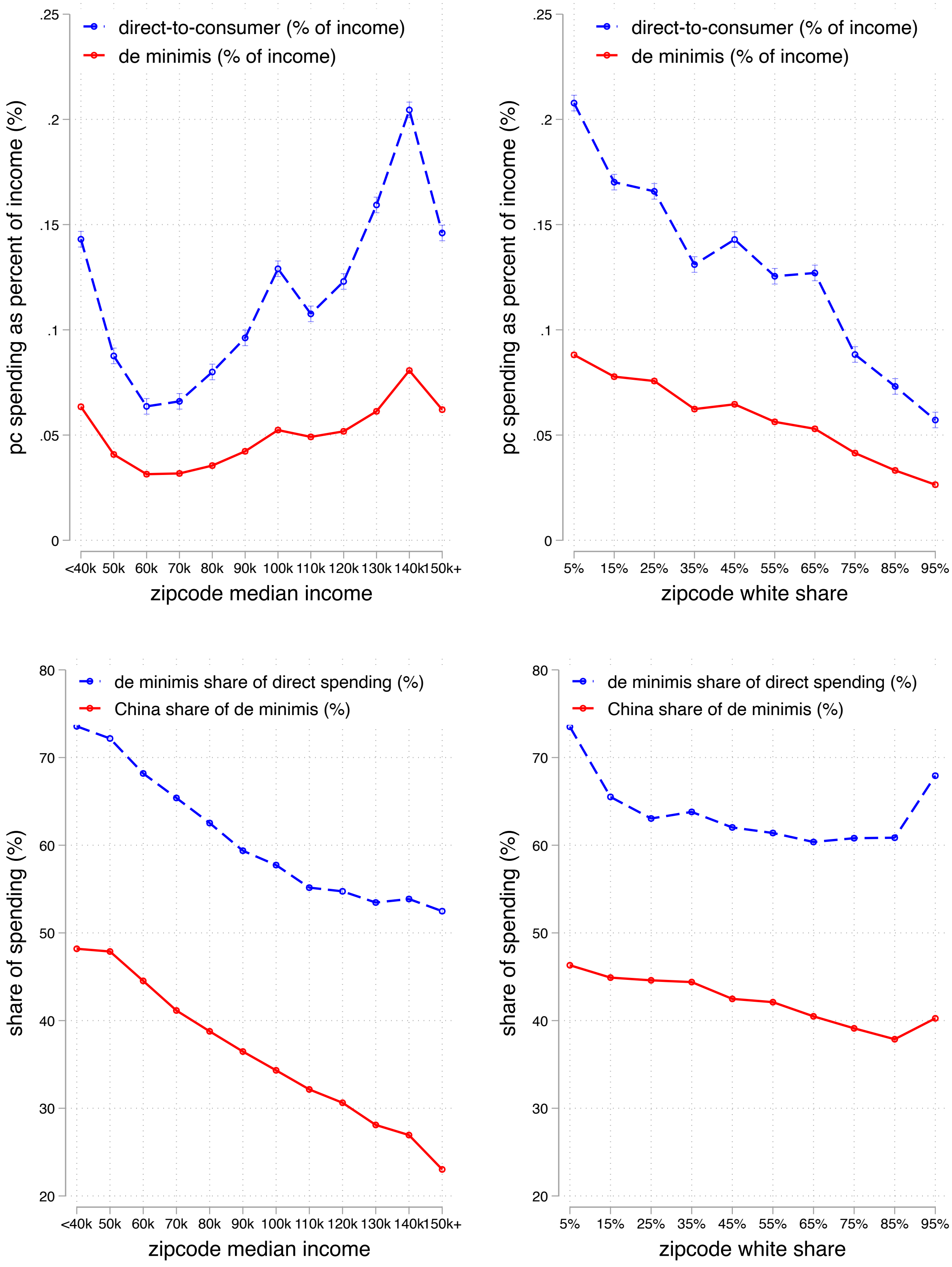
The top panel of Figure A.3 reports statistics from the CBP sample. We only observe shipments up to $1500 in this dataset, and since it is only one week of data, the shares of minimis spending in income (blue series in left axis) are very small. Nevertheless, the cross-zip code patterns in the CBP data are consistent with the carrier data: poorer zip codes spend relatively more on de minimis shipments than richer (and more white) households. The red series (right axis) shows the share of de minimis that originates from China, which is consistent with the carrier data, with lower-income zip codes concentrating relatively much more of their de minimis expenditures on goods from China. The overall Chinese share of de minimis is larger in the CBP data, indicating that the three carriers in our data are not as focused on handling shipments from China than other carriers. The pattern across white household shares is U-shaped, unlike the negative relationship in the carrier data.

An alternate method to investigate who benefits most from de minimis imports is to analyze consumer spending patterns across zip codes on the e-platforms that heavily rely on §321 for their business model. We use proprietary data from MBHS3, provided via Yale University, which compiles information on credit and debit card transactions from 2019-2023. The data contain roughly 35 billion transactions annually from 180 million individuals at hundreds of merchants (including all chain stores). We obtained total expenditures, by zip code and month, at 506 merchants operating in durable product categories: mass merchandise (e.g., Walmart, Target, Dollar General, Costco), clothing related (e.g., Forever 21, Old Navy, Gap, Shein, Temu), home improvement (e.g., Home Depot, Lowe's, Ace Hardware), sports and outdoors (e.g., Dick's, REI, Adidas), online (e.g., Amazon, Etsy), and consumer electronics (e.g., Best Buy, GameStop). These data are limited to non-cash transactions by undisclosed participating credit card issuers.

We construct the share of expenditures on the three companies in this data for which de minimis are an integral part of their business model (Shein, Temu, and AliExpress, the latter being relatively small in the US), relative to totals in the previous categories.[14] Figure A.4 plots the share

[14] International third-party sellers ship directly to consumers on Amazon and eBay through the de minimis channel. However, eBay has sizable domestic transactions, and Amazon primarily relies on importing through formal channels to domestic warehouses, and so we do not consider de minimis integral for these two companies.

FIGURE 2: DIRECT-TO-CONSUMER AND DE MINIMIS SHIPMENTS, BY ZIP CODE



Notes: The top panel reports 2021 per-capita expenditures on direct shipments (below \$5,000 , blue series) and de minimis shipments (below \$800, red series), as a share of zip code median family income. The left panel plots against zip code median family income; labels denotes +/- \$5k of the income interval (e.g., the \$60k marker contains zip codes with incomes between \$55k-\$65k). The right panel plots against zip code share of white households; labels denote +/- 5% of the white share intervals (e.g, the 35% marker contains zip codes with white shares between 30%-40%). The bottom panel reports the share of direct shipments that are de miminis (blue series) and the share of de minimis shipments from China (red series). Bars are standard errors of means. Source: carrier data, 2021.

of spending on Shein, Temu, and AliExpress. Across all merchants, the poorest zip codes spend 1.10% of the total credit card spending in the previous categories at these three companies, while the richest spend only 0.40%. The differences are starker across minority household shares: these three companies are 1.33% of spending in the least white share zip codes compared to 0.40% in the most white zip codes. These patterns confirm the findings from the carrier and CBP data.

4.5 Tariff and Administrative Fee Incidence across Groups

These facts–the poor disproportionately use de minimis imports and disproportionately sourced them from China–imply that §321 is a pro-poor tax policy. In this subsection, we analyze the incidence of tariffs and administrative fees across consumer groups.

For above-$800 shipments, we observe HS codes in two of the three carriers. We do not observe HS codes for the vast majority of de minimis shipments. So, we assume that if §321 were eliminated, these shipments would face the median applied tariff by origins in the aforementioned HS2 chapters.[15] Before March 2016, the average tariff faced by above-threshold shipments from China was 4.0%; after March 2016, average tariffs rise to 15.3%. For RW, average tariffs change from 2.7% before March 2016 to 2.1% after. Using the data from these two carriers, we can construct the (weighted) average tariff by zip code under two scenarios: 1) the average tariff with §321 in effect; and, 2) the average tariff if §321 were eliminated.

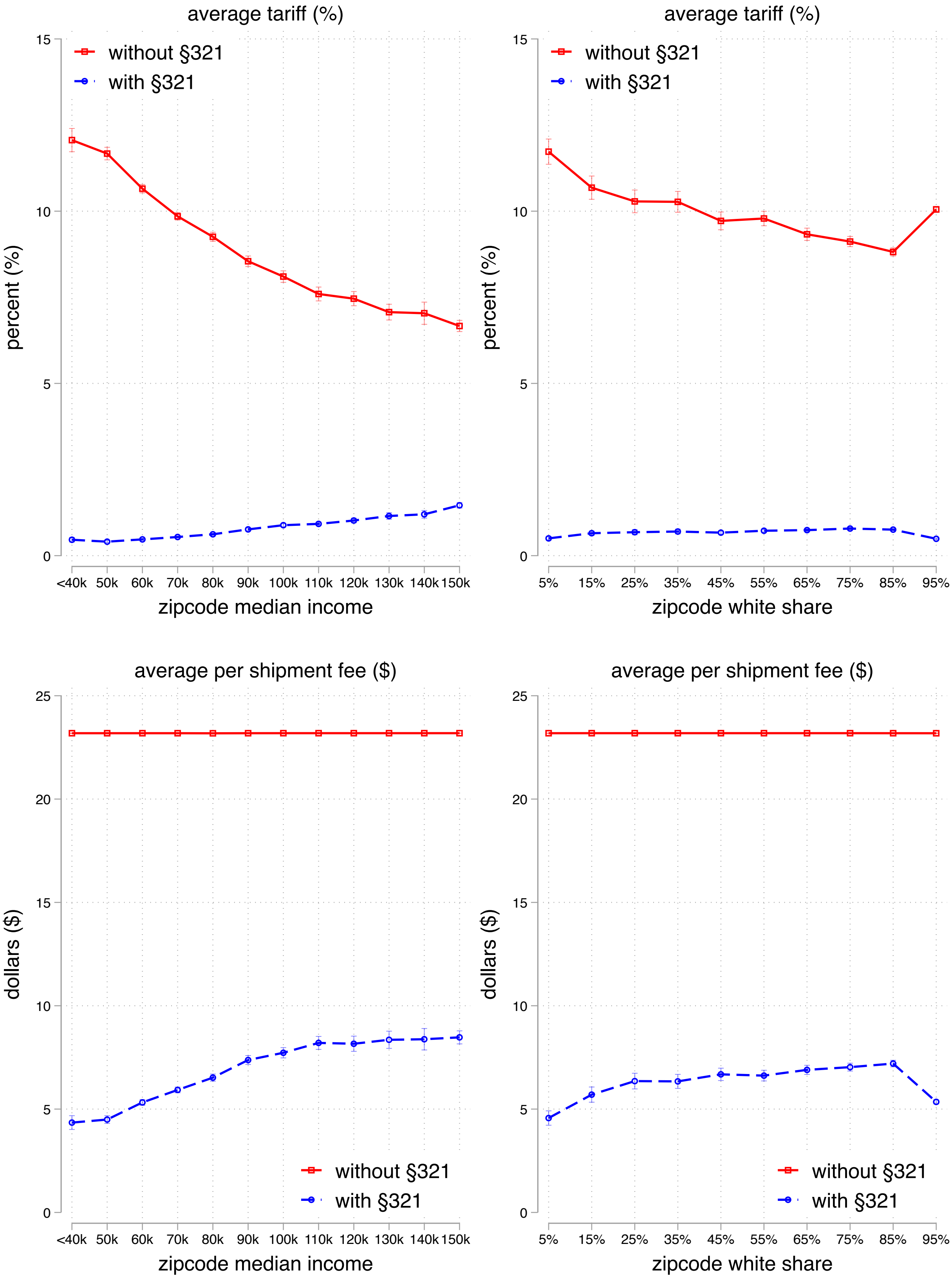
Figure 3 reports the results. The blue series reports the incidence of tariffs with §321 in place, i.e. with tariffs applied to shipments only above $800. The tariff incidence is progressive: lower income zip codes face lower tariffs than high zip codes. The (value-weighted) average tariff on the lowest-income zip code is 0.5% compared to 1.5% for the richest zip codes. The average tariffs are low because de minimis shipments are a large fraction of direct shipments up to $5,000, which is the cutoff we imposed for direct imports.

The red series removes the tariff exemption, with the big change being that tariffs on Chinese imports below $800 rise from zero to 15.3%. Naturally, the overall tariff level increases. But, more strikingly, the distributional patterns reverse: without §321, the incidence of tariffs is regressive. The poorest zip codes would face a 12.1% tariff, whereas the richest zip codes would face a 6.7% tariff. This finding echoes Acosta and Cox (2019), who find that the US tariff code on consumer goods is regressive. The tariffs faced by minority households would also be higher than zip codes with more white households if §321 were eliminated, as shown in the right panel of Figure 3.

Given that lower-income and minority households typically receive a higher proportion of direct shipments through §321, their average per-shipment administrative fee tends to be lower. Panel B of Figure 3 illustrates the average per-shipment fee under both scenarios; if §321 were removed, we apply the uniform fee of $23.19 to all shipments. This figure illustrates how eliminating §321 will affect different consumer groups. Since low-income zip codes have higher expenditure shares on de minimis, and these de minimis packages are disproportionately purchased from China, a first-order approximation to the consumer costs of eliminating de

[15] We obtain the median applied tariff by origin-month in these HS chapters from public Census import records.

FIGURE 3: TARIFF AND ADMINISTRATIVE FEE INCIDENCE



Notes: Top panel reports the value-weighted average tariff with §321 (blue series) and without §321 (red series). The figure is constructed by taking zip code expenditure shares on direct shipments in 2021 and applying the import tariffs by origin. We match product-level applied tariffs from US Census data to shipments between [$801,$5,000], which contain HS codes. For de minimis shipments (for which we do not observe HS codes), we assign the median tariff across HS 90-99, 84-85, 50-63, 64-67, and 41-43 by origin. The bottom panel reports the weighted-average administrative fee with and without §321. The blue series is constructed by applying a $23.19 fee to shipments between [$801,$5,000] and a $0 fee for de minimis shipments. The red fee applied $23.19 fee to all shipments. Bars are standard errors of means. Source: carrier data, 2021.

minimis implies that low-income consumers would be hurt more than richer consumers from imposing tariffs and customs fees on these shipments.

Finally, the bottom panel of Figure A.3 reports tariff incidence by zip code in the CBP data. A caveat is that the CBP sample did not contain any HS codes (either for the Type 86 de minimis entries or for the above-\$800 shipments). We therefore construct a zip code's tariff using median tariff by origin in those HS chapters mentioned above. The figure reveals a similar pattern of a progressive tariff policy becoming a regressive if the §321 exemptions were removed. The patterns in the CBP data are broadly consistent with the carrier data and, if anything, understate the role §321 because of the higher shares from China.

5 Evidence of Bunching

5.1 Main Results

Constructing the exact welfare impacts of §321 requires an estimate of the consumer demand elasticity, which, according to the model, can be identified by the extent of bunching in the shipment densities.

Since we observe the density of de minimis shipments under different de minimis thresholds, we can estimate the impact of the notch non-parametrically by exploiting two differences in densities: 1) the change in density from \$200 to \$800 in March 2016; and 2) the difference in shipment density to the US versus OECD countries. Rather than estimating the elasticity by matching bunching in a cross-section, this approach matches the change in bunching.

We first show the density of shipments in *levels* at two points in time–before and after March 2016–for the USA and OECD shipments. To do so, we aggregate shipments to bins of \$10 and estimate the following regression:

$$\ln c_{bodxt} = \alpha_{xdot} + \beta_b + \epsilon_{bodxt} \tag{21}$$

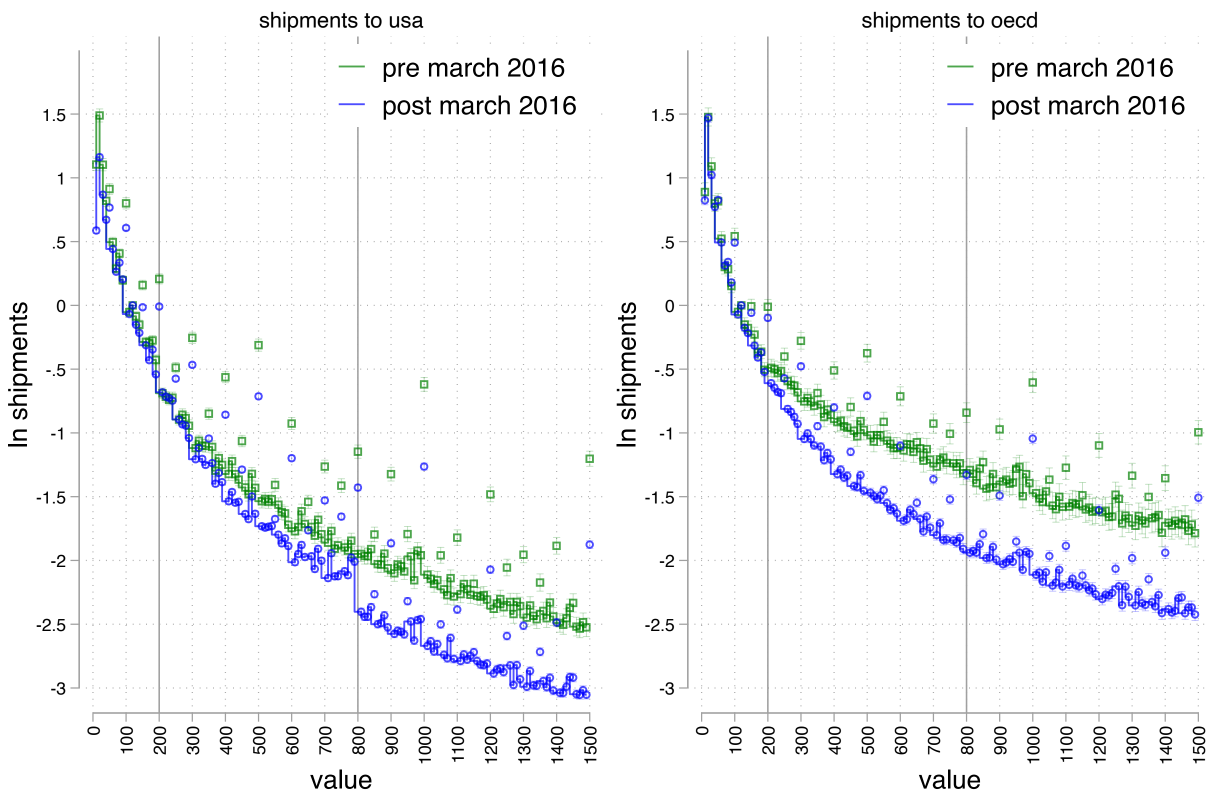
where c_{bodxt} is the count of packages in bin b from origin $o \in \{USA, OECD\}$ to destination d by carrier $x \in \{A, B, C\}$ at time t (month-year). The α_{xodt} fixed effects control for carrier-origin-destination-time fixed effects; these coefficients control for origin supply and destination demand shocks that could potentially vary by carrier (e.g., a particular carrier expands its presence in a particular origin-destination route). Standard errors are clustered by origin-time. We run this specification on four samples: shipments to USA before and after March 2016, and shipments to OECD before and after 2016.

The key parameters are the bin fixed effects, β_b, which capture the shipment density net of these shocks. The leave-out bin is \$120. If the notch had no impact, we would expect a smooth density of the β_b parameters throughout the shipment values. With a notch, shipments from the *same* origin face a different tariff and administrative fee depending on the shipment value, and the fixed effects isolate this variation.

The left panel for Figure 4 shows the estimates of β_b separately for two periods for the USA shipments: before and after March 2016. The pre-period density (green) shows a drop in packages at the $200 threshold (although the bunching below the notch and the drop in shipments above the notch is somewhat difficult to see), and the density around $800 appears smooth. In the post-period density (in blue) there is evidence of bunching in the post-period density (blue) right below $800, and then a subsequent drop in shipments above the notch. The estimate indicates that there are 41.3% fewer shipments $100 above the notched compared to $100 below the notch.

The right panel of Figure 4 reports the density of shipments to the OECD. Here, the densities are smooth around both $200 and $800 in both periods, which is expected since shipments to these destinations are not subject to the USA thresholds.

FIGURE 4: SHIPMENT DENSITY BEFORE AND AFTER MARCH 2016



Notes: Figure reports the density of shipments to the USA (left panel) and OECD (right panel) before and after March 2016. The figures plot the β_b bin fixed effects from (21). The leave-out bin is $120. Grey vertical lines denote §321 thresholds before and after March 2016. Round numbers not included in the connected line to improve visualization. Error bars denote 95% confidence intervals. Source: carrier data, all years.

A simple difference-in-difference specification allows us to identify the impact of the threshold:

$$\ln c_{bodxt} = \alpha_{xdot} + \beta_b \times \text{USA}_d \times \text{post}_t + \epsilon_{bodxt} \tag{22}$$

where now β_b is the difference-in-differences estimate of the shipment densities: the difference in the (log) number of US-bound shipments in the post-period relative to the pre-period shipments, relative to that same difference for OECD-bound shipments. Figure 5A reports the β_b fixed effects.

The figure has several messages. First, moving up shipment values, we observe *negative* bunching approaching \$200; this is expected since we are examining a difference-in-difference specification that compares the changes in post-period density with the pre-period. If the \$200 notch causes bunching in the pre-period, there should be a decline in the bin fixed effects just below \$200 in the graph. Above \$200, we see a jump up in shipments, which is again expected since shipments in the \$200-\$800 range experience a tariff cut as they are included into §321 after March 2016. Then, as one approaches \$800, we observe evidence of (positive) bunching. Finally, there is a drop in shipments above the current \$800 threshold.

Qualitatively, this figure matches the prediction from the model with two exceptions. First, the bunching in the pre-period is not as stark as in the post-period. Shipping through §321 was presumably less valuable during that time because direct-to-consumer online platforms had yet to take off, electronic clearance of de minimis shipments was limited, and tariff levels were lower. On the other hand, there is evidence of bunching as the density approaches the current \$800 notch. If the notch had no impact on shipments, we should observe a smooth density around \$800. Instead, there is an inflection point as the density approaches \$800. The drop in shipments above the notch is large: there are on average 27.0% fewer shipments \$100 above the notch versus below. Second, although we observe bunching, it is not exactly (and only) at \$800, nor is there a distinct "hole" right above the notch (in, say, the \$801-\$820 range), as the model with fully rational agents would predict. The lack of a bunch at exactly \$800 and the lack of a hole motivates in the model the introduction of exporters who optimize subject to a friction.

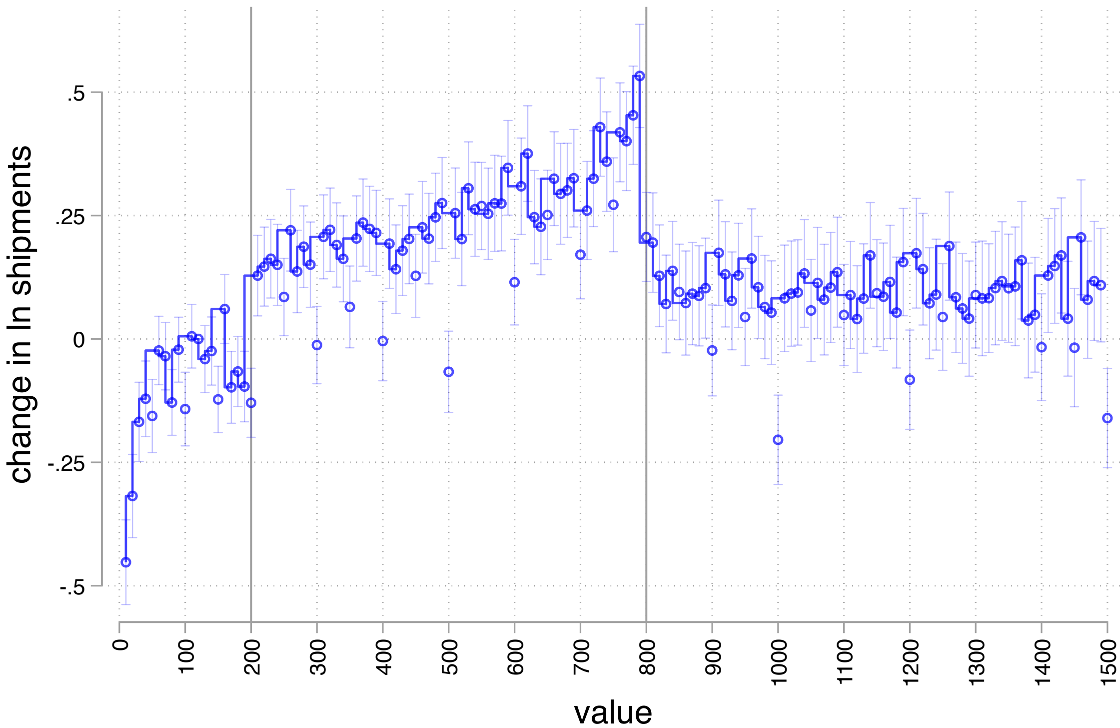
Figure 5B reports specification (22) separately for shipments from China ($o = CHN$, blue) and from the rest of the world ($o = RW$, green). The evidence of bunching from China is sharper relative to rest of world. We observe (negative) bunching at \$200, and a stark jump up just above the \$200 notch. Then, as the density approaches \$800, shipments from China of \$751-\$800 are 32.8% larger relative to \$700-\$750. Going \$100 above the notch results in 99.6% fewer shipments relative to \$100 below. The pattern is similar on shipments from RW, but not as stark (as one would expect, given that import tariffs on RW are not nearly as high as China's in the post period). In the next section, we use the differences in bunching across origins from Figure 5B to identify the within-origin demand elasticity for China (σ_{CHN}) and RW (σ_{RW}).

Finally, we can examine the shipment density in the weekly CBP data. Although it just contains one week per year from 2017 to 2022, the CBP data is valuable because, for that week, it contains the universe of shipments into the country across *all* carriers. It is possible that shippers switch to a different carrier above \$800 (e.g., decide to ship via sea instead of air) in which case, the drop in density above the notch in the previous data would reflect a switch in carrier rather than a real change in imported shipments. The drawback is that we do not have shipments from CBP in the pre-period with a lower de minimis threshold (nor, of course, shipments to OECD), and therefore can only examine the analog of the cross-sectional regression in (21) on this sample.

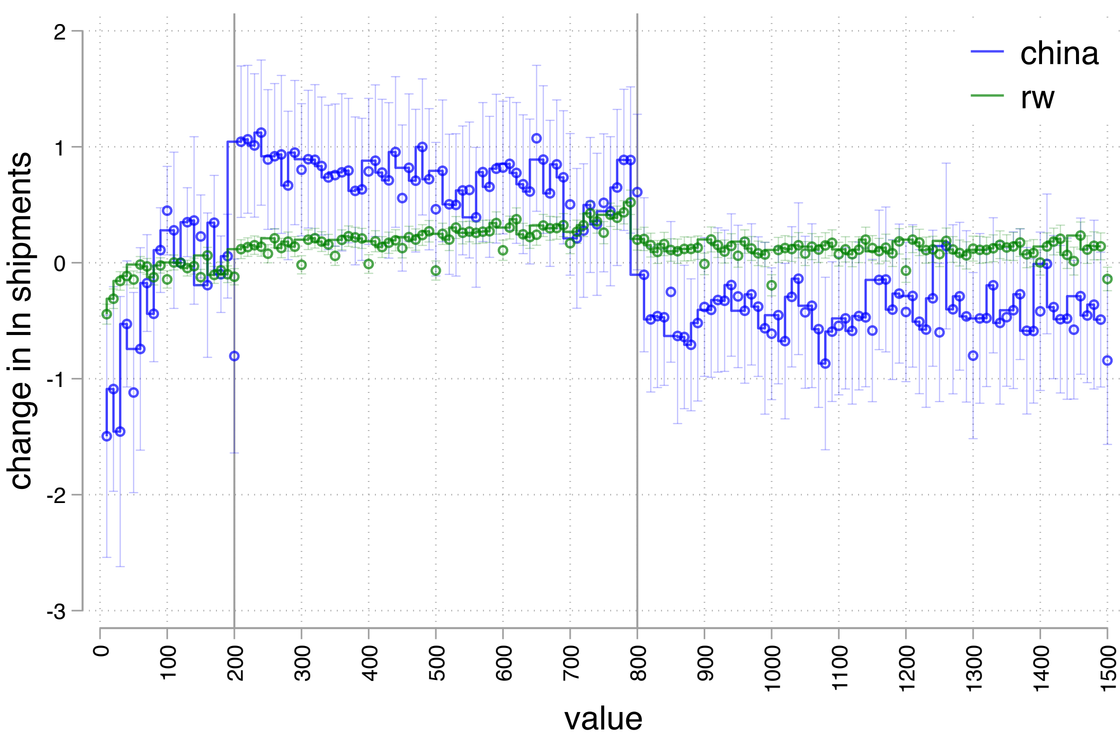
Figure A.5A plots the density. The impact of the notch is evident as the density approaches \$800, and the subsequent drop in shipments above the notch is consistent with the carrier data: \$100 above the notch on average result in 44.9% fewer shipments compared to \$100 below. Thus,

FIGURE 5: DIFFERENCE-IN-DIFFERENCES SPECIFICATION

Panel A: All Origins



Panel B: By Origin



Notes: Figure reports the density of shipments to the USA in the post period relative to pre period, and relative to the same time difference for OECD shipments. The regression specification is (22), and the figure plots the $\beta_b \times \text{USA}_d \times \text{post}_t$ fixed effects. Panel A plots shipments from all origins. Panel B estimates (22) separately for shipments from China and RW. Grey vertical lines denote §321 thresholds before and after March 2016. The leave-out bin is \$120. Error bars denote 95% confidence intervals. Round numbers not included in the connected line to improve visualization. Source: carrier data, all years.

a concern from carrier data–that shippers may switch to alternative logistics providers above the threshold–is not borne out since the CBP sample contains shipments handled by the universe of carriers. Figure A.5B shows that the drop in shipments from China between these two intervals is even starker, with 108.8% fewer shipments. Thus, the impact of the notch appears also in the administrative records from CBP (we do not use this sample to estimate the tariff elasticities because we do not observe the corresponding control densities).

5.2 Alternative Explanations

The bunching and subsequent drop in density at the threshold could partly be explained by manipulation of the number of items per package. The law explicitly prohibits sending items from a single invoice in multiple shipments. However, a consumer could spread a transaction with multiple items into multiple transactions with fewer items each, at the cost of higher shipping costs and inconvenience. If so, package values could drop below the de minimis threshold without adjustments in the item price.[16] We can explore the likely extent of this type of manipulation using the data from Carriers A and C, who provided information on the reported number of items per package.

We provide two pieces of evidence suggesting that this type of manipulation is unlikely a major force driving bunching. First, the magnitude of item manipulation around the threshold appears small. The top panel of Figure A.6 shows the number of items per package (relative to the leave-out bin $120). The pre-2016 (green) series shows that packages $100 above the threshold have only 3.9% fewer items than $100 below the threshold, while post-2016 (blue) shows that packages $100 above the threshold have only 2.8% more items. The bottom panel reports the difference-in-differences (across destinations and over time), and confirms that magnitude of changes items is small around the thresholds. Moreover, the opposite patterns across time periods (a drop in items per package at the threshold under a low threshold, and an increase under a high threshold) makes it challenging to come up with a unifying explanation based on item manipulation at the threshold.

Second, we observe bunching at the threshold among single-item packages, which contradicts item manipulation as the main force driving bunching. If items manipulation was a major determinant, it should manifest through breaking down 2-item packages into single-item packages, as 1 or 2 item packages account for the majority of value and shipments.[17] However, a two-item shipment selling above $800 split into two single-item shipments does not show up as bunching except in the unlikely event of one of the original items being priced very close to $800. Therefore, if price manipulation was absent but items manipulation was present, we should not observe bunching at $800 among single-item packages. However, among single-item packages we observe a very similar pattern of bunching as in Figure 5. The top panel of Figure A.7 reports the difference-in-differences across all origins, and the bottom panel reports the results by origin,

[16] It is unclear how salient the de minimis threshold is for consumers. Shein and Temu do not flag at check-out that packages above $800 are potentially subject to duties, while eBay and Etsy do.

[17] Collectively, in 2021, for carriers A and C, single-item packages accounted for 76.0% of de minimis shipments and 72.5% de minimis value from these carriers; and two-item packages accounted for 7.5% of shipments and 7.4% of value.

using single-item packages only. Across all origins, there are 27.1% fewer shipments $100 above versus below the notch (for China, the corresponding decline is 155.3%).

Next, it is possible that shipping costs also change discretely above $800, but the carriers confirmed that is not the case (one carrier provided charges and we verify that shipping costs are smooth around $800). Finally, while the majority of shipments go to households, it could be that commercial customers (e.g., small businesses) place relatively more orders around the threshold. We assume that imports to commercial addresses are sold to zip codes within the same group of income or demographics, but this is not an assumption we can directly check given data limitations. Still, we can examine the share of shipments to households in carrier A's data across the distribution; see Figure A.8. The share of households importing around the threshold is 13.7% lower than at the leave-out but there is no discontinuous change, suggesting that the type of importer does not change discretely around the threshold.

6 Welfare Impacts of De Minimis Imports

This section analyzes the aggregate and distributional and implications of a counterfactual policy change that eliminates §321: all shipments would face tariffs and administrative fees. Before presenting the exact analysis, we discuss a first-order approximation to the distribution of consumer losses from eliminating de minimis. This approach is "model-free" in that it only relies on the variation in empirical spending shares across consumer groups. The exact analysis, however, takes into account potential responses by consumers to higher prices, which leverages the bunching shown above, and rebates tariff revenues by to consumers.

6.1 First-Order Approximation

The spending patterns across groups grounds the distributional impacts of §321. A first-order approximation of such a policy change, which assumes complete pass through and uses only the observed spending shares, tariffs, and administrative fees yields a consumer loss of $11.1b, or $35 per person. The spending shares from the CBP sample imply even larger losses–$22.2b or $69 per person–since the import shares from China are greater in this sample.

The distribution of losses across consumer groups are reported in Figure 6. Consumers in the poorest zip codes would lose 24.8% more than the representative consumer, or 9.1% more using CBP data. In both samples, the rich tend to lose more in terms of dollars, but when express as a share of family income, the losses are larger for the poor (top-right panel).

Across racial composition, the spending shares imply that the white zip codes would experience a cost increase of 39.4% more than the representative consumer, or a 17.3% larger loss using the CBP data. In terms of both dollars and shares of income, less white households lose more.

These estimates, which leverage only the empirical spending shares, suggest the §321 is a policy that favors poorer and minority households. To obtain the exact welfare numbers, we now turn to the parameterization of the model.

6.2 Firm Types

We first address the fact that the value distributions of shipments do not feature a hole with zero mass above the threshold. In studies of labor income taxation, the lack of a hole is dealt with by assuming some form of optimization friction (Kleven and Waseem, 2013). In this spirit, we assume two types of firms: "sophisticated" firms, who understand the potential benefits from bunching and optimally price as we have described in Proposition 1; and "naive" firms, who ignore the benefits from bunching and simply price subject to high tariffs when a pricing subject to low tariffs leads to package values above the threshold. Naive firms could make extra profits by bunching; in this context, they broadly capture plausible mechanisms, such as attention costs to the potential gains from bunching or indivisibility of items that prevents an exact tailoring of the total package value to \$800.

From now on, we index pricing decisions with an upper-script $j = S, N$ (sophisticated or naive) that indexes the firm type: $v_o^j(z)$. Sophisticated firms use the pricing rule $v_o^S(z)$ presented in 13, while naive firms use the simple pricing rules without bunching:

$$v_o^N(z) = \begin{cases} v_{L,o}(z) & z < z_{L,o}, \\ v_{H,o}(z) & z \geq z_{L,o}. \end{cases} \tag{23}$$

Similarly, we write $h_o^{\omega,j}(z)$ and index the quality-adjusted distribution defined in (7) by the upper-script $j = S, N$.

6.3 Welfare Measurement

When tariffs or the de minimis threshold change, the equivalent variation of a consumer in group ω (the dollars a consumer in ω would have to receive to be left indifferent with the initial policy) is

$$ev^\omega = \underbrace{\frac{1}{\kappa}\left(\left(\hat{P^\omega}\right)^{-\kappa} - 1\right)e^\omega}_{\equiv \Delta e^\omega} + \Delta tr^\omega, \tag{24}$$

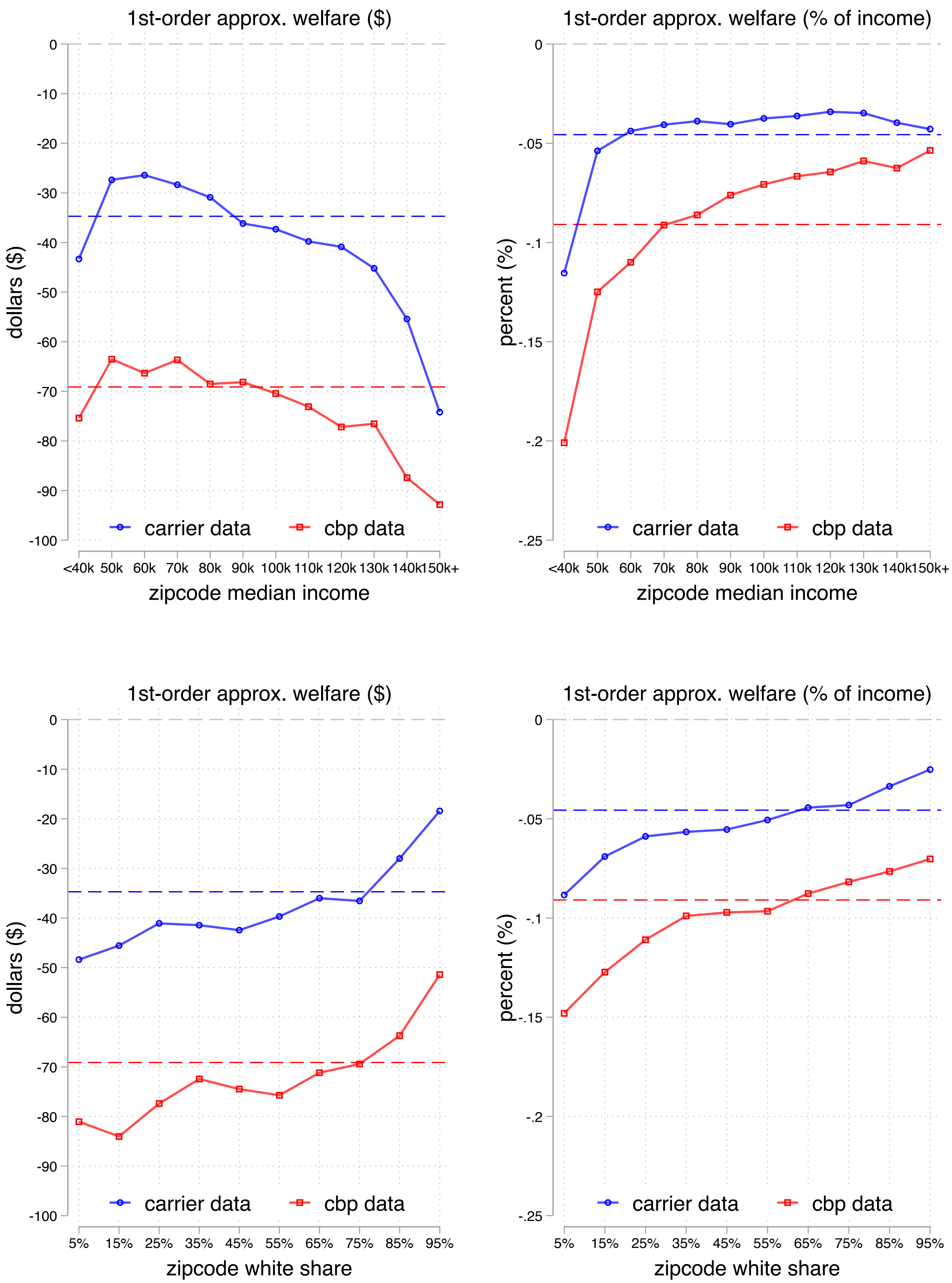
where Δx denotes the difference in a given variable x between the new and original equilibrium and $\hat{x}$ denotes their ratio.

Naturally, the welfare impact consists of two terms, corresponding to price changes between equilibria (entering through P^ω) and the changes in tariff revenue rebated to group ω, Δtr^ω. Using (2) and (A.35), the change in the overall price index is

$$\hat{P^\omega} = \left(\sum_o \lambda_o^\omega \left(\hat{P_o^\omega}\right)^{1-\gamma}\right)^{\frac{1}{1-\gamma}}, \tag{25}$$

where $\lambda_o^\omega \equiv E_o^\omega / \sum_{o'} E_{o'}^\omega$ is the share of country o in the aggregate direct expenditures by group ω.

FIGURE 6: FIRST-ORDER APPROXIMATION TO WELFARE LOSS FROM ELIMINATING §321



Notes: Figure reports the first-order approximation to the welfare loss of from removing §321 against zip code characteristics. This calculation assumes complete pass through, and uses only the observed carrier (or CBP) spending shares, tariffs, and administrative fees. The left panels report impacts in per-capita dollars and the right panel scales by median family income. Top panel reports by zip code median family income, and bottom panel reports by zip code white household share. The blue (red) series denotes estimates from carrier (CBP) data; aggregate losses denoted by the horizontal dash line.

In turn, the change in the price index from for direct goods from o among ω consumers is:[18]

$$\hat{P_o^\omega} = \left(\sum_{j=S,N} \int_z \lambda_o^{\omega,j}(z) \widehat{v_o^j(z)}^{1-\sigma_o} dz \right)^{\frac{1}{1-\sigma_o}} \tag{26}$$

where

$$\lambda_o^{\omega,j}(z) = \left(\frac{v_o^j(z)}{P_o^\omega} \right)^{1-\sigma_o} h_o^{\omega,j}(z) \text{ for } j = S, N \tag{27}$$

is the share of all varieties of type-j with unit cost equal to z in the total expenditures from origin o made by consumers in group ω.

As we have mentioned, there can be any correlation between unit costs and demand shocks. This correlation is key to assess welfare impacts, as it determines the exposure of different consumer groups. However, only the quality-adjusted measure $h_o^{\omega,j}(z)$, which combines demand shocks and measure of firms across the distribution of unit costs, matters to calculate aggregate and distributional effects. Knowing this function and the elasticities $(\sigma_o, \gamma, \kappa)$ we can fully characterize model outcomes given the policies (τ_o, v_{DM}). In the next sections, we recover each of these objects from the data, and use the model to assess the welfare impacts of de minimis.[19]

6.4 Parametrization

As a first step, we jointly calibrate the aggregate (US-level) quality-adjusted distribution $h_o^{US,j}(z)$ for $j = S, N$ (sophisticated or naive), defined as aggregating over ω, the group-specific distributions $h_o^{\omega,j}(z)$, and the substitution elasticities σ_o for each origin. Our procedure jointly calibrates σ_o and $h_o^{US,j}(z)$ for $o = CHN, RW$ to match the post-2016 density of imported packages and the change in this density between the post- and the pre-2016 periods, both of which have been estimated in the previous section. Specifically, the following steps 1 and 2 are implemented for each value of σ_o, and we search in the space of σ_o.

Step 1: Matching the Aggregate Density We condition on σ_o and calibrate $h_o^{US,j}(z)$ for $j = S, N$ to match the post-2016 density of imported packages from each origin. We impose that naive and sophisticated densities are proportional to each other within each origin o and import group ω, with constant δ_o^ω:

$$h_o^{N,\omega}(z) = \delta_o^\omega h_o^{S,\omega}(z). \tag{28}$$

Conditional on σ_o and the post-2016 policies (tariff τ_o^{post}, administrative fee $T^{post} = \$10$, and threshold $v_{DM}^{post} = \$800$), we can compute the thresholds $z_{L,o}$ and $z_{H,o}$ using (14) and (15). With this information, we can fully characterize in the model the density of total packages imported around a value v from any particular group (either for a specific group ω, or the US as whole). In particular, as shown in the Appendix, the aggregate number of packages imported to the US from

[18] To find this expression we first express (3) in relative changes and use from (13) that prices depend only unit costs.

[19] As shown in (A.47) the tariff revenue generated by group ω is also a function of these variables.

origin o on the interval $[v+\Delta_v]$ is:

$$\Delta N_o^{US}(v)=\begin{cases} v^{-\sigma_o}\left(1+\delta_o^{\omega}\right)\left[D_o^{US}h_o^{US,S}\left(z_{L,o}(v)\right)\right]\frac{\sigma_o-1}{\sigma_o}\Delta_v & v<v_{DM}, \\ v_{DM}^{-\sigma_o}\int_{z_L}^{z_H}\left[D_o^{US}h_o^{US,S}(z)\right]dz & v=v_{DM}, \\ v^{-\sigma}\delta_o^{\omega}\left[D_o^{US}h_o^{US,S}\left(z_{H,o}(v)\right)\right]\frac{\sigma_o-1}{\sigma_o}\left(1-\tau_{H,o}\right)\Delta_v & v\in\left(v_{DM},v_{H,o}(z_H)\right], \\ v^{-\sigma}\left(1+\delta_o^{\omega}\right)\left[D_o^{US}h_o^{US,S}\left(z_{H,o}(v)\right)\right]\frac{\sigma_o-1}{\sigma_o}\left(1-\tau_{H,o}\right)\Delta_v, & v>v_{H,o}(z_H). \end{cases} \tag{29}$$

where $z_{L,o}(v)$ and $z_{H,o}(v)$ are the inverse functions of $v_{L,o}(z)$ and $v_{H,o}(z)$ in (11) and (12).

We observe $\Delta N_o^{US}(v)$ over a grid of values $v\in[0,10,...,5000]$ in the post-2016 period. To implement, we assume a power function for $D_o^{US}h_o^{US,S}(z)$. We jointly parameterize δ_o^{ω} (which regulates the importance of naive firms) to exactly match the observed number of shipments in the excluded region $(v_{DM},v_{H,o}(z_H)]$, and the power function for $D_o^{US}h_o^{US,S}(z)$ to match the observed $\Delta N_o^{US}(v)$ outside the dominated range ($v\leq v_{DM}$ and $v>v_{H,o}(z_H)$).[20]

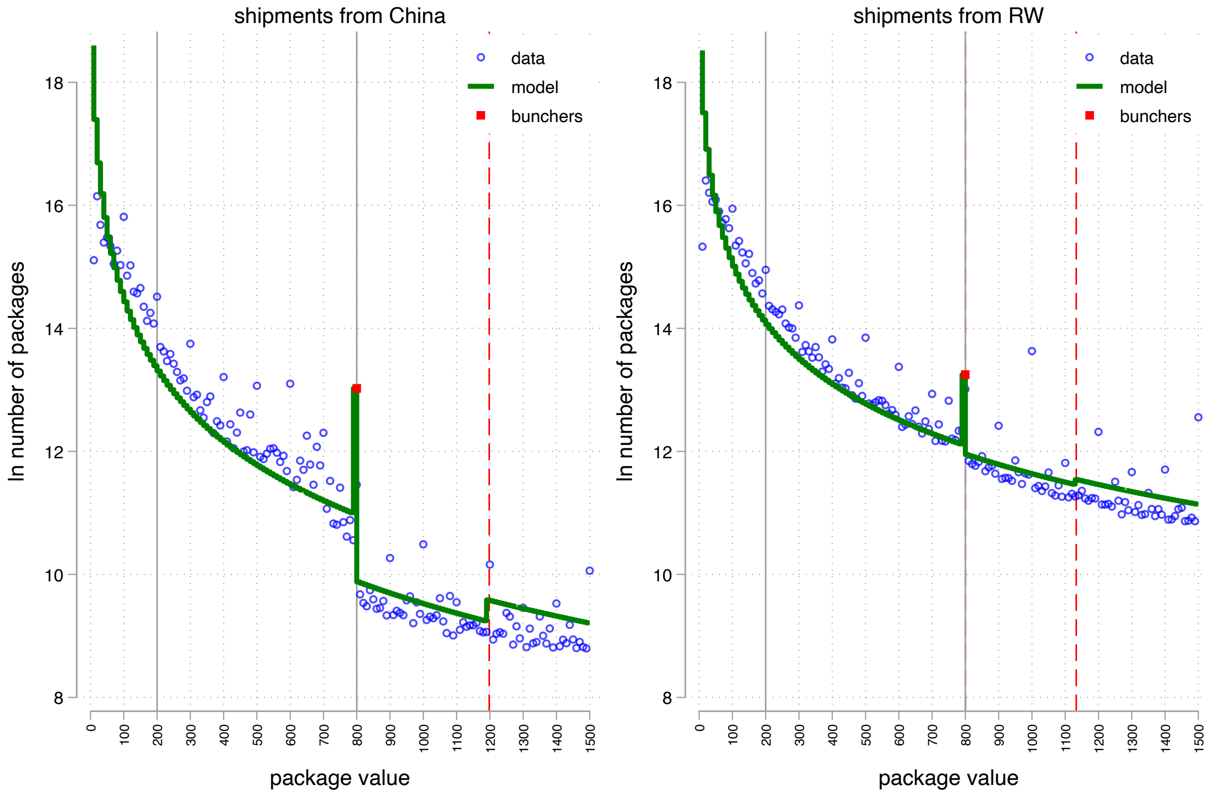
Figure 7 shows the histograms implied by the calibrated density at the estimated value for the elasticities σ_o (obtained in the next step). In the absence of "naive" firms, we would observe a hole in the dominated region corresponding to the area in between the vertical dashed lines. The procedure implies that "sophisticated" firms ship 31% of packages and 30% of value from China. Outside of this area, the density adds up the exports of both sophisticated and naive firms. Only the former group of firms bunch, with the bunchers shown in the red square in each figure. From China, the model implies a clear discontinuity at \$800. Bunching at \$800 is larger in the model than in the data, as the model lacks a mechanism to make bunching decisions more diffused below the threshold, such as product indivisibilities within shipments. From RW, where tariffs are much lower, the discontinuity is much less pronounced in both the model and data.

Step 2: Simulating the Change in Bunching from Policy Changes Using the density from the previous step, and given the value of σ_o, we simulate changes in tariffs and in the §321 threshold from the post-2016 period to the pre-2016. That is, we change tariffs on China from 15.3% to 4.0%, the average tariff in the pre period, and tariffs on RW from 2.1% to 2.7%; and, we change the threshold from \$800 to \$200. These policy changes mimic the difference-in-differences specification in (22), which estimates changes in the density over time and across origins.

We search in the space of σ_o, each time implementing steps 1 and 2, to match the empirical change in bunching at the new threshold of \$800 (from a previous threshold of \$200) from Figure 5. Specifically, we match the difference between the estimated change in the number of packages over the \$200-\$800 range and the estimated change in the number of packages in the \$800-\$1500 range. Figure 8 shows the outcome of the step 2 for China as origin. The blue series in the left panel shows the post-2016 calibrated histogram (i.e., the same as in left panel of Figure 7), and the green series is the model-based counterfactual from rolling the economy back to pre-2016. The

[20] This procedure recovers the quality-adjusted density $h_o^{US,S}(z)$ up to the scaling factor D_o^{US}. To implement counterfactuals, as shown in (26), we need to construct the density of expenditure shares by unit cost, $\lambda_o^{\omega,j}(z)$. Because they add up to 1, these shares can be constructed independently from the value of that scaling factor.

FIGURE 7: CALIBRATED DENSITY



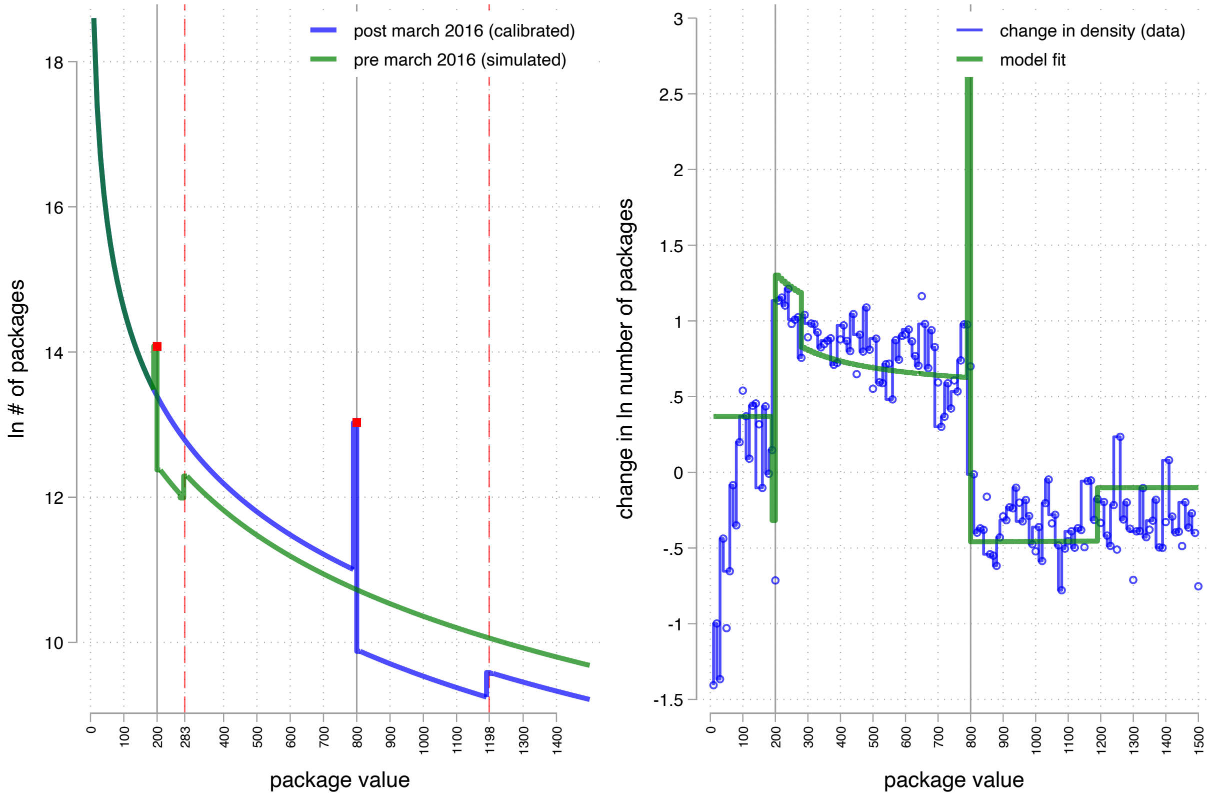
Notes: Figure shows the actual histogram (blue series), and the model-implied histogram at the calibrated values of the elasticities ($\sigma_{CH} = 4.42$, $\sigma_{RW} = 1.81$). The left panel reports the calibration for shipments from China. The right panel reports the calibration for shipments from RW. The red vertical line in each panel indicates the shipment value associated with the highest-cost buncher. The calibration is performed on shipments up to \$5,000, but the graph displays the density up to \$1500 to improve visualization.

right panel shows the difference between these two series (post minus pre) in green, and overlays in blue the empirical difference-in-differences estimate for Chinese shipments that from Panel B of Figure 5. Increasing the threshold from \$200 to \$800 leads to a sharp drop in the mass to the right of \$800 relative to the mass in the \$200-\$800 range. As we have discussed in the context of Proposition 1, the amount of bunching and therefore the size of this mass is a function of σ_o, with the amount of bunching a decreasing function of σ_o.

We find that $\sigma_{CH} = 4.42$ for China, and $\sigma_{RW} = 1.81$ for RW, matches the observed drop in the density at \$800). The model broadly replicates the fact that the changes in densities are roughly constant within the \$200-\$800 and the above-\$800 ranges, and it captures some of the decline in bunching in the below-\$200 range, but to a lesser degree than what is observed in the data.

Step 3: Estimating γ The previous steps are independent from the parameter γ, which governs consumers' substitution across origins. The CES structure at the origin-group level implies that, when policies change, the change in the value of direct-to-consumer shipments from origin o to

Figure 8: Pre and Post Densities for Chinese Imports, Model and Data



Note: Left panel shows the model-implied histogram in the calibrated (post-2016) equilibrium and the counterfactual model-implied distribution under pre-2016 tariffs and the \$200 threshold for shipments from China. The right panel shows the difference between the post- and pre- distributions in the model (the difference between blue and green series in the left panel), and the corresponding difference in the data estimated for China in Panel B of Figure 5.

group ω is:[21]

$$\Delta \ln E_o^\omega = \eta^\omega + \eta_o + (1-\gamma)\,\Delta \ln\left(P_o^\omega\right) + \varepsilon_o^\omega, \tag{30}$$

Even though policies (tariffs and the de minimis threshold) change in the same way for all importing groups, the change in the price index P_o^ω is group-specific because the spending de minimis goods, and therefore the exposure to tariffs, varies across groups.

We cannot construct an empirical analog to P_o^ω because we do not observe variety-level prices to back out demand shocks at that level–we only observe densities of spending over shipments, allowing us to back out a composite of demand shocks and the measure of firms pricing at each given value, as discussed in the previous step. Therefore, we follow an indirect indifference approach. Starting from the calibrated model in the post-period, we guess a value of γ, reduce tariffs to the pre-period, and run the following regression on model-generated outcomes:

$$\Delta \ln \left(\frac{E_{o,pre}^\omega}{E_{o,post}^\omega}\right) = \alpha^\omega + \alpha_o + \beta \lambda_{>800,post}^\omega * \Delta \ln \left(\frac{\tau_{o,pre}}{\tau_{o,post}}\right) + \varepsilon_o^\omega. \tag{31}$$

where $\lambda_{>800,post}^\omega$ is group ω share of spending above the de minimis threshold (thus, subject

[21] The unobserved fixed-effects and error term $\eta^\omega + \eta_o + \varepsilon_o^\omega \equiv \Delta \ln\left(L^\omega e^\omega\right) - (1-\gamma)\,\Delta \ln P^\omega + \Delta \ln A_o^\omega$ capture demand shocks and aggregate spending in direct shipments by the group.

to tariffs) in the post-period. The interaction of $\lambda^{\omega}_{>800,post}$ with the change in tariffs is directly observable and strongly correlated with the model-based change in the price index, $\Delta \ln \left(P_o^{\omega}\right)$ in 30. For each possible of γ, estimating this regression from the model yields an estimate $\beta\left(\gamma\right)$. Running 31 in the data finds $\beta = -1.74$ (se 0.59). Figure A.9 shows the value of $\hat{\beta}$ estimated from the data and the model-based $\beta\left(\gamma\right)$ at each value of gamma. The intersection pins down the choice of γ, which occurs at $\gamma = 18.9$.

6.5 Exact Welfare Impacts

Aggregate Impacts We first report the aggregate welfare impacts of the §321 by implementing a counterfactual elimination of the thresholds starting from the 2021 tariff level. That is, starting from the post-2016 equilibrium, we solve for the price distribution under a counterfactual policy. We then compute the welfare outcomes for both the aggregate US and by consumer group ω. Before showing the results, we first discuss a few choices involved in this calculation.

First, we use the values of σ_o calibrated from the previous subsection.[22] Given this elasticity, we re-do step 1 from the previous subsection to obtain a quality-adjusted density $h_o^{S,\omega}\left(z\right)$ that matches the observed histogram by consumer group ω and origin o, $\Delta N_o^{\omega}\left(v\right)$ defined in (29).[23] Second, the impacts defined Section 6.3 are a function of changes in price changes that are independent from demand shifters, and can therefore be computed only once using the results from Proposition 1. To compute changes in price indexes, what varies across groups is the exposure to these price changes, as inferred from the calibrated distributions $h_o^{S,\omega}\left(z\right)$. Third, when implementing this counterfactual we must take a stand on how tariff revenue is rebated. We assume that each consumer group is rebated the tariff revenue generated by its imports, so that the change in transfers to each group is equal to the group-specific tariff revenue defined in (A.48).

We perform the counterfactual simulation using the carrier data, but also report estimates from a simulation that calibrates the post-period density to the CBP data (but uses the parameters we estimate from the moments of the carrier data). The losses hinge on the customs fee that de minimis packages would face. Footnote 4 arrives at a benchmark per-shipment administrative fee of $23.19 using estimates of broker fees across different types of logistics companies. Eliminating §321 could lead to a change in this fee, depending on changes in these shares and/or changes in the broker fee (which would increase or decrease depending on broker demand, or technical change in the efficiency in brokerage services). We report aggregate impacts with fees ranging from $0 to $30.

The left panel of Table 3 reports the aggregate losses from the carrier data. The first column reports the losses to consumers from the increase in prices, the second column reports the tariff revenue gain, and the third column–the welfare loss–is the sum of the two. At the benchmark fee,

[22] To compute these outcomes, we need values for the elasticities κ (between direct imports and other goods). We use $\kappa = 0.19$, which corresponds to the substitution between imports and domestic goods estimated in Fajgelbaum et al. (2020). A caveat with this parameter is that it is estimated from Census data, so it corresponds to informal shipments above $2000 and formal shipments, not de minimis shipments.

[23] We verify that this procedure closely matches the share of direct consumer spending in de minimis goods (i.e., below the $800 threshold) in the post-216 data, as shown in the previous empirical section.

Table 3: Aggregate Impacts of Eliminating §321

	carrier data			CBP data		
fee	consumer ($b)	tariff ($b)	welfare ($b)	consumer ($b)	tariff ($b)	welfare ($b)
$0	-2.0	0.8	-1.2	-3.9	2.0	-1.9
$10	-5.5	0.6	-4.9	-10.4	2.0	-8.4
$23.19 (benchmark)	-12.4	0.6	-11.8	-19.5	5.2	-14.3
$30	-16.7	0.8	-15.8	-22.6	6.6	-15.9

Notes: Table reports the impacts of eliminating §321 at different per-shipment customs fees. Each case assumes parameters: $\{\sigma_{CHN}, \sigma_{RW}, \gamma, \kappa\} = \{4.42, 1.81, 18.92, 0.19\}$. The left (right) panel reports aggregate impacts using the carrier (CBP) data.

the aggregate welfare loss is $11.8 billion, or $37 per person (or $148 per family). As a comparison, Fajgelbaum et al. (2020) estimate the sum of consumer cost and tariff revenue gain of the 2018 US tariffs on China at $16.1 billion ($49 per person or $194 per family), and the tariffs waves through 2019 at $48.2 billion ($147 per person or $580 per family). This welfare loss scales roughly linearly with the fee structure: reducing the fee to $10 per shipment would result in a roughly 50% smaller welfare loss at $4.9 billion and a $30 fee would magnify the welfare loss to $15.8 billion. Recall that the fee is not rebated back to consumers which is why tariff gain is similar across the fee structures.

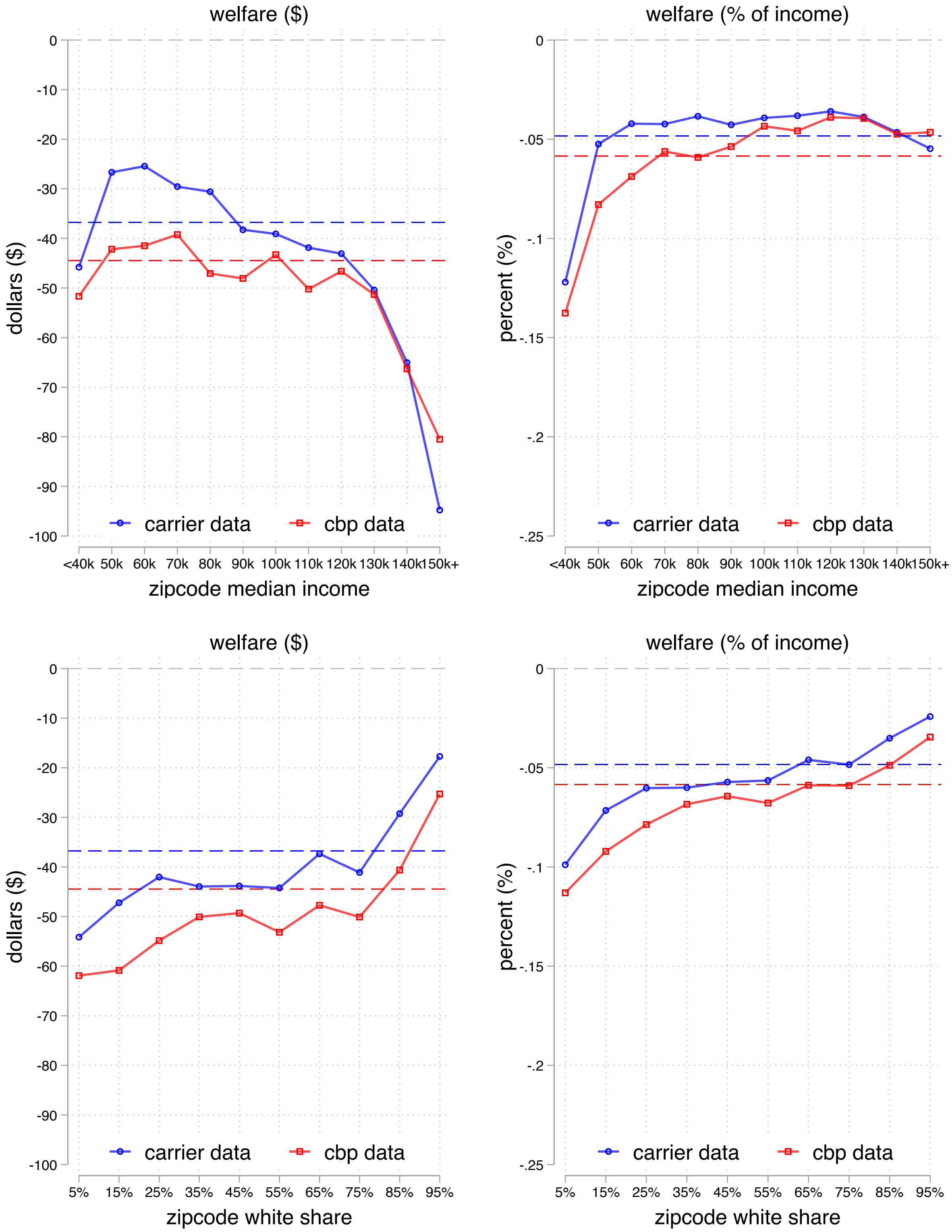
The right panel reports the estimates with the CBP data. At each fee structure, the losses from the CBP data are larger. In the benchmark case, the aggregate welfare loss is $14.3 billion. This is because the share of de minimis shipments from China is 66.9% in CBP data, compared to 37.0% in the carrier data.

Distributional Impacts We next assess the distributional welfare impacts across consumer groups. We first show in Figure A.10 the change in the price index $\hat{P}^{\omega}$ across income brackets.[24] The increase in prices is driven by both the per-shipment fee and the increase in tariffs. We find that eliminating the policy would increase the price index the most, in percentage terms, for poorer zip codes, and for zip codes with lower shares of white households. These patterns follow in large part from the reduced-form evidence showing that these groups are more likely to spend in goods originating from China and tax-exempt goods, below the $800 threshold.

Figure 9 shows the equivalent variation–the welfare impacts of the policy change. The top panel of Figure 9 reports the welfare estimates across zip code income. Our estimates imply that, in zip codes with median family income under $40k, per capita welfare would decline by $46. This compares with a $39 decline for zip codes with $100k median family income, and a decline of $95 for the richest zip codes. As a share of income, the corresponding declines for low, median and high-income zip codes are 0.12%, 0.04%, and 0.05%. Thus, we find that the lowest-income households would bear the brunt of eliminating §321.

[24] For $\hat{P}^{\omega}$, we must take a stand on the breadth of the basket of direct-expenditures. We define direct expenditures as all the goods in our data up to $5000. This choice of threshold mechanically affects the price index (with a higher threshold mechanically lowering the price index) but not the patterns across consumer groups. This choice of threshold also does not affect for the dollar-equivalent welfare changes reported for the equivalent variation, which are only a function of the initial amount spent in the varieties whose prices are changing in the counterfactual.

FIGURE 9: DISTRIBUTIONAL IMPACTS FROM ELIMINATING §321



Notes: Figure reports ev^{ω} defined in (24) against zip code characteristics. The left panels report welfare impacts in per-capita dollars and the right panel scales by median family income. Top panel reports by zip code median family income, and bottom panel reports by zip code white household share. The series is the welfare loss at $\tau_{CHN} = 15.3\%, \tau_{RW} = 2.1\%$, $T = \$23.19$, and parameters: $\{\sigma_{CHN}, \sigma_{RW}, \gamma, \kappa\} = \{4.42, 1.81, 18.92, 0.19\}$. The blue (red) series denotes estimates from carrier (CBP) data; aggregate loss denoted by the horizontal dash line.

The figure also reports the distributional consequences calibrated from the CBP sample. Consumers in the lowest-income zip codes would experience a per capita welfare decline of $52, compared to a $43 decline for zip codes with $100k income, and a decline of $80 for the richest zip codes. Thus, the CBP sample also suggests that the current §321 policy benefits lower-income consumer more.

The bottom panel of Figure 9 analyzes welfare losses by zip code white share. We find that welfare in zip codes with 5% white households would experience a decline of $54. This compares with a decline of $44 decline for zip codes with 45% white share, and a decline of $18 for the zip codes with 95% white households. As a share of income, the corresponding declines for low, median and high white shares are 0.10%, 0.06%, and 0.024%. Using the CBP sample, the corresponding per capita welfare declines in the least white zip codes would be $62compared to a $25 decline in the most white zip codes. Our estimates therefore suggest that eliminating §321 would therefore raise the cost of living disproportionately more for non-white households.

Figure A.11 reports the distributional impacts at fees ranging from $0 to $30 per shipment in both the carrier and CBP data. The per-person welfare impact scales with the fee structure and incidence across consumer groups remains as before. The main message of the table is that the quantitative impacts of eliminating §321 hinge on the size administrative fee, but the qualitative impacts across consumer groups remains unchanged.

7 Conclusion

The rise of online platforms has led to a sharp increase in direct-to-consumer shipments, particularly in the segment below "de minimis" thresholds that allow imports to enter without paying tariffs or processing fees. In the US, §321 of the 1930 Trade Act introduced a de minimis threshold for imports, which is currently set at $800.In 2023, one billion shipments entered through the channel valued at $54.5 billion.

We formally study de minimis trade policy and establish conditions under which non-zero tariffs with a threshold could dominate free trade because of term-of-trade gains generated through bunching. Using shipments from three global carriers that capture de minimis shipments, we find that de minimis imports–particularly those from China–are relatively important for lower-income zip codes. As a result, §321 is a pro-poor trade policy: it effectively converts a regressive tariff schedule to a progressive one. These spending shares drive a first-order approximation of the welfare impacts from a policy experiment that eliminates §321. Using two control densities–shipments before March 2016, when the threshold was $200, and shipments to the OECD–to measure bunching induced by the $800 threshold, we identify the demand parameters necessary for exact welfare analysis. We find that eliminating §321 would reduce the welfare of a representative consumer but disproportionately hurt the poor and minority households.

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A Model Appendix

Demand We derive the demand for each variety. First, we define direct utilities over direct consumption. Consistent with the price indexes (2) and (3), direct utility over direct-to-consumer goods is

$$x^{\omega} = \left(\sum_{o} \left(A_o^{\omega} \right)^{\frac{1}{\gamma}} \left(x_o^{\omega} \right)^{\frac{\gamma-1}{\gamma}} \right)^{\frac{\gamma}{\gamma-1}}, \tag{A.32}$$

where x_o^{ω} is the bundle of direct goods from o, given by

$$x_o^{\omega} = \left(\int_{i \in \Omega_o} \left(a_i^{\omega} \right)^{\frac{1}{\sigma_o}} \left(n_i^{\omega} \right)^{\frac{\sigma_o - 1}{\sigma_o}} di \right)^{\frac{\sigma_o}{\sigma_o - 1}}, \tag{A.33}$$

where n_i^{ω} is the number of packages of variety i consumed by each type-ω consumer.

Next, to derive demand, we note from (1) that the per-capita expenditures in direct goods, $e^{\omega} \equiv P^{\omega} x^{\omega}$, are

$$e^{\omega} = A^{\omega} \left(P^{\omega} \right)^{-\kappa}. \tag{A.34}$$

Adding up across consumers, standard CES algebra yields the aggregate expenditures of group-ω consumers in goods from o:

$$E_o^{\omega} = A_o^{\omega} \left(\frac{P_o^{\omega}}{P^{\omega}} \right)^{1-\gamma} L^{\omega} e^{\omega}, \tag{A.35}$$

while total demand among group-ω consumers for packages sold by firm i are:

$$L^{\omega} n_i^{\omega} = a_i^{\omega} D_o^{\omega} v_i^{-\sigma_o}. \tag{A.36}$$

where D_o^{ω} is a group-origin demand shifter:

$$D_o^{\omega} = E_o^{\omega} \left(P_o^{\omega} \right)^{\sigma - 1}. \tag{A.37}$$

As a result, the total number of packages shipped by firm i when it sets package value equal to v_i is:

$$\begin{aligned} N_i &\equiv \sum_{\omega} L^{\omega} n_i^{\omega} \\ &= \left(\sum_{\omega} a_i^{\omega} D_o^{\omega} \right) v_i^{-\sigma_o}. \end{aligned} \tag{A.38}$$

Welfare From (1) and (A.34), the indirect utility of each consumer in group ω can be written:

$$u^{\omega} = \frac{1}{\kappa} e^{\omega} + y^{\omega} + t^{\omega} \tag{A.39}$$

where e^{ω} is the optimal expenditure in direct goods:

$$e^{\omega} = \arg\max_{e} u^{\omega} \left(\frac{e}{P^{\omega}} \right), \tag{A.40}$$

for u^{ω} defined in (1). When tariffs change, consumers face a different distribution of prices and a tariff revenue. Between equilibria, the equivalent variation of a consumer in group ω is (24), where we have used that from (A.34) that

$$\hat{e}^{\omega} = \left(\hat{P}^{\omega}\right)^{-\kappa}. \tag{A.41}$$

Proof of Proposition 2 To obtain (20), we start by computing the total differential of u in (16) and using (17), to obtain:

$$du = -e\frac{dP}{P} + dtr. \tag{A.42}$$

From the definition of the price index in (18), and using (14) and (12), we obtain:

$$\begin{aligned}\frac{dP}{P} =& \frac{1}{1-\sigma}\left(\left(\frac{v_{DM}}{P}\right)^{1-\sigma} - \left(\frac{v_H\left(z_H;\tau\right)}{P}\right)^{1-\sigma}\right) h\left(z_H\right) dz_H + \left(\frac{v_{DM}}{P}\right)^{1-\sigma}\frac{dv_{DM}}{v_{DM}}\int_{z_L}^{z_H} h\left(z\right) dz \\ &+ \frac{d\tau}{1-\tau}\int_{z_H}^{\infty}\left(\frac{v_H\left(z;\tau\right)}{P}\right)^{1-\sigma} h\left(z\right) dz. \end{aligned} \tag{A.43}$$

In turn, totally differentiating tariff revenue (19) we obtain:

$$\begin{aligned} dtr =& d\tau\int_{z_H}^{\infty} e\left(\frac{v_H\left(z;\tau\right)}{P}\right)^{1-\sigma} h\left(z\right) dz + \tau\int_{z_H}^{\infty} d\left[e\left(\frac{v_H\left(z;\tau\right)}{P}\right)^{1-\sigma}\right] h\left(z\right) dz \\ &- \tau e\left(\frac{v_H\left(z_H;\tau\right)}{P}\right)^{1-\sigma} h\left(z_H\right) dz_H. \end{aligned} \tag{A.44}$$

The second term in the first line of this last expression is:

$$\begin{aligned}\tau\int_{z_H}^{\infty} d\left[e\left(\frac{v_H\left(z;\tau\right)}{P}\right)^{1-\sigma}\right] h\left(z\right) dz =& \left(1-\sigma\right)\frac{\tau}{1-\tau}d\tau\int_{z_H}^{\infty} e\left(\frac{v_H\left(z;\tau\right)}{P}\right)^{1-\sigma} h\left(z\right) dz \\ &+ \tau d\left(eP^{\sigma-1}\right)\int_{z_H}^{\infty} v_H\left(z;\tau\right)^{1-\sigma} h\left(z\right) dz \end{aligned} \tag{A.45}$$

Combining the last three expressions, after some manipulations yields (20). These demonstrates part (i).

To derive part (i), note that, with $v_{DM} = 0$, condition (20) becomes

$$\frac{du}{e} = -\tau\left(1+\kappa-\sigma\right)\frac{dP}{P} - \sigma\frac{\tau}{1-\tau}d\tau. \tag{A.46}$$

Moreover, in this case, $\frac{dP}{P} = \frac{d\tau}{1-\tau}$. Combining these two expressions we have $\frac{du}{e} = -\tau\left(1+\kappa\right)\frac{d\tau}{1-\tau}$, which implies $\tau^* = 0$.

For part (ii), using (13) and (25), the ratio of the price index between an equilibrium with policies (v_{DM}, τ, T) (with $v_{DM} > 0$, $\tau \in (0,1)$, and $T > 0$) and a free-trade equilibrium is:

$$\hat{P} = \left(\int_0^{z_L}\lambda^*\left(z\right) dz + \int_{z_L}^{z_H}\lambda^*\left(z\right)\left(\frac{v_{DM}}{\frac{\sigma}{\sigma-1}z}\right)^{1-\sigma} dz + \int_{z_H}^{\infty}\lambda^*\left(z\right)\left(\frac{1+T/z}{1-\tau}\right)^{1-\sigma} dz\right)^{\frac{1}{1-\sigma}},$$

where $\lambda^*\left(z\right) \equiv \left(\frac{v^*(z)}{P^*}\right)^{1-\sigma_o} h\left(z\right)$ is the share of expenditures under free-trade in varieties with unit cost equal to z, where $v^*\left(z\right)$ and P^* indicates the value of shipments and the price index under free trade. Hence, if the distribution $h\left(z\right)$ is bounded at z_H, then so is the $\lambda^*\left(z\right)$, and because $v_{DM} < \frac{\sigma}{\sigma-1}z$, then $\hat{P} < 1$.

Model-Based Histogram To construct the histogram (29), we first define the aggregate packages up to value v for any particular group (including possibly the aggregate US),

$$N_o^{\omega}(z) \equiv N_o^{\omega,S}(v) + N_o^{\omega,N}(v) = \int_0^z D_o^{\omega} \sum_{j=S,N} v_o^j(z)^{-\sigma_o} h_o^{\omega,j}(z)\, dz$$

Changing the variable of integration we then obtain the number of packages up to value v for firms of type S,

$$N_o^{\omega,S}(v) = \begin{cases} D_o^{\omega} \int_0^v V^{-\sigma} h_o^{\omega,S}(z_{L,o}(V))\, z_{L,o}'(V)\, dV, & v < v_{DM} \\ D_o^{\omega} \int_0^{v_{DM}} V^{-\sigma} h_o^{\omega,S}(z_{L,o}(V))\, z_{L,o}'(V)\, dV + D_o^{\omega} v_{DM}^{-\sigma_o} \int_{z_L}^{z_H} h_o^{\omega,S}(z)\, dz, & v = v_{DM} \\ N_o^{\omega,S}(v_{DM}) + D_o^{\omega} \int_{v_{DM}}^{v} V^{-\sigma} h_o^{\omega,S}(z_{H,o}(V))\, z_{H,o}^{A\prime}(V)\, dV. & v > v_{DM} \end{cases}$$

And, for firms of type N

$$N_o^{\omega,N}(v) = \begin{cases} D_o^{\omega} \int_0^v V^{-\sigma} h_o^{\omega,N}(z_{L,o}(V))\, z_{L,o}'(V)\, dV, & v \leq v_{DM} \\ D_o^{\omega} \int_0^v V^{-\sigma} h_o^{\omega,N}(z_{H,o}(V))\, z_{H,o}'(V)\, dV. & v > v_{DM} \end{cases}$$

The histogram (29) is constructed approximating the derivative of this function over intervals Δ_v.

Computation of Tariff Revenue in the Model Implementation The change in tariff revenue generated per capita by each member of group ω when policies change is

$$\Delta tr^{\omega} = \sum_o \sum_{j=S,N} \Delta tr_o^{\omega,j}, \tag{A.47}$$

where tariff revenue collected per consumer in group ω from firms of type $j = S, N$ from origin o is

$$tr_o^{\omega,j} = e_o^{\omega} \int_z \tau_o \left(v_o^j(z)\right) \lambda_o^{\omega,j}(z)\, dz, \tag{A.48}$$

where $e_o^{\omega} \equiv E_o^{\omega}/L^{\omega}$ is per capita spending in imports from origin o by consumers in group ω. After some manipulations, for $j = S$ firms, we have

$$\Delta tr_o^{\omega,S} = \tau_o \hat{\tau}_o \frac{e_o^{\omega} \hat{e_o^{\omega}}}{\left(\hat{P}_o^{\omega}\right)^{1-\sigma_o}} \int_{z_{H,o}\hat{z}_{H,o}}^{\infty} \hat{v_o^S}(z)^{1-\sigma_o} \lambda_o^{\omega,S}(z)\, dz - e_o^{\omega} \tau_o \int_{z_{H,o}}^{\infty} \lambda_o^{\omega,S}(z)\, dz; \tag{A.49}$$

while $j = N$ firms we have

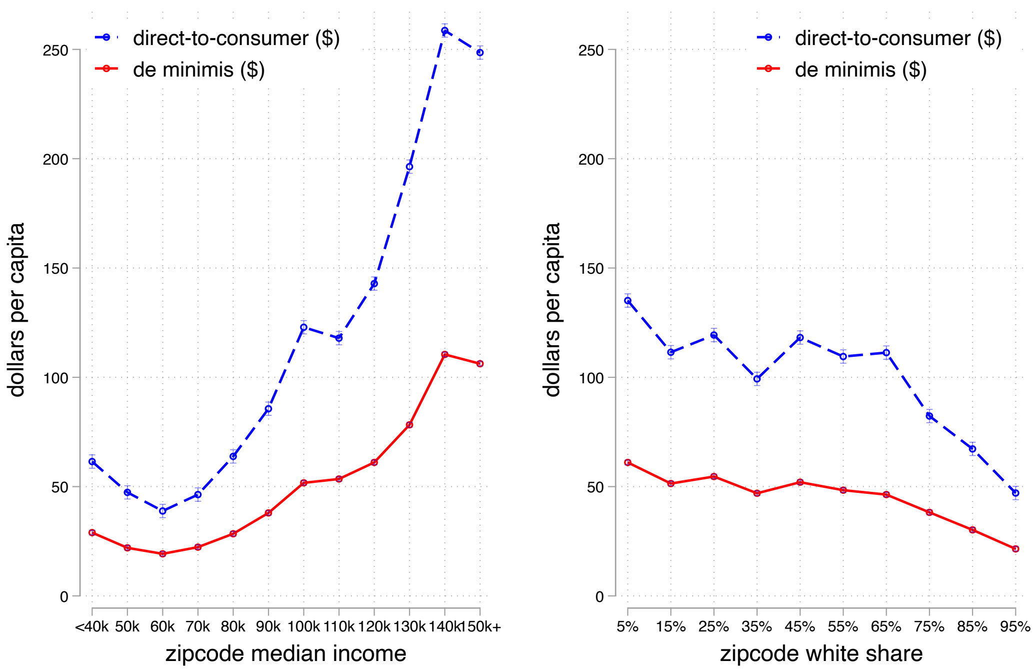
$$\Delta tr_o^{\omega,N} = \tau_o \hat{\tau}_o \frac{e_o^{\omega} \hat{e_o^{\omega}}}{\left(\hat{P}_o^{\omega}\right)^{1-\sigma_o}} \int_{z_{L,o}\hat{z}_{L,o}}^{\infty} \hat{v_o^N}(z)^{1-\sigma_o} \lambda_o^{\omega,N}(z)\, dz - e_o^{\omega} \tau_o \int_{z_{L,o}}^{\infty} \lambda_o^{\omega,N}(z)\, dz. \tag{A.50}$$

Appendix Tables and Figures

FIGURE A.1: ITEMS IN DIRECT-TO-CONSUMER SHIPMENTS

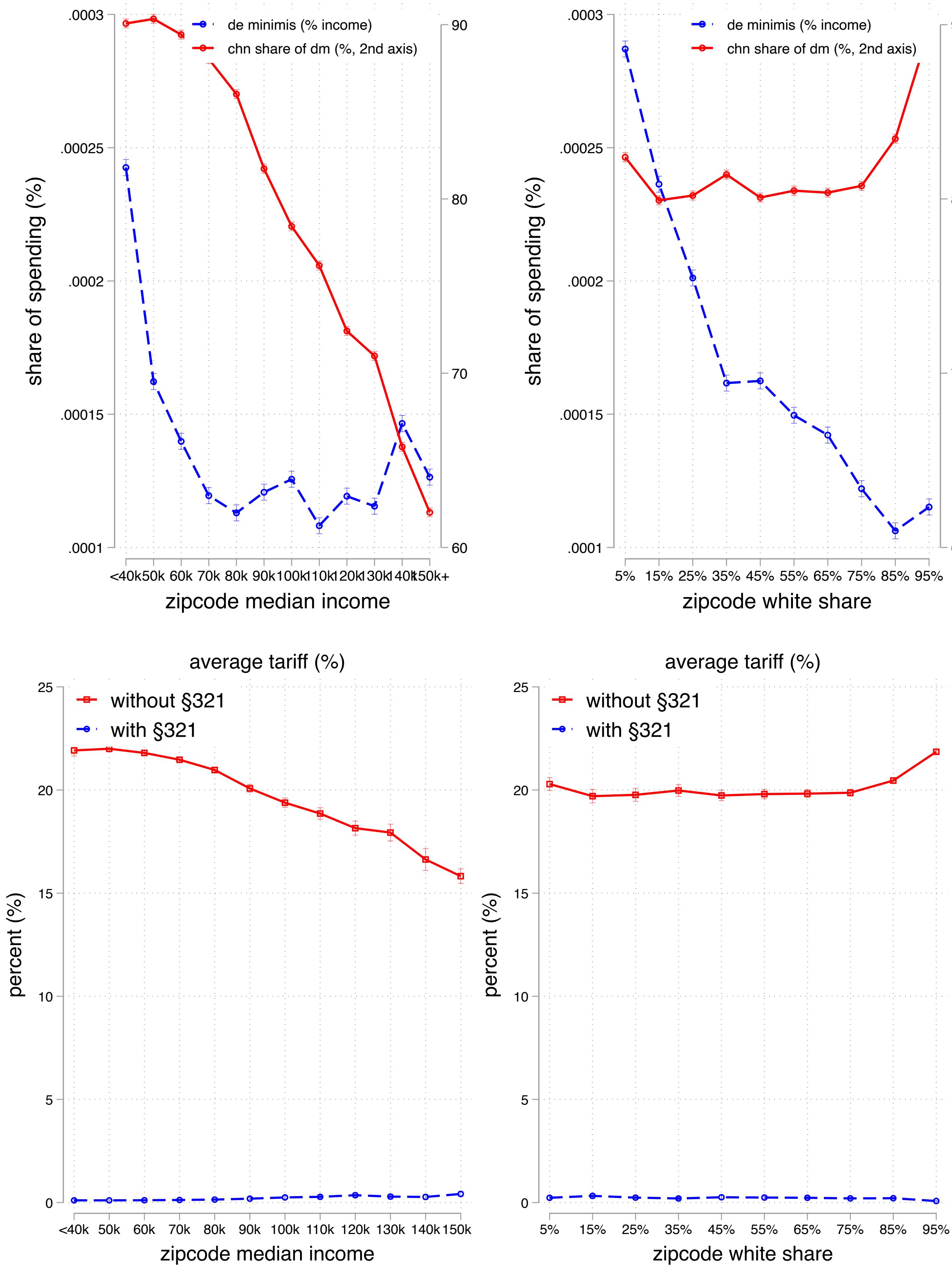
Notes: Figure displays the most common items in direct-to-consumer shipments. Item descriptions reported in carriers A and B.

FIGURE A.2: SPENDING ON DIRECT-TO-CONSUMER AND DE MINIMIS



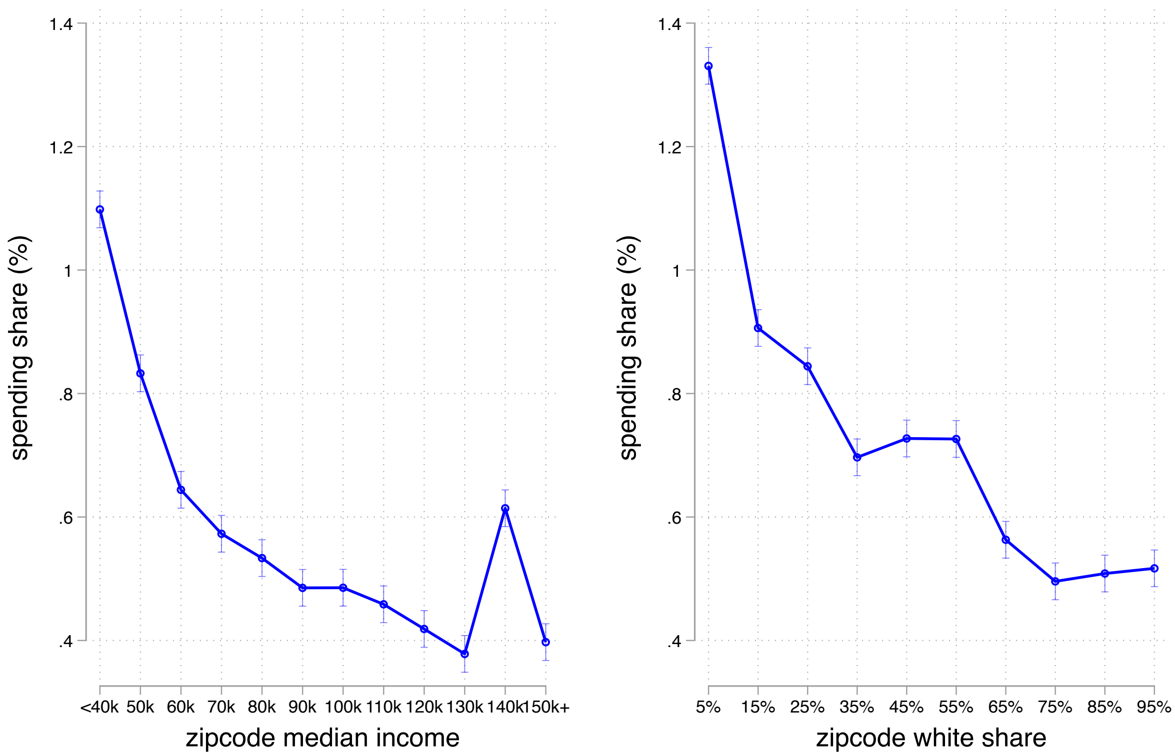
Notes: Figure reports 2021 per-capita expenditures on shipments below $5,000 (red series) and de minimis shipments (blue series). The left panel plots against zip code median family income and the right panel plots against zip code share of white households. Errors bars are standard errors of means.

FIGURE A.3: DE MINIMIS SHIPMENTS IN CBP SAMPLE, BY ZIP CODE CHARACTERISTIC



Notes: Top panel reports 2021 per-capita expenditures on de minimis shipments as a share of income across zip code median income in the CBP sample. Since this is just one week of data, the shares are small. The red series shows the share of de minimis imports from China. The bottom panel reports zip code-level tariffs from the 2021 CBP data. A zip code's tariff is the import share weighted average tariff across origins. The blue series is the average tariff with §321. The red series removes the tariff exemption from §321. Errors bars are standard errors of means. Source: CBP data, 2021.

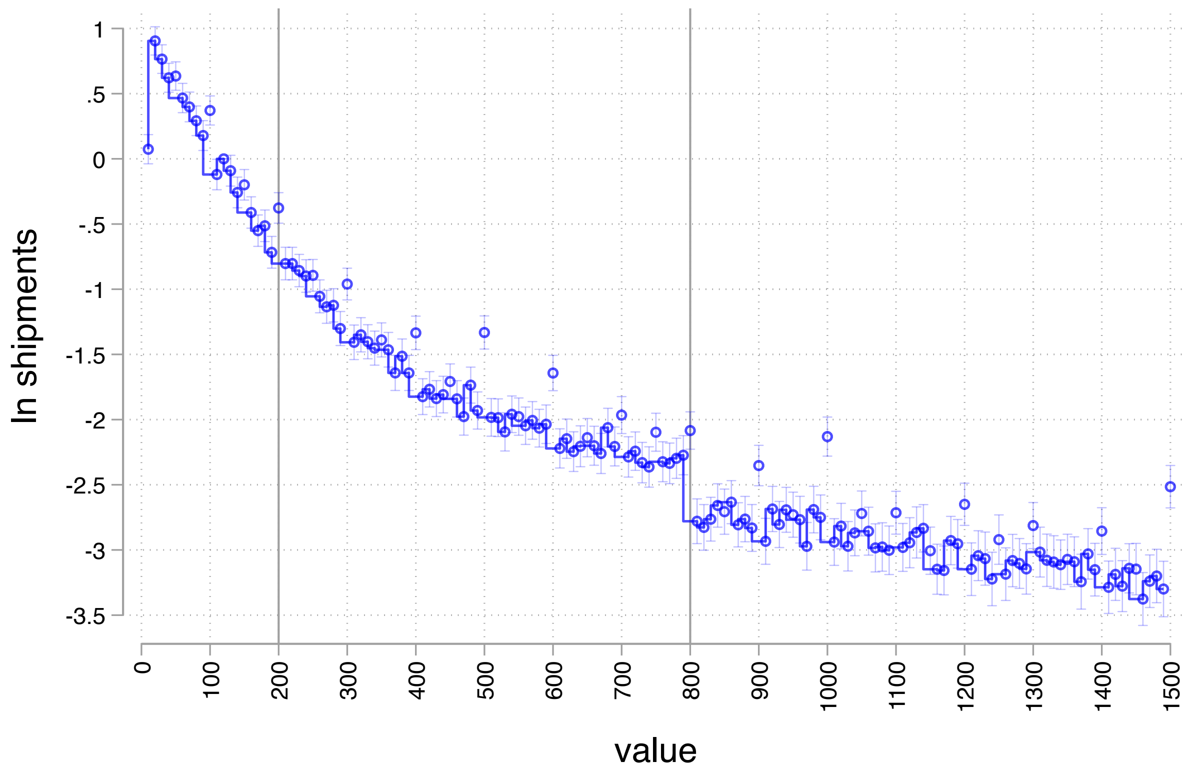
FIGURE A.4: SHARE OF ALIEXPRESS, SHEIN, AND TEMU CREDIT CARD EXPENDITURES



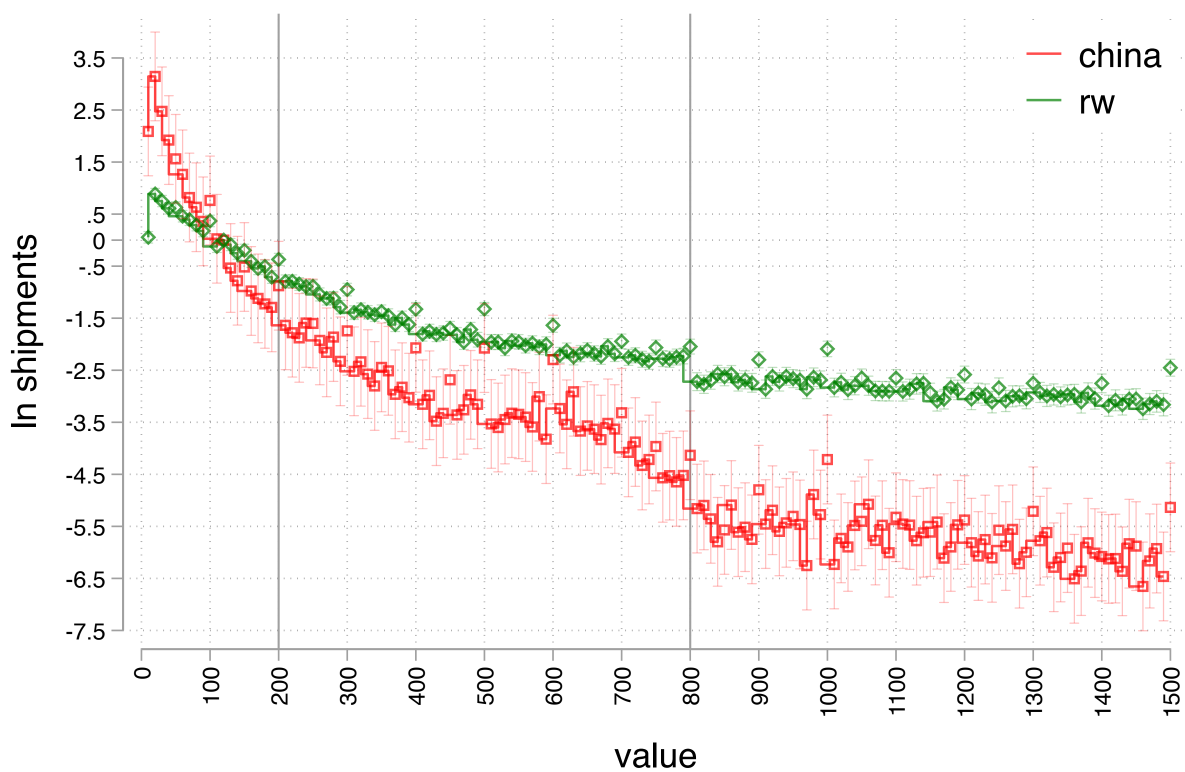
Notes: Figure reports credit share of spending at AliExpress, Shein and Temu relative to total purchases of durable products at 506 (e.g., Walmart, Amazon, Home Depot, Macy's, etc). Errors bars are standard errors of means. Source: MBHS3 transactions data, 2023.

FIGURE A.5: CBP SHIPMENT DENSITY

Panel A: All Origins



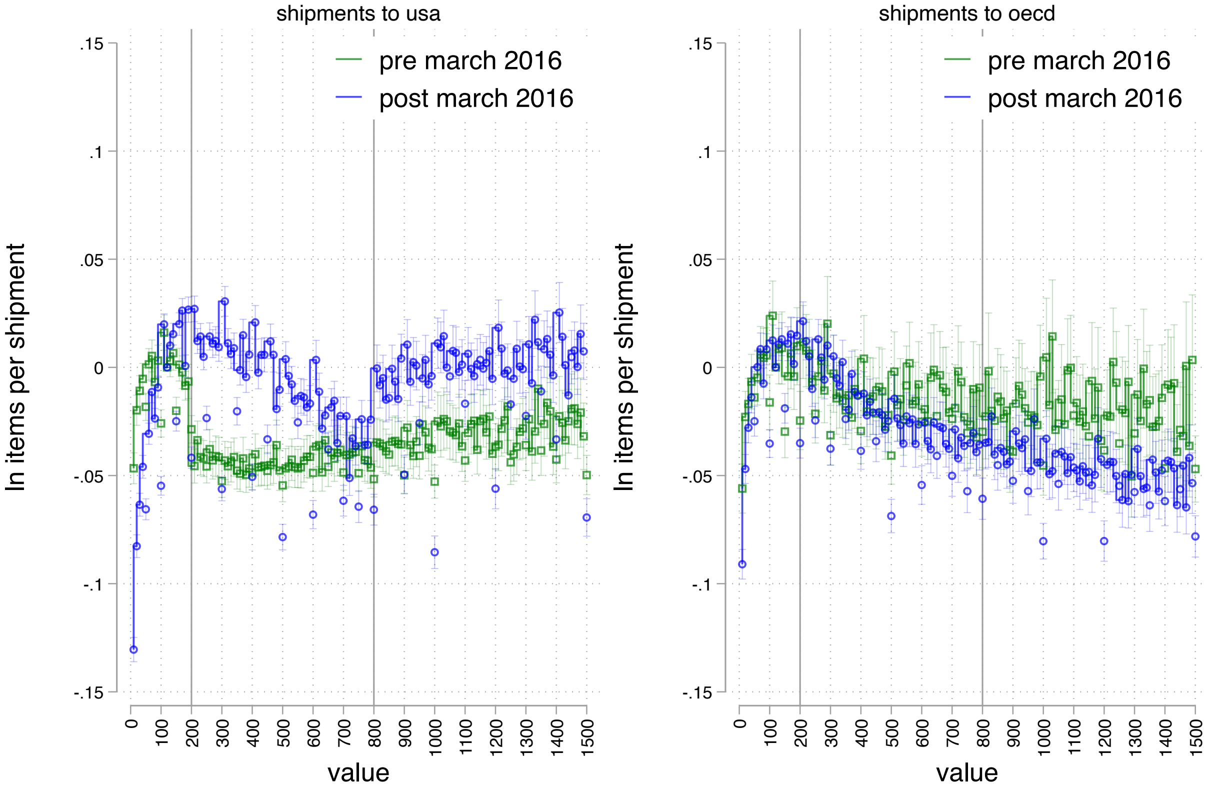
Panel B: By Origin



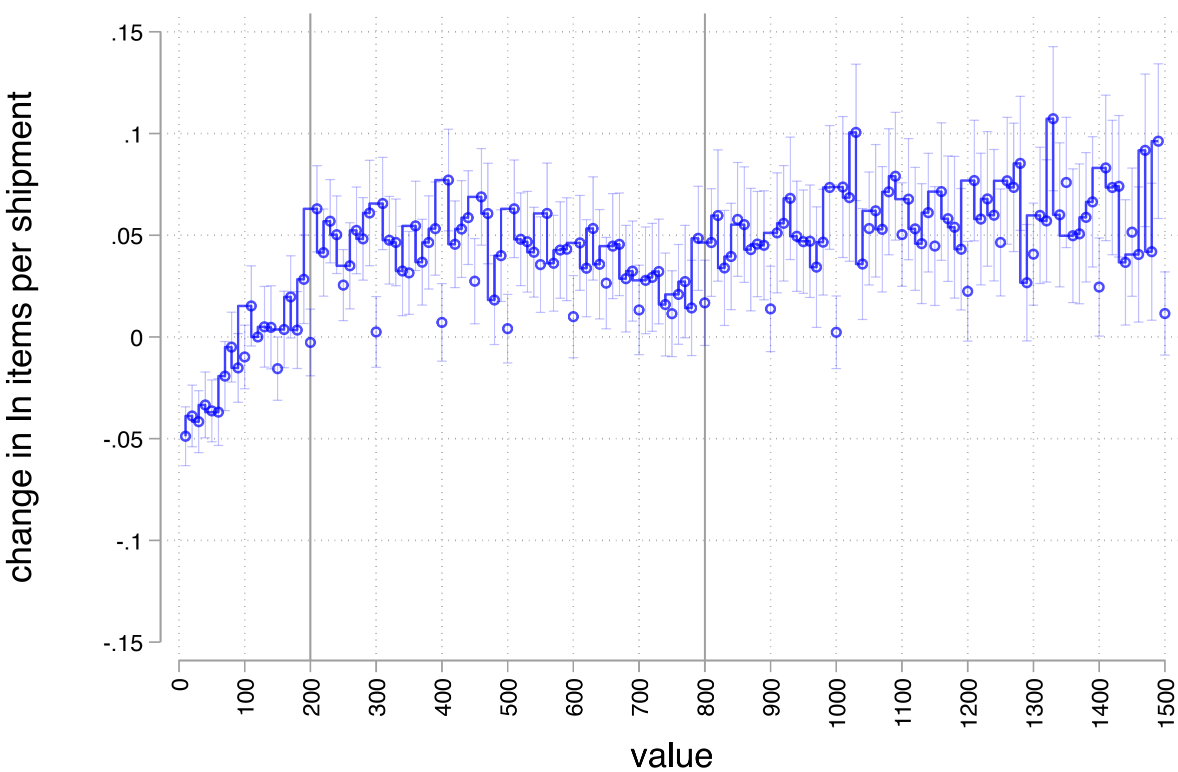
Notes: Figure examines the weekly CBP shipment data using the analog regression in (21). The top panel estimates the regression for shipments for all origins, and the bottom panel estimates it separately for China and RW. The leave-out bin is \$120. Grey vertical lines denote §321 thresholds before and after March 2016. Error bars denote 95% confidence intervals. Round numbers not included in the connected line to improve visualization. Source: CBP data, all years.

FIGURE A.6: NUMBER OF ITEMS PER SHIPMENT

Panel A: Levels



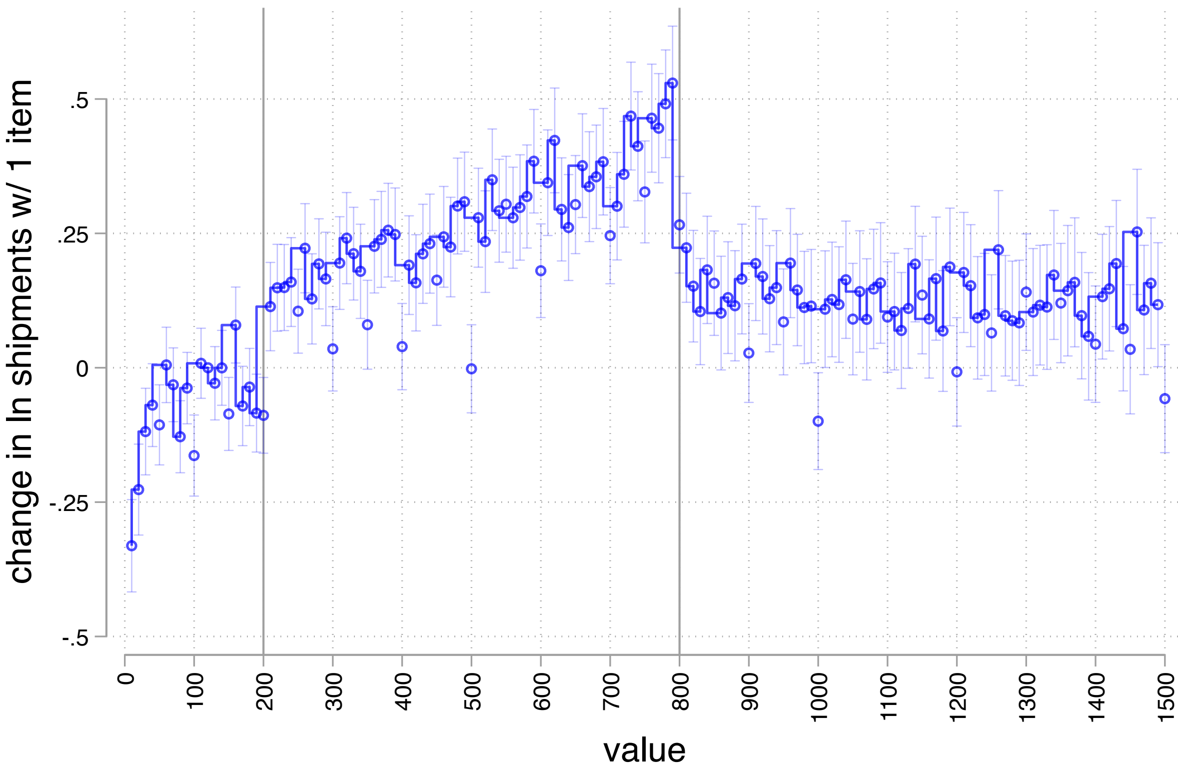
Panel B: Difference-in-Differences



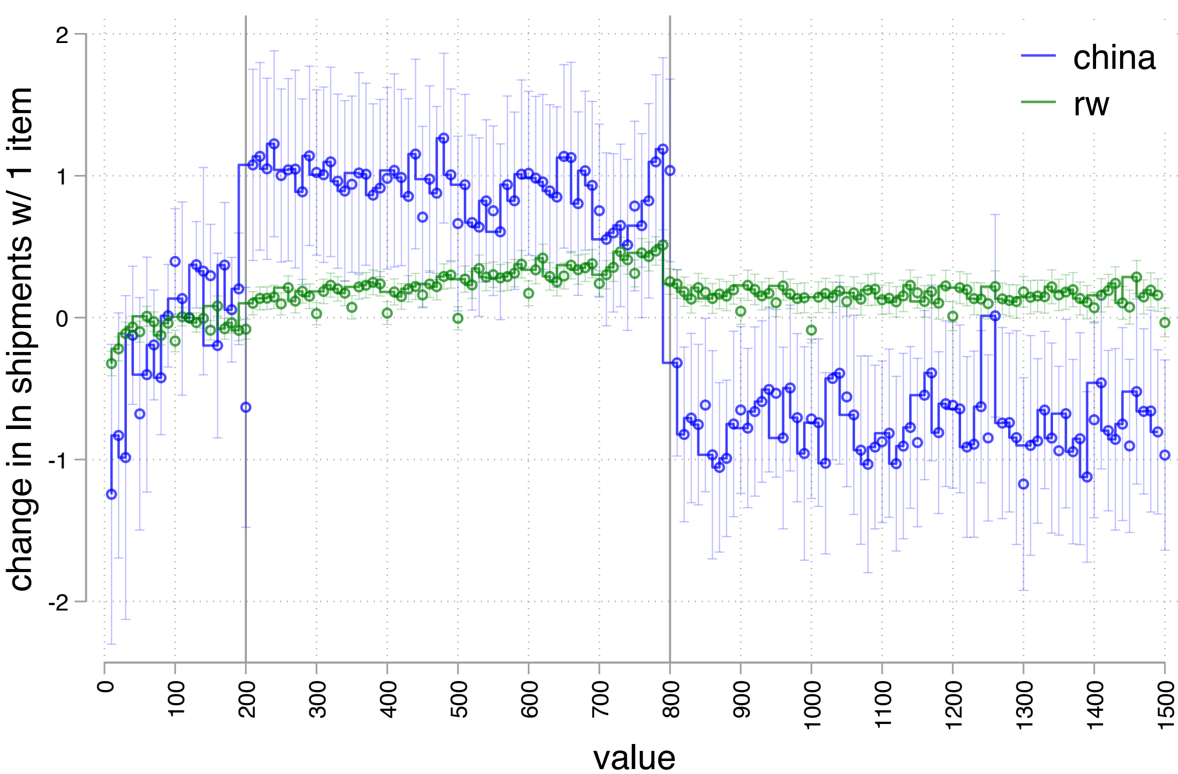
Notes: Figure reports the average number of items per package at each bin. The top panel runs regressions (21) in levels, and the bottom panels reports the difference-in-differences specification (22). Grey vertical lines denote §321 thresholds before and after March 2016. The leave-out bin is $120. Error bars denote 95% confidence intervals. Round numbers not included in the connected line to improve visualization. Source: carriers A and B, all years.

FIGURE A.7: CHANGE IN DENSITY OF ONE-ITEM SHIPMENTS

Panel A: All Origins



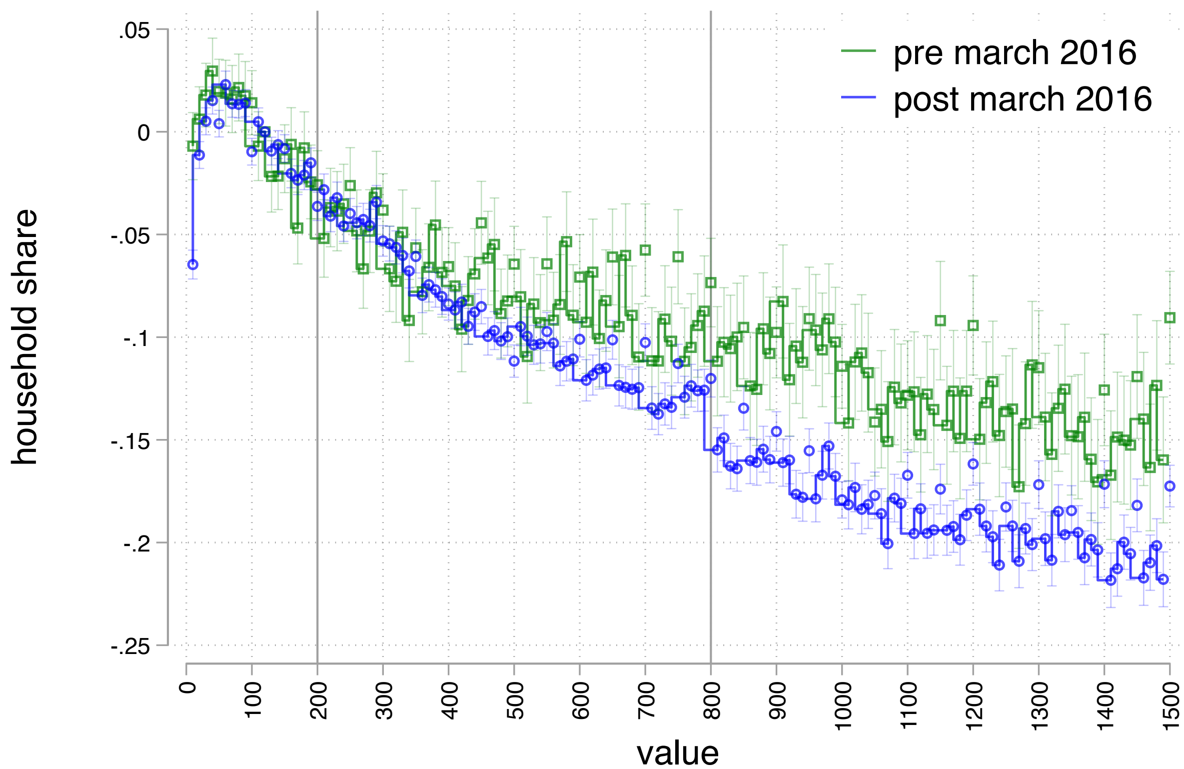
Panel B: China vs RW



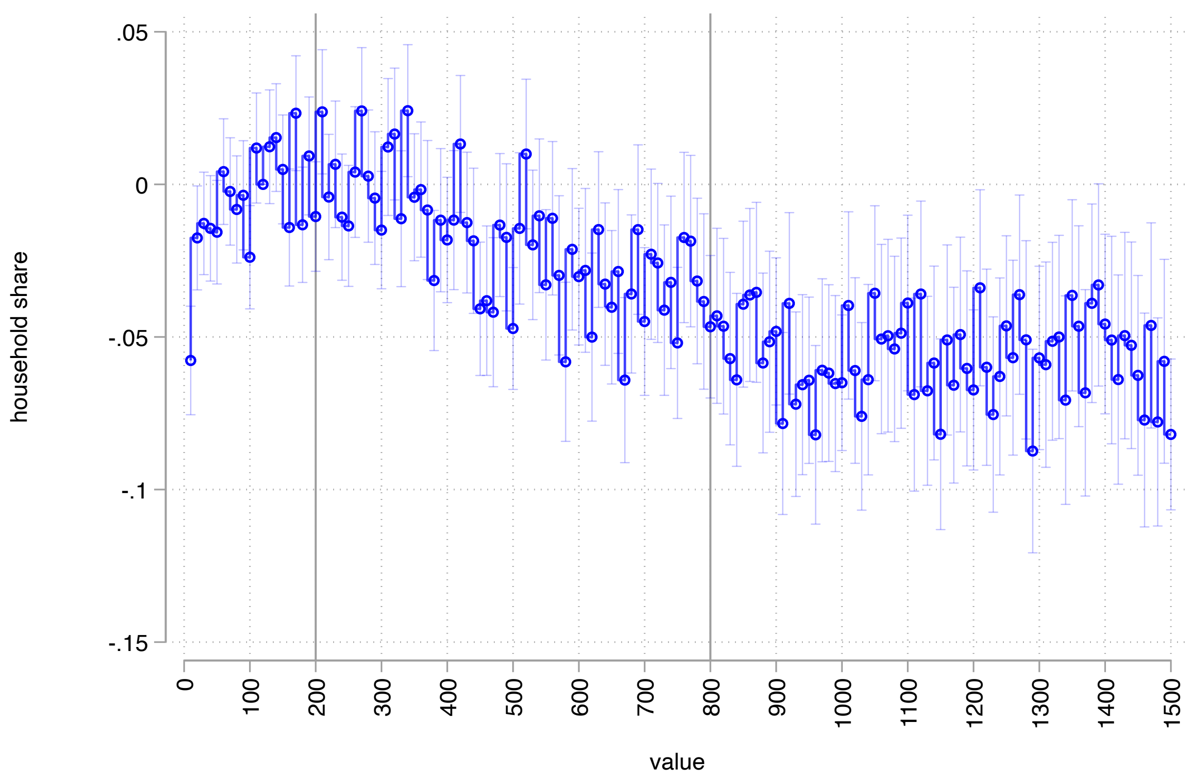
Notes: Figure reports the density of one-item shipments to the USA in the post period relative to pre period, and relative to the same time difference for OECD shipments. The regression specification is (22), and the figure plots the $\beta_b \times \text{USA}_d \times \text{post}_t$ fixed effects. The top panel plots shipments from all origins, and bottom Panel B estimates (22) separately for shipments from China and RW. Grey vertical lines denote §321 thresholds before and after March 2016. The leave-out bin is \$120. Error bars denote 95% confidence intervals. Round numbers not included in the connected line to improve visualization. Source: carriers A and B, all years.

FIGURE A.8: SHARE OF HOUSEHOLDS

Panel A: Levels

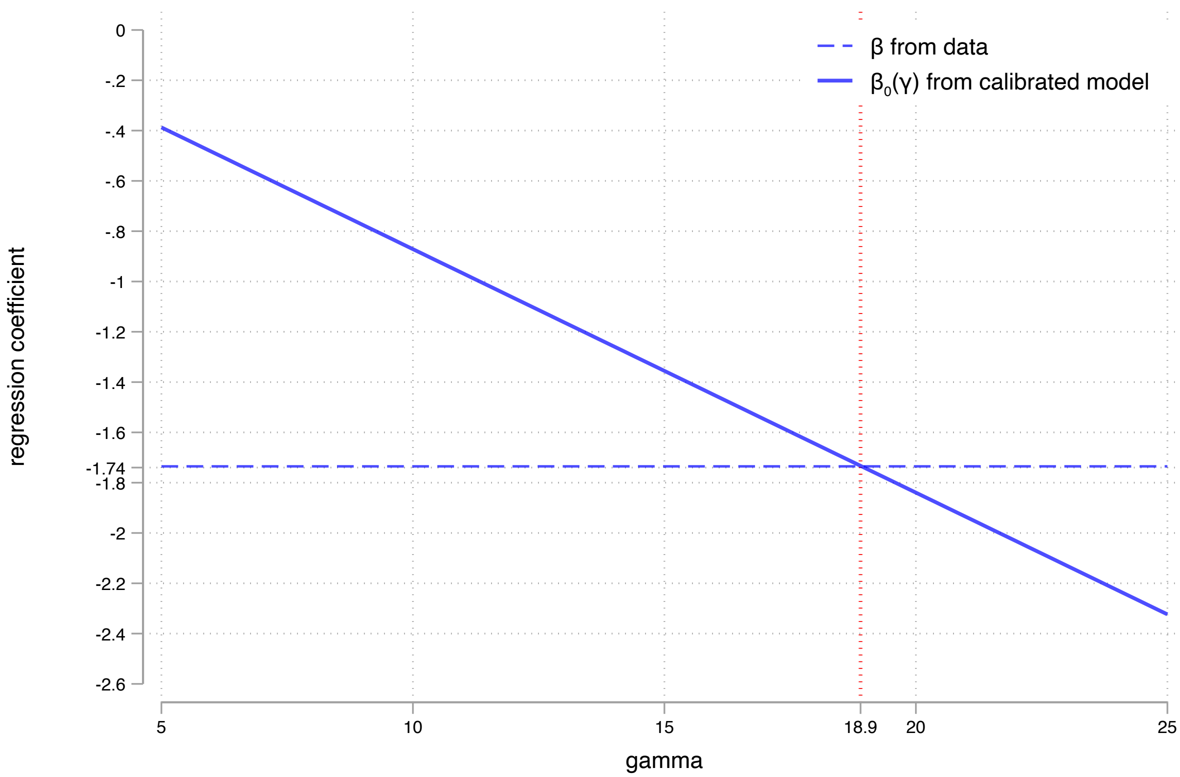


Panel B: Difference-in-Differences



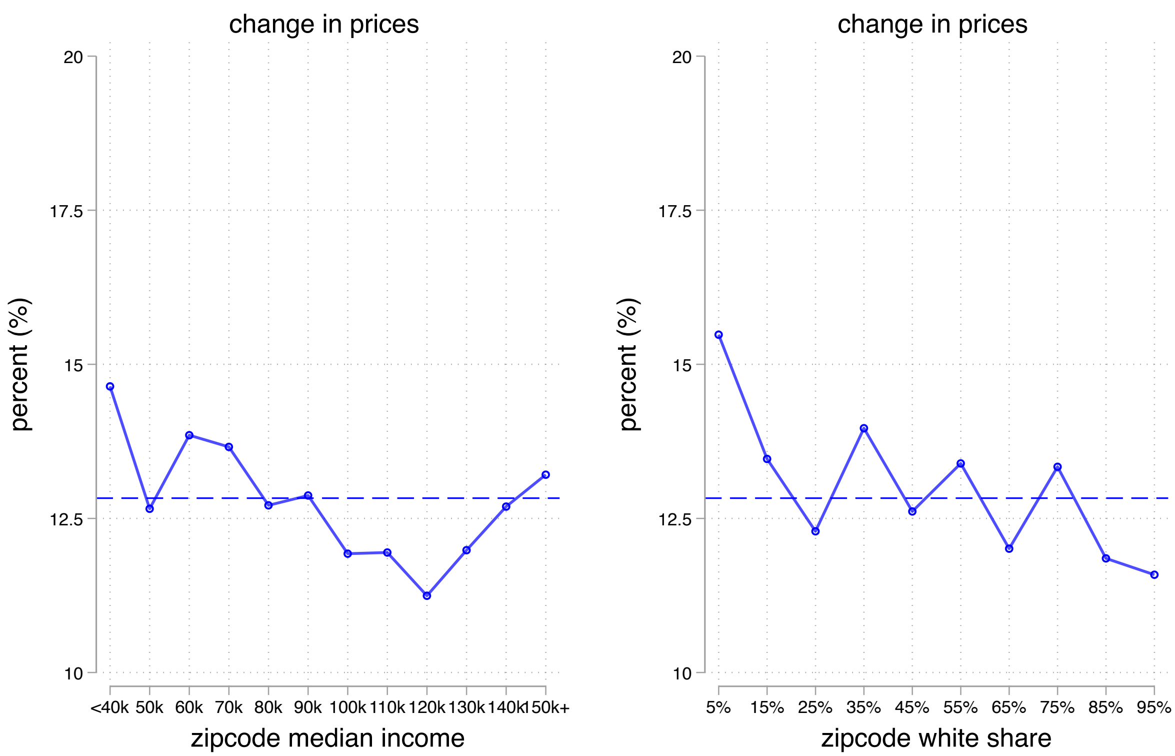
Notes: Figure reports the fraction of shipments in each bin that are sent to addresses matched to US residential zones; see Section 4.1 for details. The regression in the top panel is $hhshare_{bodxt} = \alpha_{odxt} + \beta_b + \epsilon_{bodxt}$, where the green series is run on shipments pre-March 2016 and the blue series is run on shipments post-March 2016. The bottom panel reports the difference between pre and post March 2016, $hhshare_{bodxt} = \alpha_{odxt} + \beta_b \times \text{post}_t + \epsilon_{bodxt}$. The leave-out bin is \$120. Error bars denote 95% confidence intervals. Source: carrier A, all years.

FIGURE A.9: CALIBRATION OF γ



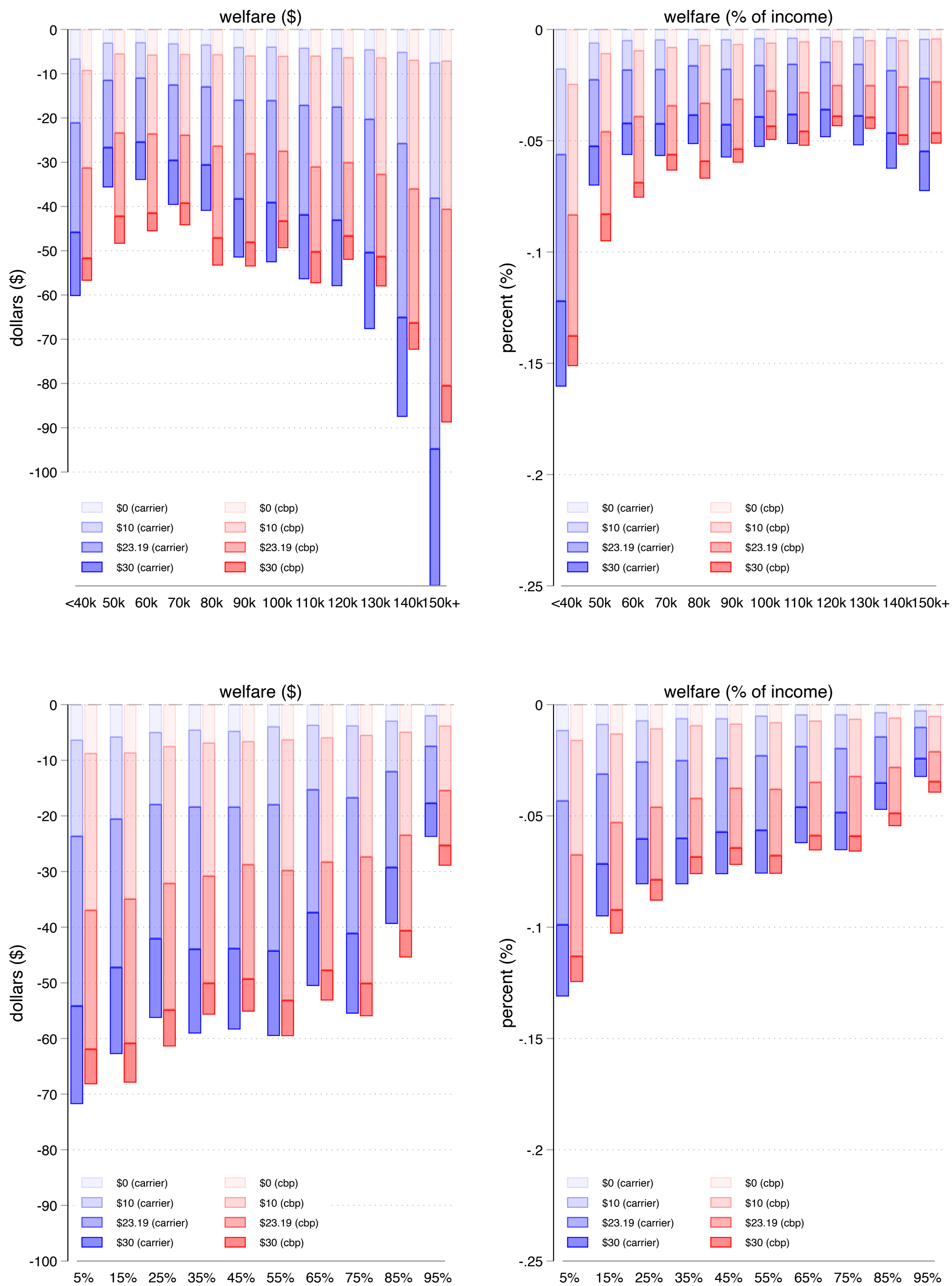
Notes: Figure reports $\hat{\beta}$ estimated from running (31) on the actual shipment densities from China and RW by income group, and $\beta_0(\gamma)$ from running the same specification on the model-implied densities generated for different values of γ. The intersection pins down cross-origin elasiticty of substitution: $\gamma = 18.9$.

FIGURE A.10: CHANGE IN PRICE INDEX



Notes: Figure reports for defined in (25). The left panel reports the price index changes by zip code median family income. The right panel reports price index changes by zip code white household share. The aggregate change in the price index is 12.83%.

FIGURE A.11: EXACT WELFARE LOSS, BY FEE



Notes: Figure reports welfare losses against zip code characteristics at fees ranging from $0 to $30 per shipment. The left panels report welfare impacts in per-capita dollars and the right panel scales by median family income. Top panel reports by zip code median family income, and bottom panel reports by zip code white household share. Within each consumer group, the blue (red) stacks are the welfare losses from carrier (CBP) data.