The Value of de Minimis Imports*

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Abstract

A U.S. consumer can import $800 worth of goods per day free of tariffs and administrative fees. Fueled by rising direct-to-consumer trade, these "de minimis" shipments have exploded in recent years, 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 U.S. Customs and Border Protection. Lower-income zip codes are more likely to import de minimis shipments, particularly from China, which suggests that the tariff and administrative fee incidence in direct-to-consumer trade disproportionately benefits the poor. Theoretically, imposing tariffs above a threshold leads to terms-of-trade gains through bunching, even in a setting with complete pass-through of linear tariffs. Empirically, bunching pins down the demand elasticity for direct shipments. Eliminating §321 would reduce aggregate welfare by $10.9-$13.0 billion and disproportionately hurt lower-income and minority consumers.

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1 Introduction

Since 2018, the U.S. has sharply raised tariffs, with their incidence falling predominantly on U.S. consumers (Fajgelbaum and Khandelwal, 2021). However, §321 of the 1930 Tariff Act allows up to $800 goods per day per person to be imported free of tariffs and administrative fees of clearing customs. 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 and are shipped 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. When compared against relevant benchmarks, in 2023 de minimis imports were 7.3% of U.S. imports of consumer goods and 4.9% of E-commerce sales, a substantial increase from just 0.7% and 1.0%, 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] Five legislative proposals to pare back §321 were recently introduced in Congress, and in September 2024 an Executive Order was issued to rescind the de minimis exemption on shipments containing products subject to 2018-19 tariffs.[2]

The growth of low-value shipments and related policy concerns are a global phenomenon. For example, the E.U. recorded 2.3 billion shipments below their €150 threshold in 2023–more than double the 2022 volume–and is moving to eliminate the exemption (FT 2024-07-03, European Commission 2023). Both developed and developing countries are debating the role of de minimis imports, given the rapid rise of direct-to-consumer trade.[3]

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 so far been limited as Census data exclude de minimis shipments. We rely on a novel dataset encompassing the universe of shipments into the U.S. handled by three global carriers. In

[1]In 2022, Shein represented 50% of the U.S. 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, Temu and Shein had 51 million and 26 million active users, compared to Amazon's 67 million(WSJ 2024-03-01), A Congressional committee has found that Shein and Temu account for 30% of total de minimis imports (Select Committee on the CCP, 2023).

[2]These legislative either restrict access to the de minimis channel for some countries (notably China) by lowering the threshold, or exclude certain products such as those experiencing import surges. The Executive Order excludes from the de minimis exemption those products subject to 2018-19 tariffs imposed under §201 and §301 of the Trade Act of 1974 and §232 of the Trade Expansion Act of 1962.

[3]South Africa eliminated its de minimis threshold in July 2024 (Sourcing Journal 2024-06-12), Turkey considerably lowered its threshold from $164 to $33 in August 2024 (Yahoo News 2024-08-13), and the Philippines added new customs fees for processing de minimis imports in March (Philippines Bureau of Customs 2024-03-24). In June 2024, Brazil imposed 20% tariffs on imports below $50 purchased through online platforms (Brazilian Report 2024-06-20). In September 2024, Chile scrapped its tax exemption for imports below its de minimis threshold of $41 (The Clinic 2024-25-09). The UK is debating its de minimis exemption (FT 2024-06-19). Minguez and Minondo (2024) document that low-value shipments are now more than half of import transactions in Spain, up from around 10% in the early 2000s. Volpe et al. (2024) find that in 2019, Peruvian consumers accounted for 38% of all import transactions into Peru.

2021, these shipments account for 36.1% of total value and 15.1% of total U.S. de minimis imports. A key feature of the data is the destination zip code, which allows 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 and with proprietary credit card spending data.

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 in 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 a (per shipment) administrative fee. The latter acts like a specific tariff, except its revenue finances administrative costs of processing above-threshold shipments rather than being rebated to consumers. In this context, the commonly studied linear tariffs are completely passed through to final consumers.[4] However, the de minimis tax notch generates 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 the demand substitution elasticity across shipments from each origin, defined in our implementation as China and Rest of the World (RW). We identify these parameters by exploiting shifts in bunching around the de minimis threshold due to policy changes, analogous to the approach in public economics that identifies labor supply elasticities from notches along the tax schedule (Kleven and Waseem, 2013).

The data reveal that direct-to-consumer shipments (defined as shipments below \$5000), their cheaper de minimis subset (below \$800), and the de minimis share originating from China are relatively more important for low-income households. 73% of direct shipments imported by the poorest zip codes are de minimis compared to 52% for the richest zip codes. The share of de minimis shipments from China also declines with income: 48% for the poorest zip codes compared to 22% for the richest.

These patterns, along with the exemptions from fees and the much higher tariffs on imports from China, imply 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%.[5] If §321 were eliminated, the

[4] The optimality of free trade versus linear tariffs in the model results from assuming an outside good that fixes wages (a reasonable assumption given de minimis' shipments' size) and constant markups. The model is thus consistent with the empirical finding of complete pass-through to US-China tariffs in datasets that exclude de minimis shipments.

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

tariff schedule would *flip* from pro-poor to pro-rich: the poorest zip codes would face average tariffs of 11.8% compared with 6.5% 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 patterns in the CBP sample. Credit card transaction data assembled from a different proprietary data provider 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.[6] A first-order approximation of the policy change, which assumes complete pass-through and uses only the carrier (or CBP) spending shares yields a consumer loss of $11.0b or $34 per person. With the CBP data, the loss is larger–$25.7b, or $80 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 23.0% more than the aggregate (or 3.7% 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 non-white 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 34.8% (or 8.9% with CBP data) more than the representative consumer.

Using the carrier data, we estimate bunching in response to the tariff notches. Qualitatively, through the lens of our model, bunching rules out purely price-taking behavior and is evidence of less-than-complete pass-through from tariffs to prices, thus implying a terms-of-trade gain. We estimate densities of shipments across value bins in four categories: shipments to the U.S. and OECD, before and after March 2016, when the U.S. de minimis threshold increased from $200 to $800. We observe bunching at the thresholds of US-bound shipments, particularly in the post-period at $800. When expressed as a difference-in-differences (post minus pre within the U.S., relative to the OECD), the density of shipments shows a sharp increase right below $800 and then a 24% drop in shipments above the notch. Consistent with higher tariffs, these results are starker for shipments from China. A range of robustness checks (such as using the CBP data, restricting to shipments with one item, controlling for product codes) deal with package splitting or compositional changes driving the results.

The exact welfare impacts incorporate the demand responses, incomplete pass-through from bunching, and tariff rebates. We pin down the within-origin demand elasticity across shipments from China and RW by matching the observed changes in bunching in response to tariffs from difference-in-differences specifications. This procedure yields an elasticity from China of 4.42 (se 0.61) and from RW of 1.81 (se 0.48). We also identify a substitution elasticity of direct shipments across origins through indirect inference that leverages differences in tariffs across origins and de

[6] Our benchmark fee for brokerage services is based on a weighted average of fees charged by various logistics providers. Section 2 provides details. We report sensitivity of the main results to alternative fees.

minimis expenditure exposure across consumer groups and origins, finding an elasticity of 19.59 (se 0.96). We calibrate the upper elasticity–between direct shipments and other expenditures–to a recent U.S. estimate of the substitution between imports and domestic goods (Fajgelbaum et al., 2020), and show results for a range of values around this calibration.[7]

Assuming that tariffs are rebated back to consumers, we find that eliminating §321 reduces aggregate welfare by \$10.9 billion (se \$1.8b). In the CBP sample, we estimate a larger decline of \$13.0 billion (se \$2.0b). To put these numbers in perspective, Fajgelbaum et al. (2020) estimate the sum of consumer cost and tariff revenue gain of the 2018 U.S. 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 \$44 per capita per year compared to a \$36 loss for zip codes with \$100k incomes and a \$89 per capita loss for the richest zip codes. When expressed as a share of household income, the corresponding declines are biased against the poor. Across racial composition, welfare in zip codes with 5% white households would experience a per capita decline of \$50, compared with declines of \$40 for zip codes with a 45% white share and \$17 with a 95% white share. That is, the per capita loss *in dollar terms* is larger for non-white households despite their lower incomes. As a result, the impact of eliminating §321 is even more pronounced across race.[8]

Our paper contributes to studies of the importance of trade for consumption, with a distinct focus on trade policy. Most related is Acosta and Cox (2019), who study the distributional bias of U.S. tariffs through consumer exposure. They digitized historical U.S. 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 favors the poor in this type of trade because of the §321 exemption. Without this exemption, tariffs would be regressive, just as Acosta and Cox (2019) find in 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

[7]The values of all three demand elasticities matter to quantify the level of welfare changes from removing de minimis but do not affect the qualitative distributional impacts.

[8]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 \$46, \$38, and \$97. For zip codes with white household shares of 5%, 55%, and 95%, the per capita tariff-exclusive losses are \$53, \$43, and \$18.

and Jaravel (2021) match consumer expenditure surveys to trade data and do not find substantial differences in import shares across U.S. 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.

Our analysis is also related to the evidence of complete pass-through of U.S. tariffs on China to U.S. import prices; see Amiti et al. (2019), Fajgelbaum et al. (2020), Flaaen et al. (2020), and Cavallo et al. (2021). 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.[9] 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.[10] Furthermore, we find that the minimal customs requirements of de minimis shipments, exempting those shipments from using brokers (agents responsible for preparing and submitting import documentation, such as assigning product codes) significantly benefit low-value shipments.

Recent papers studying the effects of E-commerce on consumption do not distinguish between domestic and international shipments of purchases via these platforms, either through de minimis or through formal imports. Dolfen et al. (2023) find that higher-income households in the U.S. 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) find that E-commerce reduces consumption prices for younger and richer households in Chinese villages. Our paper focuses on the role of low-value international shipments for welfare, studying how direct-to-consumer trade benefits different consumer groups and how these benefits depend on trade policies under debate.

The study of tax kinks and notches is prominent in the public economics literature that estimates labor supply elasticities from bunching around tax notches in the wage distribution across workers (as in Saez (2010), Chetty et al. (2011), and Kleven and Waseem (2013)).[11] Our approach to estimating the demand elasticity exploits bunching in the value distribution of shipments relative to two controls through a straightforward diff-in-diff specification. Distortive impacts of tax notches have been studied on firm decisions, with Gourio and Roys (2014) and Garicano et al. (2016) showing how size-dependent regulations lead to bunching in the French firm size distribution. As far as we know, our paper is the first study of tariff notches in international trade. While in other contexts the emphasis is on distortionary impacts, here the notch allows a country to extract surplus from foreign exporters. In addition to de minimis policies worldwide,

[9] 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.

[10] 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.

[11] See Kleven (2016) for a review of this literature.

statutory tariff lines also include notches indicating broader applicability of our framework.[12]

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 involves paying applicable duties and taxes, meeting regulatory standards, and filing paperwork. In the U.S., 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 countries have a "de minimis" policy to reduce the customs burden for low-value shipments.[13]

The U.S. 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 Tariff 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, as part of the Trade Facilitation and Trade Enforcement Act of 2015, the U.S. raised the threshold from $200 to its current value of $800 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.

[12] 6.6% of U.S. tariff lines on consumer imports, representing 5.6% of consumer imports, feature a notch in their text descriptions. We thank Lydia Cox for suggesting this calculation.

[13] 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).

Regardless of how they are cleared, de minimis shipments (between \$0-\$800) 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 (above \$2500). 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.[14]

The per-unit administrative fees play an important role quantitatively, given the small value of most shipments in our data. The brokerage services component varies across logistics companies based on the range of services they offer, so we take an average across companies. Specifically, the carriers' per-package broker fee for informal shipments is \$30; the Postal Service's fee for handling international shipments is \$8.55 (USPS, 2024); and the National Foreign Trade Council estimates a broker fee of \$20 (National Foreign Trade Council, 2024). 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. In addition, we apply the CBP's lowest merchandise processing fee on informal shipments of \$2.22 to arrive at the benchmark administrative fee of \$23.19 per shipment. We apply this fee to de minimis shipments in counterfactuals that eliminate §321, and report sensitivity to a range of fees.

De minimis shipments have only recently become quantitatively important. 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 U.S., 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 rising tariffs. By 2023, 1 billion shipments entered through §321, and through the third quarter of 2024, 1 billion packages have already entered. (CBP processed 39.1 million formal entries in 2023, although, of course, a single formal such as a container entry may contain thousands of 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 purchase 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) and its share of total E-commerce sales. In 2012, de minimis imports as a share of consumer imports was just 0.01%; by 2023, this share was 7.3%. Column 4 benchmarks de minimis imports relative to U.S. E-commerce sales: in 2012, this share was just 0.0%, but by 2023, it was 4.9%.

[14]Our counterfactual analysis explores the implications of legally treating de minimis shipments as informal entries. Formal entries, which apply to shipments valued above \$2500, are subject to an ad-valorem merchandise processing fee of 0.3464% rather than to a specific fee. Formal entries also require a surety bond to secure the release of cargo.

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%	0.0%
2013	0.07	117.9	0.01%	0.0%
2014	0.7	122.8	0.1%	0.2%
2015	1.6	138.9	0.3%	0.5%
2016	9.2	224.0	1.6%	2.4%
2017	13.0	332.3	2.1%	2.9%
2018	29.2	410.6	4.4%	5.8%
2019	56.2	503.1	8.9%	9.9%
2020	67.0	636.7	9.3%	8.3%
2021	43.5	771.5	5.3%	4.6%
2022	46.5	685.4	6.0%	4.6%
2023	54.5	1,000.0	7.3%	4.9%
2024*	47.8	1,000.0		

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 U.S. 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 2024m9. (Note: In previous versions, the fourth column erroneously normalized to the quarterly E-commerce sales).

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 U.S.) 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 a with fixed incomes per worker in terms of a numeraire. Specifically, each type-ω consumer has preferences over a bundle of imported direct-to-consumer goods and an outside good. 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 (in units of the outside good), 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 across origins o with constant elasticity of substitution γ. The associated price index is

$$P^{\omega} = \left(\sum_{o} A_{o}^{\omega} \left(P_{o}^{\omega}\right)^{1-\gamma}\right)^{\frac{1}{1-\gamma}}, \tag{2}$$

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 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 that all consumer groups face the same prices. That is, foreign exporters cannot price-discriminate across groups. As a result, demand shifters alone (rather than demand shifters and package prices) determine differences in price indexes P^{ω} and in the impacts of de minimis policy across consumer groups ω. Consumers spending more on 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 in 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 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:

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

where

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

are the tariff and the administrative fee as function of the value per package, respectively.[15] The total demand faced by firm i from origin o is:

$$N_i (v) = \left(\sum_{\omega} a_i^{\omega} D_o^{\omega}\right) v^{-\sigma_o}, \tag{6}$$

where, from the CES demand structure, D_o^{ω} is an endogenous firm-level demand shifter that includes the aggregate exogenous demand shocks A^{ω} and A_o^{ω}, the size of each group L^{ω}, and competitor's prices through the aggregate and origin-specific price indexes, P^{ω} and P_o^{ω}.

[15] This setup assumes that international shipment follow "delivery duty paid" (DDP) rules, in which the seller is responsible for paying trade costs. Based on our conversations with representatives of the carrier companies providing the data, these are the predominant rules applying to E-commerce deliveries shipping directly to consumers, as they avoid burdensome administrative costs for individual buyers. However, there are cases of "delivery duty unpaid" (DDU) shipments where the buyer is asked to cover the tariffs in a separate payment made to the logistics company (rather than through the platform where the items was purchased).

We allow for a general joint distribution of unit costs z and demand shocks a^{ω} across exporters from each origin o. To aggregate firm decisions, this joint distribution turns out to matter only through the following "quality-adjusted" measure of exporters from o with unit cost equal to z:

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

where $M_o(z)$ is the mass of firms with unit cost equal to z from origin o. The quality-adjusted measures $h_o^{\omega}(z)$ adjusts the number of firms with unit cost z from o by the average preferences that consumer group ω has over these firms (entering through $\mathbb{E}_o[a^{\omega}|z]$).

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:

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

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

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

The profits $\pi_i^L(z)$ and $\pi_i^H(z)$ correspond to what firm i with unit cost z shipping through the de minimis and the standard channel, respectively, would obtain. 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 over marginal cost, i.e.,

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

and

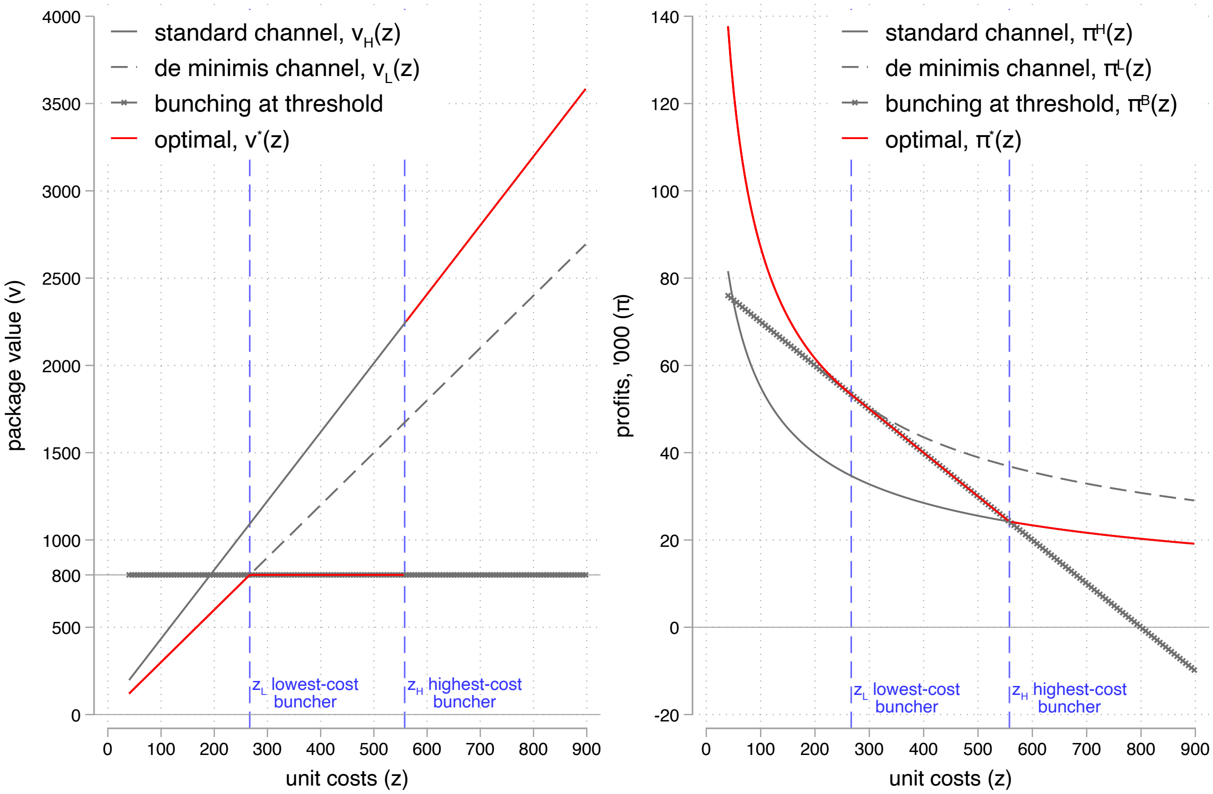
$$v_{H,o}(z) \equiv \frac{\sigma_o}{\sigma_o - 1} \frac{z + T_o}{1 - \tau_o}. \tag{12}$$

These pricing functions are depicted in the left panel of Figure 1. The profits in Figure 1 are shown assuming a constant demand shifter $d_i = d$ entering in $N_i(v)$, while the prices in Figure 1 do not impose assumptions on demand shifters.

The intermediate case, $\pi_i^B(z)$, are the profits that firm i would obtain if it bunched 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 firm's profit at its optimal choice of package value v, $\pi_i^*(z) \equiv \max_v \pi_i(v; z)$ for $\pi_i(v; z)$ defined in (4), is shown in red in the right panel of Figure 1, with associated optimal pricing 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

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 under zero tariffs and fees or under positive tariffs and fees, respectively. The "bunching at threshold" schedule corresponds to firms pricing at the $800 threshold.

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 v_{DM}. 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 set package value 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 a $z_{H,o}$ such that $\pi_i^B(z_{H,o}) = \pi_i^H(z_{H,o})$.

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 of σ from the Mass of Bunchers

Analogous to Kleven and Waseem (2013) who estimate labor supply elasticities from income tax notches, Proposition (1) provides a basis to identify the elasticity σ_o. The condition that determines the highest-cost buncher $z_{H,0}$, $\pi_i^B(z_{H,o}) = \pi_i^H(z_{H,o})$, can be re-expressed in terms of the relative size $\frac{v_{H,o}}{v_{DM}}$ of the "hole" of the density of values:

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

According to the model, no firm should price in $[v_{DM}, v_{H,o}]$. Given σ_o, this condition depends on observable policy parameters (threshold v_{DM}, tariffs τ_o, administrative fee T) and on the shipment value $v_{H,o}$ set by the highest-cost buncher. Using this condition, given a density $h_o(z)$ of exporters, we obtain the total shipments made by bunchers at v_{DM} as function of the policy parameters and σ_o.[16] Visually, this mass of bunchers shows up as a mass point at v_{DM} in the histogram of shipments over package values.

[16]The mass of bunchers is $D_o v_{DM}^{-\sigma_o} \int_{z_L}^{z_{H,o}} h_o(z)\, dz$. Combining the pricing rule $v_o^*(z)$ with (15) we obtain the highest-cost buncher $z_{H,o}$ as a function of the policy parameters (v_{DM}, τ_o, T) and σ_o. Similarly, (1) gives the lowest-cost buncher $z_{L,o}$ as function of the policy parameters and σ_0. We have defined the density in (7) for one specific

The parametrization in Section 6 simultaneously calibrates the density $h_o(z)$ and the elasticity σ_o such that the model-implied histogram of shipments and the policy-induced change in the mass of bunchers match their empirical counterparts. 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 firms optimizing subject to frictions.

This approach identifies σ_o because the size of the hole $[v_{DM}, v_{H,o}]$, and, therefore, the mass of bunchers, shrinks with σ_o. The intuition is that the higher is this elasticity, the smaller are profits overall and, in particular, the smaller is the range of unit costs above the lowest-cost buncher z_L such that, within this range, a firm can still make positive profits by lowering prices to v_{DM}. This logic can be seen clearly by noting that the mass of bunchers disappears as $\sigma_o \to \infty$; this limit approximates perfect competition, where firms price at marginal cost. In this case, no firm above z_H can still make profits by lowering the price to v_{DM}, and the pricing function (13) becomes:

$$\lim_{\sigma\to\infty} v_o^*(z) = \begin{cases} z & z < v_{DM}, \\ \frac{z+T_o}{1-\tau_o} & z \geq v_{DM}. \end{cases} \tag{16}$$

In this extreme case, because there are no markups there is no leeway for price manipulation: highest and lowest unit cost bunchers converge to the threshold ($z_L = z_H = v_{DM}$) and no firm with unit cost above v_{DM} can set the price at v_{DM} and still make positive profits. The horizontal segment in the left panel of Figure 1 disappears and the size of the hole in the pricing distribution attains its minimum. As a result, the density of shipments over prices does not exhibit bunching.

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

$$u = \frac{1}{\kappa}e + y + tr, \tag{17}$$

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

$$e = AP^{-\kappa}, \tag{18}$$

$$P = \left(\int_0^{z_L} v_L(z)^{1-\sigma} h(z)\,dz + v_{DM}^{1-\sigma}\int_{z_L}^{z_H} h(z)\,dz + \int_{z_H}^{\infty} v_H(z;\tau)^{1-\sigma} h(z)\,dz\right)^{\frac{1}{1-\sigma}}, \tag{19}$$

$$tr = \tau e \int_{z_H}^{\infty}\left(\frac{v^*(z;\tau)}{P}\right)^{1-\sigma} h(z)\,dz, \tag{20}$$

group $h_o^\omega(z)$. When we aggregate to the U.S. market, the histogram over packages identifies σ_o from the aggregate quality-adjusted density, $h_o(z) = \sum_\omega h_o^\omega(z)$, which measures the importance of firms of productivity z from origin o in the entire U.S. market.

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*

$$\frac{du}{e} = \left[\underbrace{\frac{1}{\sigma - 1}\left(\left(\frac{v_{DM}}{P}\right)^{1-\sigma} - \left(\frac{v_H(z_H;\tau)}{P}\right)^{1-\sigma} \right)}_{\textit{terms-of-trade change at the threshold}} - \underbrace{\tau \left(\frac{v_H(z_H;\tau)}{P}\right)^{1-\sigma}}_{\textit{tariff change}} \right] h(z_H)\, dz_H$$
$$- \underbrace{\frac{dv_{DM}}{v_{DM}} \int_{z_L}^{z_H} \lambda(z)\, dz}_{\textit{bunchers' price change}} - \underbrace{\left[\tau(1+\kappa-\sigma)\frac{dP}{P} + \sigma \frac{\tau}{1-\tau} d\tau \right]}_{\textit{"standard" welfare impact}} \int_{z_H}^{\infty} \lambda(z)\, dz \qquad (21)$$

where $\lambda(z) \equiv (v(z)/P)^{1-\sigma} h(z)$ 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 $h(z)$ has sufficient mass below the highest-cost buncher z_H.

Expression (21) 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 in the model 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 gains of a higher threshold are shown in the first line of (21). 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: lost tariff revenue from the new bunchers (the "tariff change" term in the first line of (21)); and higher prices set by infra-marginal bunchers (the "bunchers' price change" term in the second line of (21)). The latter would be visually represented by a marginal 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 $h(z)$ and the various demand elasticities. However, 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 mass on bunchers (i.e., below z_H) would imply a lower price index than under free trade. This would happen for instance if $h(z)$ was bounded above at z_H. In that case, the "optimal" import price schedule would be uniformly below the "dm channel" schedule –corresponding to free trade– for all firms with positive mass. Therefore, the policy bundle with $v_{DM} > 0$ and $\tau > 0$ would be preferred to free trade, because it would lead to both a lower (tariff inclusive) consumer price index and to the same (zero) tariff revenue. Moreover, such an equilibrium be always constructed for a bounded exporter unit-cost distribution $h(z)$ by raising 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 (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 (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 U.S. tariffs that has been identified by recent empirical evidence using datasets that exclude de minimis shipments (Fajgelbaum and Khandelwal, 2021).

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 shipments above the de minimis threshold we observe the ten-digit HS code.[17] 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 carriers' shipments to the U.S. for 2021; that year, the carriers handled 157 million shipments worth $319 billion.

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 mitigate concerns about this data field. First, CBP audits the §321 channel, and undervaluation is subject to penalties such as fines, delays, seizures, and 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 transaction value. Third, carriers reserve the right to inspect packages, as they are concerned with undervaluations because of potential auditing.

The carriers do not carry a flag for whether the consignee is a household or a business. This distinction carries no weight for our analysis of aggregate impacts. For distributional impacts, this distinction is also not relevant if businesses sell either to residents of their own zip code or to residents of zip codes with similar income or demographics as their own zip code. Nevertheless, we define "direct-to-consumer shipments" as shipments with $v \in (\$0, \$5000]$, i.e., excluding shipments with $0 declared value (gifts) and high-value shipments that are unlikely to be imported directly by households. This restriction removes 8.9% of shipments.

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); 67.7% of shipments (67.9% of value) match a specified land-use. Conditional on a match, 75.3% went to households (68.5% of value), with the rest going to commercial, industrial, recreational, or agricultural land use. In contrast, when including shipments above $5,000, the share of household-bound shipments that go to households does not change much–74.9%–but the value share falls to 59.4%. 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 116.8 million shipments (15.1% of aggregate §321 shipments) worth $15.7 billion (36.1% of aggregate de minimis imports).[18] Across all years, our data includes 350m de minimis shipments.

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

[17] 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 2021 shipments.

[18] In 2021, all express carriers (including those not in our data) handled 30% of de minimis shipments, accounting 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.

and Exportation") or 63 ("Immediate Exportation"). They do not clear U.S. customs and, therefore, are not subject to U.S. trade policy but are transshipped through the USA, presumably given the carrier's network of air routes. As explained below, these shipments serve as an additional counterfactual policy density. We restrict attention to OECD destinations, as their demand would resemble U.S. demand given similar income levels.

We obtained, via a FOIA request, CBP shipment-level data on transactions below $1500.[19] CBP provided us with only one week of data per year from 2017 to 2022 (the first week of December) on the grounds that the volume of data was too large. These data contain, for this week in each year, the universe of shipments under $1500 into the U.S. across *all* carriers. We observe the date, declared value, origin, and destination zip code for each imported transaction. Across all years, in the CBP data we observe 4.5m 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. 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 shipments in the carrier 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. 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), fabrics (polyester, cotton), accessories (necklaces, 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 with HS codes fall within are reported 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.

4.3 Demographics

We use street addresses and zip codes to link demographic characteristics to shipment destinations. Carrier A provided street addresses and states but not zip codes, so 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),

[19] A FOIA request for shipments handled by the U.S. 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	0.69
2018	A	3.6	34.3	4.3	2.0	1.0	6.2	0.074	1.00
2019	A	4.2	36.5	4.6	2.1	1.1	6.5	0.048	0.80
2020	A B* C	7.9	64.6	8.5	3.9	2.2	11.1	0.043	1.04
2021	A B C	15.7	116.8	17.3	8.0	2.8	11.0	0.042	0.96
2022	B* C*	3.6	25.9	5.1	2.4	0.01	0.01		
total		40.0	349.6	49.7	25.4	9.58	47.5	0.263	4.49

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.

and merge household income and socio-economic characteristics from University of Michigan's ICPSR. Across zip codes, the average median household 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 $30.8.

The top panel of Figure 2 reports per capita expenditures as a share of median household income against zip code median income, separately for direct-to-consumer and de minimis shipments. We find a U-shaped pattern in both series, with the poorest and richest zip codes spending roughly the same as a share of income, and about twice as much as $70k income zip code. The right panel of Figure 2 shows expenditure income shares against zip code share of white households. We find that zip codes with the lowest white shares spend the most, suggesting that group-specific preferences, rather than just non-homotheticities, play a role in shaping the demand for direct shipments. In fact, minority zip codes spend more in absolute dollar terms than whiter zip codes despite lower incomes, revealing their importance for this group.[20]

[20] Figure A.2 shows the expenditures in dollars. Richer zip codes naturally spend more, but the poorest zip codes spend more in absolute value than moderately richer zip codes. Similarly, zip codes with high minority household shares have the *highest* spending in absolute value on direct-to-consumer shipments. Table A.1 shows that these patterns are robust when simultaneously controlling for income and income squared, white household share, population density, and state FEs.

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: 73% of direct purchases compared to 52% for the wealthiest zip codes. The right panel shows that the de minimis share of direct expenditures is U-shaped with respect to white household share, with a share of 73% in the least white zip codes.

The red series shows the share of shipments from China within de minimis. There is a negative relationship between China's de minimis import share and zip code income: 48% for the lowest-income zip codes' compared to 22% for the richest zip codes. The patterns are similar although not as sharp by white share.

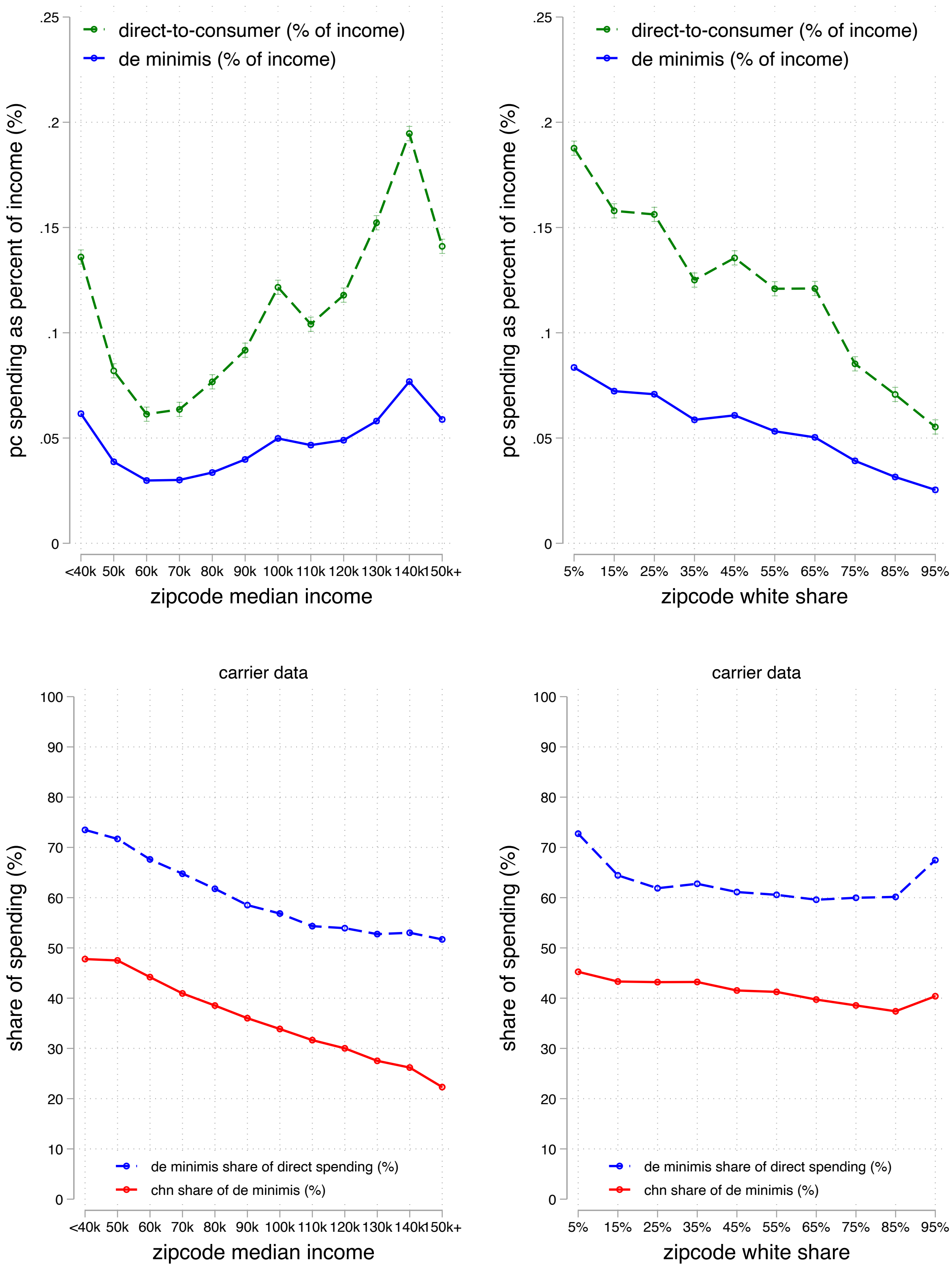
The top panel of Figure A.3 reports statistics from the CBP sample. We only observe shipments up to $1500 in this dataset, and since it is only one week of data, the shares of de minimis spending in income are very small (blue series in left axis). Nevertheless, the cross-zip code patterns in the CBP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

An alternate way to investigate who spends relatively more on de minimis imports is by looking at consumer spending patterns on the e-platforms that are known to heavily rely on §321 as part of their business model. We use proprietary data from MBHS3, provided via Yale University, which compiles information on credit and debit card transactions. In 2023, the data contain roughly 37 billion transactions purchased by 180 million individuals at hundreds of merchants, including chain stores. We obtained total expenditures by zip code and month at 482 merchants operating in durable product categories: mass merchandise (e.g., Walmart, Target, Costco), clothing related (e.g., Forever 21, Old Navy, Gap), home improvement (e.g., Home Depot, Lowe's), sports and outdoors (e.g., Dick's, REI), online (e.g., Amazon, Etsy, Shein, Temu), and consumer electronics (e.g., Best Buy, GameStop). These data are limited to non-cash transactions by undisclosed participating credit card issuers.

For each zip code 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), relative to totals in the previous categories.[21] Figure A.4 plots this share against zip code income. Collectively, the three companies account for 0.5% of spending across the 482 merchants. Across all merchants, this share is 1.10% in the poorest zip codes and only 0.40% in the richest. The differences are starker across minority household shares: these three companies are 1.34% of spending in durable categories in the least white share zip codes compared to 0.52% in the most

[21] International third-party sellers can ship directly to consumers on Amazon and eBay through the de minimis channel. However, eBay has sizable domestic transactions and sellers on Amazon primarily rely on formal importing channels to domestic warehouses.

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 \$5000, blue series) and de minimis shipments (below \$800, red series), as a share of zip code median household income. The left panel plots against zip code median household 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 from China (red series). Bars are standard errors of means. Source: carrier data, 2021.

white zip codes. These patterns are consistent with 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 source de minimis imports 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 and therefore can assign an origin-product tariff to each shipment. But, as mentioned above, HS codes are unavailable for the vast majority of de minimis shipments. Therefore, we assume that if §321 were to be eliminated, de minimis shipments from a given origin would face the median applied tariff by origin within the set of aforementioned HS chapters.[22] The tariff in these chapters from China was 4.0% before March 2016; and 15.3% afterward. For RW, average tariffs changed from 2.7% before March 2016 to 2.1% afterwards. Using these tariff rates, we construct a spending-weighted average tariff for each zip code in the post-2016 period under two scenarios: 1) the average applied tariff with §321 in effect; and, 2) the average tariff if §321 were eliminated and spending patterns did not change.

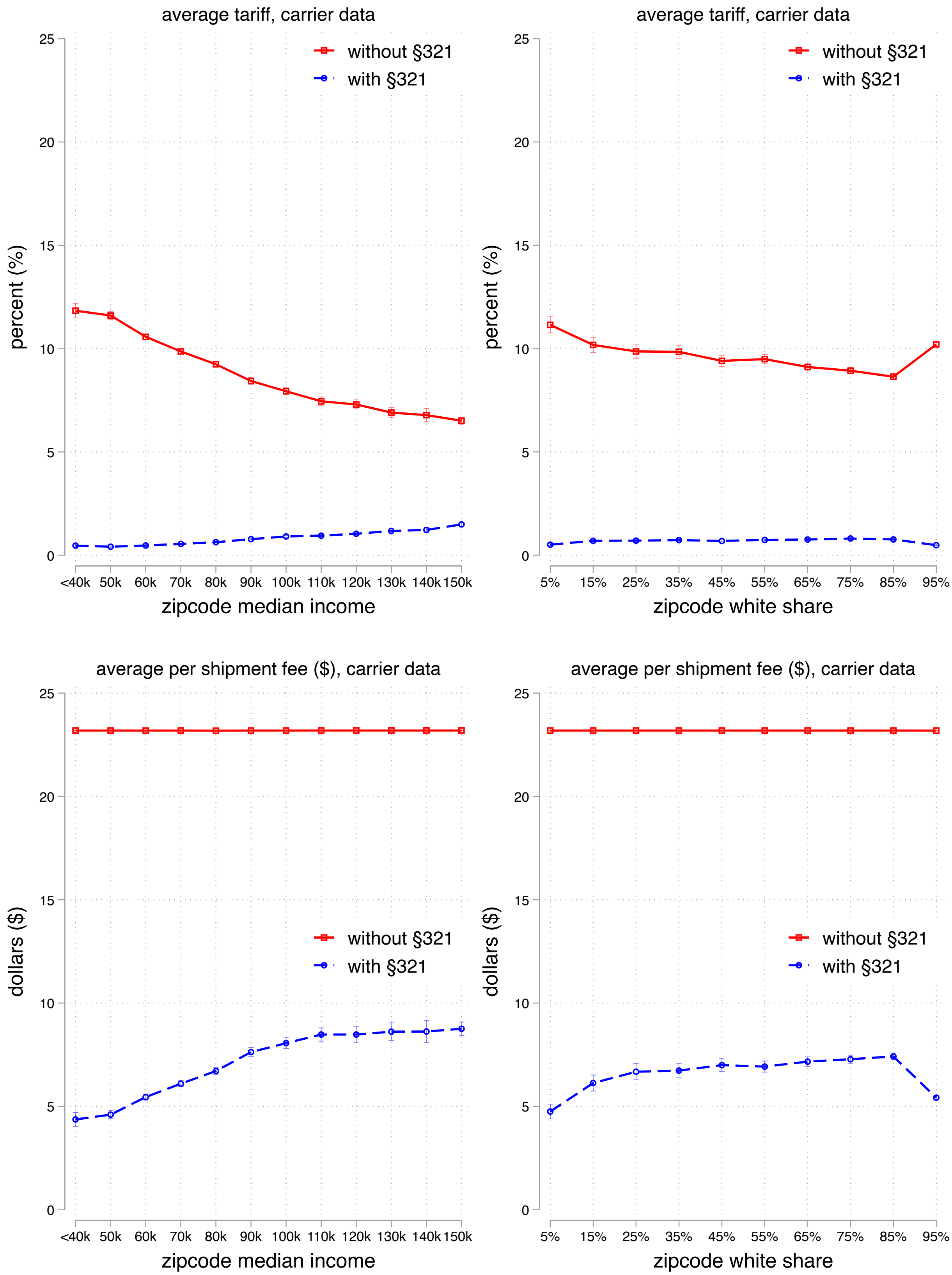
The top panel of Figure 3 reports the results. The blue series reports the incidence of tariffs with §321 in place, i.e., with tariffs applied to shipments only above $800. The left panel shows the tariff incidence is progressive: lower-income zip codes face lower tariffs than higher-income zip codes. The (value-weighted) average tariff on the lowest-income zip code is 0.5% compared to 1.5% for the richest ones. The average tariffs are low because de minimis shipments are a small fraction of direct shipments up to $5000, which is the cutoff we impose 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 becomes regressive. The poorest zip codes would face a 11.8% tariff, whereas the richest zip codes would face a 6.5% tariff. This finding echoes Acosta and Cox (2019), who find that the U.S. 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. The right panel shows the results against racial composition; the patterns suggest that minority zip codes would experience higher tariff increases if de minimis was to be abolished.

The bottom panel of Figure 3 repeats the analysis using the fee of $23.19 rather than the tariff. If §321 were removed, we apply that fee to all shipments. We again see a progressive incidence pattern under the current policy, and a lower average fee paid by the least-white zip codes.

Figure A.3 reports tariff incidence by zip code in the CBP data. A caveat is that the CBP sample does not contain HS codes (neither for the Type 86 de minimis entries nor for the above-$800 shipments), so we simply assign the median tariff by origin (within the HS chapters mentioned

[22] We obtain the median applied tariff by origin-month across these HS2 codes using public Census import records, and then average across months within the year.

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 U.S. 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,$5000] and a $0 fee for de minimis shipments. The red series applied $23.19 fee to all shipments. The thin bars are standard errors of means. Source: carrier data, 2021.

above). We then construct a zip code's tariff by constructing a value-weighted average using spending shares across origins. The figure reveals a similar pattern of a progressive tariff policy becoming 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 of §321 because of the higher shares from China in the CBP data.

The results in this section show how eliminating §321 will affect different consumer groups. Since low-income and less-white zip codes have higher expenditure shares on de minimis, and these packages are disproportionately purchased from China, eliminating de minimis will hurt these consumer groups relatively more by increasing the tariffs and fees on the goods they purchase. Our quantification in Section 6 calculates these impacts after estimating the framework we have presented in the previous section. To implement the model, we first need to identify bunching in the data, which we do next.

5 Evidence of Bunching

5.1 Main Results

Constructing the exact welfare impacts of §321 requires an estimate of the consumer demand elasticity, which, using the model, can be identified by the extent of bunching in the shipment densities. We estimate the size of bunching and the impact of the notch 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 U.S. versus OECD countries.

We first show the density of shipments in *levels* 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 separately on four subsamples of the data: shipments to destination $d = USA$ before and after March 2016, and shipments to $d = OECD$ before and after 2016:[23]

$$\ln c_{bodxt} = \alpha_{odxt} + \beta_b + \epsilon_{bodxt} \tag{22}$$

where c_{bodxt} is the count of packages in bin b from origin o, across all countries of origin, to destination $d \in \{USA, OECD\}$ by carrier $x \in \{A, B, C\}$ at time t (month-year). The α_{odxt} are carrier-origin-destination-time fixed effects that controls 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.

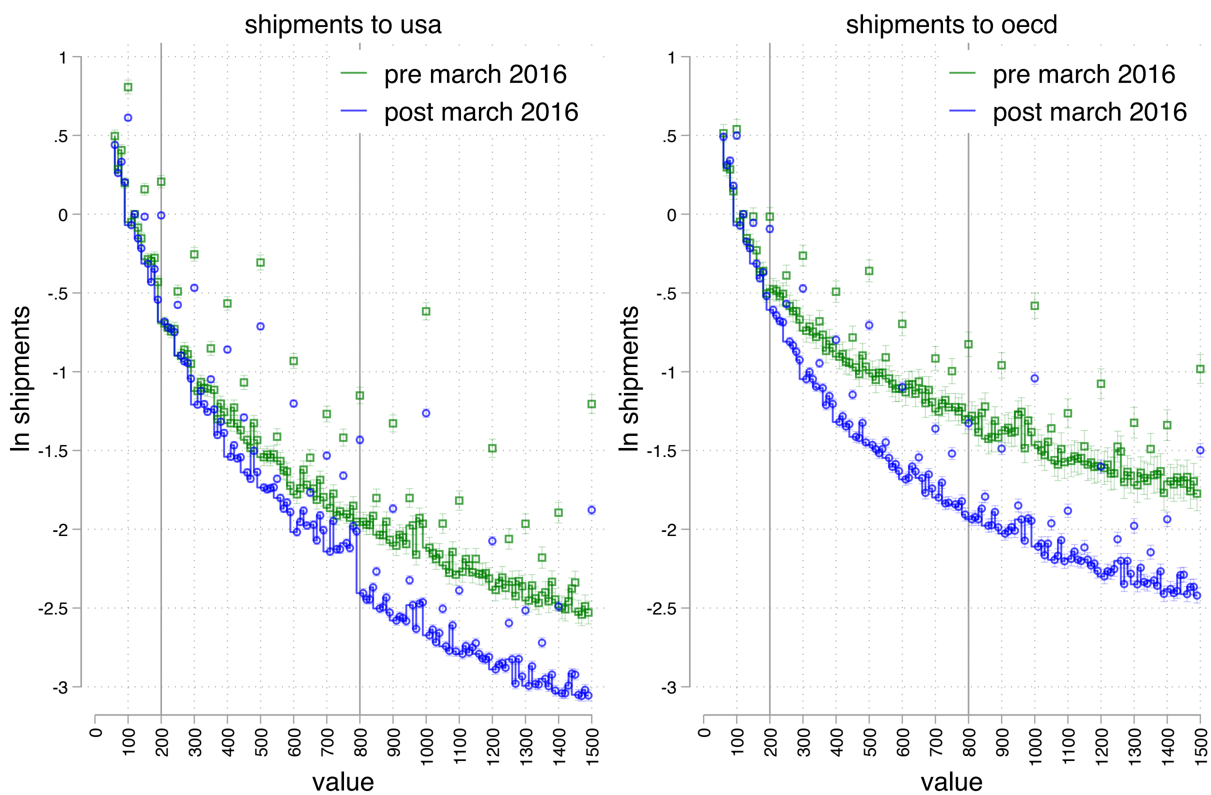
The key parameters are the bin fixed effects β_b, the shipment density after controlling for $odxt$ fixed effects. The leave-out bin is \$120. If the de minimis rule had no impact, we would expect a smooth density of the β_b parameters throughout the shipment values. The left panel for Figure 4 shows the estimates of β_b separately for two periods (before and after March 2016) for the USA bound shipments. In the pre-period (green) the density around \$800 appears smooth,

[23] This binning procedure places all shipments with $v \in (\$790, \$800]$ in the \$800 bin, shipments with $v \in (\$780, \$790]$ in the \$790 bin, and so forth.

while in the post-period (blue) there is evident bunching right below \$800, with a subsequent drop in shipments above the notch; there are 34% fewer shipments \$100 above the notched compared to \$100 below the notch. Although we observe bunching, it is not exactly (and only) at \$800, nor is there a distinct "hole" right above the notch; these features motivate introducing exporters who optimize with frictions in the model. Around \$200, corresponding to the tax in the pre-period, pre-period bunching is not clearly visible at this scale but is noticeable in the differences-in-differences below.

The right panel of Figure 4 shows the densities of shipments to the OECD. Here, both densities seem smooth around both \$200 and \$800 in both periods. This is expected since shipments to these destinations are not subject to the USA thresholds but rather thresholds ranging from \$15 (Canada) to \$750 (Australia), the average being \$180. In both panels, outliers are clustered at some round numbers, a phenomenon partially controlled for in the diff-in-diff specification below.

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 (22). 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. Standard errors clustered by origin-time; error bars denote 95% confidence intervals. Source: carrier data, all years.

A difference-in-difference specification allows us to better identify the impact of the threshold. We implement this specification by pooling over both periods and destinations to run:

$$\ln c_{bodxt} = \alpha_{odxt} + \beta_b \times \text{USA}_d \times \text{post}_t + \epsilon_{bodxt} \quad (23)$$

where now β_b is the pre-period 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 estimates. The figure shows a discrete jump in shipments within the $200-$800 value range. This pattern is what we expect, given that the shipments in this range experience a tariff and administrative fee cut as they are included within §321 after March 2016. The drop to the left of $200 is consistent with bunching at $200 in the pre-period going away in the post-period. Similarly, the jump at $800 is consistent with bunching $800 in the post-period, which was not present in the pre-period. The drop in shipments above $800 is large: there are on average 24% fewer shipments $100 above the notch versus below.

Figure 5B reports specification (23) separately for shipments from China ($o = CHN$, blue) and from the rest of the world ($o \neq CHN$, 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 39% larger relative to $700-$750. Going $100 above the notch results in 63% fewer shipments relative to $100 below. The pattern is similar for shipments from RW, but not as large (as one would expect, given that import tariffs on RW did not increase over time as they did on China). 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}).[24]

5.2 Alternative Explanations

Item Restructuring The bunching and subsequent drop in density at the threshold could partly be explained by adjusting the number of items per package. The law explicitly prohibits "restructuring"–sending items from a single invoice in multiple shipments–but a consumer could spread a transaction with multiple items into multiple transactions with fewer items each. This strategy would entail both shipping and convenience costs for the consumer; if these costs are less than the taxes passed through to consumers, we may see a jump in shipments below the threshold resulting from package composition rather than reductions in item values.[25] We can explore the likely extent of this strategy using the data from Carriers A and C, who provided information on the reported number of items per package.

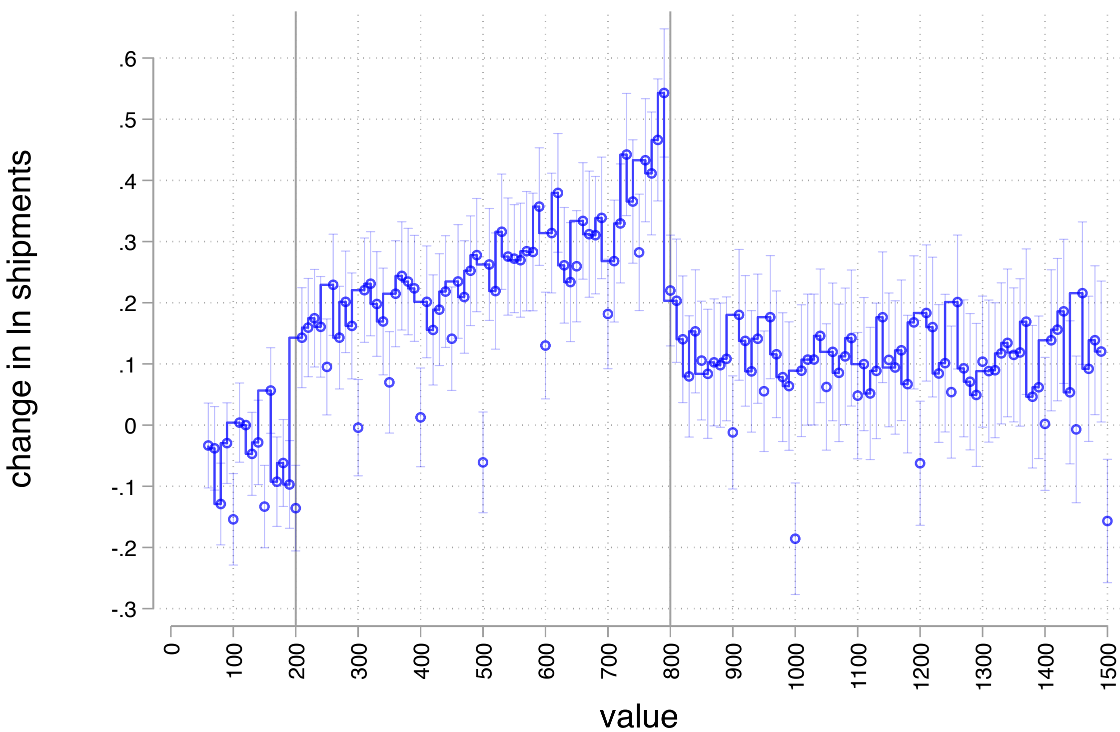
We provide two pieces of evidence suggesting that this type of restructuring is unlikely a major force driving bunching. First, the magnitude of item restructuring around the threshold appears small. The top panel of Figure A.6 re-estimates (22) using the average number of items per shipment as the dependent variable. The pre-2016 (green) series shows that packages $100

[24] We also report a specification that aggregates over carriers and across all rest-of-the world (RW) origins which collapses the data to the two-origin (CHN, RW)-destination-time level; this collapsed dataset masks the carriers' identities and can be released publicly. We then run the analogous difference-in-difference specification, and report the results in Figure A.5. The figure reveals a similar impact of the notches as seen with the granular data.

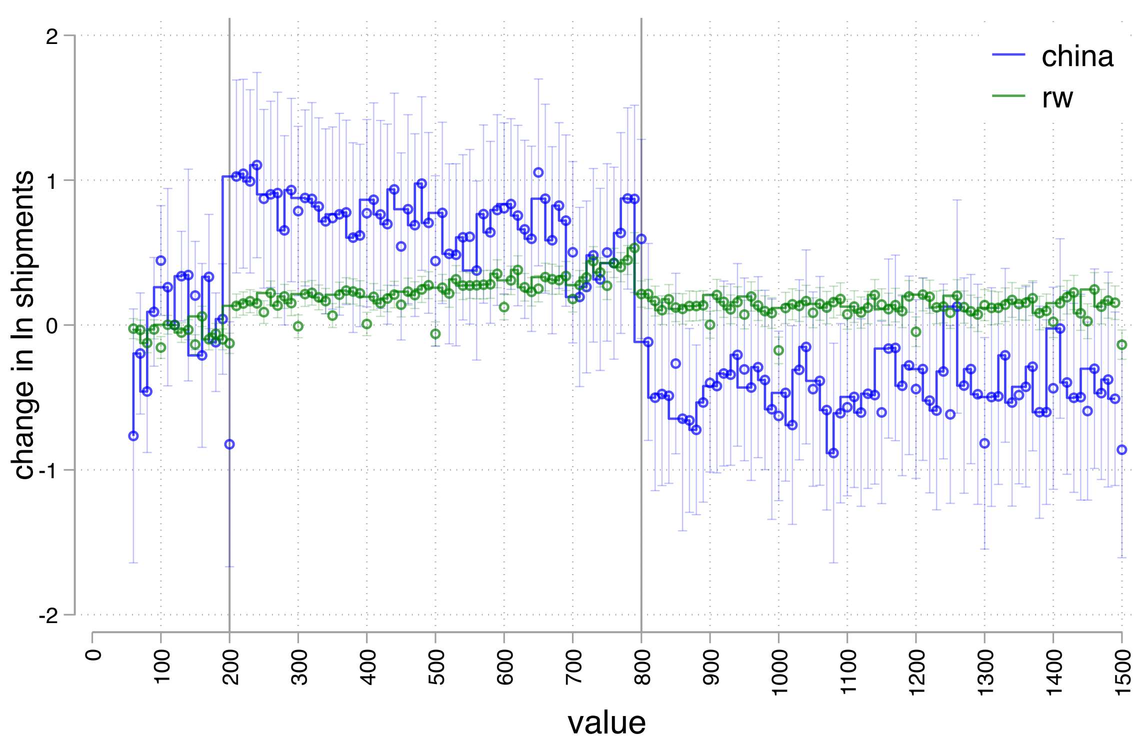
[25] It is unclear how salient the de minimis threshold is for consumers. Shein and Temu do not flag at check-out that packages above $800 are potentially subject to duties, while eBay and Etsy do.

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 (23), 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 (23) separately for shipments from China and RW. Grey vertical lines denote §321 thresholds before and after March 2016. The leave-out bin is $120. Standard errors clustered by origin-time; error bars denote 95% confidence intervals. Round numbers not included in the connected line to improve visualization. Source: carrier data, all years.

above the threshold have 4% *fewer* items than \$100 below the threshold, while post-2016 (blue) shows that packages \$100 above the threshold have only 3% *more* items. The bottom panel reports the diff-in-diff (across destinations and over time), and confirms that the magnitude of changes in items is small around the thresholds. Moreover, the opposite patterns observed across periods (the increase in items per package at the \$200 threshold and the decrease at the \$800 threshold) make it difficult to come up with a unifying explanation based on item restructuring at the threshold.

Second, 1- or 2-item packages account for most of value and shipments in our sample.[26] Among these shipments, restructuring can only happen when 2-item packages are split into two single-item packages. Without any item price reduction, this restructuring is unlikely to result in bunching except if (only) items within 2-item shipments were disproportionally priced very close to \$800, an unlikely event. Therefore, if item price reductions were absent but item restructuring was present, we should not observe bunching at \$800 among single-item packages. However, Figure A.7A shows very similar bunching pattern when re-estimating (23) on single-item packages.

Product Mix It is possible that the mix of products changes at the notch due to the additional trade costs if certain products are more sensitive to these costs. To assess this concern, we re-examine the density of single-item shipments controlling for product composition. Since we do not typically observe HS codes below the notch, we cluster the item descriptions that accompany the shipments in Carriers A and C into 100 product groups p , and add α_{odxpt} FEs to (23). Figure A.7B reports the change in density; the bunching patterns are similar to the baseline results, suggesting that the notch does not trigger changes in product composition.

Carrier Composition Shippers could switch to a different carrier above \$800 (e.g., decide to ship via sea instead of air), in which case the drop above the notch would reflect a switch in carrier rather than a true change in imported shipments.[27] To address this concern 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. 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, we can only examine the analog of the cross-sectional regression in (22) on this sample. Figure A.8A 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 results in 36% fewer shipments compared to \$100 below. As the CBP sample contains shipments handled by the universe of carriers, this result minimizes the concern that bunching simply reflects reallocation into other carriers. Figure A.8B shows that the drop in shipments from China between these two intervals is even starker, with 66% fewer shipments.

[26] 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; and two-item packages accounted for 7.5% of shipments and 7.4% of value.

[27] It is possible that shipping costs also change discretely above \$800, but the carriers confirmed this is not the case.

Thus, the impact of the notch appears in official CBP data (though we do not use this series to calibrate the tariff elasticities since we do not observe the corresponding control densities).

Household versus Business Composition 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 households' share of shipments using carrier A's data. Figure A.9 re-estimates (23) with the share of shipments imported by households within each bin. The figure indicates that the household share near the threshold is only 4% lower compared to the $$120 leave-out, and there is no discontinuous change beyond the threshold.

6 Consumer Welfare Impacts of De Minimis Imports

This section analyzes the aggregate and distributional and implications of a counterfactual policy change that eliminates §321. In this scenario, the tariff on shipments arriving from China is 15.3%, and from RW it is 2.1%. All shipments incur the $23.19 administrative fee.

6.1 First-Order Approximation

We first show a first-order approximation to the distribution of consumer losses. This approach is "model-free" in that it only relies on the variation in observed spending shares across consumer groups and on the assumption of full pass-through of tariffs and fees to prices. Thus, the spending patterns across groups we discussed in Section 4.4 ground the distributional impacts of §321.

In aggregate, the 2021 shares of de minimis imports coming from China and from RW were 37% and 63%, respectively. The average shipment value in the carrier data was $134, implying an average ad-valorem equivalent tax to the administrative fee of 17%. Combining this rate with the tariff, prices for de minimis shipments would rise in aggregate by roughly 24.2%. To a first order approximation, keeping spending and goods composition constant, the consumer cost of de minimis imports would increase by:

$$\underbrace{\$45.5\text{b}}_{\text{2021 DM}} \times \underbrace{\left[\underbrace{15.3\% \times 37\%}_{\uparrow\text{price CHN imports}} + \underbrace{2.1\% \times 63\%}_{\uparrow\text{ price RW imports}} + \underbrace{\$23.19/\$134}_{\text{advalorem eq fee}} \right]}_{24.2\%}, \tag{24}$$

which corresponds to an aggregate consumer loss of $11.0b, or $34 per person. The spending shares from the CBP sample imply even larger losses, $25.7b or $80 per person. This difference is due to the reported share of de minimis shipments from China being higher in the CBP data (67%).

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 in Proposition 1; and, "naive" firms who ignore these benefits and simply price without realizing a de minimis policy is in effect. Adding naive firms, who could make extra profits by bunching, broadly captures plausible mechanisms leading to imperfect bunching, such as attention costs or rigidities in price adjustments.

Henceforth, we index firm types according to their pricing decisions with an upper-script $j = S, N$ (sophisticated or naive). Sophisticated firms use the pricing rule $v_o^S(z)$ presented in 13, while naive firms use the following pricing rules without bunching:

$$v_o^N(z) = \begin{cases} v_{L,o}(z) & z < z_{L,o}, \\ v_{H,o}(z) & z \geq z_{L,o}. \end{cases} \tag{25}$$

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 Consumer Welfare Measurement

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

$$ev^{\omega} = \underbrace{\frac{1}{\kappa}\left(\left(\hat{P^{\omega}}\right)^{-\kappa} - 1\right) e^{\omega}}_{\equiv \Delta e^{\omega}} + \Delta tr^{\omega}, \tag{26}$$

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

As usual, 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.37), the change in the overall price index is

$$\hat{P^{\omega}} = \left(\sum_o \lambda_o^{\omega} \left(\hat{P_o^{\omega}}\right)^{1-\gamma}\right)^{\frac{1}{1-\gamma}}, \tag{27}$$

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.

To obtain the change in the price index for direct goods from o among ω consumers, we first express (3) in relative changes and then use from (13) that prices depend only unit costs. Then:

$$\hat{P_o^{\omega}} = \left(\sum_{j=S,N} \int_z \lambda_o^{\omega,j}(z) \, \widehat{v_o^j(z)}^{1-\sigma_o} dz\right)^{\frac{1}{1-\sigma_o}} \tag{28}$$

where

$$\lambda_o^{\omega,j}(z) = \left(\frac{v_o^j(z)}{P_o^\omega}\right)^{1-\sigma_o} h_o^{\omega,j}(z) \text{ for } j = S, N \tag{29}$$

is the share of all varieties sold by type-j firms (sophisticated or naive) with unit cost equal to z in the total direct import expenditures from origin o by consumers in group ω.

As discussed earlier, there can be any correlation between unit costs and demand shocks. This correlation is key to assessing 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 the 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 the model outcomes given the policies $(\tau_{o,} v_{DM})$ including the tariff revenue generated by group ω, as shown in appendix condition (A.49). 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.

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) and the substitution elasticities σ_o for each origin. The US-level distribution $h_o^{US,j}(z)$ is defined as the aggregation of the group-specific distributions $h_o^{\omega,j}(z)$. 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 diff-in-diff estimated in the previous section. We implement the following steps 1 and 2 for a given σ_o, and then search over σ_o to match the change in bunching estimated in the diff-in-diff of the previous section. Given σ_o, step 3 obtains the elasticity γ between origins.

Step 1: Matching the Density and Share of Sophisticated post-2016 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 the naive and sophisticated densities are proportional to each other within each origin o and import group ω, with constant δ_o^ω:

$$h_o^{N,\omega}(z) = \delta_o^\omega h_o^{S,\omega}(z). \tag{30}$$

Conditional on σ_o and the post-2016 policies ($\tau_{CHN}^{post} = 15.3\%$, $\tau_{RW}^{post} = 2.1\%$, $T^{post} = \$23.19$, $v_{DM}^{post} = \$800$), we compute the thresholds $z_{L,o}$ and $z_{H,o}$ using (14) and (15). With this information, we characterize in the model the histogram of shipments across bins of value v as function of the unobserved densities. In particular, as shown in the Appendix A, the aggregate number of packages imported to the U.S. from origin o on the interval $[v + \Delta_v]$ in a given time period is:

$$\Delta N_o^{US}(v) = \begin{cases} v^{-\sigma_o}\left(1+\delta_o^{\omega}\right)\left[D_o^{US} h_o^{US,S}\left(z_{L,o}(v)\right)\right]\frac{\sigma_o-1}{\sigma_o}\Delta_v & v < v_{DM}, \\ v_{DM}^{-\sigma_o}\int_{z_L}^{z_H}\left[D_o^{US} h_o^{US,S}(z)\right]dz & v = v_{DM}, \\ v^{-\sigma}\delta_o^{\omega}\left[D_o^{US} h_o^{US,S}\left(z_{H,o}(v)\right)\right]\frac{\sigma_o-1}{\sigma_o}\left(1-\tau_{H,o}\right)\Delta_v & v \in \left(v_{DM}, v_{H,o}(z_H)\right], \\ v^{-\sigma}\left(1+\delta_o^{\omega}\right)\left[D_o^{US} h_o^{US,S}\left(z_{H,o}(v)\right)\right]\frac{\sigma_o-1}{\sigma_o}\left(1-\tau_{H,o}\right)\Delta_v, & v > v_{H,o}(z_H). \end{cases} \tag{31}$$

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. According to the model, in the dominated region $(v_{DM}, v_{H,o}(z_H)]$ there should be no shipments without naive firms. Therefore we jointly parameterize the function $D_o^{US} h_o^{US,S}(z)$ (assumed to take a power form) to match the observed $\Delta N_o^{US}(v)$ outside the dominated region $(v_{DM}, v_{H,o}(z_H)]$ and δ_o^{ω} (which regulates the importance of naive firms) to exactly match the observed number of shipments within that region.[28]

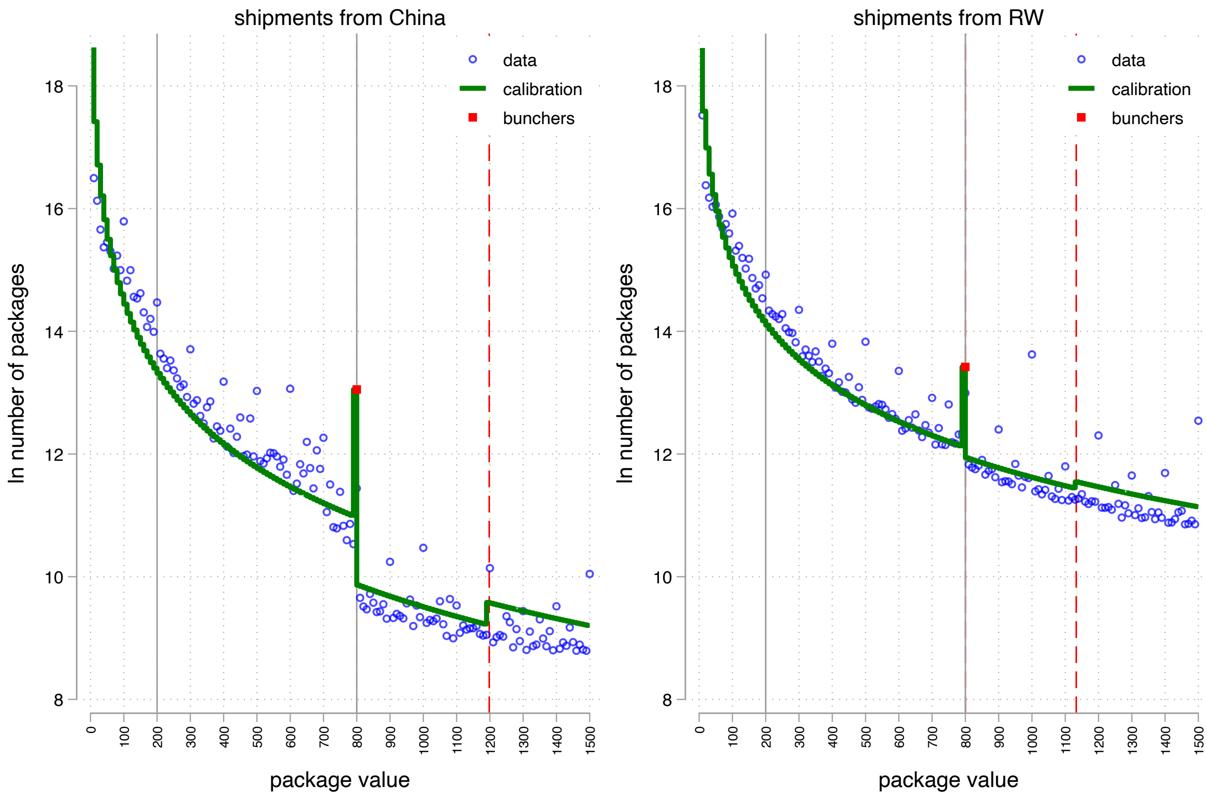
Figure 6 shows the histograms implied by the calibrated density at the estimated value for the elasticities σ_o (obtained in the next step). In the absence of "naive" firms, we would observe a hole in the dominated region corresponding to the area in between the vertical dashed lines. The procedure implies that "sophisticated" firms ship 32% of packages and 31% 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. 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 the Post-2016 to the Pre-2016 Period 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 diff-in-diff specification in (23), 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 7 shows the outcome of step 2 for China. The blue series in the left panel shows the post-2016 calibrated histogram (the same as the left panel of Figure 6), and the green series is the model-based counterfactual from rolling the economy back to pre-2016. The right panel shows

[28]This procedure recovers the quality-adjusted density $h_o^{US,S}(z)$ up to the scaling factor D_o^{US}. However, to implement counterfactuals, as shown in (28), 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 6: CALIBRATED DENSITY



Notes: Figure shows the actual histogram (blue series), and the model-implied histogram at the calibrated values of the elasticities: $\sigma_{CH} = 4.42$ (se 0.61), $\sigma_{RW} = 1.81$ (se 0.48). 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 $5000, but the graph displays the density up to $1500 to improve visualization.

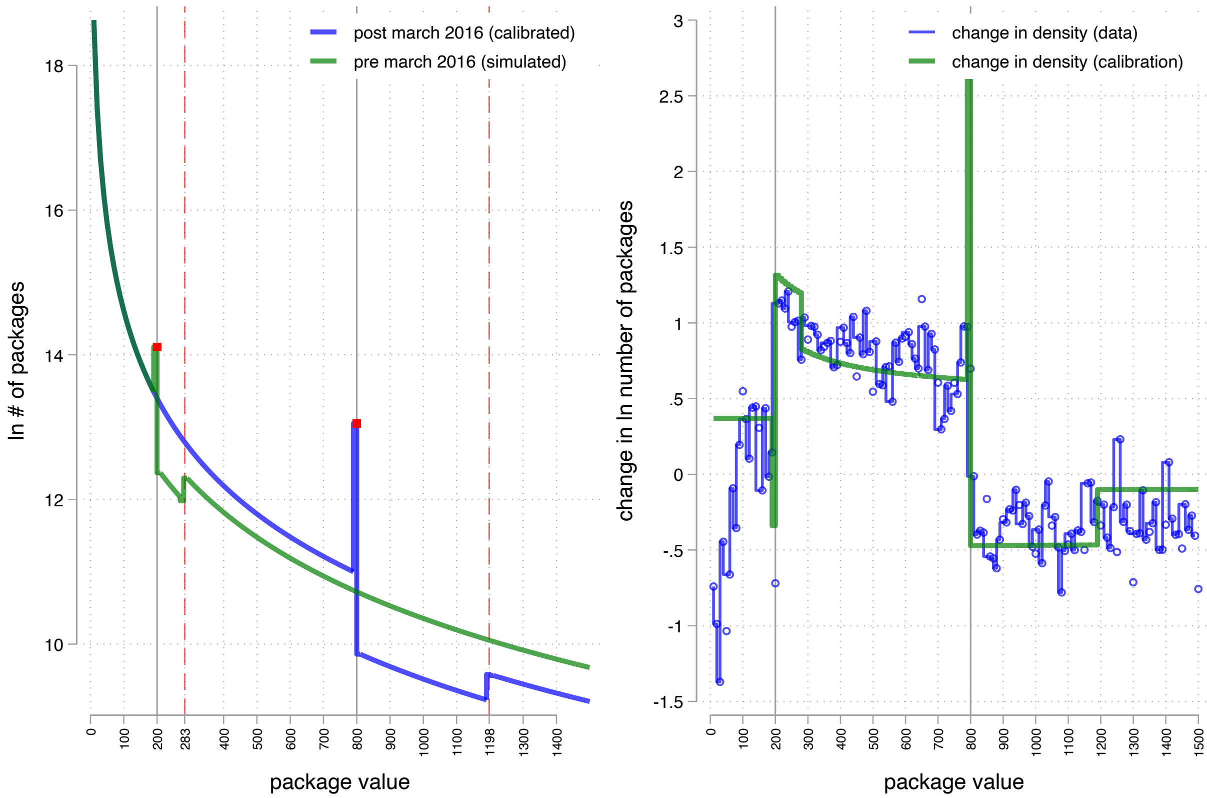
the difference between these two series (post minus pre) in green, corresponding to the diff-in-diff within the model, and overlays in blue the empirical diff-in-diff estimate for Chinese shipments (from Figure 5B). Increasing the threshold from $200 to $800 leads to a sharp drop in the mass to the right 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.

The procedure yields $\sigma_{CH} = 4.42$ (se 0.61) for China, and $\sigma_{RW} = 1.81$ (se 0.48) for RW.[29] 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,

[29]Standard errors are calculated by constructing a 25 bootstrap samples from the shipment data. For each sample, we run specification (23) and implement the full model calibration, and then construct the standard errors for the parameters and welfare numbers.

FIGURE 7: PRE AND POST DENSITIES FOR CHINESE IMPORTS, MODEL AND DATA



Note: The 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.

when policies change, the change in the value of direct-to-consumer shipments from origin o to group ω is:

$$\Delta \ln E_o^\omega = \eta^\omega + \eta_o + (1-\gamma)\,\Delta \ln P_o^\omega + \varepsilon_o^\omega, \tag{32}$$

where 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. 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-ω specific because the spending in 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 shipment values). We can only back out a composite of demand shocks and the measure of firms' pricing at each given value, as discussed in the previous step.

However, having calibrated σ_o and the exporter densities in the post-2016 period, we can generate the model-based $\Delta \ln P_o^\omega$ corresponding to rolling policies back to pre-2016 while keeping demand shifters constant in the post-period, with the associated model-based change in expenditures $\Delta \ln E_o^\omega$ from the post- to pre-period. Moreover, the model-based price index change $\Delta \ln P_o^\omega$ for group ω is strongly correlated with that group's share of spending above the de minimis threshold (thus, subject to tariffs) in the post-period times the tariff change. This reasoning motivates an indirect indifference approach to estimate γ. Starting from the calibrated model in the post-2016 period, we guess a value of γ, reduce tariffs to the pre-period, and run the following regression on model-generated outcomes:

$$\Delta \ln \left(\frac{E^\omega_{o,pre}}{E^\omega_{o,post}} \right) = \alpha^\omega + \alpha_o + \beta \lambda^\omega_{>800,post} * \Delta \ln \left(\frac{\tau_{o,pre}}{\tau_{o,post}} \right) + \varepsilon^\omega_o. \tag{33}$$

where $\lambda^\omega_{>800,post}$ is group ω share of spending above the de minimis threshold in the post-period. For each γ, estimating this regression from the model yields an estimate $\beta(\gamma)$. Running (33) in the data yields $\beta = -1.78$ (se 0.61). Figure A.10 shows the value of $\hat{\beta}$ estimated from the data and the model-based $\beta(\gamma)$ estimated at each value of gamma. The intersection pins down the choice of γ, giving $\gamma = 19.59$ (se 0.96). This high elasticity suggests a high substitutability in direct imports across origins. It is higher than the within-origin across-variety elasticity (σ), which is consistent with the fact that, from an origin, the direct shipments span large price differences, likely reflecting variation in product attributes and quality.

6.5 Exact Consumer Welfare Impacts

We first report the aggregate welfare impacts of eliminating §321. Starting from the post-2016 equilibrium, we solve for the price distribution under a counterfactual policy imposing tariffs and fees on all shipments using the results from Proposition 1. We then compute the welfare outcomes for both the aggregate U.S. and by consumer group ω.[30] For the $\omega-$specific results we need to obtain a quality-adjusted density $h_o^{S,\omega}(z)$ by consumer group ω and origin o, which we obtain by re-doing step 1 from the previous subsection to match the observed histogram by group and origin, $\Delta N_o^\omega(v)$ defined in (31).[31] To compute the equivalent variation (26) we also need the elasticity κ (substitution 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, which excludes de minimis shipments. We show that the results are robust to a range of values of κ around this value.

Aggregate Impacts 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 using the parameters we estimate from the moments of the carrier data). The losses hinge on the customs fee that de minimis packages would face. As discussed in Section 2, we arrive at a benchmark per-shipment administrative fee of \$23.19 using estimates of broker fees across

[30] The level of demand shifters for direct imports is chosen such that aggregate spending in de minimis is normalized to match the 2021 level of spending in de minimis goods. When implementing policy counterfactuals 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 the change in transfers to each group is equal to the group-specific tariff revenue defined in (A.50).

[31] 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..

Table 3: Aggregate Impacts of Eliminating §321

	carrier data			CBP data		
administrative fee	consumer ($b)	tariff ($b)	welfare ($b)	consumer ($b)	tariff ($b)	welfare ($b)
$0	-1.8	0.7	-1.1	-3.5	1.7	-1.7
	(0.01)	(0.1)	(0.1)	(0.04)	(0.1)	(0.03)
$10	-5.0	0.5	-4.5	-9.8	1.8	-8.0
	(0.3)	(0.1)	(0.2)	(0.5)	(0.5)	(0.1)
$23.19 (benchmark)	-11.5	0.6	-10.9	-18.1	5.1	-13.0
	(2.1)	(0.3)	(1.8)	(1.0)	(2.9)	(2.0)
$30	-15.4	0.8	-14.6	-20.8	6.1	-14.7
	(2.2)	(0.5)	(1.7)	(0.9)	(1.9)	(2.8)

Notes: Table reports the impacts of eliminating §321 at different per-shipment customs fees. Each case assumes parameters: $\{\sigma_{CHN}, \sigma_{RW}, \gamma, \kappa\} = \{4.42, 1.81, 19.59, 0.19\}$. The left (right) panel reports aggregate impacts using the carrier (CBP) data. Bootstrapped standard errors reported in parentheses.

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 changes to the efficiency of brokerage services like automated HS classification). We therefore report impacts with fees ranging from $0 to $30.

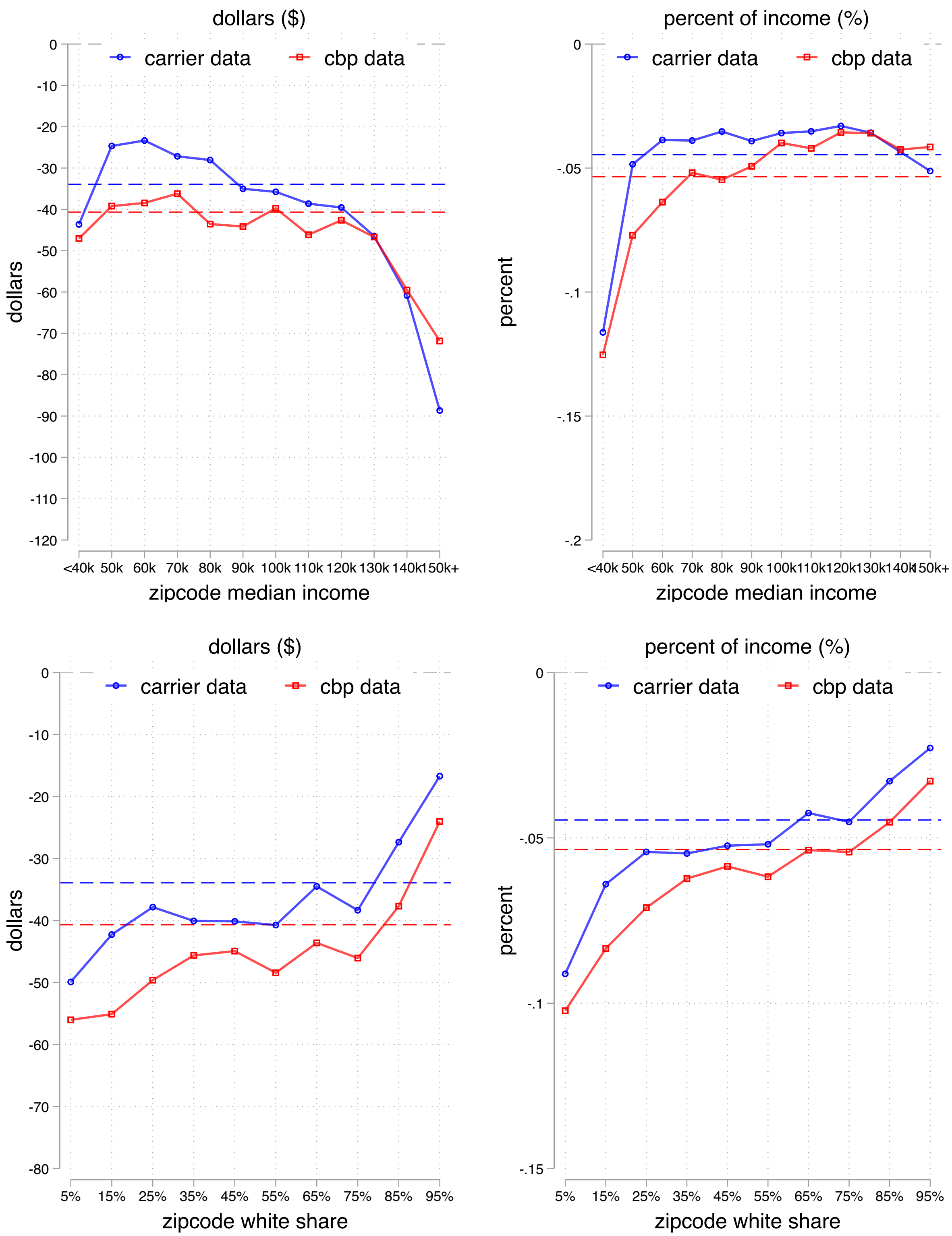
Table 3 reports the aggregate losses from the carrier data. The first column reports the losses to consumers from the increase in prices (the first term in (26)), the second column reports the tariff revenue gain (the second term in (26)), and the third column–the consumer welfare impact–is the sum of the two. At the benchmark fee, the aggregate consumer welfare loss is $10.9 billion (se $1.8b), or $34 per person (se $6) and $136 per family (se $23). As a comparison, Fajgelbaum et al. (2020) estimate the sum of consumer cost and tariff revenue gain of the 2018 U.S. 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 in proportion to the fees : reducing the fee to $10 per shipment would result in a welfare loss of $4.5 billion (se $0.2b), and a $30 fee would magnify the welfare loss to $14.6 billion (se $14.6b). Recall that the fee is not rebated back to consumers (it enters as a higher marginal cost of foreign exporters) which is why the 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 $13.0 billion (se $2.0b). Again, this is due to the higher import shares from China in CBP data.[32]

[32] Different values of κ impact the level of the welfare effects but not the distributional bias. Moreover, the aggregate welfare impacts are not very sensitive to considerable changes in κ.

Increasing from $\kappa = 0.19$ to $\kappa = 1.38$ (corresponding to matching twice the estimated elasticity of substitution between imports and domestic goods in Fajgelbaum et al. (2020)) reduces the aggregate loss from eliminating de minimis from $10.9 billion to $10.4 billion, and setting $\kappa = 10.9$ (corresponding to matching ten times that estimate) lowers the loss to 7.5 billion.

FIGURE 8: DISTRIBUTIONAL IMPACTS FROM ELIMINATING §321



Notes: Figure reports ev^{ω} defined in (26) against zip code characteristics. The left panels report welfare impacts in per-capita dollars and the right panel scales by median household income. Top panel reports by zip code median household 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: $\{\sigma_{CHN}, \sigma_{RW}, \gamma, \kappa\} = \{4.42, 1.81, 19.59, 0.19\}$. The blue (red) series denotes estimates from carrier (CBP) data; aggregate loss denoted by the horizontal dash line.

Distributional Impacts We next assess the distributional welfare impacts across consumer groups. Figure 8 shows the equivalent variation–the welfare impacts of the policy change.[33] The top panel reports the welfare estimates across zip code income. Our estimates imply that in zip codes with median household income under $40k, per capita welfare would decline by $44. This compares with a $36 decline for zip codes with $100k median income, and a decline of $89 for the richest zip codes. As a share of income, the corresponding declines for low, middle-, 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.

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 $47, compared to a $40 decline for zip codes with $100k income, and a decline of $72 for the richest zip codes. Thus, the CBP sample also suggests that the current §321 policy benefits lower-income consumers more.

The bottom panel of Figure 8 analyzes welfare losses by zip code white share. We find that welfare in zip codes with 5% white households would experience a decline of $50. This compares with a decline of $40 decline for zip codes with a 45% white share and a decline of $17 for the zip codes with a 95% white households. As a share of income, the corresponding declines for low, middle, and high white shares are 0.09%, 0.05%, and 0.02%. Using the CBP sample, the corresponding per capita welfare decline in the least white zip codes would be $56 compared to a $24 decline in the most white zip codes. Eliminating §321 would raise the cost of living disproportionately more for non-white households.

Figure A.12 reports the distributional impacts for fees ranging from $0 to $30 per shipment in both the carrier and CBP data. The per-person welfare impact scales with the fees, but the relative incidence across consumer groups remains similar for different values of the fees. The main message of the table is that the quantitative impacts of eliminating §321 hinge on the size of the administrative fee, but the qualitative impacts across consumer groups remain unchanged.

7 Conclusion

The rise of online platforms has led to a rapid growth in direct-to-consumer shipments worldwide. Consumers can now directly import goods instead of buying them from domestic or online retailers who use domestic warehouses. This shift has been facilitated both by logistics and E-commerce technologies and by "de minimis" policies, which exempt low-value shipments from tariffs and complex customs procedures. In 2023, the U.S. processed one billion shipments valued at $54.5 billion through the de minimis channel. Many countries are debating whether or not to roll back their de minimis policies, with the U.S., E.U., and several other countries taking significant

[33]Figure A.11 reports the first-order approximation to consumer welfare loss across zip code demographics stemming exclusively from higher prices and without including tariff revenues. The pattern is quite similar to the exact calculations, but the first-order losses are larger because they do not account for tariff revenue redistribution nor fewer shipments purchased as a result of higher prices.

steps in this direction in mid 2024.

This paper provides a framework for assessing the value of de minimis imports. We establish conditions under which non-zero tariffs with a threshold dominate free trade because of term-of-trade gains generated through bunching. Using data on millions of individual shipments from three global carriers that capture de minimis shipments to the U.S., we find that these imports are relatively important for lower-income zip codes. As a result, §321–the provision with U.S. trade policy that codifies the de minimis exemption–is a pro-poor trade policy: it effectively turns a regressive tariff schedule into a progressive one. Our analysis quantifies the welfare impacts of eliminating §321 on a representative consumer and shows doing so would disproportionately hurt low-income 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

$$x^{\omega} = \left(\sum_{o} \left(A_{o}^{\omega}\right)^{\frac{1}{\gamma}} \left(x_{o}^{\omega}\right)^{\frac{\gamma-1}{\gamma}} \right)^{\frac{\gamma}{\gamma-1}}, \tag{A.34}$$

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

$$x_{o}^{\omega} = \left(\int_{i \in \Omega_{o}} \left(a_{i}^{\omega}\right)^{\frac{1}{\sigma_{o}}} \left(n_{i}^{\omega}\right)^{\frac{\sigma_{o}-1}{\sigma_{o}}} di \right)^{\frac{\sigma_{o}}{\sigma_{o}-1}}, \tag{A.35}$$

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

$$e^{\omega} = A^{\omega} \left(P^{\omega}\right)^{-\kappa}. \tag{A.36}$$

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

$$E_{o}^{\omega} = A_{o}^{\omega} \left(\frac{P_{o}^{\omega}}{P^{\omega}} \right)^{1-\gamma} L^{\omega} e^{\omega}, \tag{A.37}$$

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

$$L^{\omega} n_{i}^{\omega} = a_{i}^{\omega} D_{o}^{\omega} v_{i}^{-\sigma_{o}}, \tag{A.38}$$

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

$$D_{o}^{\omega} = E_{o}^{\omega} \left(P_{o}^{\omega}\right)^{\sigma-1}. \tag{A.39}$$

Combining (1)-(A.39), the total number of packages shipped by firm i when it sets package value equal to v_i is:

$$\begin{aligned} N_{i} &\equiv \sum_{\omega} L^{\omega} n_{i}^{\omega} \\ &= \left(\sum_{\omega} a_{i}^{\omega} D_{o}^{\omega} \right) v_{i}^{-\sigma_{o}} \\ &= \left[\sum_{\omega} a_{i}^{\omega} \underbrace{L^{\omega} A^{\omega} A_{o}^{\omega} \left(P^{\omega}\right)^{\gamma-\kappa-1} \left(P_{o}^{\omega}\right)^{\sigma-\gamma}}_{\equiv D_{o}^{\omega}} \right] v^{-\sigma_{o}}, \end{aligned} \tag{A.40}$$

corresponding to (6).

Welfare From (1) and (A.36), the indirect utility of each consumer in group ω can be written:

$$u^{\omega} = \frac{1}{\kappa} e^{\omega} + y^{\omega} + t^{\omega} \tag{A.41}$$

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

$$e^{\omega} = \arg\max_{e} u^{\omega} \left(\frac{e}{P^{\omega}} \right), \tag{A.42}$$

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 (26), where we have used that from (A.36) that

$$\hat{e}^{\omega} = \left(\hat{P}^{\omega}\right)^{-\kappa}. \tag{A.43}$$

Proof of Proposition 1 The pricing rules $v_{L,o}(z)$ and $v_{H,o}(z)$ in (17) follow from standard CES profit maximization. Below $z_{L,o}$, the firm will clearly set $v_{L,o}(z)$ because $\pi_i^L(z) > \max\left(\pi_i^H(z), \pi_i^B(z)\right)$. Above $z_{L,o}$, the firm will choose the pricing corresponding to $\max\left(\pi_i^H(z), \pi_i^B(z)\right)$. At $z_{L,o}$, we must have $\pi_i^H(z) < \pi_i^B(z)$ because at that point $\pi_i^B(z) = \pi_i^L(z)$. However, $\lim_{z\to\infty} \pi_i^B(z) < 0 < \lim_{z\to\infty} \pi_i^H(z) = 0$ so the two profit functions will intersect. Using the definitions of $\pi_i^H(z)$ and $\pi_i^B(z)$, every point satisfying $\pi_i^B(z_{H,o}) = \pi_i^L(z_{H,o})$ must satisfy (15).

Proof of Proposition 2 To obtain (21), we start by computing the total differential of u in (17) and using (18), to obtain:

$$du = -e\frac{dP}{P} + dtr. \tag{A.44}$$

From the definition of the price index in (19), and using (14) and (12), we obtain:

$$\begin{aligned}\frac{dP}{P} =& \frac{1}{1-\sigma}\left(\left(\frac{v_{DM}}{P}\right)^{1-\sigma} - \left(\frac{v_H(z_H;\tau)}{P}\right)^{1-\sigma}\right)h(z_H)\,dz_H + \left(\frac{v_{DM}}{P}\right)^{1-\sigma}\frac{dv_{DM}}{v_{DM}}\int_{z_L}^{z_H} h(z)\,dz \\ &+ \frac{d\tau}{1-\tau}\int_{z_H}^{\infty}\left(\frac{v_H(z;\tau)}{P}\right)^{1-\sigma} h(z)\,dz.\end{aligned} \tag{A.45}$$

In turn, totally differentiating tariff revenue (20) we obtain:

$$\begin{aligned}dtr =& d\tau\int_{z_H}^{\infty} e\left(\frac{v_H(z;\tau)}{P}\right)^{1-\sigma} h(z)\,dz + \tau\int_{z_H}^{\infty} d\left[e\left(\frac{v_H(z;\tau)}{P}\right)^{1-\sigma}\right] h(z)\,dz \\ &- \tau e\left(\frac{v_H(z_H;\tau)}{P}\right)^{1-\sigma} h(z_H)\,dz_H.\end{aligned} \tag{A.46}$$

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

$$\begin{aligned}\tau\int_{z_H}^{\infty} d\left[e\left(\frac{v_H(z;\tau)}{P}\right)^{1-\sigma}\right] h(z)\,dz =& (1-\sigma)\frac{\tau}{1-\tau}d\tau\int_{z_H}^{\infty} e\left(\frac{v_H(z;\tau)}{P}\right)^{1-\sigma} h(z)\,dz \\ &+ \tau d\left(eP^{\sigma-1}\right)\int_{z_H}^{\infty} v_H(z;\tau)^{1-\sigma} h(z)\,dz\end{aligned} \tag{A.47}$$

Combining the last three expressions, and after some manipulations, yields (21).

To derive part (i), note that, with $v_{DM} = 0$, condition (21) becomes

$$\frac{du}{e} = -\tau(1+\kappa-\sigma)\frac{dP}{P} - \sigma\frac{\tau}{1-\tau}d\tau. \tag{A.48}$$

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

For part (ii), using (13) and (27), 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:

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

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

Model-Based Histogram To construct the histogram (31), we first define the aggregate packages up to value v for any particular group (including possibly the aggregate U.S.),

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

Changing the variable of integration, the number of packages up to value v for firms of type S is:

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

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 (31) 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

$$\Delta tr^{\omega} = \sum_o \sum_{j=S,N} \Delta tr_o^{\omega,j}, \tag{A.49}$$

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

$$tr_o^{\omega,j} = e_o^{\omega} \int_z \tau_o \left(v_o^j (z) \right) \lambda_o^{\omega,j} (z)\, dz, \tag{A.50}$$

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

$$\Delta tr_o^{\omega,S} = \tau_o \hat{\tau}_o \frac{e_o^{\omega} \hat{e}_o^{\omega}}{\left(\hat{P}_o^{\omega} \right)^{1-\sigma_o}} \int_{z_{H,o} \hat{z}_{H,o}}^{\infty} \hat{v_o^S} (z)^{1-\sigma_o} \lambda_o^{\omega,S} (z)\, dz - e_o^{\omega} \tau_o \int_{z_{H,o}}^{\infty} \lambda_o^{\omega,S} (z)\, dz; \tag{A.51}$$

while $j = N$ firms we have

$$\Delta tr_o^{\omega,N} = \tau_o \hat{\tau}_o \frac{e_o^{\omega} \hat{e}_o^{\omega}}{\left(\hat{P}_o^{\omega} \right)^{1-\sigma_o}} \int_{z_{L,o} \hat{z}_{L,o}}^{\infty} \hat{v_o^N} (z)^{1-\sigma_o} \lambda_o^{\omega,N} (z)\, dz - e_o^{\omega} \tau_o \int_{z_{L,o}}^{\infty} \lambda_o^{\omega,N} (z)\, dz. \tag{A.52}$$

Appendix Tables and Figures

TABLE A.1: DE MINIMIS SPENDING PATTERNS

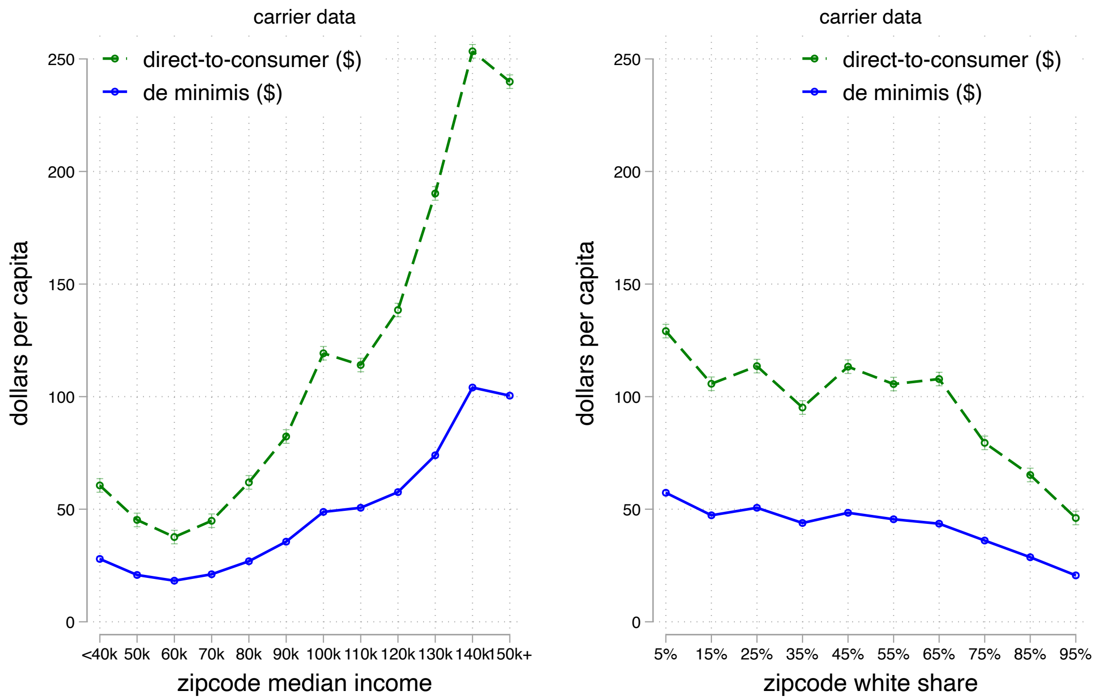
	(1) direct shipments (% inc)	(2) dm share (%)	(3) chn share of dm (%)	(4) tariff w/ §321	(5) tariff w/out §321
log p50 income	-1.63***	-95.61***	85.81***	-5.35***	-2.21
	(0.20)	(14.38)	(9.24)	(0.72)	(3.32)
log median income sq	0.07***	3.72***	-4.35***	0.26***	-0.01
	(0.01)	(0.64)	(0.41)	(0.03)	(0.15)
% white share	-0.12***	-1.62**	-7.97***	0.05	-1.79***
	(0.01)	(0.68)	(0.44)	(0.03)	(0.15)
log pop density	0.01***	-2.11***	-0.32***	0.08***	-0.31***
	(0.00)	(0.07)	(0.05)	(0.00)	(0.02)
State FEs	Yes	Yes	Yes	Yes	Yes
R2	0.03	0.13	0.29	0.09	0.18
N	32,191	32,191	32,186	31,817	31,816

Notes: Table reports zip code level regressions of de minimis spending patterns on zip code median household income, fraction of white households, population density, and state FEs. source: carrier data.

FIGURE A.1: ITEM DESCRIPTIONS

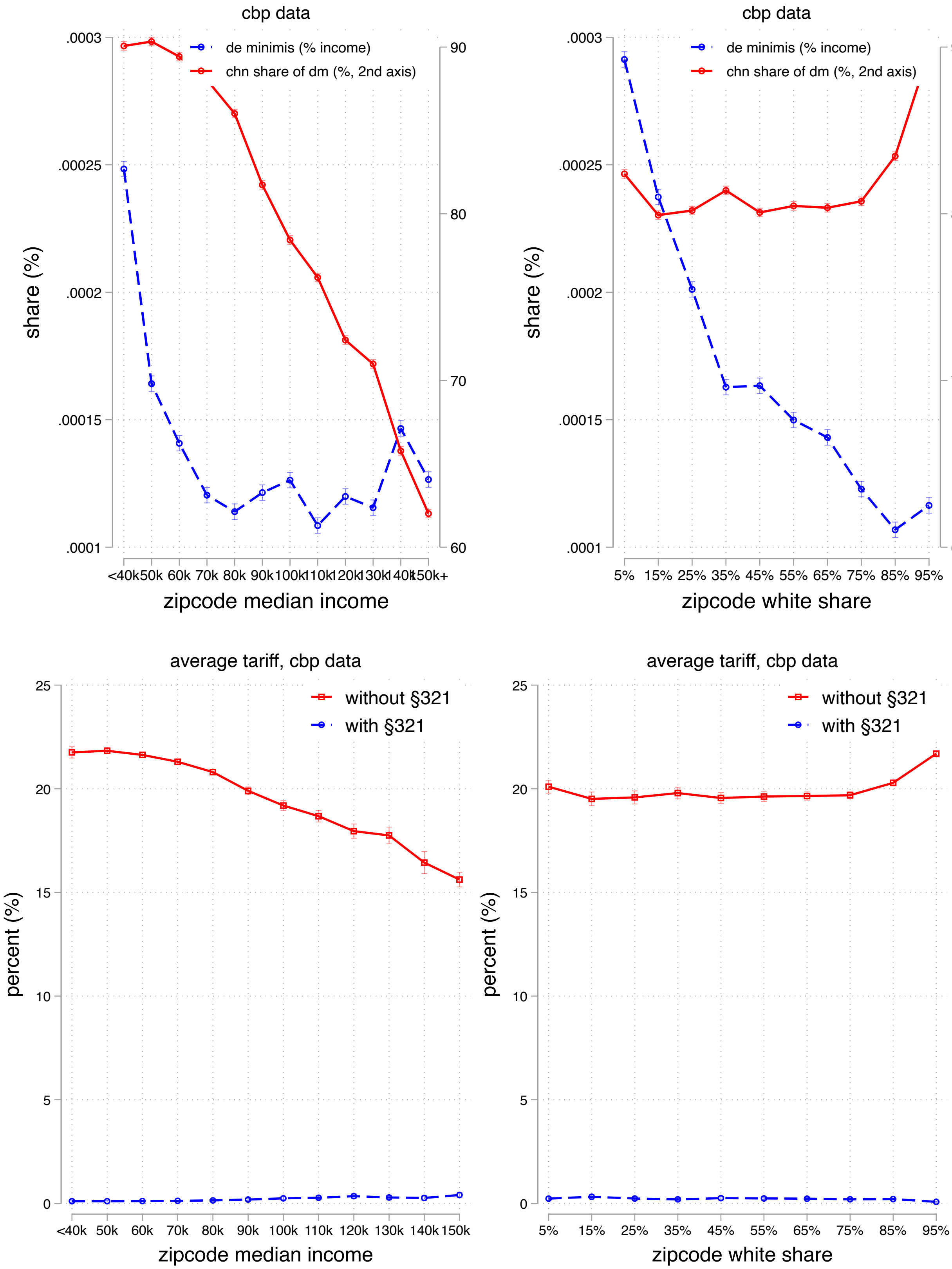
Notes: Figure displays the most common items in direct-to-consumer shipments. Item descriptions reported in carriers A and B.

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



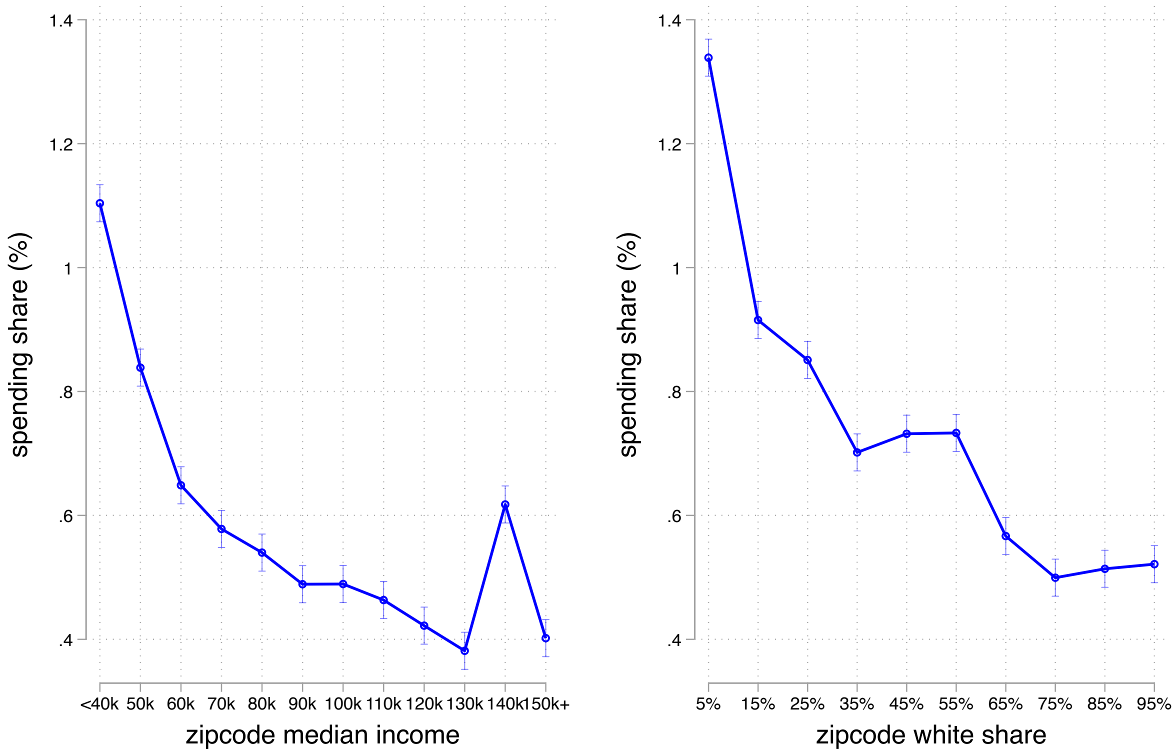
Notes: Figure reports 2021 zip code per-capita expenditures on direct-to-consumer shipments ($\leq$\$5000, green series) and de minimis shipments ($\leq$\$800, blue series). The left panel plots against zip code median household income and the right panel plots against zip code white household share. Error bars denote 95% confidence intervals.

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



Notes: Top panel reports 2021 zip code 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 spending 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. Error bars denote 95% confidence intervals. Source: CBP data, 2021.

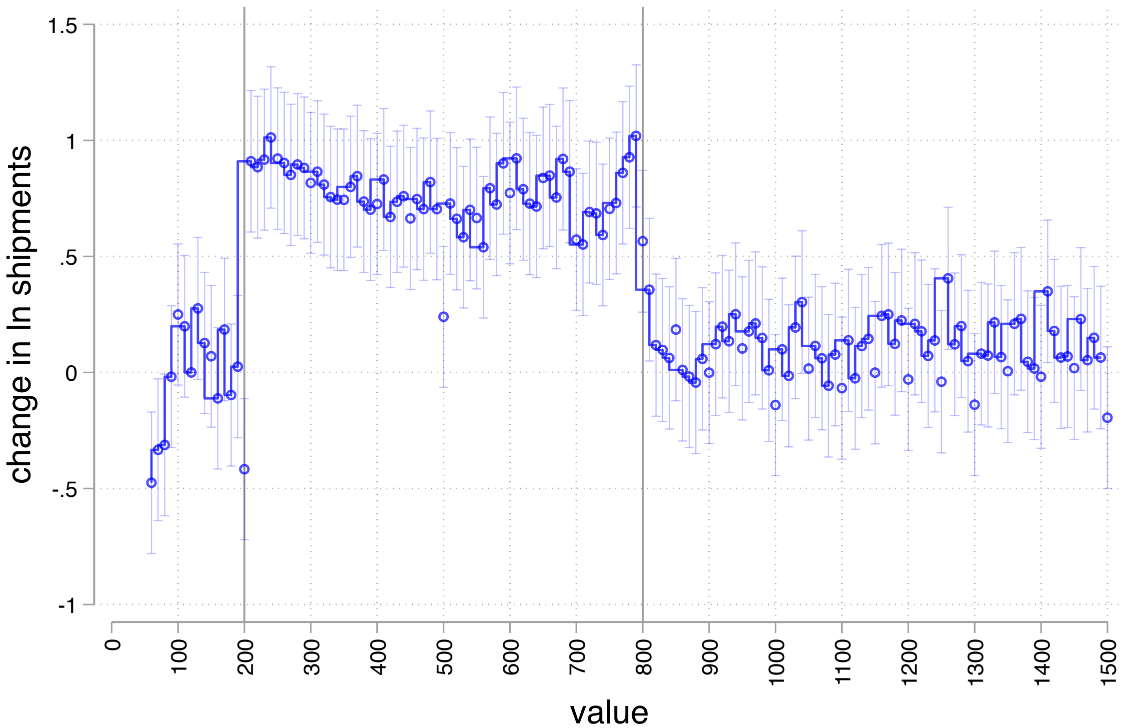
FIGURE A.4: SHARE OF ALIEXPRESS, SHEIN, AND TEMU CREDIT CARD EXPENDITURES



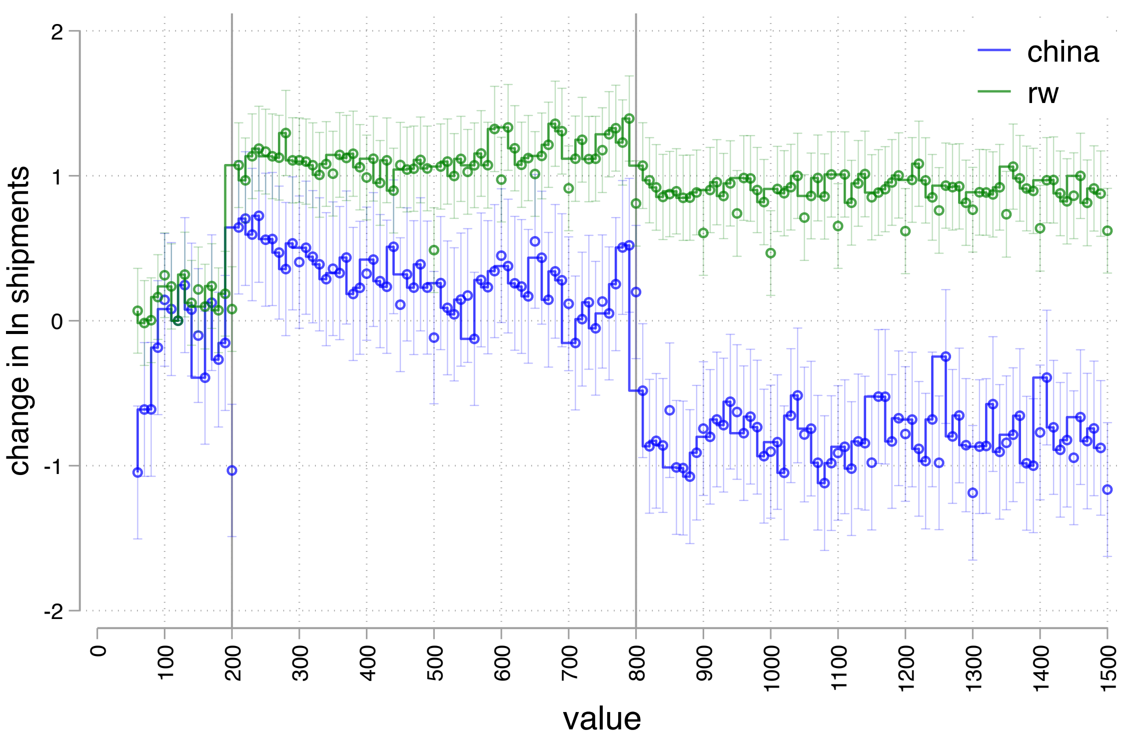
Notes: Figure reports credit share of spending at AliExpress, Shein and Temu relative to total purchases of non-food household products across 482 vendors (e.g., Walmart, Amazon, Home Depot, Macy's, etc). Error bars denote 95% confidence intervals. Source: MBHS3 transactions data, 2023.

FIGURE A.5: DIFFERENCE-IN-DIFFERENCES SPECIFICATION WITH AGGREGATED DATA

Panel A: All Origins



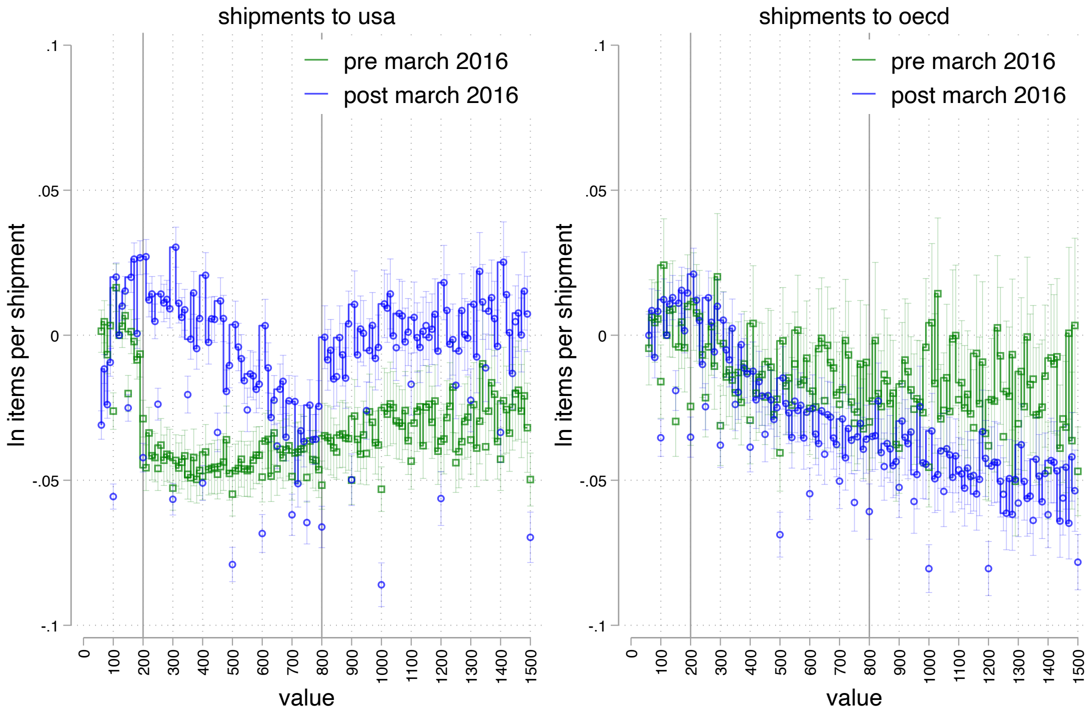
Panel B: By Origin



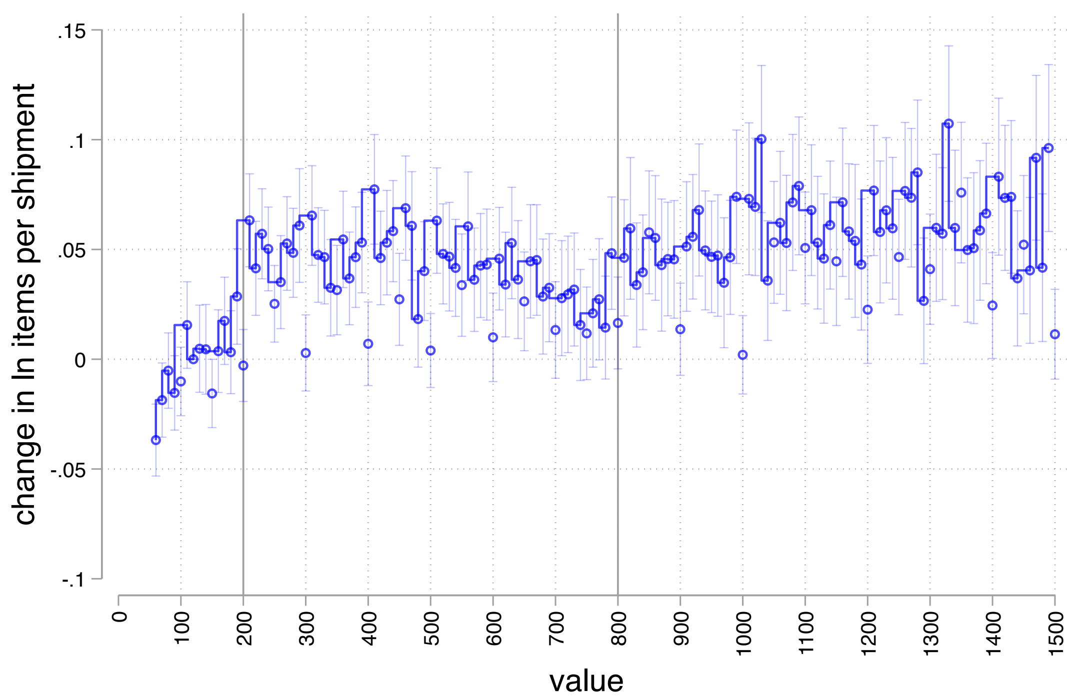
Notes: Figure based on data that collapses over non-China origins and carriers, aggregating shipments at the two-origin (China vs RW)-destination-time level. The figure plots the $\beta_b \times \text{USA}_d \times \text{post}_t$ fixed effects from re-running specification (23). Panel A plots shipments from all origins. Panel B estimates (23) separately for shipments from China and RW. Grey vertical lines denote §321 thresholds before and after March 2016. The leave-out bin is $120. Srror bars denote 95% confidence intervals. Round numbers not included in the connected line to improve visualization. Source: carrier data, all years.

FIGURE A.6: NUMBER OF ITEMS PER SHIPMENT

Panel A: Levels

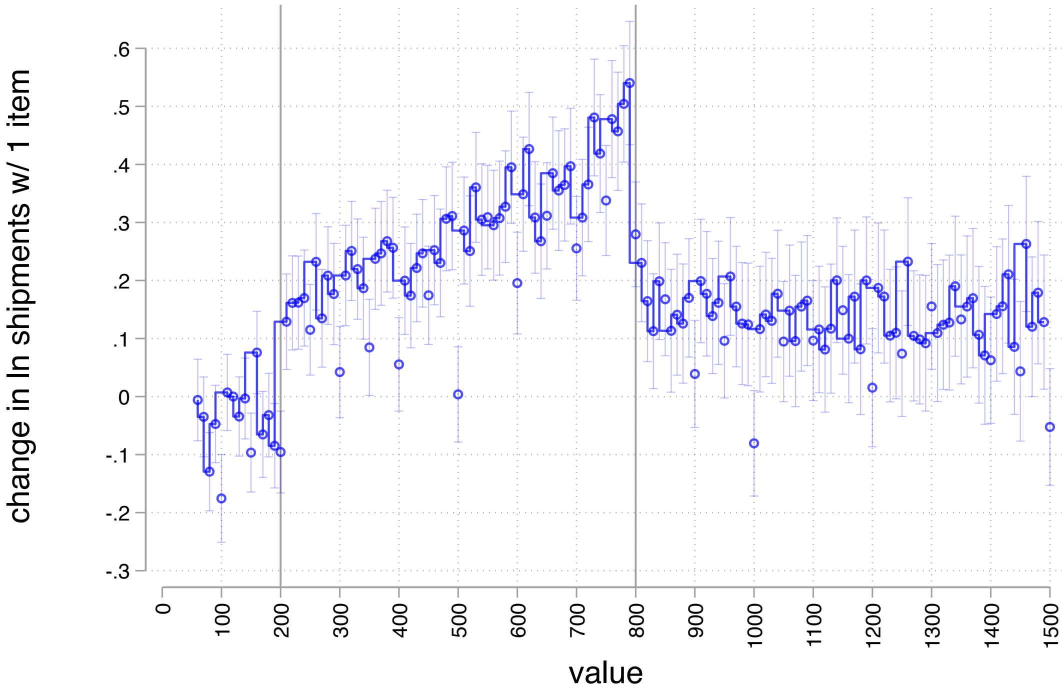


Panel B: Difference-in-Differences

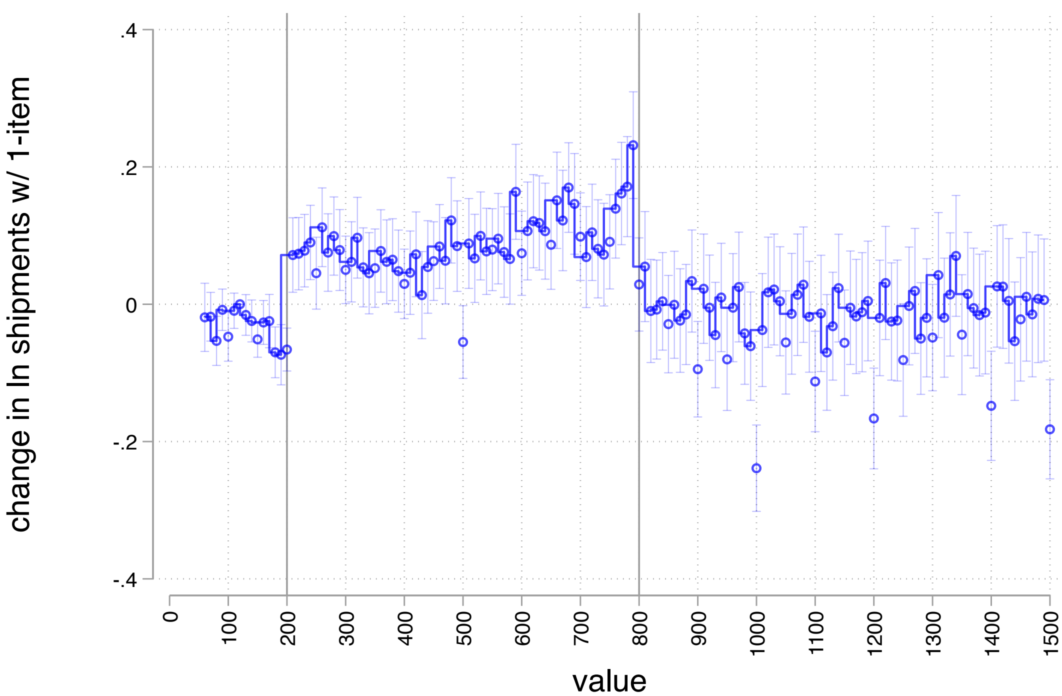


Notes: Figure examines the average number of items per package at each bin. The top panel runs regressions (22) in levels, and the bottom panels reports the diff-in-diff specification (23). Grey vertical lines denote §321 thresholds before and after March 2016. The leave-out bin is $120. Standard errors clustered by origin-time; error bars denote 95% confidence intervals. Round numbers not included in the connected line to improve visualization. Source: carriers A and C, all years.

FIGURE A.7: CHANGE IN DENSITY OF ONE-ITEM SHIPMENTS
Panel A: One-Item Shipments



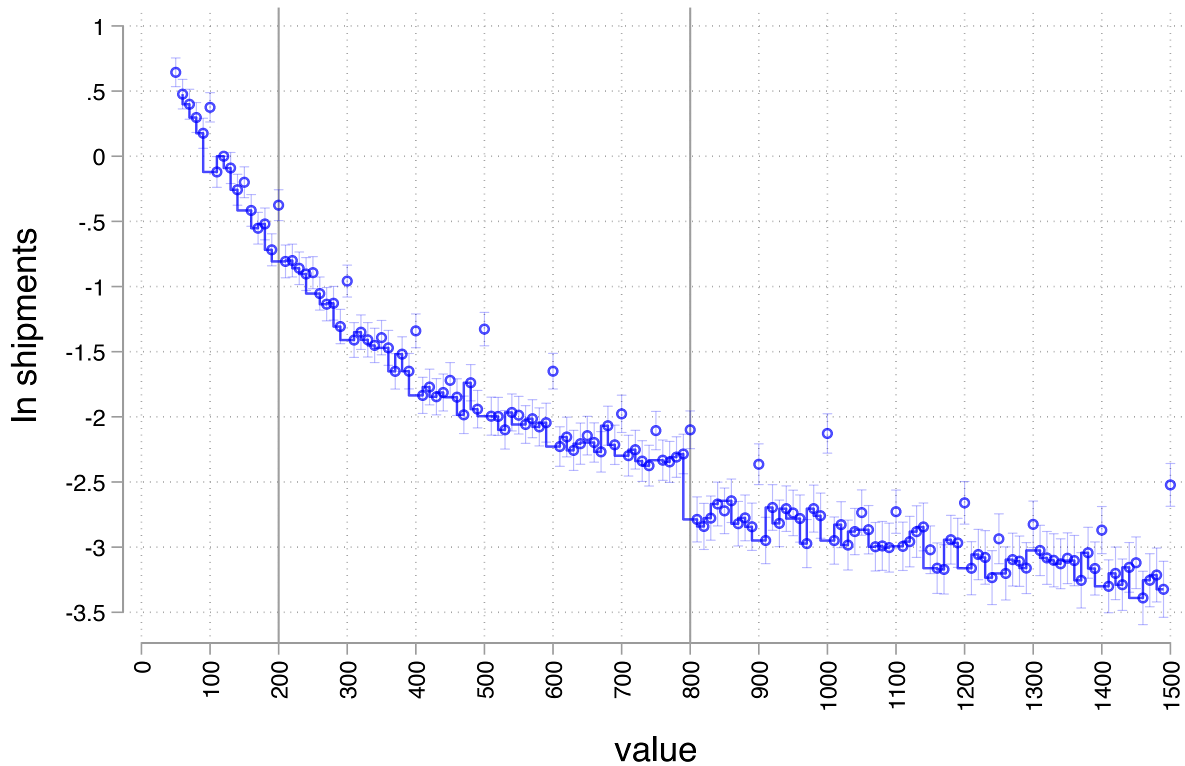
Panel B: One-Item Shipments, with Product FEs



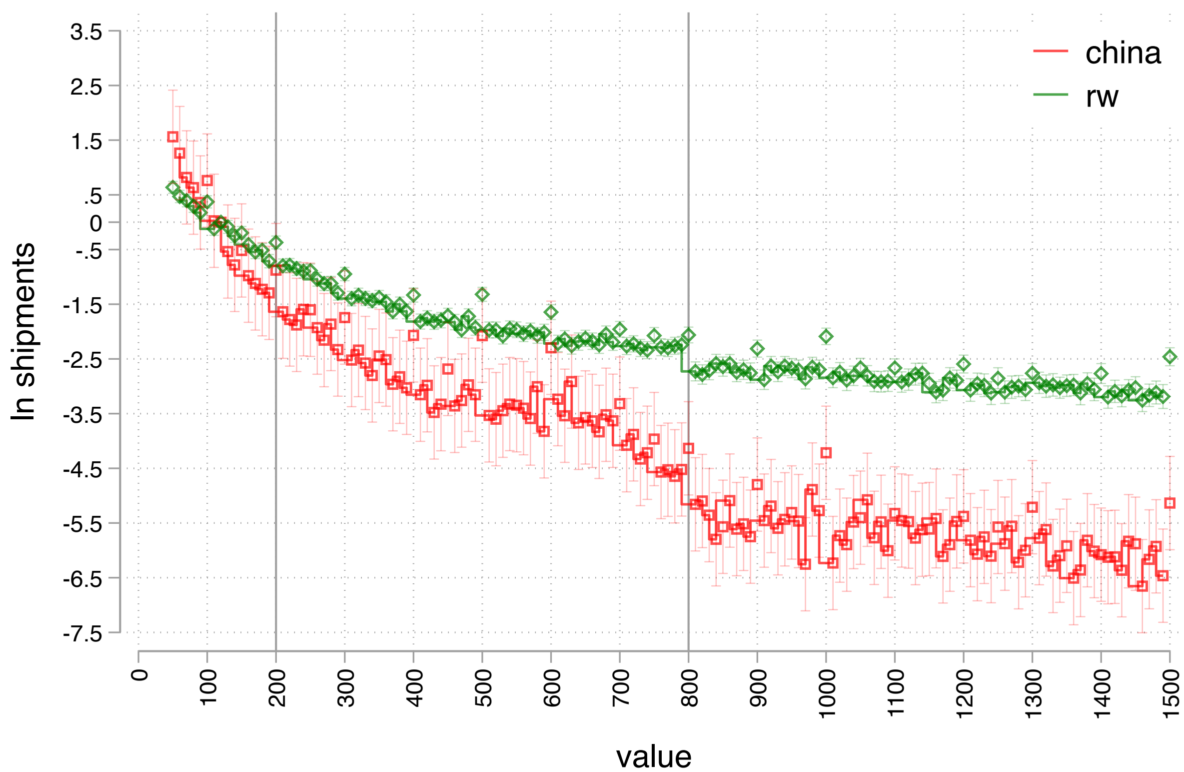
Notes: Figure reports the density of one-item shipments to the USA in the post-period relative to pre-period, and relative to the same time difference for OECD shipments. The regression specification is (23), and the figure plots the $\beta_b \times \text{USA}_d \times \text{post}_t$ fixed effects. Panel A estimates (23) using one-item shipments from all origins. Panel B re-estimates (23) on one-item shipments with α_{odxpt}, where p denotes a product group determined by clustering item descriptions into 100 groups. Grey vertical lines denote §321 thresholds before and after March 2016. The leave-out bin is $120. Standard errors clustered by origin-time; error bars denote 95% confidence intervals. Round numbers not included in the connected line to improve visualization. Source: carriers A and C, all years.

FIGURE A.8: CBP SHIPMENT DENSITY

Panel A: All Origins



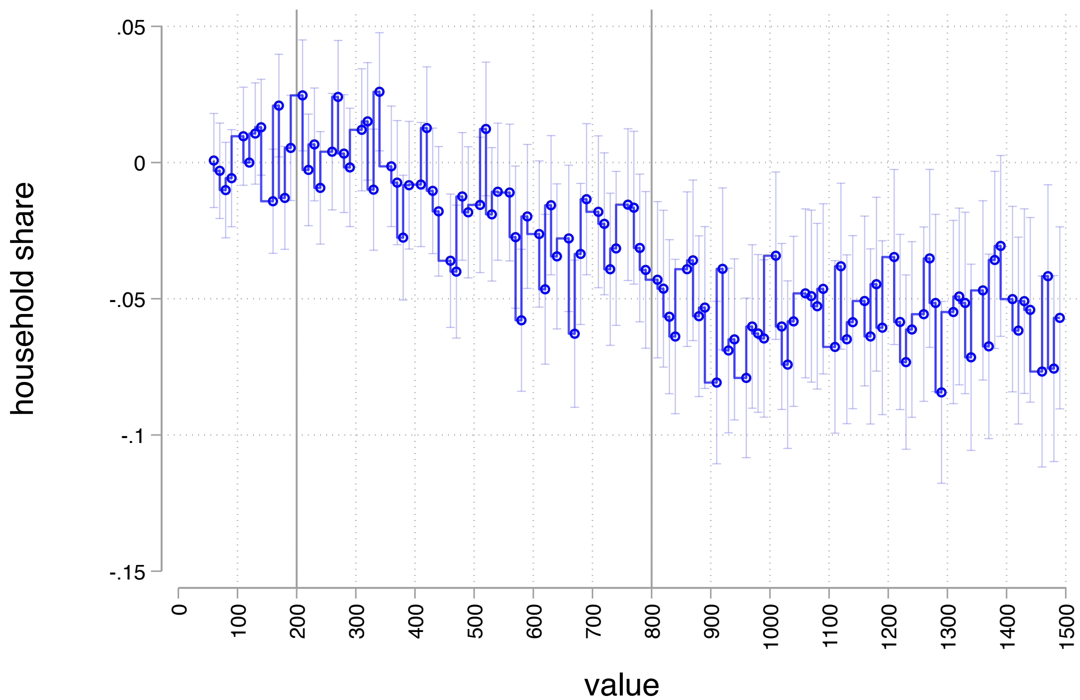
Panel B: By Origin



Notes: Figure examines the weekly CBP shipment data using the analog regression in (22). 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. Standard errors clustered by origin-time; error bars denote 95% confidence intervals. Round numbers not included in the connected line to improve visualization. Source: CBP data, all years.

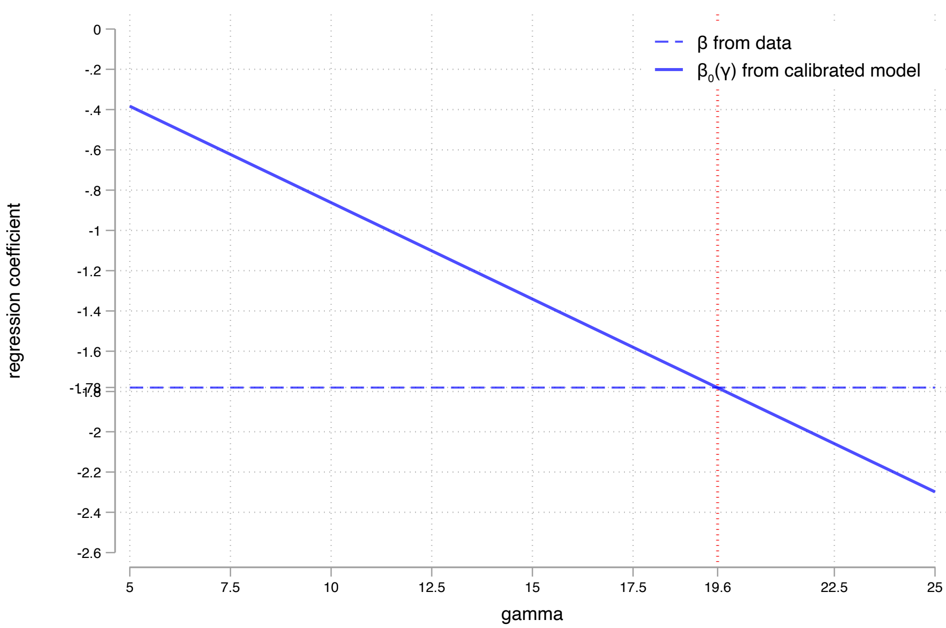
FIGURE A.9: SHARE OF HOUSEHOLDS

Difference-in-Differences



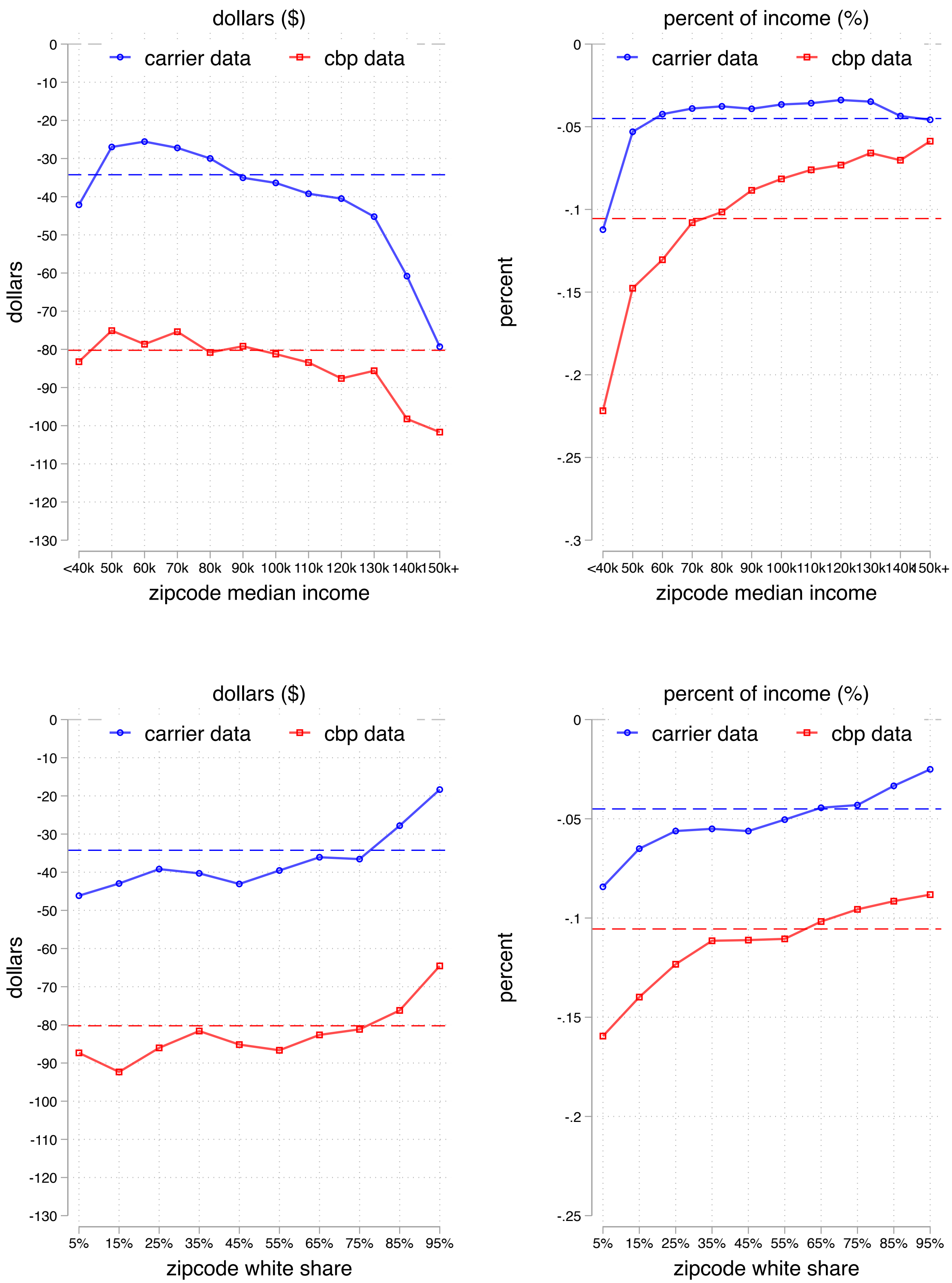
Notes: Figure analyzes the fraction of shipments in each bin that are sent to addresses matched to U.S. residential zones. The regression is analogous to (23), but with $hhshare_{bodt}$ as the dependent variable. The leave-out bin is \$120 . Standard errors clustered by origin-time; error bars denote 95% confidence intervals. Source: carrier A, all years.

FIGURE A.10: CALIBRATION OF γ



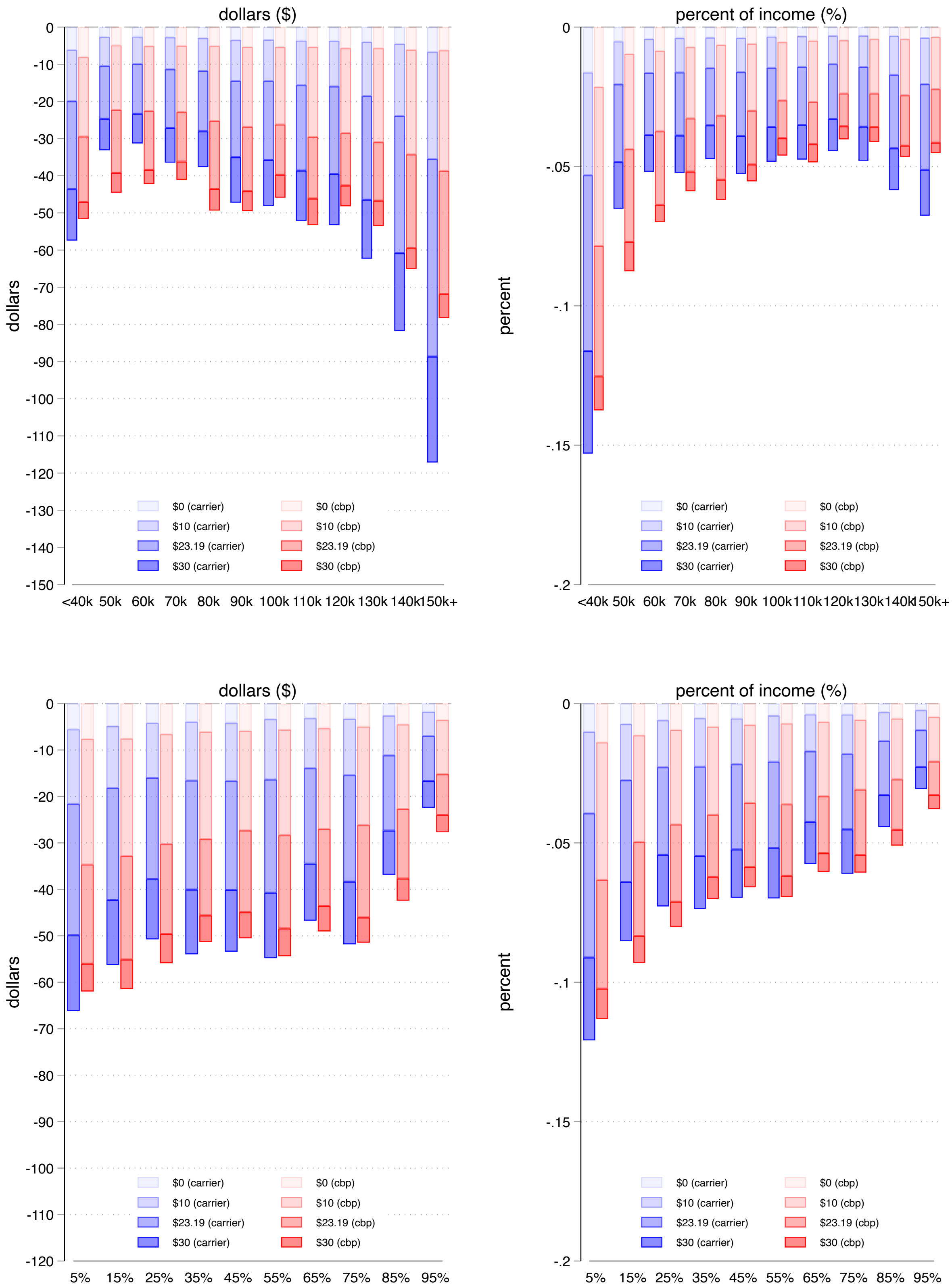
Notes: Figure reports $\hat{\beta}$ estimated from running (33) on the actual shipment densities from China and RW by income group, and $\beta_0(\gamma)$ from running the same specification on the model-implied densities generated for different values of γ. The intersection pins down the cross-origin elasticity of substitution: $\gamma = 19.6$.

FIGURE A.11: FIRST-ORDER APPROXIMATION TO WELFARE LOSS FROM ELIMINATING §321



Notes: Figure reports the first-order approximation consumer loss from removing §321 against zip code characteristics. The left panels report impacts in per-capita dollars and the right panel scales by median household income. Top panel reports by zip code median household 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.

FIGURE A.12: 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 household income. Top panel reports by zip code median household 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.