The Value of De Minimis Imports*

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Abstract

Section 321 of the 1930 Trade Act allows up to $800 in imports per person per day to enter the US duty-free and with minimal customs burden. 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 most from this type of trade, and what are the policy implications? We analyze the full distribution of direct-to-consumer imports using data from three major international carriers and from Customs Border Protection. We find that lower-income zipcodes are more likely to import de minimis shipments, particularly from China, suggesting that the tariff incidence in direct-to-consumer trade is pro-poor. Theoretically, imposing tariffs above a threshold leads to terms-of-trade gains, even in a setting with complete pass-through to linear tariffs. We identify bunching at $800 relative to the shipment density in 2016 (subject to a $200 threshold) or to OECD countries (subject to low thresholds), informing the demand elasticity for direct shipments. Eliminating §321 would reduce aggregate welfare by $10.6-$14.8 billion, with this loss disproportionally hurting lower-income and minority consumers.

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1 Introduction

Since 2018, the US has sharply raised tariffs on key trading partners, including China, with tariff incidence falling predominantly on US consumers (Fajgelbaum and Khandelwal, 2021). However, §321 of the 1930 Trade Act allows up to \$800 goods per day per person to be imported free of both taxes and much of the administrative costs of clearing customs, such as broker and processing fees. The consumer burden of these tariff and administrative costs therefore depends on whether a shipment has entered through this "de minimis" channel. In recent years, de minimis imports have exploded, fueled by streamlined customs processing, high tariffs, and an emergent type of international trade that ships directly to consumers purchasing through online retail platforms. For such transactions, online orders bypass domestic warehousing by shipping 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 \$49.4 billion, up from just \$0.05 billion in 2012. Scaled against natural benchmarks, de minimis imports are 6.6% of US imports of consumers goods and 17.4% of e-commerce sales, a substantial increase from just 0.7% and 3.9%, respectively, from 2012-2017. One billion de minimis shipments entered the country in 2023, up from 110.5 million shipments in 2012. De minimis shipments are an integral strategy of some of the world's largest and fastest-growing retailers that ship directly to consumers, such as Shein and Temu.[1] Two recent proposals in Congress consider modifying the scope of §321.[2]

This paper studies direct-to-consumer trade and its subset of de minimis shipments below \$800. We document who benefits the most from these types of shipments, and we assess the aggregate and distributional welfare consequences of potential changes by Congress to §321 trade policy. Research on these questions has been limited, as Census data exclude import transactions below \$2000. We rely on a novel dataset encompassing the universe of international shipments handled by three carriers into to the US. Collectively, in 2021, our data account for 36.1% of total value and 17.0% of total US de minimis shipments. A key feature of the data is that we observe shipments' destination address or zipcode, allowing us to link each shipment to income and demographic characteristics of buyers. We complement these data with a sample of shipments from the universe of carriers obtained from Customs Border Protection (CBP) via FOIA, and document that the three carriers are broadly representative of the universe of de minimis shipments.

To carry out the analysis, we develop a framework to examine the economic impacts of allowing for duty-free and streamlined customs procedures for de minimis shipments. The framework has standard heterogeneous exporters with monopolistic competition operating

[1] In 2022, Shein represented 50% of the US fast-fashion retail market, larger than Zara and H&M combined, according to Bloomberg Second Measure. Temu, whose product offerings extend beyond apparel, surpassed Shein's sales in May 2023 according to the WSJ. Both companies' iPhone apps have recently been in the top 10 among all apps, with Temu #1 in August 2023. In January 2024, Shein and Temu had 26 million and 51.4 million active users, compared to Amazon's 67 million active users ("Amazon's New Focus: Fending off Rivals Temu and Shein", WSJ 2024.03.21).

[2] The "Import Security and Fairness Act" would prevent "non-market" economies from using the de minimis channel, and the "De Minimis Reciprocity Act of 2023" would bar some countries, including China, from accessing §321 and impose the reciprocal de minimis threshold that US shipments face in other countries (all countries have a de minimis threshold lower than the US).

subject to de minimis rules, and selling packages to heterogenous consumers who vary in their preferences for direct shipments. When the value of a shipment exceeds the threshold, it is subject to (ad-valorem) tariffs and to administrative fees. The latter acts as a specific tariff, with revenue from these fees allocated to finance the administrative costs of processing above-threshold shipments. We show that a de minimis threshold acts as a tax notch that results in a novel source of terms-of-trade gains for the importing economy: firms who would, in the absence of tariffs, price in a range of values above the threshold will, with the threshold, lower their prices and bunch at the notch. Compared to free trade, this tax policy is preferred when the mass of imports is sufficiently biased to low-value shipments. Assuming an outside good that fixes wages (a reasonable assumption given de minimis' shipments' size) and constant markups, the framework implies that standard linear tariffs are inferior to free trade, and is consistent with the empirical finding of complete tariff pass-through in datasets that do not include de minimis shipments. Hence, a minimum threshold with a positive tariff can dominate free trade even in circumstances where free trade is otherwise optimal when the only instrument is linear tariffs.

We use the framework to guide the empirical analysis of §321 and the direct shipments to final consumers to which this policy is intimately linked. Quantifying the impacts of §321 requires two key empirical moments. First, to inform the relative preferences for direct and de minimis shipments, we need the density of shipments over package values by consumer groups, which we define across zipcodes by their median income or demographics. Second, to inform the demand substitution across shipments of different value, we exploit shifts in the density of shipment values due to policy changes. We consider the difference in the shipment value density relative to two control densities: a) shipments before March 2016, when then de minimis threshold was $200 rather than $800; and b) shipments to non-USA destinations, which are subject to lower de minimis thresholds. Through the lens of the framework, the change in bunching around the $800 notch pins down the elasticity of substitution across varieties from a given origin. The approach is analogous to studies in public economics that identify labor supply elasticities using bunching at notches along the income tax schedule (Kleven and Waseem, 2013).

The densities across zipcodes reveal that direct-to-consumer shipments (defined as shipments below $5,000 in our data), their cheaper de minimis subset (below $800), and the subset of de minimis that originates from China are relatively more important for low-income households. Specifically, expenditures on direct shipments, as a share of median income, is U-shaped with zipcode income: zipcodes with median incomes below $40k spend roughly similar amounts as the richest zipcodes, and both import roughly twice the amount of intermediate-income zipcodes. Moreover, low-income households spend relatively more on de minimis shipments: 74% of direct shipments imported by the poorest zipcodes are de minimis compared to 52% for the richest zipcodes. Furthermore, the share of de minimis shipments from China declines with income: 48% for the poorest zipcodes compared to 23% for the richest.

These patterns, along with the exemptions from tariffs and the significantly higher tariffs on imports from China, suggest that §321 functions as a pro-poor trade policy: the average tariff on direct shipments to the poorest zipcodes–0.5%–is lower than to the richest zipcodes–1.5%.[3] If §321 was not in effect, the tariffs on shipments from China and RW would be roughly 24% and 1.4%; as a result, the tariff schedule would flip from pro-poor to pro-rich: the poorest zipcodes would face average tariffs of 12.1% compared with 6.7% for the richest zipcodes. Moreover, in the absence of de minimis, all shipments would incur an administrative fee of $23.19, which can sizable for low-value shipments.[4] Since lower-income households import a higher proportion of their shipments via the de minimis channel, eliminating §321 would disproportionately increase the average administrative fee of their imports compared to wealthier households.

We also leverage information on the destination zipcode to examine impacts across demographics beyond income, such as share of minority households–an important distinction to gauge distributional effects of trade (USTR 2023, ITC 2023). Under §321, zipcodes with low white household shares face slightly lower tariffs than whiter zipcodes, but this pattern reverses without the exemptions offered by §321: zipcodes with 5% white household shares would face 11.7% tariffs compared to 10.1% tariffs for zipcodes with 95% white shares. These patterns across consumer groups remain qualitatively similar using the CBP sample.

We consider a policy counterfactual that removes the $800 minimum threshold exemption currently codified in §321. In this counterfactual scenario, all shipments would be subject to the current tariffs and to a (per shipment) administrative fee of $23.19. The welfare analysis requires an estimate of consumers' demand and foreign firms' pricing responses (including the change in bunching), and of the tariff revenue that can be rebated to consumers. The observed changes in bunching pin down the within-origin demand elasticity across shipments from China and Rest of World (RW). Specifically, using the carrier data we estimate non-parametric densities of shipments across value bins in four categories: shipments to the US and OECD, and before and after March 2016. This period marks a threshold change in the US from $200 to $800, while the OECD countries maintain lower de minimis thresholds. We observe bunching at the thresholds, particularly in the post period at $800. When expressed as a difference-in-differences, across all origins we observe a rise in the relative density of shipments right below $800, and then a 27.0% drop in shipments above the notch. When we restrict the analysis to shipments from China, this drop is starker.[5] The CBP sample also shows evidence of bunching below the notch and a subsequent decline in

[3] These average tariffs are low because we consider only shipments up to $5,000, of which de minimis shipments are a large fraction. We can only determine the tariff incidence by consumer group from these direct shipments, and not from purchases from traditional retail stores.

[4] CBP levies a merchandise processing fee and requires shipments to use a licensed broker on shipments above $800. The fee for brokerage services varies by logistics provider, range of services offered, and quantity discounts, making it difficult to pin down the broker fee. The carriers indicate that their per-package informal shipments is $30.00. The Postal Service's fee for handling international shipments is $8.55 (United States Postal Service, 2024). The National Foreign Trade Council estimates a broker fee of $20.00. In 2023, express carriers handled 19% of de minimis shipments, Postal Service handled 8%, and other logistics providers handled the remaining 73%; using these weights, we arrive at an average broker fee $20.97. We then apply the CBP's lowest merchandise process fee on informal shipments–$2.22–to arrive at the total administrative fee of $23.19 per shipment.

[5] The difference-in-differences density plots also reveal no sharp bunching exactly at $800 nor a distinct "hole" just above the notch. The model accounts for these facts by introducing an optimization friction in some shippers. Additionally, we confirm that the pattern of bunching is qualitatively similar when focusing on shipments with only one item.

shipments above $800, suggesting that shipments above $800 are not simply re-routed to other logistics companies. The observed changes in bunching are matched by elasticities of substitution across shipments from China of 3.13 and from the rest of word (RW) of 2.26. We identify the cross-origin demand elasticity through indirect inference that leverages differences in tariffs across origins, finding an elasticity of 4.60.

Using observed shipment densities from the carrier data, a first-order approximation that assumes complete pass through and uses only the spending shares, tariffs, and administrative fees yields a $12.5 billion consumer loss from eliminating §321. Computing the exact welfare changes from the model, which incorporates incomplete pass-through through bunching in the price responses and tariff revenue rebated to consumers, we find that eliminating §321 reduces aggregate welfare by $10.6 billion. In the CBP sample we find a larger decline of $14.8 billion, as these data reports a greater share of shipments from China than the carrier data. Compared to the first-order costs, the exact analysis implies a larger consumer burden from eliminating §321, in part because eliminating the threshold worsens the terms-of-trade gains through bunching, but a smaller overall welfare loss because it accounts for tariff revenue. To put these numbers in perspective, Fajgelbaum et al. (2020) estimate the sum of consumer cost and tariff revenue gain of the 2018 US tariffs at $16.1 billion, and of the tariffs waves through 2019 at $48.2 billion.

The aggregate estimates mask distributional consequences from eliminating §321. The per capita welfare losses are inverted U-shaped: median incomes below $40k would lose $45 per capita per year compared to a $35 loss for zipcodes with $100k incomes and an $81 per capita loss for the richest zipcodes. When expressed as a share of income, the corresponding declines are biased against the poor: for low, median and high income zipcodes, respectively, are 0.12%, 0.03%, and 0.05%. We also examine how the policy would affect zipcodes that vary in their share of white households. We find that welfare in zipcodes with 5% white households would experience a per capita decline of $50, compared with declines of $39 for zipcodes with 45% white share and $16 in 95% white share. As a share of income, the corresponding declines for low, median and high white shares are 0.09%, 0.05%, and 0.02%. In sum, the lowest-income and non-white households would bear the brunt of eliminating §321.[6]

Several papers have found evidence of complete pass-through of US tariffs on China to US import prices; see Amiti et al. (2019), Fajgelbaum et al. (2020), Flaaen et al. (2020), and Cavallo et al. (2021). However, analyses of public trade data or of the Census' Longitudinal Firm Trade Transactions Database are unable to assess the importance of de minimis imports because they only compile import transactions above $2000.[7] In contrast, our finding of bunching implies that the de

[6]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: $52 (0.14% of income), $39 (0.04% of income), $90 (0.05% of income). The per-capita losses, excluding tariff rebates for zipcodes with white household shares of 5%, 55% and 95% are: $57 (0.10% of income), $44 (0.06% of income), $18 (0.02% of income).

[7]Census data, including both the public files and the confidential firm-level LFFTD, are compiled from CBP Form 7501 (Kamal and Ouyang, 2020). These data therefore capture all formal entries and a subset of informal entries, but are blind to de minimis shipments. This is by design since §321 is meant to reduce bureaucratic procedures.

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.[8] Our paper also relates to the work studying non-tariff barriers, specifically as customs facilitation.[9] We find that the minimal requirements for clearing customs on de minimis shipments, including the savings on brokers–agents who prepare and submit import documentation, assign product codes, ensure regulatory compliance, and facilitate the shipment through the port of entry–significantly benefit low-value shipments.

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

Several papers have studied the distributional effects of trade through consumption in response to shocks other than tariffs. A key challenge in this literature is that households' consumption of imports are rarely directly observed. Using cross-country and cross-industry data, Fajgelbaum and Khandelwal (2016) estimate a trade framework with non-homothetic demand to measure unequal gains from trade across consumers through differences in their expenditure baskets. They find that poor consumers concentrate more spending on traded goods, concluding that 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 survey and scanner data to measure differential consumer exposure to large devaluations in Mexico and Switzerland. Hottman and Monarch (2020) and Borusyak and Jaravel (2021) match consumer expenditure surveys to trade data and do not find substantial differences in import shares across US households, suggesting weak distributional impacts. In Mexico, Atkin et al. (2018) find that the entry of foreign retailers favored richer households. Our data allow us to observe imports directly shipped to consumers.

Section 321 has not received much academic attention due to the data limitations we have described, and it has become economically relevant only recent years.[10] Recent papers, however,

[8] Flaaen et al. (2020) study washing machines which are purchased from retailers and 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 from the Automated Commercial Environment (ACE), the electronic data collection system for processing imports. It is unclear how the IPP stratified sampling applies on entries that do not carry product codes such as de minimis. Moreover, as discussed in Section 2, de minimis imports are not required to clear through ACE; in 2020, the year closest to their study, 19% de minimis entries were captured by ACE.

[9] See Anderson and van Wincoop 2004, Volpe Martincus et al. 2015, and the survey chapter by Ederington and Ruta 2016.

[10] Hufbauer et al. (2018) argued that Canada and Mexico should raise their de minimis threshold to encourage more

have studied how e-commerce affects consumption patterns. Dolfen et al. (2023) find that higher-income households benefit relatively more from online platforms, but do not differentiate between domestic and international e-commerce (either through de minimis or through formal imports distributed via domestic warehouses).[11] Jo et al. (2022) find that e-commerce lowered price dispersion across locations in Japan; and Couture et al. (2021) implement a randomized trial that connects an e-commerce platform with 100 villages in China, finding that e-commerce reduces cost of retail consumption for younger and richer households. Our paper focuses on the role of low-value shipments for welfare, studying how the benefits of direct-to-consumer imports vary by demographics, such as income and race, and how they are affected by US trade policy currently under debate.

Methodologically, our framework and approach to estimate the tariff elasticity are designed to exploit bunching in the shipment density around a tax notch. A tax notch is the defining feature of de minimis trade policies across the world, with large heterogeneity in the value of the threshold.[12] Estimation based on kinks or notches has been commonly used in the public economics literature to estimate, for instance, labor supply elasticities; see Saez (2010), Chetty et al. (2011), Kleven and Waseem (2013), and the review by Kleven (2016). In our setting, we exploit two control shipment densities over values that are not subject to the $800 threshold (shipments to the US prior to March 2016, and to OECD countries). As a result, we can identify the extent of bunching induced by the current threshold through a standard difference-in-differences estimator.

The remainder of the paper is organized as follows. Section 2describes the details of §321 trade policy and de minimis imports. Section 3 provides a framework for analyzing imports that are subject to a minimum threshold for tariffs. Section 4 describes the data and provides summary statistics. Section 5.1 examines the density of shipments around the threshold. Section 6 implements the model and provides a welfare analysis of §321.

2 De Minimis Imports and §321 Trade Policy

The process of importing shipments involves paying applicable duties and taxes, meeting regulatory standards, and filing paperwork. In the US, most import transactions require filing 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. To reduce customs burden for low-value shipments, most countries have a "de minimis" policy.[13]

The US has streamlined procedures for importing two types of low-value shipments: §321 entries ($0-$800) and informal entries ($801-$2500). §321 was codified in 1938 by amending the

trade within NAFTA.

[11] Companies such as AliExpress, Ebay, Temu, and Shein match final consumers to overseas manufacturers who then ship directly to consumers Although Amazon's business model primarily relies on importing through formal channels to domestic warehouses that then ship to consumers, international third-party sellers can ship directly to consumers on Amazon's platform.

[12] E.g., it is $750 in Australia, $188 in UK, $15 in Canada, and on average $190 in Europe.

[13] The world average is $145 and the OECD average, excluding the US, is $180 (Global Express Association).

1930 Trade Act to allow low-value imports to enter the country free of tariff duties and (most) customs processing fees, and with minimal paperwork. In March 2016, the US raised the threshold from $200 to $800, its current value, as part of the Trade Facilitation and Trade Enforcement Act of 2015 to reduce transaction costs associated with imported shipments for consumers. The limit is $800 per person per day. §321 prohibits importers from breaking up 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, such as the Food and Drug Administration or the US Department of Agriculture.

Entry through §321 occurs by physically or electronically presenting a manifest to CBP. Carriers of de minimis shipments include express air carriers, postal service, and non-express carriers (via air, land, and sea); in 2023, these carriers handled 19%, 8%, and 73% of de minimis shipments, respectively. Before 2018, express air and truck carriers could file de minimis shipments electronically through the Automated Manifest System (AMS), while other carriers would physically present the manifest. In 2018, CBP initiated a "type 86" pilot that expanded electronic de minimis entries via the Automated Commercial Environment (ACE) to all carriers; 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 require HS codes for shipments through ACE. §321 shipments are exempt from tariff duties, do not require a broker, and are not subject to a processing fee (except for express carriers, which are subject to a $1.27 per-package fee).

Informal entries between $801-$2500 are subject to duties and taxes (if applicable) and require filing CBP Form 7501, just like formal entries (shipments above $2500), but, unlike formal entries, do not require a surety bond (ensuring payment of duties and compliance) and can be immediately released by CBP upon payment of duties and taxes. Informal shipments are subject to two types of administrative costs: a merchandise processing fee ranging from $2.22 to $9.99 per package, and require a a broker to clear customs. As noted in footnote 4, our benchmark analysis assumes a per-package administrative fee–inclusive of both the processing fee and the broker fee–of $23.19 on informal shipments.

Until recently, §321 has not been quantitatively important for US imports. The left panel of Table 1 reports the total shipments and value of §321 imports. Aggregate imports increased from just $0.05 billion in 2012 to $49.4 billion in 2023, peaking at $67.0 billion during the 2020 pandemic lockdowns. Column 2 reports the volume of shipments. In 2012, 110.5 million de minimis shipments entered the US. This number more than doubles to 224.0 million, the year the threshold increased to $800. By 2019, 503.1 million shipments entered, driven by the expansion of electronic clearance of de minimis shipments and rising tariffs. By 2023, 1 billion shipments entered through §321. As comparison, CBP processed 39.1 million formal-channel entries (although a single formal

Table 1: §321 Import Statistics

	CBP Official Statistics		US Consumer Spending	
year	value ($b) (1)	entries (m) (2)	consumer imports (%) (3)	e-commerce (%) (4)
2012	0.05	110.5	0.01%	0.1%
2013	0.07	117.9	0.01%	0.1%
2014	0.7	122.8	0.1%	0.9%
2015	1.6	138.9	0.3%	1.8%
2016	9.2	224.0	1.6%	9.2%
2017	13.0	332.3	2.1%	11.1%
2018	29.2	410.6	4.4%	22.2%
2019	56.2	503.1	8.9%	36.8%
2020	67.0	636.7	9.4%	30.4%
2021	43.5	771.5	5.3%	17.8%
2022	46.5	685.4	6.0%	18.1%
2023	49.4	1,000.0	6.6%	17.4%
2024*	32.8	705.1		

Notes: Panel reports official statistics for §321 imports (columns 1-2) obtained through a FOIA and CBP Publication 2036-1022 and CBP E-Commerce Statistics. Prior to March 2016, the de minimis import threshold was $ 200 and increased to $800 afterwards. Column 3 reports the share of §321 import values to aggregate US spending on consumer imports (excluding autos and food), and column 4 reports the share relative to aggregate E-commerce sales. The latter two statistics are from Census and pulled from the FRED database (series A652RC1Q027SBEA and ECOMSA). * denotes data through April 30.

entry may contain many more items than a single de minimis entry). As of April 30, 705 million packages have already entered in 2024. The magnitudes illustrate the importance of a de minimis channel for reducing the burden of administering customs.

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. Thus, two natural benchmarks that gauge the growth and importance of de minimis imports are: its share of imports of consumer goods (excluding food and autos, series A652RC1Q027SBEA on FRED) and its share of total e-commerce sales (series ECOMSA on FRED).

In 2012, de minimis imports as a share of consumer imports was just 0.01%. In 2023, this share was 6.6%. The table indicates a large jump in this share after 2018, likely driven by the combined effect of streamlined electronic submission procedures for de minimis shipments and the rising tariffs from the trade war. Column 4 benchmarks de minimis imports relative to US e-commerce sales (series ECOMSA retrieved from St. Louis FRED). In 2012, this share was just 0.1%, but by 2023, de minimis imports were 17.4% total e-commerce sales.

Finally, one can also benchmark relevance by the duties avoided. Through a FOIA request, CBP provided the universe of de minimis shipments for the first week of December in 2017 to 2021. In this sample, 70.7% of shipments originate from China in 2021. Applying the median tariff in the aforementioned HS chapters from China and the other origins that year, we estimate that in 2021 consumers avoided paying $7.8 billion in duties, or 9.2% total duties according to 2021 Census data.

3 Framework

This section introduces a framework to understand the consequences of imposing a de minimis threshold on imports. The threshold acts as a tax notch and induces bunching, and we show how this feature is used to identify the tariff elasticities. We also study the welfare implications of de minimis and derive the conditions under which a de minimis trade policy is optimal relative to free trade.

3.1 Consumers

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

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

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

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

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

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

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

3.2 Firms

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

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

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

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 processing fee as function of the value per package (both are positive only if the value is above the threshold). The total demand faced by the firm is:

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

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

We assume a mass of firms $M_o(z)$ with unit cost equal to z from origin o. To aggregate firm decisions, the joint distribution of unit costs and demand shifters matters only through the following "quality-adjusted" measure of firms with unit cost equal to z from country o:

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

The quality-adjusted measures captures the importance that firms with unit cost z from origin o have for consumer group ω, be that because of their number (entering through $M_o(z)$) or because of the 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 zero customs clearance fees, or it can send shipments through the standard channel at prices above v_{DM}, and face tariffs and a customs fee. Producers may be differentially appealing across consumer groups, and consumer tastes may be correlated with unit production costs (and therefore prices). Across firms from o, we allow for a general joint measure of unit costs z and demand shocks a^{ω} across groups.

To characterize the optimal pricing strategy, it is useful to define three profit functions as function of unit costs:

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

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

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

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

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

and

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

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

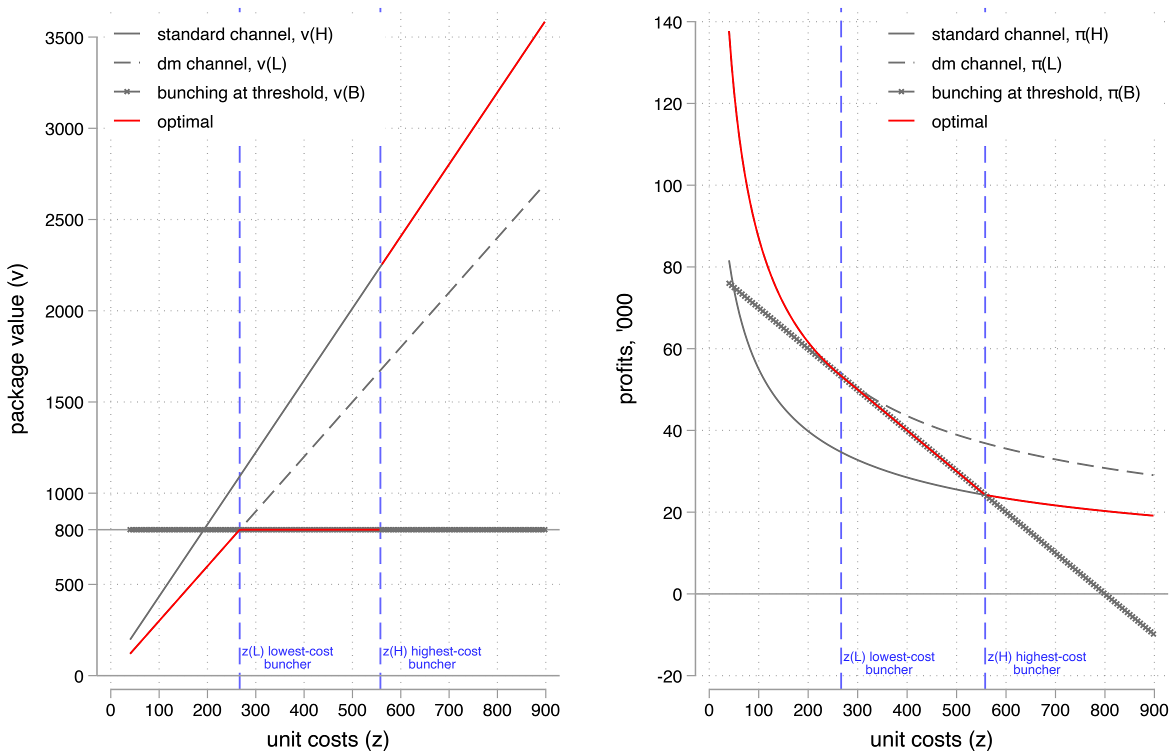
The intermediate case, $\pi_i^B(z)$, are the profits of firm i if it bunches at the threshold, setting price v_{DM}. The profits and corresponding price as function of unit cost are shown in the hashed lines in Figure 1. Conditional on bunching, profits are linearly decreasing in unit cost; otherwise,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

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

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

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

FIGURE 1: PROFITS AND PRICING



Notes: Figure illustates optimal profits and package values when exporters face a de minimis trade policy. The "zero tariffs" ("high tariffs") schedules correspond to the profits and prices conditional on operating under these tariffs. The "bunching at threshold" schedule corresponds to pricing at the de minimis threshold of $800.

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 $z_{H,o}$, set the standard markup taking into account the ad-valorem tariff (τ_o) and the per-unit administrative cost (T). Firms with unit cost z, in between these thresholds, are bunchers. The following proposition summarizes these results.

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

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

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

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

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

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

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

3.4 Identification

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

3.5 Optimal De Minimis Trade Policy

Standard trade policies typically impose a uniform ad-valorem tariff across all shippers from a given origin (in a given product or industry). 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 of our framework consisting of a single consumer group ω importing from a single origin o. In this context, a representative agent's indirect utility is

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

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

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

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

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

and where conditions (14) and (15) determine 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 v_{DM}, relative to initial expenditures e, the welfare change of the representative consumer is*

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

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

Compared to this benchmark, a threshold potentially generates welfare-enhancing terms-of-trade effects. The potential gains of a higher threshold are shown in the first line of (20). Starting from a threshold v_{DM} with associated highest-cost buncher z_H, increasing the threshold generates a first-order reduction in prices by marginally increasing the threshold z_H; the price reduction is equal to the size of discontinuity in scheduled labeled "optimal" that is seen in the left panel of Figure 1. In other words, the original highest-cost buncher, originally pricing *much* above v_{DM}, lowers its price to the new value of the threshold. This gain comes at the cost of lost tariff revenue and of a higher price for all the original bunchers (i.e, the horizontal segment in the bottom panel of Figure 1 shifts up).

These price effects hold marginally, and whether a positive threshold with a tariff is desirable compared to free trade is a quantitative question that depends on the shape of the quality-adjusted distribution of firm unit costs $h(z)$ and the various demand elasticities. However, it can be shown that the combination of the tariff with a threshold can indeed be preferable to free trade, as mentioned in part (ii) of the proposition. Consider the price schedules in the left panel of Figure 1. In the "optimal" schedule chosen by exporters, corresponding to $v_{DM} > 0$, a density $h(z)$ with enough relative mass on bunchers would imply a lower price index than under free trade. This would be the case if the support of $h(z)$ was bounded at z_H (i.e., the vertical segment). In that case, the "optimal" price schedule would be uniformly below the "zero tariffs" schedule under free trade for all firms with positive mass. In this example, the policy bundle with $v_{DM} > 0$ and $\tau > 0$ must be necessarily preferred to free trade, because it leads to both a lower (tariff inclusive) consumer price index and to the same (zero) amount of tariff revenue. As long as the support of the exporter unit-cost distribution $h(z)$ is bounded, such a policy can be constructed by raising the value of the threshold v_{DM} in order to increase the location of the highest-cost buncher.

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

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

4 Data & Summary Statistics

4.1 Carrier Shipments Data

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

One concern with the declared value field is the potential for misreporting. We are unable to determine the extent of misreporting in the carrier data. However, a few institutional features make us confident about this data field. First, according to an analysis of CBP audits of §321 by the Trade Support Network, 8.68 million shipments sent through §321 in 2021—1.13% of total de minimis shipments that year— were deemed by CBP as "ineligible value", meaning that these shipments exceeded the $800 limit and had to enter through the informal or formal entry channels. This suggests that CBP does conduct audits in the §321 channel.[14] Second, undervaluation is subject to penalties–fines, delays, seizures, and potential flagging of future shipments. Third, 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 to not underreport the declared value. Finally, carriers reserve their right to audit packages themselves, as they are concerned with undervaluations because of potential auditing.

A second challenge with the carrier data is identifying the set of direct-to-consumer shipments, as opposed to imports by firms. The carriers do not carry a flag for whether the consignee is a household or commercial business. For our analysis, we define direct-to-consumer shipments as shipments below $5,000and remove shipments above this cutoff. While arbitrary, we believe that shipments above this value are unlikely to be purchased directly by consumers. This restriction removes 3.8% of the observations in the data.

We assess this cutoff threshold using the street addresses provided by carrier A, which can be overlaid with a land-use classification raster file developed by McShane et al. (2022). Of the 81% of shipments (77% of value) that match to a specified land use, 76% went to households (68% of value), 16% went to commercial land-use (18% of value), and 8% went to industrial, recreational or agricultural land-use (14% of value).[15] We do not utilize this zoning flag to further trim shipments since we cannot perform the exercise for carriers B and C, for whom we only observe the destination zipcode.[16]

Table 2 reports statistics from the carrier data. The first column reports the coverage by carrier, with "*" denoting that at least one month from the carrier is missing that year. In 2021, we have complete data across the three carriers and months. Column 2 reports aggregate values. In 2021,

[14] The audit statistics do not break out "ineligible" shipments between express carriers and others. However, they do break out the number of seized packages (e.g., intellectual property violations from counterfeits) by express, postal service, and non-express carriers (e.g., logistics companies who use land or sea). They find that two-thirds of the seized packages were handled by postal service and non-express carriers, suggesting that express carrier achieve higher compliance in §321.

[15] Including shipments above $5,000, the share of shipments that go to households does not change much–76%–but its value share falls to 59%.

[16] We assume that if a shipment happens to arrive at a commercial address, the items are consumed locally within the zipcode.

the underlying transactions aggregate to \$15.7 billion, or 36.1% of aggregate de minimis imports that year. Collectively, in that year, the data contain 130.9 million shipments that year (column 3), or 17.0% of aggregate §321 shipments. Across all years, we analyze 373 million de minimis shipments.

Columns 3-4 provide annual value and entry statistics for imports between \$801 and \$5,000. Columns 5-6 report samples of shipments to OECD destinations below \$5,000. These shipments are included in the carrier data (for carriers A and B) because they fall into CBP entry type 62 ("Transportation and Exportation") or 63 ("Immediate Exportation"). They do not clear US customs and therefore are not subject to US trade policy, but are transshipped through the USA, presumably given the carrier's network of air routes. As explained below, these shipments can serve as an additional counterfactual density. We restrict attention to OECD destinations, as their demand would resemble US demand given similar levels of income.

According to official CBP statistics, in 2021, all express carriers handled 30% of de minimis shipments.[17] Moreover, the vast majority of de minimis shipments arrived by air–86%. So, the air shipments in our data reflect the dominant mode of §321 imports.

We also filed a FOIA request to CBP for shipment-level data on transactions below \$1500.[18] CBP initially denied this request on the grounds that the volume of data was too large, and eventually provided us with one week per year from 2017 to 2022 (the first week of December). In total, we have 5.1 million shipments across all years, collectively valued at \$263 million.

4.2 Product Descriptions and Tariffs

What types of products are shipped directly to consumers? As mentioned earlier, shipments cleared through the AMS, which includes the bulk of the express carrier shipments, do not require HS codes, but "type 86" entries do contain codes. However, item descriptions are required and data from two of the carriers do contain the text from this field. Figure A.1 provides a visual representation of the common words that appear in the item descriptions in the direct-to-consumer shipments. The items appear to be products that consumer would purchase at retail shops, such as women's clothing (dresses, blouses), men's clothing (pants, suits), accessories (necklace, decor, nails), electronics, as well as materials (polyester, cotton, polyurethane).

We do observe HS codes for shipments above the de minimis threshold (and in two carriers, we observe type 86 entries that have HS codes but they are only 0.13% of 2021 shipments). Under the assumption that shipments just above the threshold contain similar products as shipments below the threshold, we can broadly infer the types of products arriving through the de minimis channel (and potential tariffs if §321 was eliminated). For shipments that are up to \$50 above the threshold, we find that 81.6% of shipments contain HS codes in the following two-digit HS

[17] The share of the express segment of de minimis is declining; as noted above, in 2023, express carriers 19% of de minimis.

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

TABLE 2: CARRIER DATA

year	carrier (1)	§321 Shipments to USA [$0,$800] value ($b) (2)	entries (m) (3)	Non §321 Imports [$801,$5,000] value ($b) (4)	entries (m) (5)	Shipments to OECD (≤$5,000) value ($b) (6)	entries (m) (7)
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
2018	A	3.6	34.3	4.3	2.0	1.0	6.2
2019	A	4.2	36.5	4.6	2.1	1.1	6.5
2020	A B* C	7.9	68.5	8.5	3.9	2.2	11.1
2021	A B C	15.7	130.9	17.3	8.0	2.8	11.0
2022	B* C*	3.6	31.3	5.1	2.4	0.01	0.01
total		40.0	373.0	49.7	25.4	9.58	47.6

Notes: The right table reports summary statistics from the carrier data. Column 1 reports the source carrier; "*" denotes incomplete data that year. Columns 2-3 report total value and shipments for §321 imports into US. Columns 4-5 report stats for non-§321 imports under $5,000. Columns 6-7 report statistics of transshippments under $5,000 handled by carriers A and B to OECD (excluding USA) destinations (carriers A and B provided non-USA bound transshipments).

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 product categories reflect consumer products and are consistent with the item descriptions. Therefore, we assume that if §321 were eliminated, direct-to-consumer shipments would face the median applied US tariff from origins in these chapter.[19] Before March 2016, the average tariff faced by shipments from China is 4.0%, and rises to 23.9% by 2022. For RW, the average tariff before March 2016 is 2.7%, and in 2022 it is 1.4%.

4.3 Demographics

We use a combination of street addresses and zipcodes to link demographic characteristics to shipment destinations. Carrier A provided street addresses and states, but not zipcodes; for this carrier, we infer zipcodes from ArcGIS and achieve a match rate of 87%. Carriers B and C provided zipcodes, but not addresses. We match the package zipcodes to ZIP Code Tabulation Areas (ZCTA), and merge socio-economic characteristics from University of Michigan's ICPSR, as well as median family income by ZCTA from the American Community Survey. Across zipcodes, the average median family income is $76k and the average share of (non-hispanic) white households is 77%.

4.4 Summary Statistics

We document expenditures on direct-to-consumer shipments across zipcodes for 2021, the year of full data coverage. We construct per capita measures by aggregating shipments to the zipcode and dividing by zipcode 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 zipcodes is $32.6.

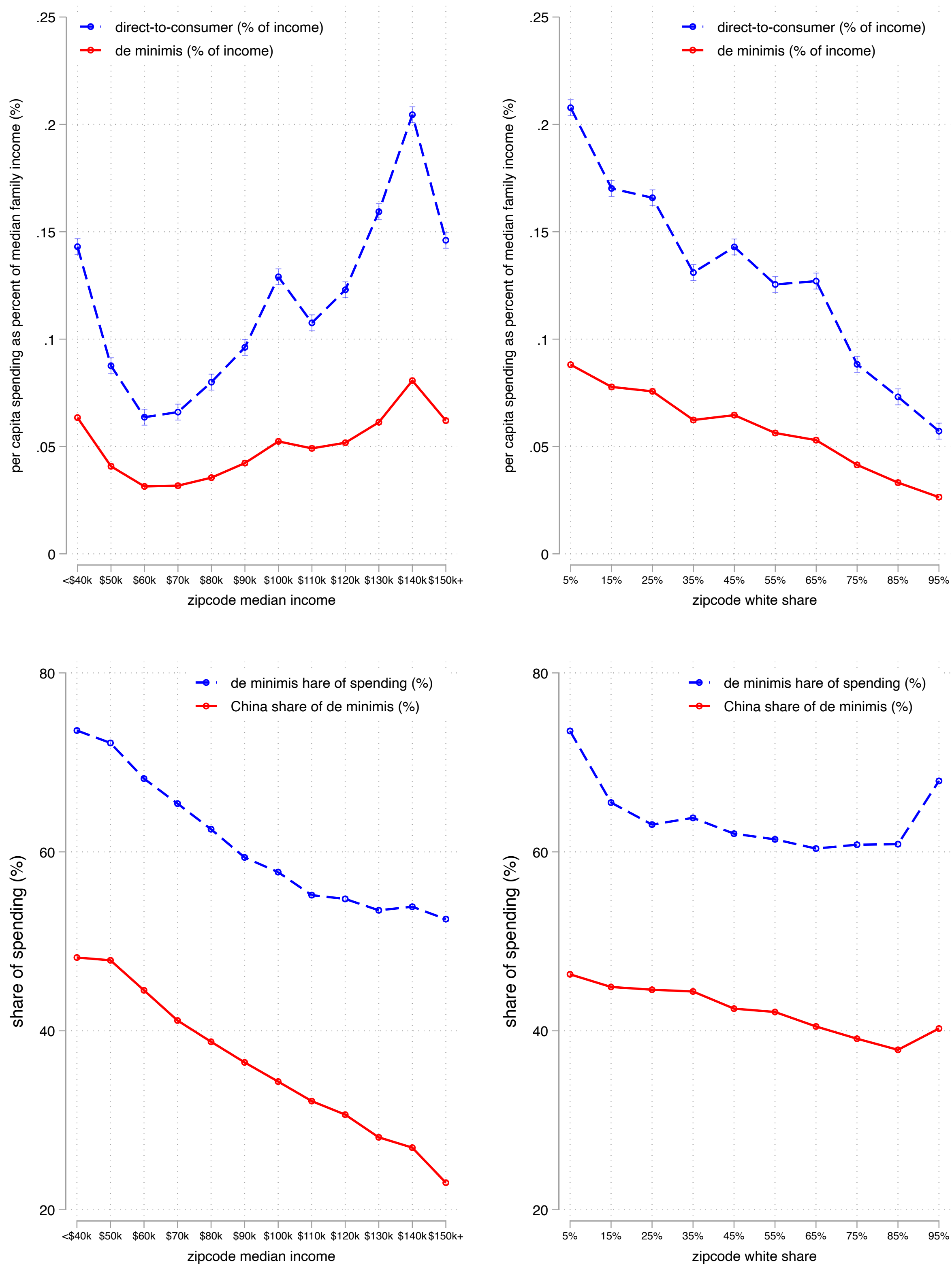
[19] We obtain the median applied tariff by origin-month in these HS chapters from public Census import records.

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

The bottom panel of Figure 2 reports the share of direct shipments that are de minimis (blue series). Lower-income zipcodes report a much larger fraction of spending on de minimis: the lowest income zipcodes spend 74% of direct purchase on de minimis imports, compared to 52% for the wealthiest zipcodes. The right panel shows that de minimis share of expenditures is U-shaped with respect to white household share, with a de minimis share of 74% in the direct spending of the 0-5% white share group.

Within de minimis imports, the red series shows the import share from China. There is a negative relationship between China's import share and zipcode income: 48% of the lowest income zipcodes' purchases of de minimis shipments are from China, compared to 23% for the richest zipcodes. The pattern is also overall decreasing in the white share, though not as stark as with respect to income.

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



Notes: Figure correlates 2021 per-capita expenditures on direct shipments (red series) and de minimis shipments (below $800, blue series), as a share of zipcode median family income. The left panel plots against zipcode median family income; labels denotes +/- $5k of the income interval (e.g., the $60k marker contains zipcodes with incomes between $55-$65k). The right panel plots against zipcode share of white households; labels denote +/- 5% of the white share intervals (e.g, the 35% marker contains zipcodes with white shares between 30%-40%). Standard errors of the means reported in brackets.

These two facts–the poor disproportionately make use of de minimis and their de minimis imports are disproportionately sourced from China–imply that §321 is a progressive tax policy. As discussed above, we do not observe product codes for de minimis imports, but we can estimate what the tariff would be without §321 using the origin of shipments. For above-$800 shipments, we directly observe a HS code in two of the three carriers. Thus, using the data from these two carriers, we can construct the (weighted) average tariff by zipcode under two scenarios: 1) the actual tariff with §321 in 2021; and, 2) the tariff if §321 was eliminated. Note that this exercise does not include the potential increase in customs and broker fees; the formal analysis below accounts for this.

Figure 3 reports the results. The blue series reports the incidence of tariffs with §321 in place, i.e. with tariffs applied to shipments only above $800. The tariff incidence is progressive: lower income zipcodes face lower tariffs than high zipcodes. The (value-weighted) average tariffs on the lowest-income zipcode is 0.5% compared to 1.5% for the richest zipcodes.

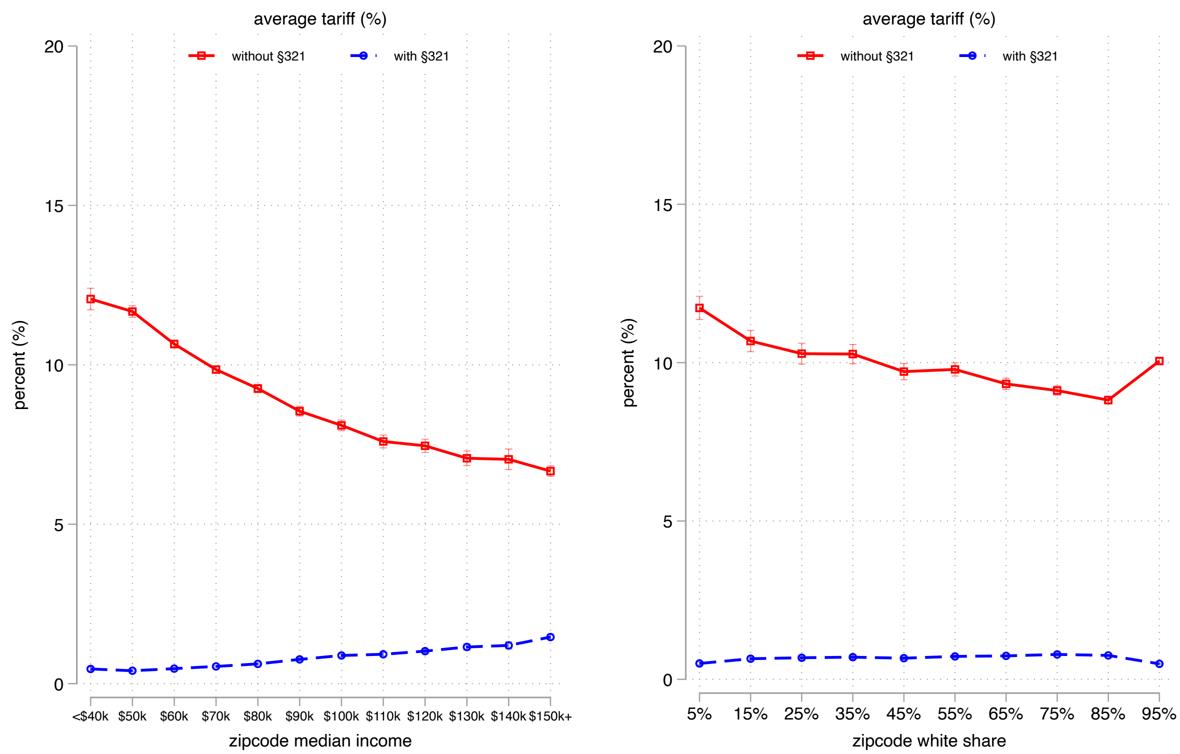
The red series removes the tariff exemption, with the big change being that tariffs on Chinese imports rise from zero to 23.9%. Naturally the overall tariff level increases. But, more strikingly, the distributional patterns reverse: without §321, the incidence of tariffs is regressive. The poorest zipcodes would face a 12.1% tariff, whereas the richest zipcodes would face a 6.7% tariff. This finding echoes Acosta and Cox (2019), who find that the US tariff code on consumer goods is regressive. The tariffs faced by minority households would also be higher than zipcodes with more white households if §321 was eliminated, as shown in the right panel of Figure 3.

Given that lower-income and minority households typically receive a higher proportion of direct shipments through §321, their average per-shipment administrative fee tends to be lower. Figure A.4 illustrates the average per-shipment fee under both scenarios; if §321 was removed, we apply the uniform fee of $23.19 to all shipments.

This figure provides a back-of-the-envelope estimate for how eliminating §321 would affect different consumer groups. Since low-income zipcodes have higher expenditure shares on de minimis, and these de minimis packages are disproportionately purchased from China, a first-order approximation to the consumer costs of eliminating de minimis implies that low-income consumers would be hurt more than richer consumers from imposing tariffs and customs fees on these shipments.

Table A.1 reports the correlations while controlling for income, white household share, population density, and state fixed effects. Column 1 shows that direct shipment as a share of income positively correlates with income and negatively correlates with white share, within state and controlling for population density. Columns 2 indicates that the de minimis share of direct shipments negatively correlates with income and white household shares. Column 3 further shows that within de minimis, poorer and minority households spend more on imports from China. Thus, column 4 continues to find that the tariff rate faced by zipcodes with §321 in place is progressive–lower income zipcodes face lower tariffs. It also shows that minority household shares face lower tariffs, but this coefficient is not statistically significant. Finally, column 5 shows that

FIGURE 3: TARIFF INCIDENCE, BY ZIPCODE



Notes: Figure reports the value-weighted average tariff with §321 in effect (blue series) and removing §321 (red series). The fiugre is constructed by taking zipcode expenditure shares on direct shipments in 2021 and applying the average tariffs on imports from RW and China. Standard errors of the mean reported in brackets.

eliminating §321 would reverse the tariff incidence across zipcodes: zipcodes with lower income and more minority households would face higher tariffs.

Finally, as mentioned above, CBP provided shipments for one-week from 2017-2021. We use these data to assess the representativeness of the carrier data, as one concern is that the types of consumers who use the carriers may differ from those who import through other express carriers or the postal service. The top panel of Figure A.3 reports the 2021 per capita de minimis share of median income and China share of de minimis across zipcodes. We only observe shipments up to $1500, not $5000, so we do not report the direct shipment shares; and, since it is only one week of data, the income shares (blue) are very small. Nevertheless, the cross-zipcode patterns in the CBP data are consistent with the carrier data: poorer zipcodes spend relatively more on de minimis shipments than richer (and more white) households. The red series (right axis) shows the share of de minimis that originates from China. This is also consistent with the carrier data, with lower income zipcodes concentrating much more of their de minimis expenditures on goods from China. The Chinese share, however, is larger in the CBP data, indicating that other carriers of de minimis shipments are focused more on Chinese exporters than the three carriers. The pattern across white household shares is U-shaped, unlike the negative relationship in the carrier data. Figure A.5 reports tariff incidence by zipcode in the CBP data with the caveat that the CBP sample did not contain HS codes (either for de minimis shipments or for above-$800 shipments). Therefore, we construct a zipcode's tariff using median tariff by origin in the aforementioned HS chapters. The figure reveals a similar pattern of a progressive tariff policy becoming a regressive one if §321 was eliminated. The patterns in the CBP data are broadly consistent with the carrier data, and if anything, understate the role §321 because the higher shares from China.

5 Impact of De Minimis Thresholds

5.1 Evidence of Bunching

The typical approach to estimating elasticities using notches is to exploit bunching in the density around the notch; see Kleven (2016). This method typically fits a high-order polynomial to recover the parameters of the density, but excludes a window where agents are affected by the notch. The assumption is that, in the absence of the notch, the density in the excluded range can be predicted by the parameters of the density function well above and below the notch. The marginal buncher is then empirically identified from the difference between the actual and the counterfactual density around the notch. This approach is powerful for examining a cross-sectional data at a point in time. Thanks to observing the density of de minimis shipments under different thresholds, we can estimate the impact of the notch non-parametrically without fitting a polynomial to the density. We do this by exploiting two differences: 1) the change in density from \$200 to \$800 in March 2016; 2) the difference in shipment density to the US versus OECD countries.[20]

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

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

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

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

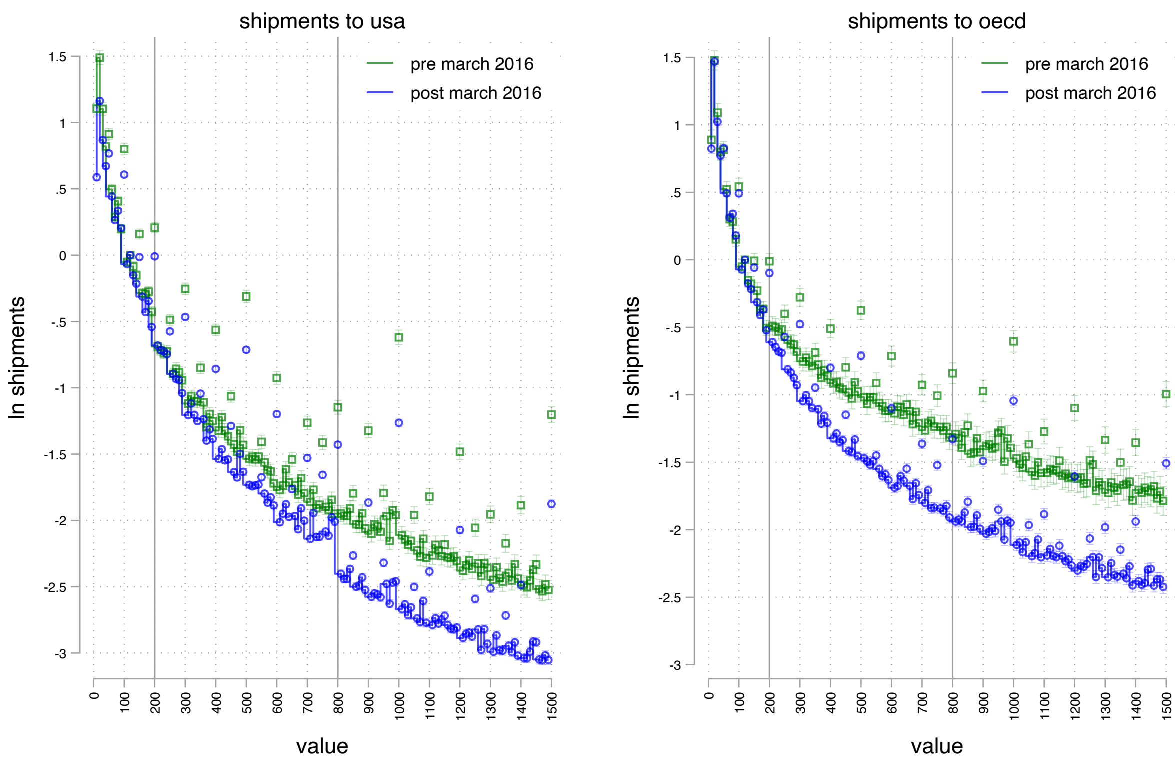
The left panel for Figure 4 shows estimates of β_b separately for two periods for the USA shipments: before and after March 2016. The pre-period density (green) shows a drop in packages at the \$200 threshold, although both bunching below the notch and the drop in shipments above

[20] The average threshold across OECD countries is \$180 and is quite diffuse: the standard deviation is \$157.

the notch is difficult to see in this graph. In the pre-period series, the density around \$800 appears smooth. However, there is evidence of bunching in the post-period density (blue) right below \$800, and then a subsequent drop in shipments above the notch: there are \$41.3% fewer shipments \$100 above the notched compared to \$100 below the notch.

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

FIGURE 4: SHIPMENT DENSITY BEFORE AND AFTER MARCH 2016



Notes: Figure reports the density of shipments to the USA and OECD before and after March 2016. Panel A reports the β_b bin fixed effects from (21) regressed on shipments before (green) and after (blue) March 2016 for the USA. Panel B reports the corresponding estimates for the OECD shipments. The leave out bin is \$120. Grey vertical lines denote §321 thresholds before and after March 2016. Error bars denote 95% confidence intervals.

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

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

where now β_b is the difference-in-differences estimate of the shipment densities: the difference in the (log) number of US-bound shipments in the post-period relative to the pre-period shipments, relative to that same difference for OECD-bound shipments. The control densities are used to isolate the impacts of the notches on USA shipments in each period. Figure 5A reports the β_b fixed effects.

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

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

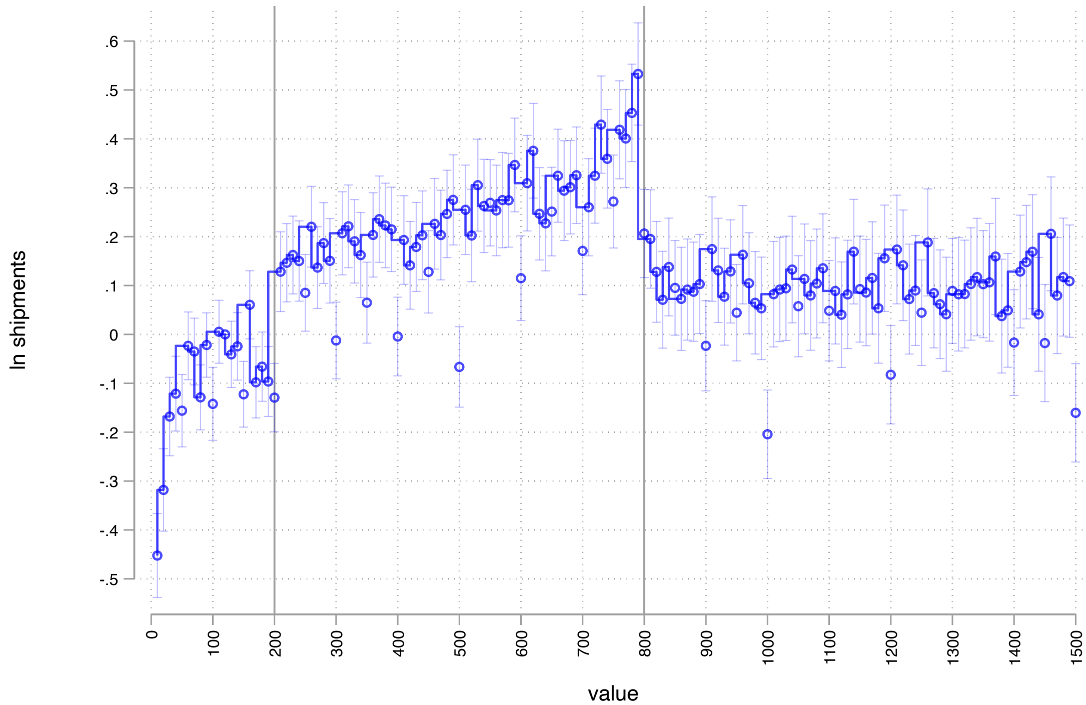
Figure 5B reports specification (22) separately for shipments from China ($o = CHN$, blue) and from the rest of the world ($o = RW$, green). The evidence of bunching from China is sharper relative to rest of world. We observe (negative) bunching at \$200, and a stark jump up just above the \$200 notch.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

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

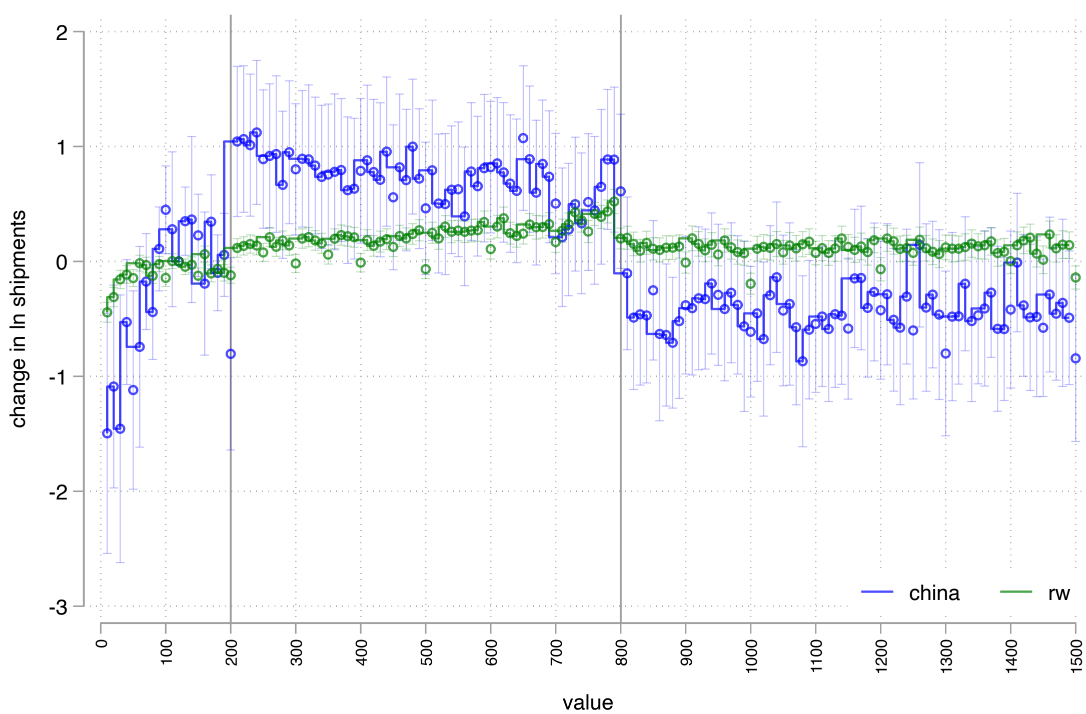
Figure A.6A plots the density. The impact of the notch is evident as the density approaches \$800, and the subsequent drop in shipments above the notch is consistent with the carrier data: \$100 above the notch on average result in 44.9% fewer shipments compared to \$100 below. Thus,

FIGURE 5: DIFFERENCE-IN-DIFFERENCES SPECIFICATION

Panel A: All Origins



Panel B: By Origin



Notes: Figure reports the density of shipments to the USA in the post period relative to pre period, and relative to the same time difference for OECD shipments. The regression specification is (22), and the figure plots the $\beta_b \times \text{USA}_d \times \text{post}_t$ fixed effects. Panel A uses shipments from all origins, and Panel B estimates (22) separately for Chinese and rest-of-world shipments. Grey vertical lines denote §321 thresholds before and after March 2016. The leave-out bin is $120. Error bars denote 95% confidence intervals.

a concern from carrier data–that shippers may switch to alternative logistics providers above the threshold–is not borne out in CBP data, which contains the universe of shipments by logistics providers. Figure A.6B shows that the drop in shipments from China between these two intervals is even starker, with 108.8% fewer shipments. Thus, the impact of the notch appears also in the administrative records from CBP, although we do not use this sample to estimate the tariff elasticities since we do not observe the corresponding control densities.

5.2 Alternative Explanations

This section examines two potential alternative explanations for bunching: freight charges could change at the threshold, and firms or consumers could break down shipments. We also examine if there is a discrete change from residential destinations to commercial destinations around the threshold.

First, we demonstrate that shipping costs do not change discretely at the threshold values. This was confirmed to us by the carriers, and carrier C provided freight charges. Figure A.7 shows how freight costs change across the destination, with no evidence of changes at the $800 threshold (this carrier only provided data from 2020 onwards and did not provide transshipments to non-USA destinations, so we do not have control densities to compare against).

Second, the bunching and subsequent drop in density at the threshold could partly be explained by manipulation of the number of items per package. Recall that the law explicitly prohibits firms from sending items of a single invoice over multiple shipments. However a consumer could spread a transaction with multiple items into multiple transactions across days, at potentially higher shipping and convenience costs. Thus, firms or consumers could adjust the number of items such that each package value drops below $800, without any changes in a given item's price. Across all imports, single-item shipments are 76.0% of de minimis shipments and 72.5% of de minimis value.

The top panel of Figure A.8 shows the number of items per package (relative to the leave-out bin $120). The pre-2016 (green) series shows a drop in the number of items per package right above the $200 threshold at that time, which is consistent with shippers splitting shipments, so that the total package value is below the threshold. However, the drop in the number of items is small: packages right above the threshold have only 5% fewer items than below the threshold. The post-2016 (blue) series appears to have fewer items per shipment relative in the $600-$800 range compared to above the $800 threshold, but again the difference is quantitatively small–less than 5% fewer items per package. The bottom panel reports the difference-in-differences (across destinations and over time), and again, the magnitude of changes is small around the threshold.

Nevertheless, we can examine the robustness of the impact of the notch to this concern by re-estimating (22) on *single-item* packages. We can do this using carriers A and C who provide the number of items; collectively, in 2021, single-item packages accounted for 76.0% of de minimis shipments and 72.5% de minimis value from these carriers. The top panel of Figure A.9 reports the difference-in-differences across all origins, and the bottom panel reports the results by origin.

We observe a very similar pattern as the main figures in Figure 5, which is consistent with item manipulation not being quantitatively important at the threshold. Across all origins, there are 27.1% fewer shipments \$100 above versus below the notch (for China, the corresponding decline is 155.3%).

Finally, while the majority of shipments go to households, it could be that commercial customers place relatively more orders around the threshold. We assume that imports to commercial addresses are consumed locally, but this is not an assumption we can directly check given data limitations. Still, we can examine the share of shipments to households in carrier A's data across the distribution; see Figure A.10. The share of households importing around the threshold is 13.7% lower than at the leave-out but there is no discontinuous change, suggesting that the type of importer does not change discretely around the threshold.

6 Model Implementation and Welfare

This section parameterizes the model to obtain aggregate and distributional impacts of counterfactual de minimis policies. We first show how we address the missing hole in the shipment density right above the notch, then present the expressions to measure welfare, and discuss how we parametrize the key tariff elasticities and underlying firm heterogeneity. We then examine policy counterfactuals that eliminate §321.

6.1 Firm Types

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

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

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

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

6.2 Welfare Measurement

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

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

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

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

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

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

In turn, the change in the price index from for direct goods from o among ω consumers is:[21]

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

where

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

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

As we have mentioned, there can be any correlation between unit costs and demand shocks. This correlation is key to assess welfare impacts, as it determines the exposure of different consumer groups. However, only the quality-adjusted measure $h_o^{\omega,j}(z)$, which combines demand shocks and measure of firms across the distribution of unit costs, matters to calculate aggregate and distributional effects. Knowing this function and the elasticities $(\sigma_o, \gamma, \kappa)$ we can fully characterize model outcomes given the policies (τ_o, v_{DM}). In the next sections, we recover each of these objects from the data, and use the model to assess the welfare impacts of de minimis.[22]

6.3 Parametrization

As a first step, we jointly calibrate the aggregate (US-level) quality-adjusted distribution $h_o^{US,j}(z)$ for $j = S, N$ (sophisticated or naive), defined as aggregating over ω, the group-specific distributions $h_o^{\omega,j}(z)$, and the substitution elasticities σ_o for each origin. Our procedure jointly

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

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

calibrates σ_o and $h_o^{US,j}(z)$ for $o = CHN, RW$ to match the post-2016 density of imported packages and the change in this density between the post- and the pre-2016 periods, both of which have been estimated in the previous section. Specifically, the following steps 1 and 2 are implemented for each value of σ_o, and we search in the space of σ_o.

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

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

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

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

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

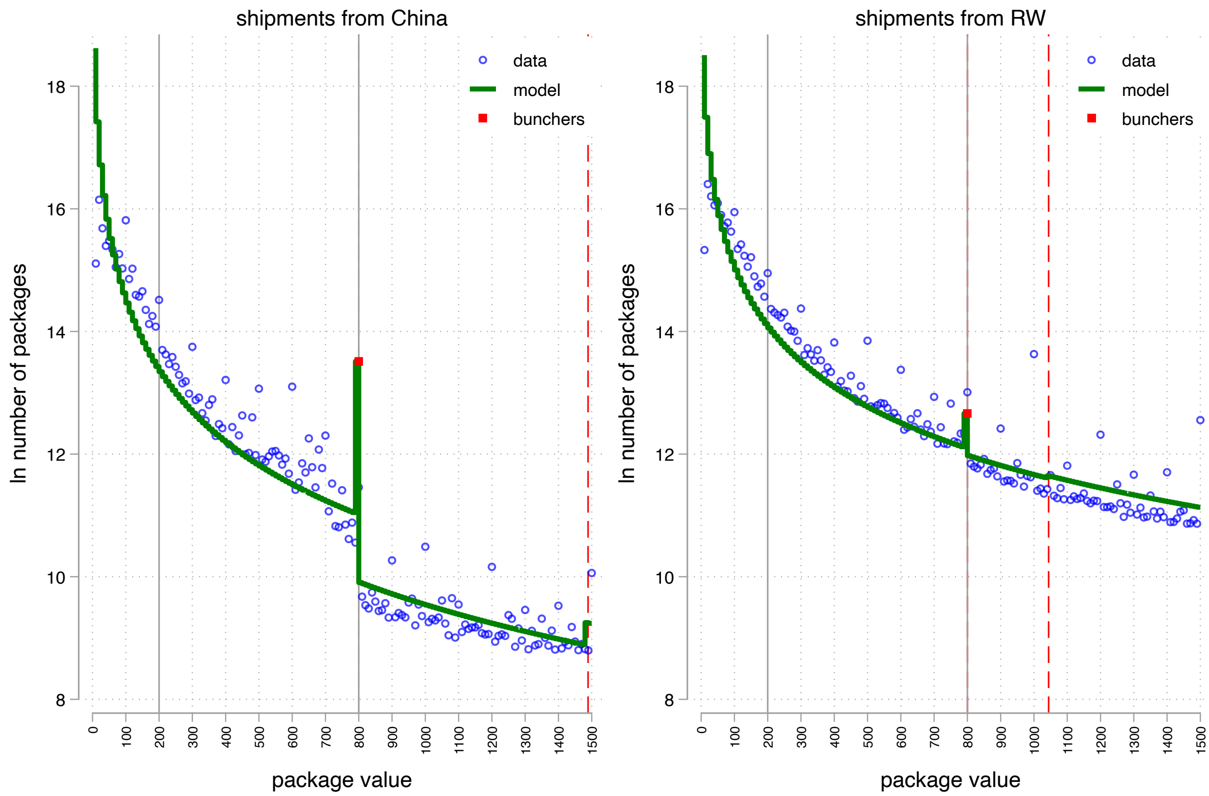
We observe $\Delta N_o^{US}(v)$ over a grid of values $v \in [0, 10, ..., 5000]$ in the post-2016 period. To implement, we assume a power function for $D_o^{US}h_o^{US,S}(z)$. We jointly parameterize δ_o^ω (which regulates the importance of naive firms) to exactly match the observed number of shipments in the excluded region $(v_{DM}, v_{H,o}(z_H)]$, and the power function for $D_o^{US}h_o^{US,S}(z)$ to match the observed $\Delta N_o^{US}(v)$ outside the dominated range ($v \le v_{DM}$ and $v > v_{H,o}(z_H)$).[23]

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

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

threshold, such as product indivisibilities within shipments. From other origins, where tariffs are much lower, the discontinuity is absent in both model and data.

FIGURE 6: CALIBRATED DISTRIBUTION

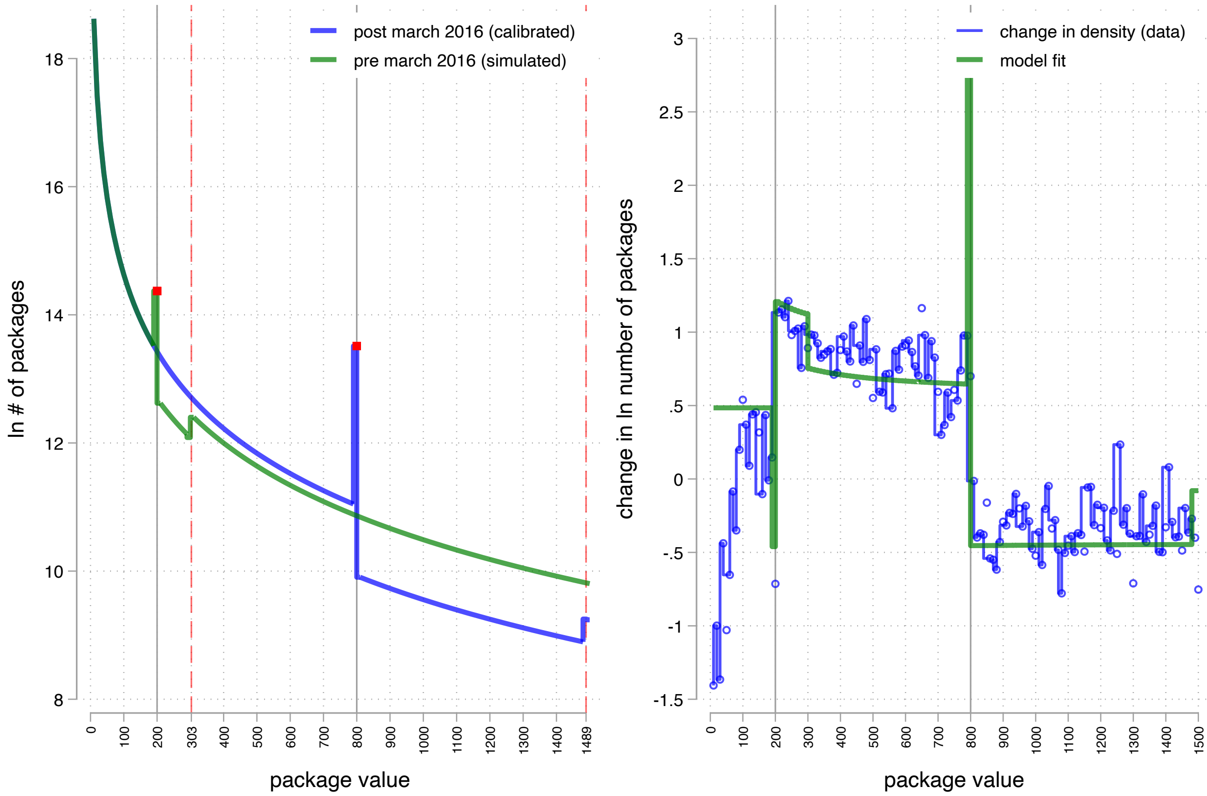


Notes: Figure shows the actual and model-implied histogram at the calibrated values of the elasticities ($\sigma_{CH} = 3.13$, $\sigma_{RW} = 2.26$). The left panel reports the calibration for shipments from China. The right panel reports the calibration for shipments from RW. The red vertical line in each panel indicates the highest cost buncher. The calibration is performed on shipments up to $5,000, but the graph displays the density up to $1500 to improve visualization.

Step 2: Simulating the Change in Bunching from Policy Changes Using the density from the previous step, and given the value of σ_o, we simulate changes in tariffs and in the §321 threshold from the post-2016 period to the pre-2016. That is, we change tariffs on China from 23.9% to 4.0%, the average tariff in the pre period, and tariffs on RW from 1.4% to 2.7%; and, we change the threshold from $800 to $200. These policy changes mimic the difference-in-differences specification in (22), which estimates changes in the density over time and across origins.

We search in the space of σ_o, each time implementing steps 1 and 2, to match the empirical change in bunching at the new threshold of $800 (from a previous threshold of $200) from Figure 5. Specifically, we match the difference between the estimated change in the number of packages over the $200-$800 range and the estimated change in the number of packages in the $800-$1500 range. Figure 7 shows the outcome of the step 2 for China as origin. The blue series in the left panel shows the post-2016 calibrated histogram (i.e., the same as in left panel of Figure 6), and the green series is the model-based counterfactual from rolling the economy back to pre-2016. The right panel shows the difference between these two series (post minus pre) in green, and overlays

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



Note: Top left shows the model-implied histogram in the calibrated (post-2016) equilibrium and the counterfactual model-implied histogram given pre-2016 tariffs and threshold at the calibrated values of the elasticity ($\sigma_{CH} = 3.13$), $\sigma_{RW} = 2.26$). The right panel shows the difference between the post- and pre- distributions in the model and in the data. Each of these series is demeaned.

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

We find that $\sigma_{CH} = 3.13$ for China, and $\sigma_{RW} = 2.26$ for RW, matches the observed drop in the density at \$800). The model broadly replicates the fact that the changes in densities are roughly constant within the \$200-\$800 and the above-\$800 ranges, and it captures some of the decline in bunching in the below-\$200 range, but to a lesser degree than what is observed in the data.

Step 3: Estimating γ The previous steps are independent from the parameter γ, which governs consumers' substitution across origins. The CES structure at the origin-group level implies that, when policies change, the value of direct-to-consumer shipments from origin o to group ω is:[24]

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

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

We cannot construct P_o^ω because we do not observe variety-prices to back out residual demand shocks at that level–we only observe densities of spending over shipments, allowing us back out a composite of demand shocks and firm-level efficiency, as discussed in the previous step. Therefore, we follow an indirect indifference approach. Specifically, we the following regression in the data and in the model:

$$\Delta \ln E_o^\omega = \alpha^\omega + \beta\left(Share_{post} > 800\right)_o^\omega * \Delta \ln \left(\tau_o^\omega\right) + \varepsilon_o^\omega. \tag{31}$$

We run this regression in the data, obtaining an estimates for $\hat{\beta}$. We run the same regression in the model for each candidate value of γ, generating coefficients $\beta\left(\gamma\right)$, and search in the space of γ such that $\beta_0\left(\gamma\right) = \hat{\beta}$. The regression using the data yields $\beta = -0.31$, and we estimate (31) for model-generated densities at different values of gamma. Figure A.11 shows the value of $\hat{\beta}$ and the corresponding $\beta_0\left(\gamma\right)$ at each value of gamma. The intersection pins down the choice of γ, which occurs at $\gamma = 4.6$. As a comparison, Fajgelbaum et al. (2020) estimate a within-product cross-origin elasticity equal to 2.53.

6.4 Welfare Impacts of Eliminating De Minimis

Aggregate Impacts We first report the aggregate welfare impacts of the §321 by implementing a counterfactual elimination of the thresholds starting from the 2021 tariff level. That is, starting from the post-2016 equilibrium, we solve for the price distribution under a counterfactual policy. We then compute the welfare outcomes for both the aggregate US and by consumer group ω as defined in Section 6.2. Before showing the results, we first discuss a few choices involved in this calculation.

First, we use the values of σ_o calibrated from the previous subsection.[25] Given this elasticity, we re-do step 1 from the previous subsection to obtain a quality-adjusted density $h_o^{S,\omega}\left(z\right)$ that matches the observed histogram by consumer group ω and origin o, $\Delta N_o^\omega\left(v\right)$ defined in (29).[26] Second, the impacts defined Section 6.2 are a function of changes in price changes that are independent from demand shifters, and can therefore be computed only once using the results from Proposition 1. To compute changes in price indexes, what varies across groups is the exposure to these price

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

[25]To compute these outcomes, we need values for the elasticities κ (between direct imports and other goods). We use $\kappa = 1.19$, the substitution between imports and domestic goods from Fajgelbaum et al. (2020). A caveat with this parameter is that it is estimated from Census data, so it corresponds to informal shipments above \$2000 and formal shipments, not de minimis shipments.

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

TABLE 3: AGGREGATE IMPACTS OF ELIMINATING §321

	carrier data			CBP data		
fee	consumer ($b)	tariff ($b)	welfare ($b)	consumer ($b)	tariff ($b)	welfare ($b)
$0	-3.7	2.2	-1.5	-7.4	2.2	-2.6
$10	-7.1	1.7	-5.5	-12.9	1.7	-9.1
$23.19 (benchmark)	-12.0	1.3	-10.6	-18.3	1.3	-14.8
$30	-15.4	1.3	-14.1	-21.0	1.3	-17.4

Notes: Table reports the impacts of eliminating §321 at different per-shipment customs fees. Each case assumes parameters: $\{\sigma_{CHN}, \sigma_{RW}, \gamma, \kappa\} = \{3.13, 2.26, 4.60, 1.19\}$.

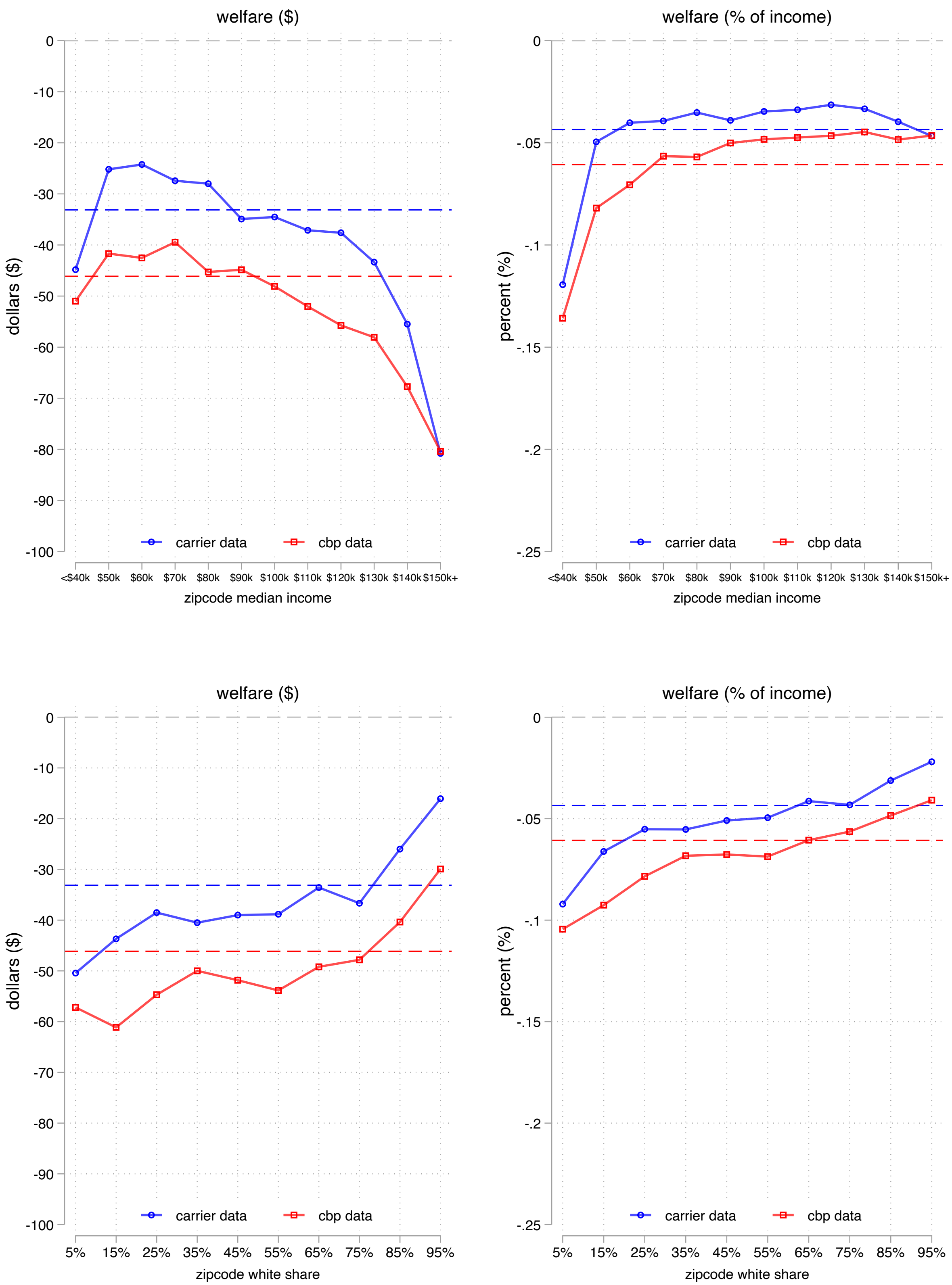
changes, as inferred from the calibrated distributions $h_o^{S,\omega}(z)$. Third, when implementing this counterfactual we must take a stand on how tariff revenue is rebated. We assume that each consumer group is rebated the tariff revenue generated by its imports, so that the change in transfers to each group is equal to the group-specific tariff revenue defined in (48).

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

The left panel of Table 3 reports the aggregate losses from the carrier data. The first column reports the losses to consumers from the increase in prices, the second column reports the tariff revenue gain, and the third column–the welfare loss–is the sum of the two. At the benchmark fee, the aggregate welfare loss is $10.6 billion, or $33 per person (or $133 per family). As a comparison, Fajgelbaum et al. (2020) estimate the sum of consumer cost and tariff revenue gain of the 2018 US tariffs on China at $16.1 billion ($49 per person or $194 per family), and the tariffs waves through 2019 at $48.2 billion ($147 per person or $580 per family). This welfare loss scales roughly linearly with the fee structure: reducing the fee to $10 per shipment would result in a roughly 50% smaller welfare loss at $5.5 billion and a $30 fee would magnify the welfare loss to $14.1 billion; recall that the customs fee is not rebated back to consumers and so 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 $14.8 billion. This is because the share of de minimis shipments from China is 66.9% in CBP data, compared to 37.0% in the carrier data.

FIGURE 8: CHANGE IN WELFARE BY ZIPCODE INCOME AND WHITE SHARE



Notes: Figure reports ev^w defined in (24) against zipcode characteristics. The left panels report welfare impacts in per-capita dollars and the right panel scales by median family income. Top panel reports by zipcode median family income, and bottom panel reports by zipcode white household share. The series is the welfare loss at 2022 tariffs and $T = \$23.19$ using parameters $\{\sigma_{CHN}, \sigma_{RW}, \gamma, \kappa\} = \{3.15, 2.26, 4.60, 1.19\}$. 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 A.12 shows the change in the price index $\hat{P}^{\omega}$ across income brackets.[27] The increase in prices is driven by both the per-shipment fee and the increase in tariffs. We find that eliminating the policy would increase the price index the most, in percentage terms, for poorer zipcodes, and for zipcodes with lower shares of white households. These patterns follow in large part from the reduced-form evidence we have presented in the previous evidence, where we have shown that these groups are more likely to spend in goods originating from China and tax-exempt goods, below the $800 threshold. Because China is subject to higher tariffs and de minimis affects goods below $800, these groups tend to be the ones that stand to lose more, in relative terms, if the threshold is eliminated. Figure A.13 converts these changes in prices to the increase in cost of the basket of goods for consumers. When expressed as share of income, the right panel reveals that a policy change would raise the costs most for lower-income and minority consumers.

Figure 8 shows the equivalent variation–the welfare impacts of the policy change–which is the difference between Figure A.13 and the tariffs rebated back to each consumer group. The top panel of Figure 8 reports the welfare estimates across zipcode income. Our estimates imply that, in zipcodes with median family income under $40k, per capita welfare would decline by $45. This compares with a $35 decline for zipcodes with $100k median family income, and a decline of $81 for the richest zipcodes. As a share of income, the corresponding declines for low, median and high-income zipcodes are 0.12%, 0.03%, and 0.05%. Thus, we find that the lowest-income households would bear the brunt of eliminating §321.

The bottom panel of Figure 8 analyzes welfare losses by zipcode white share. We find that welfare in zipcodes with 5% white households would experience a decline of $50. This compares with a decline of $39 decline for zipcodes with 45% white share, and a decline of $16 for the zipcodes with 95% white households. As a share of income, the corresponding declines for low, median and high white shares are 0.09%, 0.05%, and 0.022%. Our estimates therefore suggest that eliminating §321 would therefore raise the cost of living disproportionately more for non-white households.

Figure A.14 reports the distributional impacts at fees ranging from $0 to $30 per shipment in both the carrier and CBP data. The per-person welfare impact scales with the fee structure and incidence across consumer groups remains as before.

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

7 Conclusion

We study §321 section of the 1930 Trade Act, that allows imports to enter the country without paying tariffs or processing fees. While all countries have "de minimis" policies, the US threshold of $800 is the highest in the world and its de minimis imports have exploded in recent years.

We establish conditions under which a non-zero tariffs with a de minimis policy could dominate free trade because the threshold induces bunching below the notch, generating a term-of-trade gain for the country. Using a unique database of shipments that span the full distribution of values and the destination zipcodes, we document that expenditures on de minimis imports are relatively important for lower-income zipcodes, and that these zipcodes disproportionately import from China. Given the high tariffs on imports from China from the US-China trade war, this suggests that §321 benefits low-income consumers by effectively converting a regressive tariff schedule to a progressive schedule. We also document that notch induces bunching around the threshold, and identify the extent of bunching by examining the density of shipments relative to two control densities: shipments prior to March 2016, when the threshold was $200, and shipments to the OECD. The shipment densities across zipcodes, the extent of bunching around the notch, and tariffs across origins pin down key elasticities to quantify the impacts of §321. We find that eliminating §321 would disproportionately hurt the poor and minority households, and that it would lead to aggregate welfare losses.

Our preliminary estimates do not account for a couple of important margins that we intend to incorporate. First, we plan to use the tariff variation across origins to pin down the substitution across countries. Second, we plan to study substitution between de minimis imports and domestic retailers, who are more likely to import in bulk or source domestically, using a sample of consumers' purchases at domestic retail stores. This margin is important to parametrize the demand substitution between de minimis shipments and other expenditures, as well as potential losses of domestic employment.

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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

$$x^{\omega} = \left(\sum_{o} \left(A_{o}^{\omega}\right)^{\frac{1}{\gamma}} \left(x_{o}^{\omega}\right)^{\frac{\gamma-1}{\gamma}} \right)^{\frac{\gamma}{\gamma-1}}, \tag{32}$$

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

$$x_{o}^{\omega} = \left(\int_{i \in \Omega_{o}} \left(a_{i}^{\omega}\right)^{\frac{1}{\sigma_{o}}} \left(n_{i}^{\omega}\right)^{\frac{\sigma_{o}-1}{\sigma_{o}}} di \right)^{\frac{\sigma_{o}}{\sigma_{o}-1}}, \tag{33}$$

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

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

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

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

$$E_{o}^{\omega} = A_{o}^{\omega} \left(\frac{P_{o}^{\omega}}{P^{\omega}} \right)^{1-\gamma} L^{\omega} e^{\omega}, \tag{35}$$

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

$$L^{\omega} n_{i}^{\omega} = a_{i}^{\omega} D_{o}^{\omega} v_{i}^{-\sigma_{o}}. \tag{36}$$

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

$$D_{o}^{\omega} = E_{o}^{\omega} \left(P_{o}^{\omega}\right)^{\sigma-1}. \tag{37}$$

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

$$\begin{aligned} N_{i} &\equiv \sum_{\omega} L^{\omega} n_{i}^{\omega} \\ &= \left(\sum_{\omega} a_{i}^{\omega} D_{o}^{\omega} \right) v_{i}^{-\sigma_{o}}. \end{aligned} \tag{38}$$

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

And, for firms of type N

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

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

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

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

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

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

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

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

while $j = N$ firms we have

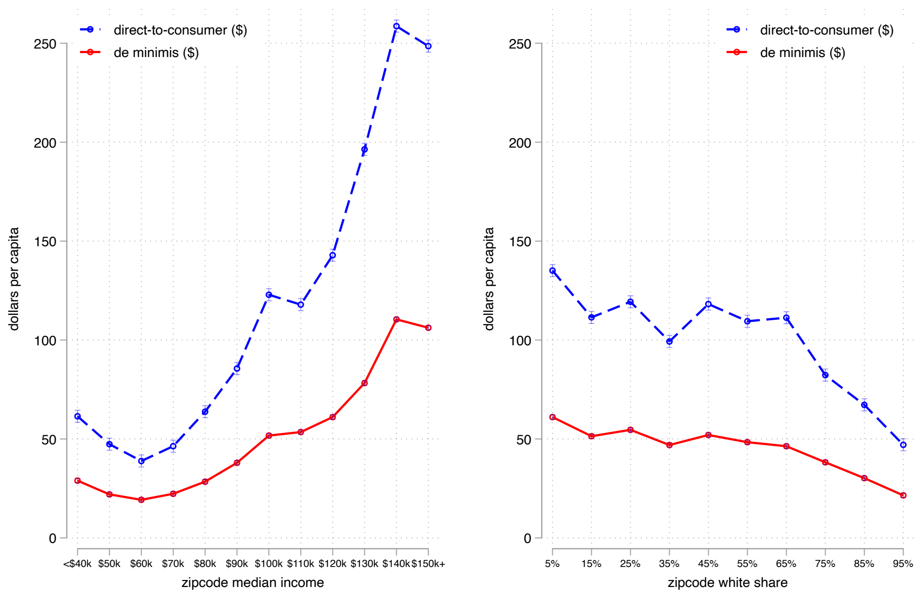
$$\Delta tr_o^{\omega,N} = \tau_o \hat{\tau}_o \frac{e_o^{\omega} \hat{e_o^{\omega}}}{\left(\hat{P}_o^{\omega}\right)^{1-\sigma_o}} \int_{z_{L,o}\hat{z}_{L,o}}^{\infty} \hat{v_o^N}(z)^{1-\sigma_o} \lambda_o^{\omega,N}(z)\, dz - e_o^{\omega} \tau_o \int_{z_{L,o}}^{\infty} \lambda_o^{\omega,N}(z)\, dz.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

Appendix Tables and Figures

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

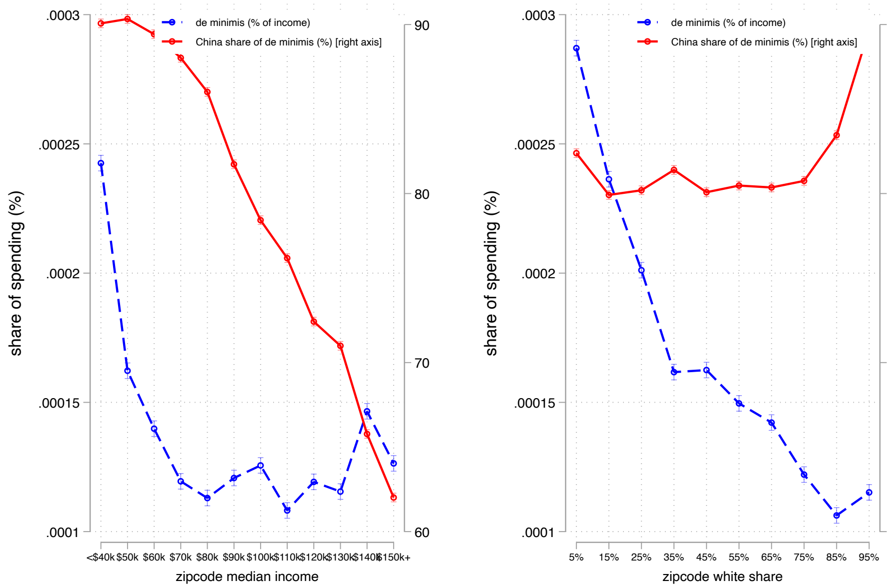
Notes: Figure displays the most common items in direct-to-consumer shipments. The items are reported in carriers A and B shipments, processed using standard text processing (remove stop words, stemming).

FIGURE A.2: DIRECT-TO-CONSUMER AND DE MINIMIS SHIPMENTS, BY ZIPCODE CHARACTERISTIC



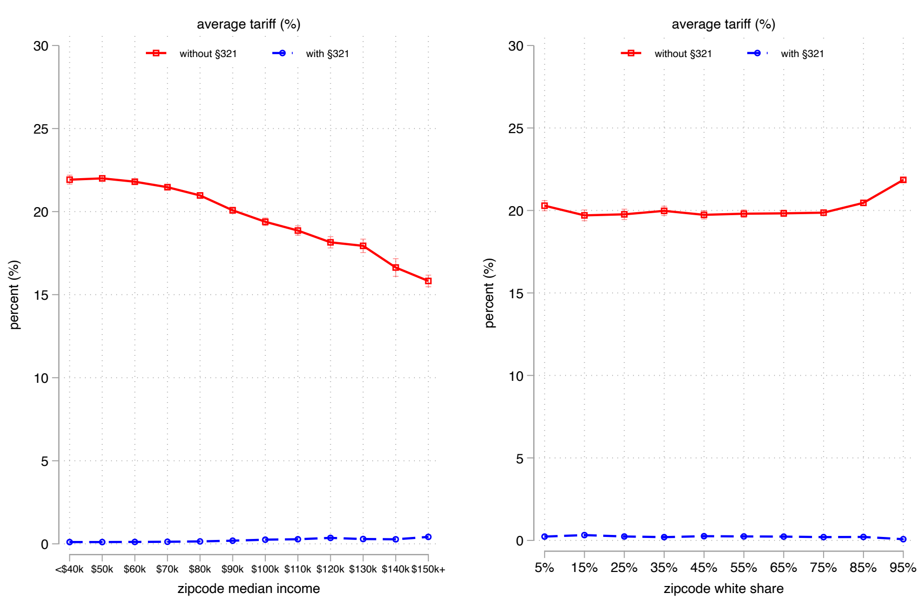
Notes: Figure correlates 2021 per-capita expenditures on shipments below $ 5,000 (red series) and de minimis shipments (blue series). The left panel plots against zipcode median family income and the right panel plots against zipcode share of white households. Standard errors of the means reported in brackets.

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



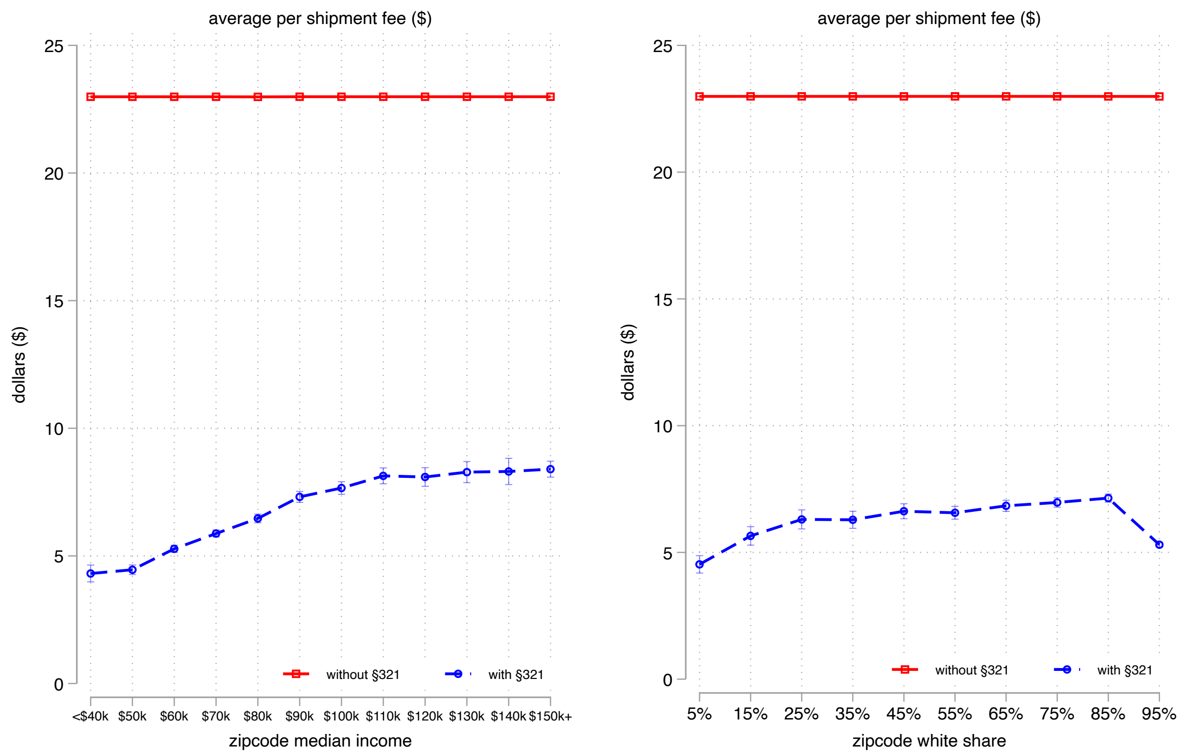
Notes: Figure examines the weekly CBP shipment data from 2021. The blue series correlates per-capita expenditures has a share of income across zipcode median income. Recall that since this is just one week of data, the shares are small. The red series shows the share of de minimis imports from China. Standard errors of the means reported in brackets.

FIGURE A.5: TARIFF INCIDENCE, CBP SAMPLE



Notes: Figure reports the zipcode-level tariffs from the 2021 CBP data. A zipcode'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. Standard errors of the means reported in brackets.

FIGURE A.4: ADMINISTRATIVE FEE INCIDENCE, BY ZIPCODE



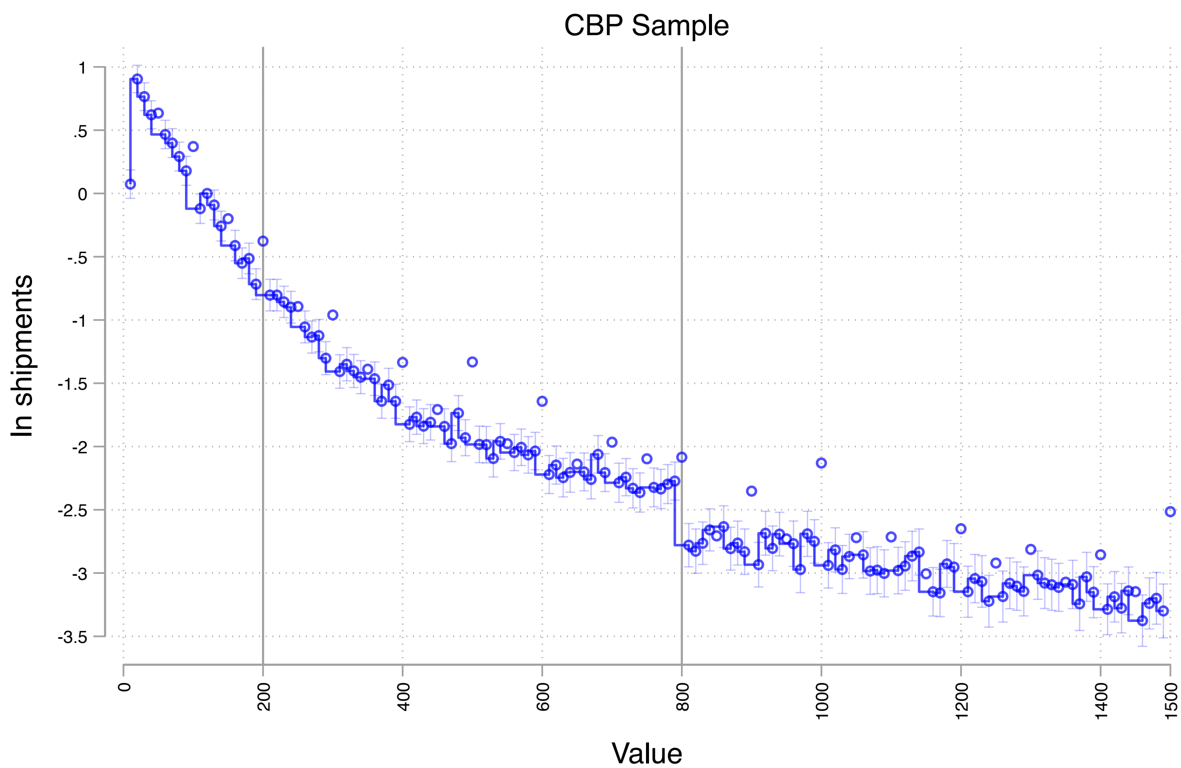
Notes: Figure reports the average per-shipment administrative fee with §321 in effect (blue series). The series is constructed by applying a $23.19 fee to shipments over $800 and a fee of $0 for shipments under $800. The red series removes the fee exemption by eliminating §321 and applying the $23.19 fee to all direct shipments. Standard errors of the mean reported in brackets.

TABLE A.1: DIRECT SHIPMENTS, DE MINIMIS AND TARIFFS: REGRESSIONS

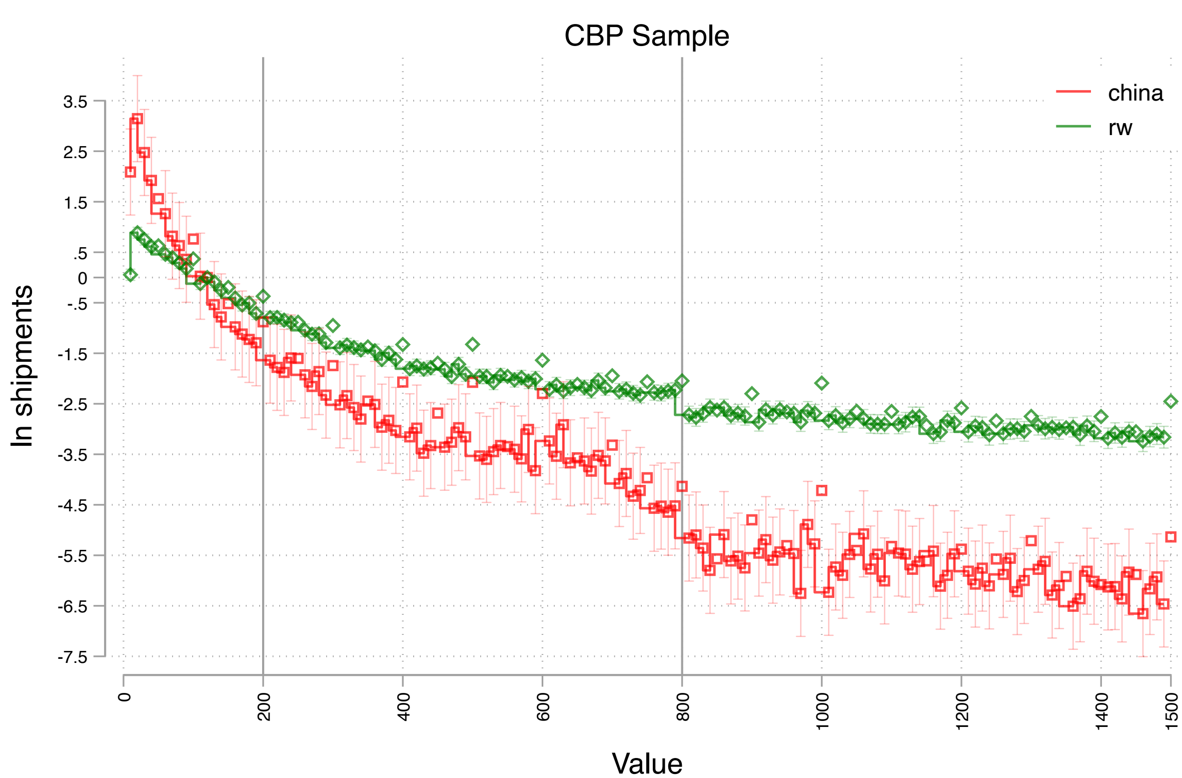
	(1) direct shipments (% inc)	(2) dm share (%)	(3) chn share of dm (%)	(4) tariff w/ §321	(5) tariff w/out §321
log p50 income	0.02**	-11.94***	-12.23***	0.51***	-2.59***
	(0.01)	(0.50)	(0.32)	(0.02)	(0.11)
% white share	-0.14***	-1.80***	-7.76***	0.02	-1.96***
	(0.01)	(0.67)	(0.43)	(0.03)	(0.14)
log pop density	0.01***	-2.00***	-0.34***	0.07***	-0.31***
	(0.00)	(0.07)	(0.05)	(0.00)	(0.01)
State FEs	Yes	Yes	Yes	Yes	Yes
R2	0.02	0.13	0.26	0.09	0.15
N	32,203	32,192	32,188	31,804	31,803

Notes: Table correlates outcomes against zipcode characteristics. Column 1 is direct shipments (shipments under $5,000) as a share of zipcode median family income. Column 2 is de minimis shipments as a share of direct shipments. Column 3 is the share of shipments from China within de minimis shipments. Column 4 is the average tariff faced by the zipcode with §321. Column 5 is the average tariff if §321 were eliminated, holding spending shares constant. All columns control for state fixed effects. Clustered standard errors by state reported in parentheses.

Figure A.6: CBP Shipment Density
Panel A: All Origins

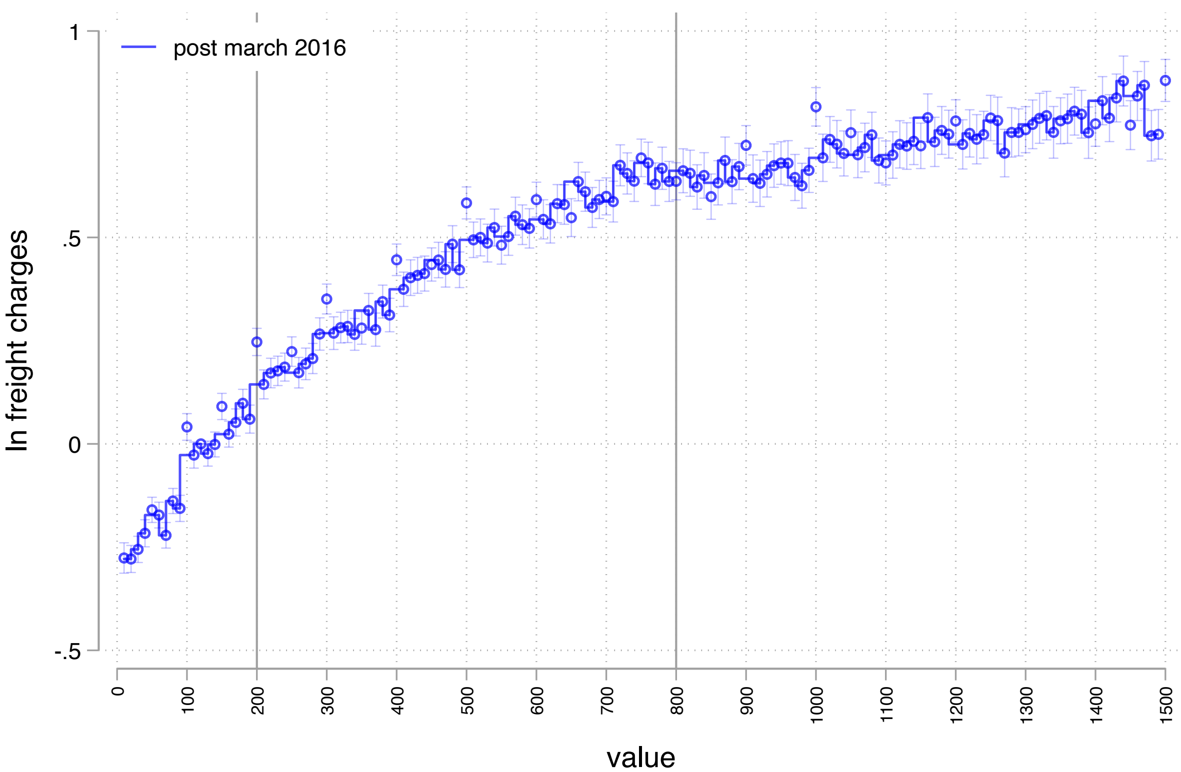


Panel B: By Origin



Notes: Figure examines the weekly CBP shipment data from 2021 using the analog regression in (21). The top panel is for all origins, and the bottom panel separates China and RW.The leave out bin is $120. Grey vertical lines denote §321 thresholds before and after March 2016. Error bars denote 95% confidence intervals.

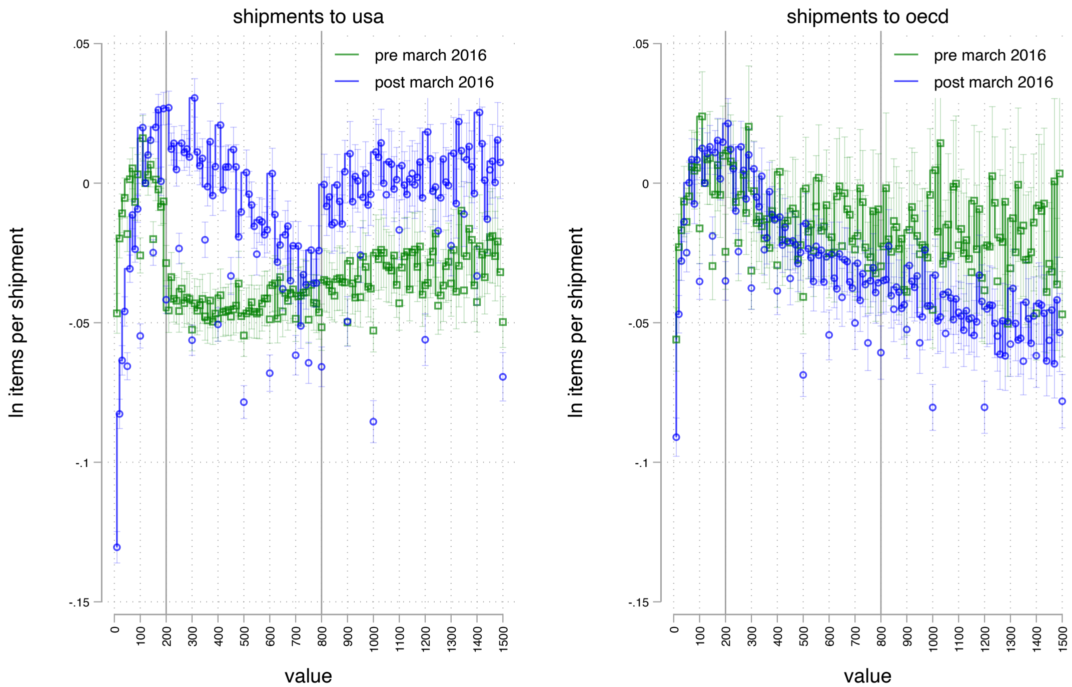
FIGURE A.7: FREIGHT CHARGES



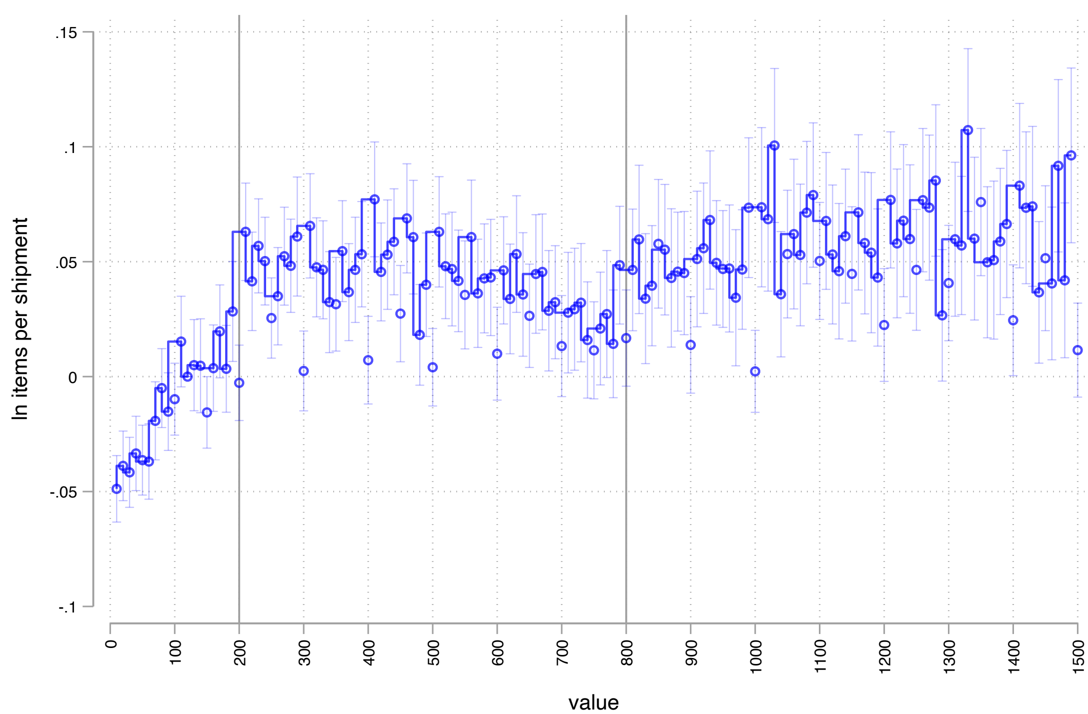
Notes: Figure shows relative freight charges across the shipment value distribution The leave out bin is \$120. Grey vertical lines denote §321 thresholds before and after March 2016. Error bars denote 95% confidence intervals. Data for carrier C, who provided data 2020 onwards and did not provide transshipped packages to non-USA destinations.

FIGURE A.8: NUMBER OF ITEMS PER SHIPMENT

Panel A: Levels



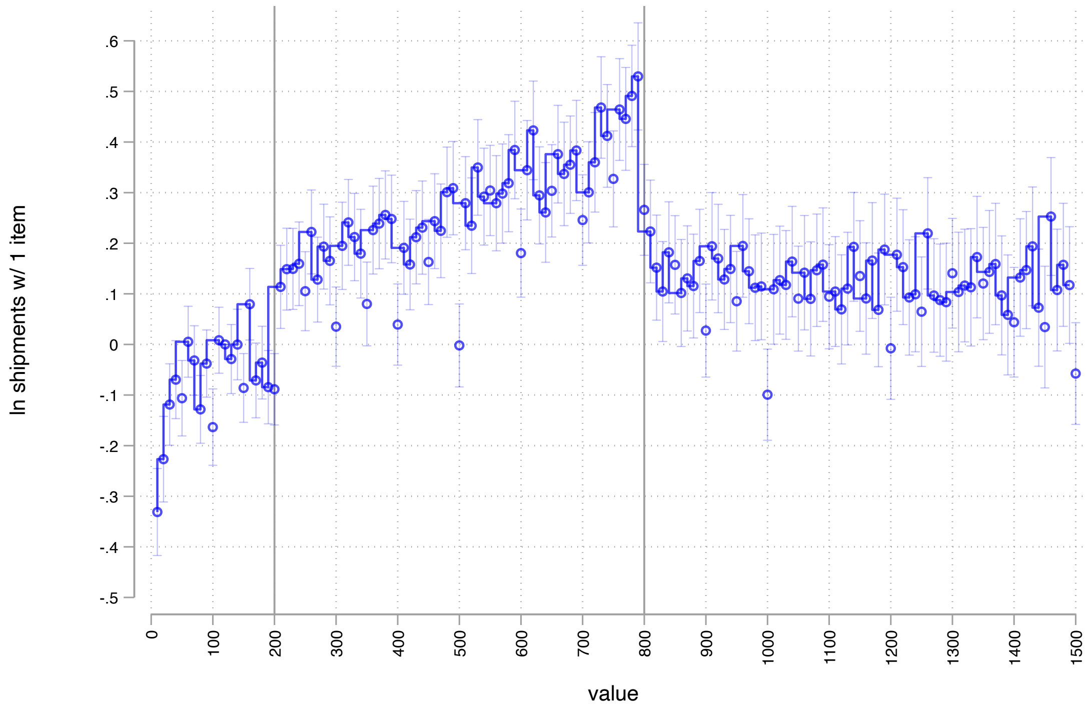
Panel B: Difference-in-Differences



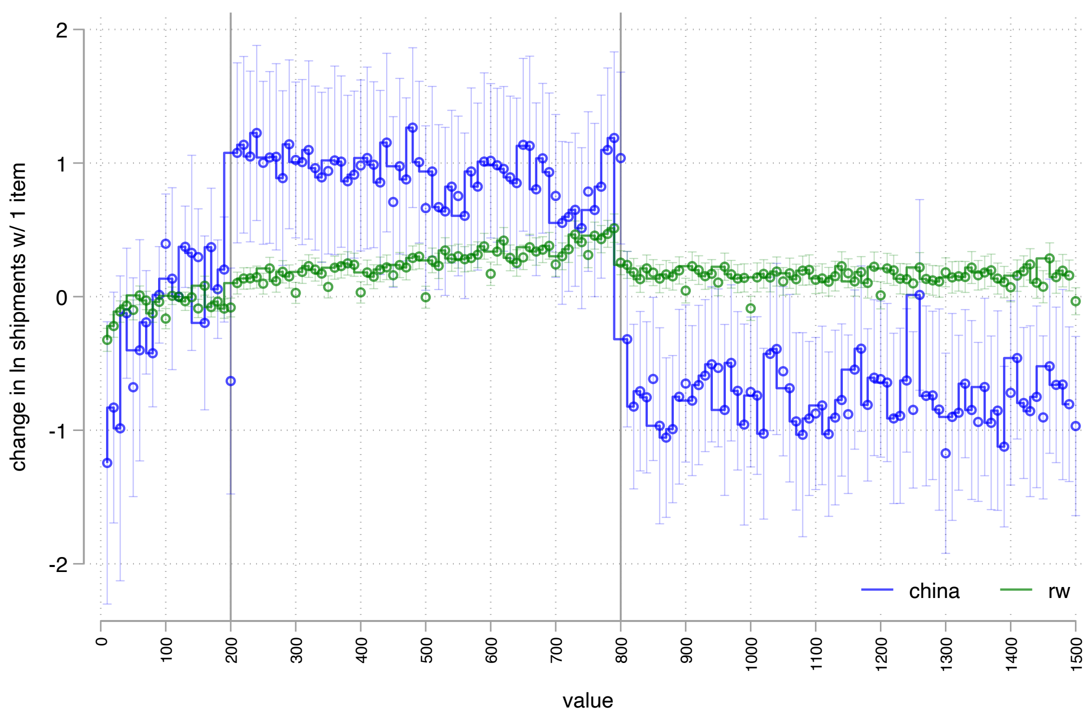
Notes: Figure reports the average number of items per package at each bin. The top panel runs regressions (21) in levels, and the bottom panels reports the difference-in-differences specification (22) Grey vertical lines denote §321 thresholds before and after March 2016. The leave-out bin is $120. Error bars denote 95% confidence intervals. Data is from carriers A and B.

FIGURE A.9: CHANGE IN DENSITY OF ONE-ITEM SHIPMENTS

Panel A: All Origins



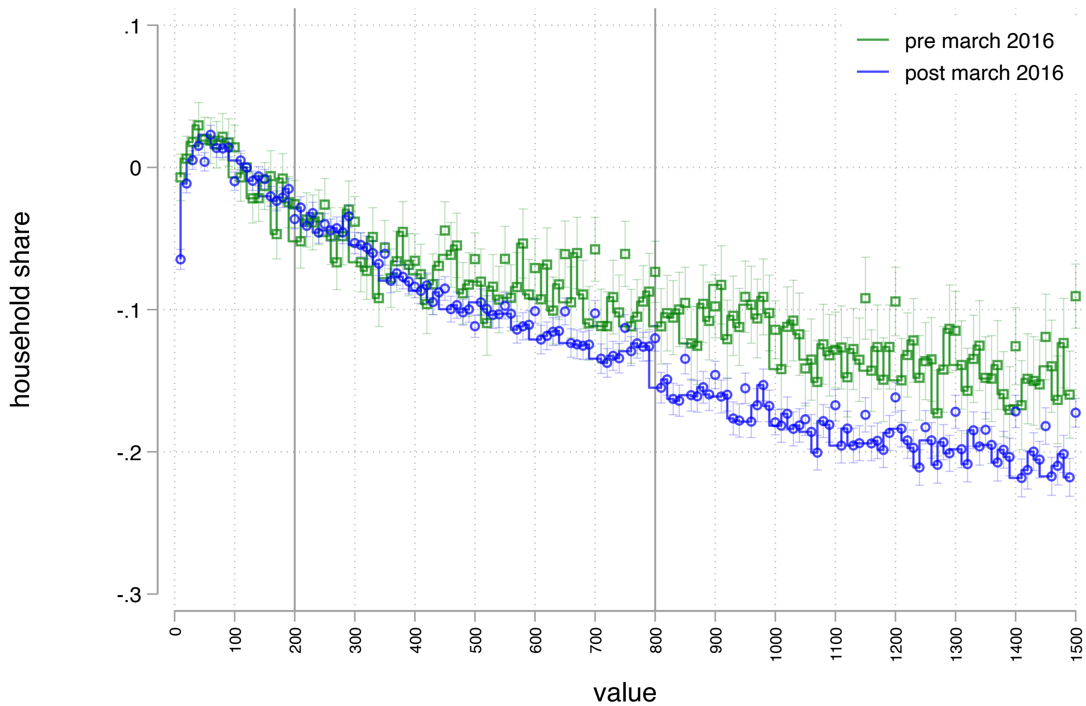
Panel B: China vs RW



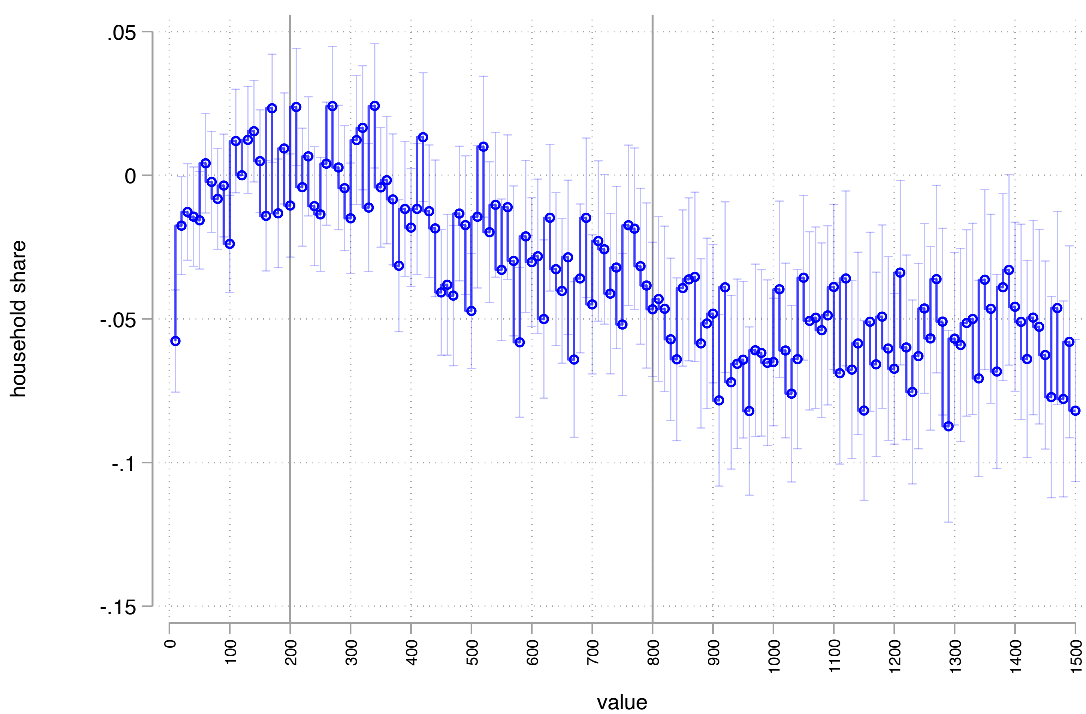
Notes: Figure reports the number of shipments containing one item at each bin. The top panel runs (22) for all origins, and the bottom panels reports results separately for China and RW. Grey vertical lines denote §321 thresholds before and after March 2016. The leave-out bin is $120. Error bars denote 95% confidence intervals. Data is from carriers A and B.

Figure A.10: Share of Households

Panel A: Levels

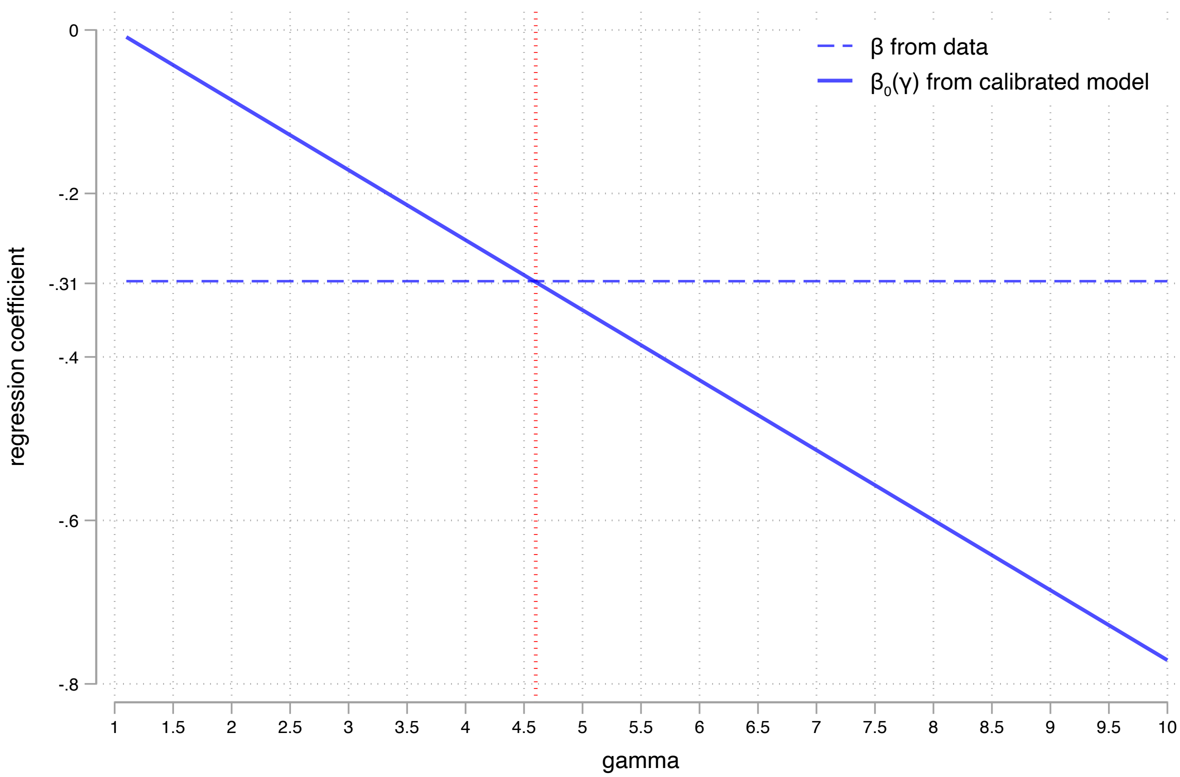


Panel B: Difference-in-Differences



Notes: Figure reports the fraction of shipments in each bin that are sent to addresses matched to US residential zones; see Section 4.1 for details. The regression in the top panel is $hhshare_{bodxt} = \alpha_{odxt} + \beta_b + \epsilon_{bodxt}$, where the green series is run on shipments pre-March 2016 and the blue series is run on shipments post-March 2016. The bottom panel reports the difference between pre and post March 2016, $hhshare_{bodxt} = \alpha_{odxt} + \beta_b \times \text{post}_t + \epsilon_{bodxt}$. Grey vertical lines denote §321 thresholds before and after March 2016. The leave-out bin is \$120. Error bars denote 95% confidence intervals. Data is from carrier A.

FIGURE A.11: CALIBRATION OF γ

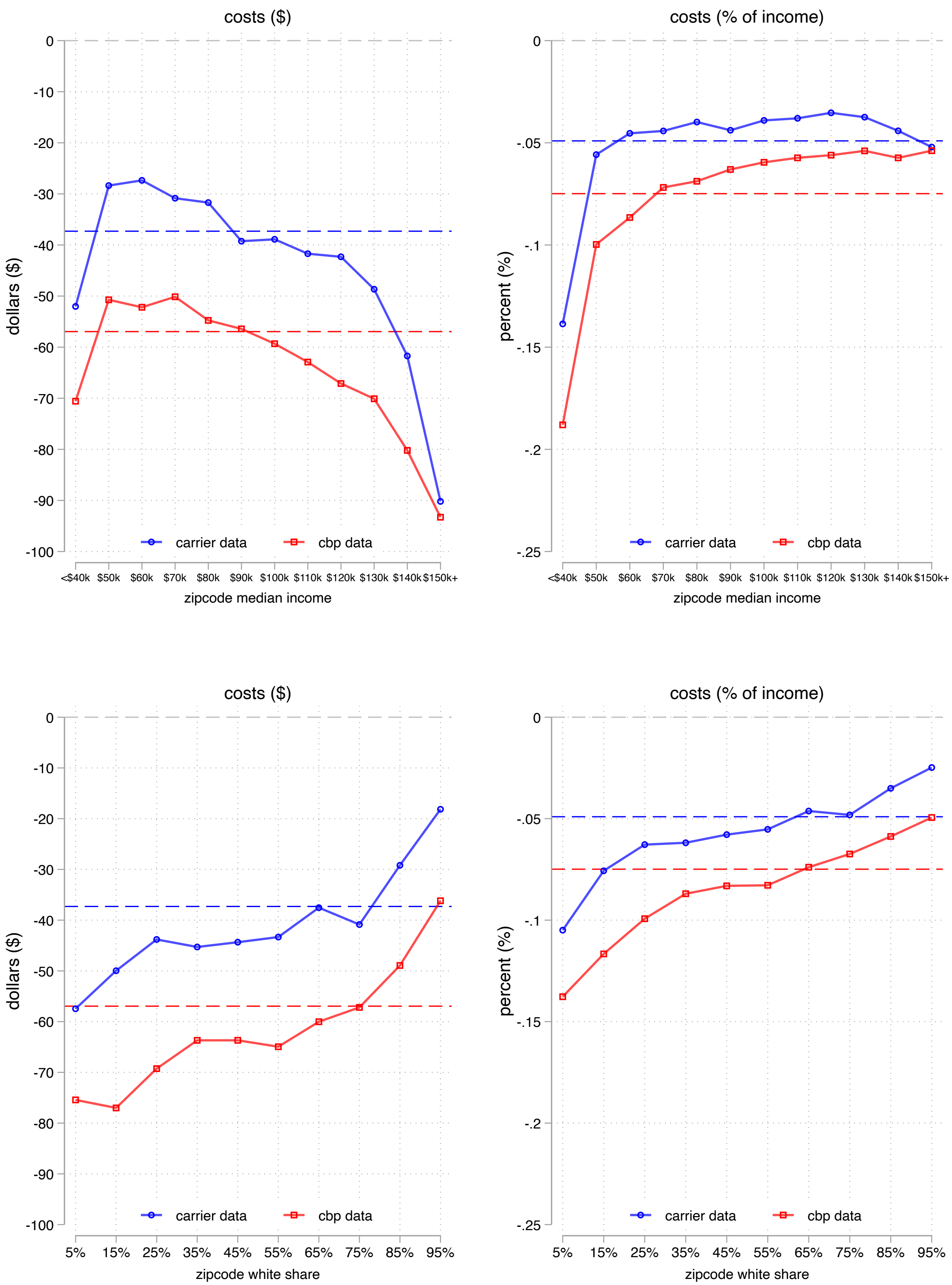


Notes: Figure reports $\hat{\beta}$ estimated from running (31) on the actual shipment densities for two origins (China and RW) and income groups, and $\beta_0(\gamma)$ from running the same specification on the model-implied densities generated for different values of γ. The intersection pins down choice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

FIGURE A.12: CHANGE IN PRICE INDEX

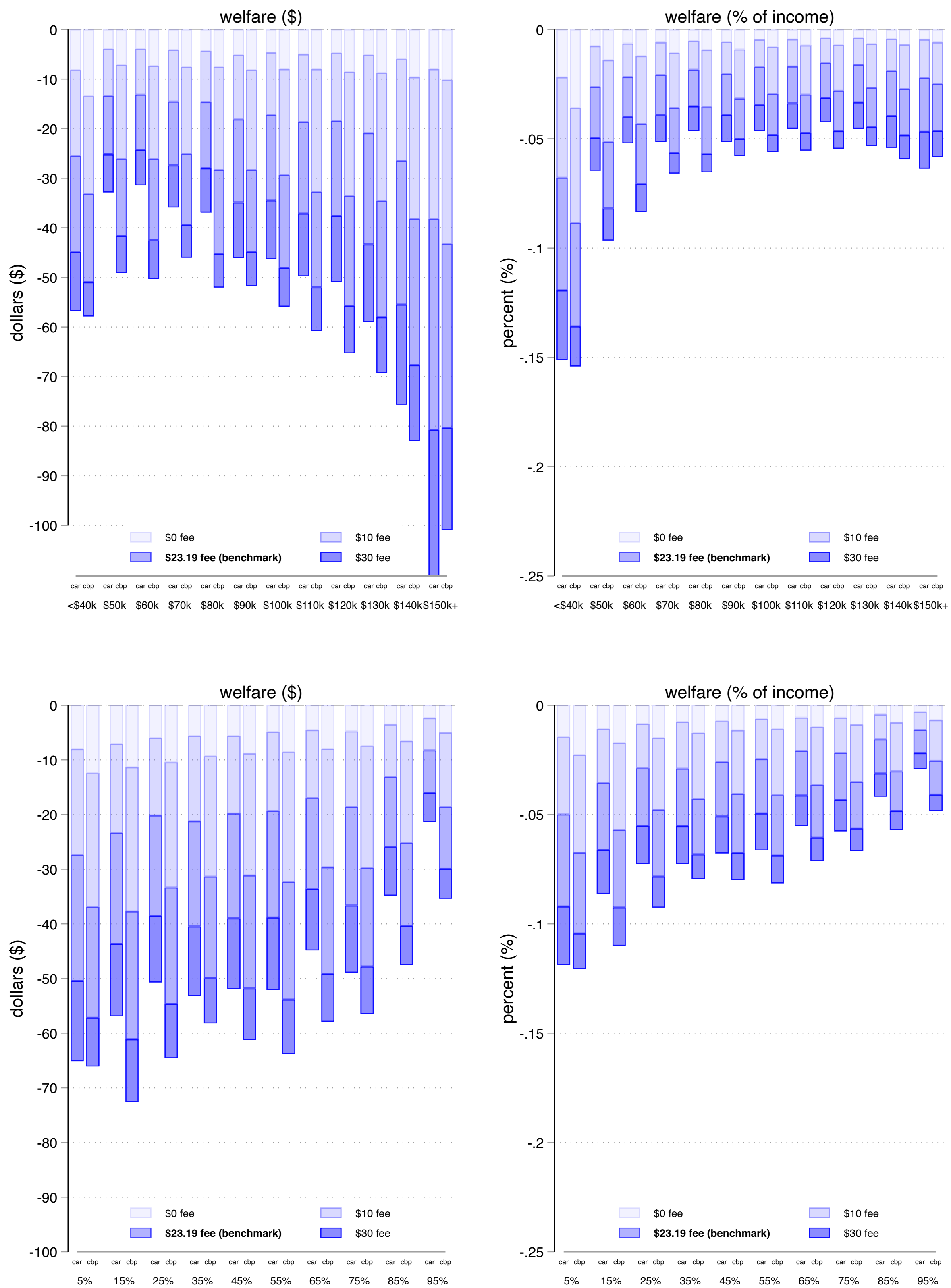
Notes: Figure reports for defined in 25. The left panel reports the price index changes by zipcode median family income. The right panel reports price index changes by zipcode white household share. The aggregate change in the price index is 13.14%.

FIGURE A.13: CHANGE IN CONSUMER COST BY ZIPCODE INCOME AND WHITE SHARE



Notes: Figure reports the change in consumer costs against zipcode characteristics. The left panels report impacts in per-capita dollars and the right panel scales by median family income. Top panel reports by zipcode median family income, and bottom panel reports by zipcode white household share,. The series is the welfare loss at 2022 tariffs and $T = \$23.19$ using parameters $\{\sigma_{CHN}, \sigma_{RW}, \gamma, \kappa\} = \{3.13, 2.26, 4.60, 1.19\}$. The blue (red) series denotes estimates from carrier (CBP) data; aggregate loss denoted by the horizontal dash line.

FIGURE A.14: CHANGE IN WELFARE BY ZIPCODE INCOME AND WHITE SHARE, BY FEE



Notes: Figure reports ev^w defined in (24) against zipcode characteristics at fees ranging from \$0 to \$30 per shipment. The left panels report welfare impacts in per-capita dollars and the right panel scales by median family income. Top panel reports by zipcode median family income, and bottom panel reports by zipcode white household share. Within each consumer group, the left stack are the estimates from the carrier data and the right stack are the estimates from the CBP data.