Direct-to-Consumer Trade and De Minimis Imports*

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Abstract

Section 321 of the 1930 Trade Act allows up to $800 imports per day per person to arrive free of duties and the administrative burden of clearing customs. In recent years, these de minimis shipments have exploded due to higher US tariffs on China and the rise of online "direct-to-consumer" trade. Census trade data only compile transactions above $2000, missing these shipments. We use a proprietary dataset with the full distribution of international courier shipments into the United States to systematically examine direct-to-consumer imports and the §321 policy. We find that lower-income zipcodes are more likely to import direct-to-consumer and de minimis shipments, in particular from China. As a result, the tariff incidence within direct-to-consumer trade is pro-poor. Theoretically, imposing tariffs with an exemption threshold leads to terms-of-trade gains, even in settings with complete pass-through to linear tariffs. We find bunching at the $800 threshold, implying less-than-complete pass-through and informing the demand elasticity for direct shipments. Through tariff revenue and consumer losses, eliminating de minimis implies an aggregate welfare loss of $5.3 billion, with this loss disproportionally hurting lower-income and minority consumers.

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1 Introduction

In 2018, the US abandoned its long-standing commitment to free trade by raising import tariff on trade partners. Average tariffs increased from 3.7% to 20.8%, the bulk of which was targeted on Chinese imports and the resulting incidence fell 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 of much of the administrative costs of clearing customs. The consumer burden faced by the increase in tariffs on Chinese imports therefore depends on whether a shipment has entered through this "de minimis" channel. Subsequently, de minimis imports have exploded, fueled both by higher tariffs and by 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 from overseas directly to consumers through international package carriers (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 17.3% of e-commerce sales, a substantial increase from just 0.7% and 3.9%, respectively, prior to the trade war. The volume of shipments is staggering: in 2023, 1 billion shipments entered through the §321 channel. 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] Tariff avoidance is controversial and two proposals in Congress currently seek to modify the scope of §321.[2]

This paper studies direct-to-consumer trade and its subset de minimis shipments below $800. We document who benefits the most from these types of shipments, and we assesses the aggregate and distributional welfare consequences of potential changes by Congress to §321 trade policy.[3] We rely on a novel dataset encompassing the universe of international shipments handled by three carriers into to the US. Census data cannot examine de minimis imports because they exclude import transactions below $2000. In contrast, our dataset spans the entire distribution of shipments through these carriers. Collectively, in 2021, our data account for 36.1% of total value and 17.0% of total US de minimis imports. Compared against a sample obtained from Customs Border Patrol (CBP) via FOIA, the carrier data are broadly representative of the universe of de minimis shipments. A key feature of the data is that we observe shipments' destination address or zipcode,

[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)

[3] Hufbauer et al. (2018) argue that Canada and Mexico should raise their de minimis threshold to encourage more trade within NAFTA, but do not analyze shipment level data.

allowing us to link each shipment to income and demographic characteristics of buyers.

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 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 the usual distortions from trade costs: (ad-valorem) tariffs, and a customs fee that pricing-wise act as a specific tariff albeit without generating revenue. 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 biased towards 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 tree trade (and is consistent with the empirical finding, mentioned above, 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 in a standard trade model that has linear tariffs.

We use the framework to guide an empirical analysis of §321 and the de minimis shipments to final consumers to which this policy is intimately linked. Quantifying the impacts of §321 requires two key empirical moments. The first moment is the density of shipments over package values by consumer groups, defined across zipcodes by their median income or fraction of white households; these moments are raw data and require no estimation. The second moment exploits shifts in 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 considerably 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 intuition is analogous to approaches in public economics that identify labor supply elasticities using bunching at notches along the income tax schedule (Kleven and Waseem, 2013). While typical approaches identify the elasticity from bunching in the cross section, we exploit changes to the threshold and tariff across origins over time relative to a comparison set of shipments to non-USA destinations.

The densities across zipcodes reveal that direct-to-consumer imports, and especially the cheaper subset of these imports corresponding to de minimis shipments, are important for low-income households. Per capita expenditures on direct shipments, as a share of median income, is U-shaped: zipcodes with median incomes below \$45k spend roughly similar amounts as a share of income as zipcodes with 100k incomes, and both import more than twice that of a zipcode with \$70k income. Moreover, the de minimis' share of these direct imports is strongly pro-poor. There is a strong negative relationship between the de minimis share of direct shipments and median income: 74% of direct shipments by the poorest zipcodes are de minimis compared to 52% for the richest zipcodes. Furthermore, the share of de minimis shipments from China is strongly negative with median income: 48% for the poorest zipcodes compared to 23% for the richest zipcodes. If imported through formal channels, these Chinese shipments would face tariffs of roughly 24%. Thus, §321 is a progressive trade policy: the average tariff on direct shipments imported by the poorest zipcodes–0.5%–is lower than the richest zipcodes–1.1%. If §321 was eliminated, the tariff schedule would become regressive: the poorest zipcodes would face tariffs of 12.1% compared with 7.4% for the richest zipcodes.

The patterns across zipcode minority shares also reveal systematic patterns.[4] §321 implies that zipcodes with low white household shares face slightly lower tariffs than whiter zipcodes, but this pattern reverses without the tariff exemptions offered by §321: zipcodes with 0-10% white household shares would face 11.6% tariffs compared to 9.9% tariffs for zipcodes with 90-100% white shares.

We consider a policy counterfactual that removes the $800 minimum threshold exemption currently codified in §321. This means that all shipments would be subject to current tariffs and to a (per shipment) customs processing fee of $10 (which includes a merchandise processing fee and a broker fee).[5] A first-order approximation that uses only the observed spending shares and the tariffs across origins yields a $6.9 billion consumer loss to eliminating §321.

Exact welfare analysis requires an estimate of consumers' demand and foreign firms' pricing responses (including the change in bunching) to changes in the de minimis threshold, and of the extra tariff revenue that can be rebated to consumers. Using the difference-in-differences change in bunching around the $800 notch (the pre- to post- 2016 change in bunching of shipments to USA vs OECD), we estimate an elasticity of substitution across varieties from China of 3.43 and an elasticity across varieties from the rest of word (RW) of 4.03. We find that eliminating §321 reduces aggregate consumer welfare by $5.3 billion. Compared to the first-order costs reported above, exact analysis implies a larger consumer cost from eliminating de minimis (because it accounts for terms-of-trade) but a lower 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 on China at $16.1 billion.

The aggregate estimates mask distributional consequences from eliminating §321. The per capita welfare losses are inverted U-shaped: median incomes below $45k would lose $27 per capita compared to a $18 loss for zipcodes with $95k-$105k incomes and a $39 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 0.07%, 0.02%,

[4]USTR (2023) and International Trade Commission (2023) highlight the need to examine impacts of trade along demographics beyond income and education. In future versions we will examine impacts across additional characteristics, such as retail density and age.

[5]Customs Border Patrol (CBP) levies a merchandise processing fee and requires shipments to use a licensed broker on shipments above $800.

and 0.02%. Thus, we find that the lowest-income households would bear the brunt of eliminating §321.

Alternatively, we can examine how the policy would affect zipcodes that vary in their share of white households. We find that welfare in zipcodes with 0-5% white households would experience a decline of $36 per person. This compares with a decline of $19 per person for zipcodes with 50-55% white share and a decline of $5 per person for the zipcodes with 95-100% white households. As a share of income, the corresponding declines for low, median and high white shares are 0.07%, 0.02%, and 0.007%. Eliminating §321 would therefore raise the the cost of living disproportionately more for non-white households.

A central force driving shipments into the de minimis channel is the high tariffs on Chinese imports. Indeed, the volume of shipments strongly falls for imports from China just above $800, suggesting reallocation from formal shipments into the §321. 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). In contrast, our finding of bunching implies that the de minimis threshold leads to terms-of-trade manipulation: bunching occurs because firms that would have otherwise priced above the threshold lower their prices to avoid the tariff. 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.[6]

Our paper also contributes to studies of the importance of trade for consumption, with a distinct focus on trade policy. Acosta and Cox (2019) comprehensively studies 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. An appealing feature of 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.

More broadly, several papers have studied the distributional effects of trade exposure and trade shocks through consumption. 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

[6]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, 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, de minimis imports are not required to submit information through ACE; in 2020, the year closest to their study, only 19% de minimis entries were captured by ACE (although in 2023, 63% of de minimis shipments were captured by ACE).

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.

De minimis shipments have also increased because of technological advances that allow consumers to import directly through e-commerce platforms, and bypass domestic retailers or wholesalers who import through the formal channel (e.g., in bulk through containers). As mentioned above, online platforms such as AliExpress, Temu, and Shein match final consumers to overseas manufacturers, and these manufactures may then ship items through the §321 channel. In the case of Amazon, international third-party sellers may also utilize §321 to send items directly to consumers, rather than shipping in bulk to Amazon's domestic warehouses. Our analysis therefore also contributes to a growing literature studying e-commerce that reflects the changing patterns of consumers globally. Dolfen et al. (2023) use credit card data to examine e-commerce purchases, finding that households above $50k benefit relative more. Jo et al. (2022) find that e-commerce raised welfare in Japan due to the reduction in price dispersion across locations. Couture et al. (2021) implement a randomized trial that connects an e-commerce platform with 100 villages in China to estimate consumer impacts, finding that e-commerce reduces cost of retail consumption for younger and richer households in these villages. Our paper focuses on the role of imports for welfare, inspecting how the benefits of direct-to-consumer imports vary by demographics, such as income and race, and are affected by US trade policy.

Finally, our approach to estimate the tariff elasticity exploits 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.[7] Estimation based on kinks or notches has been used extensively in the public finance literature to estimate labor supply elasticities; see Saez (2010), Chetty et al. (2011), Kleven and Waseem (2013), and the review by Kleven (2016). The typical approach fits a high-order polynomial to a cross-sectional pre-tax income distribution, excluding a window where agents are affected by the notch. The assumption is that, in the absence of the notch, the density in this excluded range can be predicted by the density outside the range. The labor supply elasticity is then identified from the difference between the actual and the counterfactual density around the notch. This standard approach is powerful for examining a cross-sectional data at a point in time. We exploit that we observe two control shipment densities over values that are not subject to the $800 threshold: shipments to the US prior to March 2016, when the notch was $200, and to OECD countries, which have lower de minims thresholds. As a result, we can non-parametrically identify the extent of bunching

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

induced by the current threshold through a standard difference-in-differences estimator. For the welfare quantification, we need to parameterize the shipment density, but we do so quite flexibly using high-order polynomials. The demand elasticity is then obtained to match the difference in bunching between the actual and the control densities, both of which are observed.

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, 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 in the world have a "de minimis" policy.[8]

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 1930 Trade Act to allow low-value imports to enter the country free of tariff duties and 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. This $800 limit holds for each shipper to each consignee per day. Entry through §321 occurs by presenting a manifest or commercial invoice, and CBP captures the origin, declared value, consignee address and description of the items. CBP does not require HS codes to be declared (since no duties are assessed), and does not impose any customs processing fees. Importantly, §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 a 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 ("PGA"), such as the Food and Drug Administration, US Department of Agriculture, etc.

On the other hand, informal entries 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. Informal shipments are subject to a merchandise processing fee ranging from $2.22 to $9.99 per package, and requires these shipments to be cleared using a licensed customs broker. Processing fees are not applied to §321 entries, nor are customs brokers required. Our

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

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%	1%
2015	1.6	138.9	0.3%	2%
2016	9.2	224.0	1.6%	9%
2017	13.0	332.3	2.1%	11%
2018	29.2	410.6	4.4%	22%
2019	56.2	503.1	8.9%	37%
2020	67.0	636.7	9.4%	30%
2021	43.5	771.5	5.3%	18%
2022	46.5	685.4	6.0%	18%
2023	49.4	1,000.0	6.6%	17%
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. * denotes data through April 30.

benchmark analysis assumes a per-package administrative fee of $10 on informal shipments.

De minimis imports have received little attention by researchers for two reasons. The first reason is data constraints. Census data that are available for researchers, including both the public files and the confidential firm-level LFFTD, are compiled from Form 7501 and include import transactions above $2000. These data therefore capture all formal entries and a subset of informal entries, but are blind to §321 imports (Kamal and Ouyang 2020). This is by design since §321 is meant to reduce bureaucratic procedures.

Second, 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 2023, 1 billion shipments entered through §321. As comparison, CBP processed 39.1 million formal-channel entries (although a single formal entry may contain many more items than a de minimis entry). As of April 30, 705 million packages have entered in 2024, on pace for roughly 1.2 billion shipments this year. The magnitudes illustrate the importance of a de minimis channel for reducing the burden of administering customs. If each §321 shipment was subject to the $10 fee that informal entries pay, in 2022 this would have resulted in between $6.9 billion. As a benchmark, total tariff duties in 2022 was $91.1 billion.

Since HS codes are not attached to de minimis imports, the precise breakdown by product is not knowable. In the carrier data, discussed below, we observe HS codes for shipments above the de minimis threshold (and for a small fraction of de minimis shipments where HS codes were provided). 81.6% of shipments just $50 above the threshold contain codes that broadly reflect consumer goods: 90-99 (miscellaneous), 84-85 (machinery and electrical), 50-63 (textiles), 64-67 (footwear and headgear), and 41-43 (hides, skins, leather, furs). This suggests that the §321 channel is used to import consumer goods, and is consistent with a direct-to-consumer business strategy that bypasses domestic warehouses. It motivates two benchmarks to gauge the growth and importance of de minimis imports: its share of imports of consumer goods (column 3) and its share of total e-commerce sales (column 4).

Imports of consumer goods (excluding food and autos) are from Census data that apply end-use categories to the HS codes.[9] 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, which suggests the rising tariffs from the trade war shifted imports into the §321 channel.

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 nearly a fifth of total e-commerce sales.

Finally, one can also benchmark relevance by the duties avoided. Through a FOIA request, we were provided a breakdown of §321 shipments across top exporters from 2018-2021: 57.9% of shipments originate from China, followed by Canada, UK, Mexico, HK and Germany. Collectively, these six countries account for 80.5% of de minimis shipments. Applying the median tariff in the aforementioned HS chapters from these origins and the rest of world, we estimate that in 2022 consumers avoided paying \$6.6 billion in duties, or 7.2% total duties.[10]

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

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

[9]Consumer imports is retrieved from St. Louis FRED (series A652RC1Q027SBEA). Since §321 imports are excluded from Census data and do not have HS codes attached to them, we believe this series excludes §321 imports.

[10]A caveat with this calculation is that we have the breakdown of shipments volume, not value.

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 a set Ω_o of heterogeneous exporters. Exporters vary in per-shipment marginal costs z (inclusive of shipping costs) and group-specific demand shocks $\{a^{\omega}\}$.

Exporters 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:

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

where

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

are the tariff and the 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:

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

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

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:

$$\pi_i^L(z) \equiv \max_v (v - z) N_i(v), \tag{7}$$

$$\pi_i^B(z) = (v_{DM} - z) N_i(v_{DM}), \tag{8}$$

$$\pi_i^H(z) \equiv \max_v [(1 - \tau_o) v - z - T] N_i(v). \tag{9}$$

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 left panel of Figure 1. For these firms, optimal prices are the standard constant markup over marginal cost, i.e.,

$$v_{L,o}(z) = \frac{\sigma_o}{\sigma_o - 1} z \tag{10}$$

and

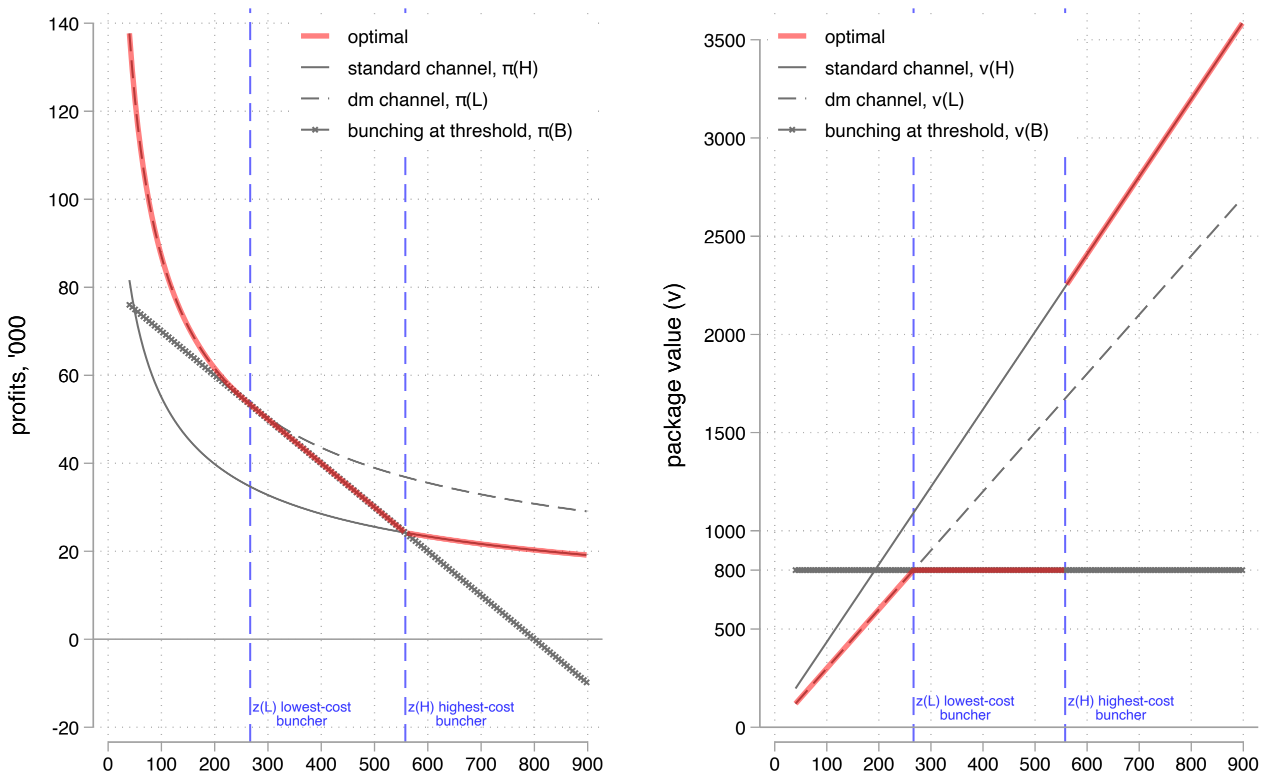
$$v_{H,o}(z) \equiv \frac{\sigma_o}{\sigma_o - 1} \frac{z + T_o}{1 - \tau_o}. \tag{11}$$

These pricing functions are depicted in the right 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 left panel of Figure 1, with associated prices in the right 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,

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.

where $v_{L,o}(z_{L,o}) = v_{DM}$, the profits of de minimis shippers and bunchers are tangent.

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

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

In sum, the optimal package value set by firms with unit cost z from origin o, shown in red in the bottom 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*

$$v_o(z) = \begin{cases} v_{L,o}(z) & z < z_{L,o} \\ v_{DM} & z \in [z_{L,o}, z_{H,o}), \\ v_{H,o}(z) & z \geq z_{H,o}, \end{cases} \tag{12}$$

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

$$z_{L,o} = \frac{\sigma_o - 1}{\sigma_o} v_{DM}; \tag{13}$$

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:

$$\frac{1}{\sigma_o}\left(\frac{v_{DM}}{v_{H,o}(z_{H,o})}\right)^{\sigma_o} + \frac{\sigma_o - 1}{\sigma_o} = \frac{1 + T/v_{DM}}{1 - \tau_o}\left(\frac{v_{DM}}{v_{H,o}(z_{H,o})}\right). \tag{14}$$

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 $N_i(v)$. Hence, the thresholds are only a function of unit costs. 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 (14) 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 (12) 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 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 Welfare Measurement

Our goal is to use the model to assess the distribution of welfare effects across consumers from potential changes to de minimis thresholds and tariffs, including current policy proposals and optimal policies. In this section we specify the equations used to carry on these calculations and in the next we describe the incentives of a planner to impose de minimis policy.

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

$$ev^{\omega} = \underbrace{\frac{1}{\kappa}\left(\left(\hat{P}^{\omega}\right)^{-\kappa} - 1\right)e^{\omega}}_{\equiv \Delta e^{\omega}} + \Delta tr^{\omega}, \tag{15}$$

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

$$\hat{P}^{\omega} = \left(\sum_{o} \lambda_{o}^{\omega}\left(\hat{P}_{o}^{\omega}\right)^{1-\gamma}\right)^{\frac{1}{1-\gamma}}, \tag{16}$$

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:[11]

$$\hat{P}_{o}^{\omega} = \left(\int_{z} \lambda_{o}^{\omega}(z)\,\widehat{v_{o}(z)}^{1-\sigma_{o}} dz\right)^{\frac{1}{1-\sigma_{o}}} \tag{17}$$

A key component of this expression is $\lambda_{o}^{\omega}(z)$, defined as the share of all varieties with unit cost equal to z in the direct expenditures on goods from country o by consumer group ω:[12]

$$\lambda_{o}^{\omega}(z) = \left(\frac{v_{o}(z)}{P_{o}^{\omega}}\right)^{1-\sigma_{o}} h_{o}^{\omega}(z), \tag{18}$$

where $h_{o}^{\omega}(z)$ is the "quality-adjusted" measure of firms with unit cost equal to z from country o:

$$h_{o}^{\omega}(z) \equiv \mathbb{E}_{o}\left[a^{\omega}|z\right] M_{o}(z), \tag{19}$$

where $M_{o}(z)$ is the mass of firms with unit cost equal to z. This adjusted density combines the measure of firms of a given unit cost from a given origin with the average taste that consumers of type ω have for this group.

As we have mentioned, there can in principle 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, we only care about the quality-adjusted measure $h_{o}^{\omega}(z)$, which combines demand shocks and unit costs, 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 following sections, we recover each of these objects from the data, and use the model to assess the welfare impacts of de minimis.

[11] To find this expression first express (3) in relative changes and use from (12) that prices depend only unit costs.

[12] To obtain this expression, start from the definition $\lambda_{o}^{\omega}(z) \equiv \frac{\int_{i:z(i)=z} v_{i} n_{i}^{\omega} di}{\int_{i\in\Omega_{o}} v_{i} n_{i}^{\omega} di}$ and then use (12), (19), and (36).

3.6 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. To simplify the exposition, we do so 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

$$u = \frac{1}{\kappa}e + y + tr, \tag{20}$$

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

$$e = AP^{-\kappa}, \tag{21}$$

$$P = \left(\int_0^{z_L} v_L\left(z\right)^{1-\sigma} h\left(z\right)dz + v_{DM}^{1-\sigma}\int_{z_L}^{z_H} h\left(z\right)dz + \int_{z_H}^{\infty} v_H\left(z;\tau\right)^{1-\sigma} h\left(z\right)dz\right)^{\frac{1}{1-\sigma}}, \tag{22}$$

$$tr = \tau e \int_{z_H}^{\infty}\left(\frac{v\left(z;\tau\right)}{P}\right)^{1-\sigma} h\left(z\right)dz, \tag{23}$$

and where conditions (13) and (14) determine the thresholds z_L and z_H as function of the policies, (v_{DM}, τ). In these expressions, $v_L\left(z\right)$ and $v_H\left(z;\tau\right)$ are the pricing functions below and above the threshold defined in (10) and (11).

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

Proposition 2. *(i) 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*

$$\begin{aligned}\frac{du}{e} = &\left[\underbrace{\frac{1}{\sigma-1}\left(\left(\frac{v_{DM}}{P}\right)^{1-\sigma} - \left(\frac{v_H\left(z_H;\tau\right)}{P}\right)^{1-\sigma}\right)}_{\text{terms-of-trade gain at the threshold}} - \underbrace{\tau\left(\frac{v_H\left(z_H;\tau\right)}{P}\right)^{1-\sigma}}_{\text{tariff loss}}\right] h\left(z_H\right)dz_H - \underbrace{\Lambda^B\frac{dv_{DM}}{v_{DM}}}_{\text{bunchers' price increase}} \\ &- \underbrace{\left[\tau\left(1+\kappa-\sigma\right)\frac{dP}{P} + \sigma\frac{\tau}{1-\tau}d\tau\right]}_{\text{"standard" welfare loss}}\int_{z_H}^{\infty}\lambda\left(z\right)dz\end{aligned} \tag{24}$$

where Λ^B is the expenditure share of buncher. These tradeoffs imply that:

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

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

Expression (24) summarizes the welfare effects from de minimis policy. In the absence of de minimis ($v_{DM} = z_L = z_H = 0$), the terms in the first line vanish and only the "standard welfare impact" from the second line remains. This term captures changes in tariff-inclusive consumer prices (through dP) and in tariff revenue. Through this term, with $v_{DM} = 0$, as stated in part (ii), 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 (24). 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 right 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 (iii) of the proposition. Consider the price schedules in the right 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, and achieves a high level of compliance.[13] 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. Therefore, we remove shipments above $5,000–while arbitrary, shipments above this value are more likely to be purchased by firms. This restriction removes 3.8% of the observations in the sample. We can assess this cutoff threshold using the street addresses

[13] 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.

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).[14] We do not further remove non-residential shipments in the analysis since we are unable to perform the same match for carriers B and C, for whom we only observe the destination zipcode. We further assume that if a shipment happens to arrive at a commercial address, the items are consumed locally within the zipcode.

To assess the representativeness of the carrier data with respect to the universe of §321 imports, we obtained through a FOIA request to CBP some aggregate statistics of de minimis shipments. In 2021 the vast majority of de minimis shipments arrived by air (85.7%) with land (truck or rail) accounting for 14.1% and vessels for just 0.2%. So, the air shipments in our data reflect the dominant mode of §321 imports. The same FOIA request also indicated that private carriers collectively handled more than 29.9% of 2021 de minimis shipments.[15] We also filed a FOIA request to CBP for shipment-level data on transactions below $1500, which we use to assess the representativeness of carrier data across zipcodes. [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, 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.

[14] Including shipments above $5,000, the share of shipments that go to households does not change much–76%–but its value share falls by 16 percentage points to 59%.

[15] The FOIA requested indicated that the US postal service handled 14.0%. The remaining shares are handled by an unspecified type of carrier and/or come from carriers (both private and public) through the CBP data pilot. Since private carriers are participating in the data pilot we conclude that carriers handled more than 29.9% of shipments.

[16] 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). 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

		§321 Shipments to USA [$0,$800]		Non §321 Imports [$801,$5,000]		Shipments to OECD (≤$5,000)	
year	carrier (1)	value ($b) (2)	entries (m) (3)	value ($b) (4)	entries (m) (5)	value ($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.

4.2 Product Descriptions and Tariffs

What types of products are shipped directly to consumers? Since §321 trade policy is meant to reduce customs burden, for example, by not requiring de minimis shipments to fill out certain CBP forms or to use customs brokers, de minimis shipments do not contain HS codes. This makes it difficult know precisely what kinds of products are purchased directly by consumers. However, data from two carriers provide a description of the items inside the packages that we can analyze. 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 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. Under the assumption that shipments just above the threshold contain similar products as shipments below the threshold, we can broadly infer the potential tariffs that de minimis shipments may face if §321 is 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 chapters: 41-43, 50-67, 84-85, and 90-99. As mentioned above, these categories contain products that final consumers are likely to purchase from retail outlets, and is consistent with the item descriptions, and more broadly, the types of platforms that are using de minimis shipments to reach consumers directly. We, therefore, assume that if §321 were eliminated, direct-to-consumer shipments would face the median applied US tariff from origins in these chapter.[17] 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 2.2%, and in 2022 it is 0.0%.

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

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 2021 per capita de minimis expenditures of \$131. The carrier data are about one-third of total de minimis values, and average per capita expenditures on de minimis imports across zipcodes is \$32.6.

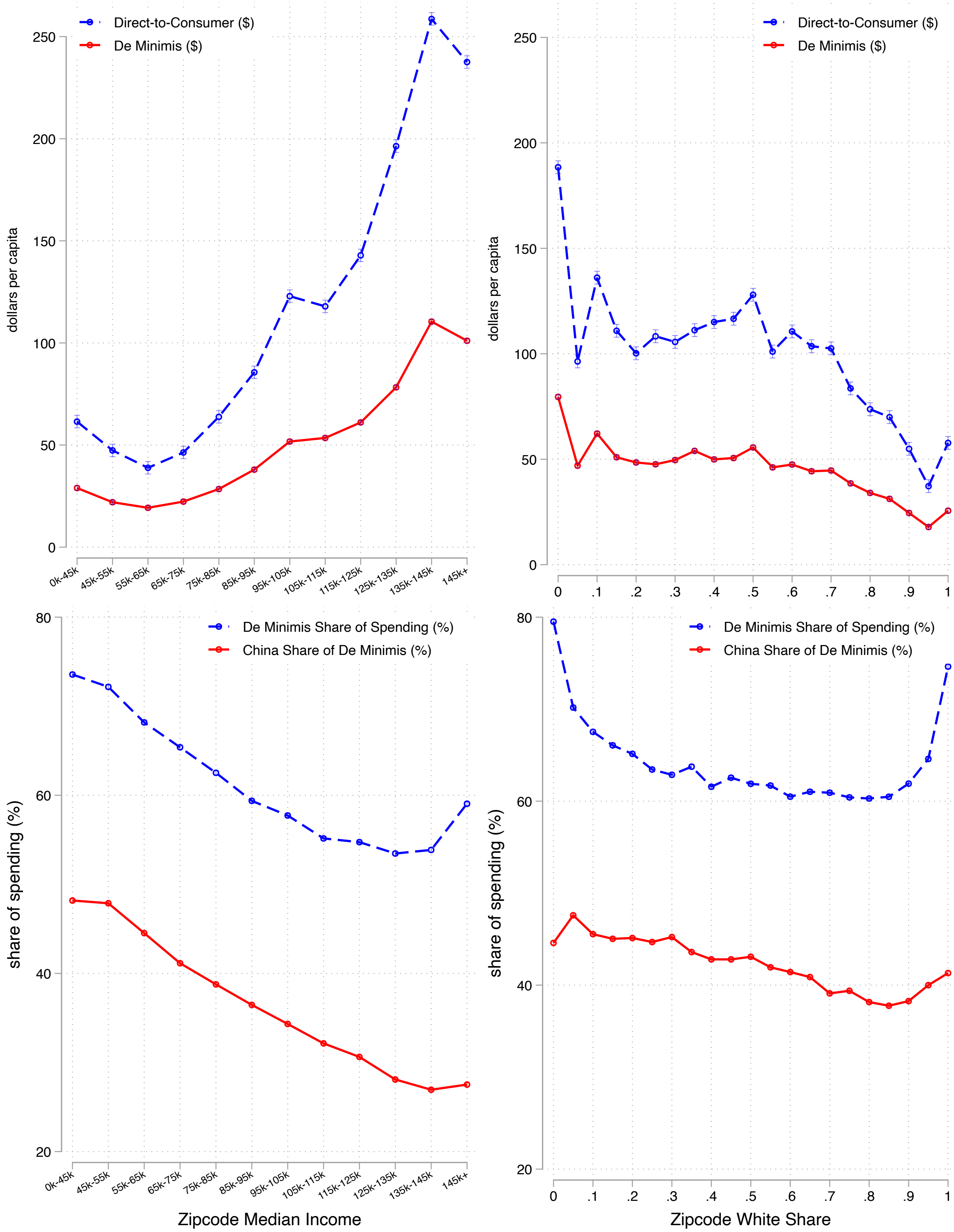
The top panel of Figure 2 reports per capita expenditures on all shipments below \$5,000and on de minimis shipments against zipcode median family income. Richer zipcodes naturally spend more, but the lowest-income zipcodes spend more than slightly richer zipcodes. When expressed as a share of family income, Appendix Figure A.2 reveals 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. 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 blue series in the bottom panels of Figure 2 reports the share of direct shipments that are de minimis. 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 80% 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.

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

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



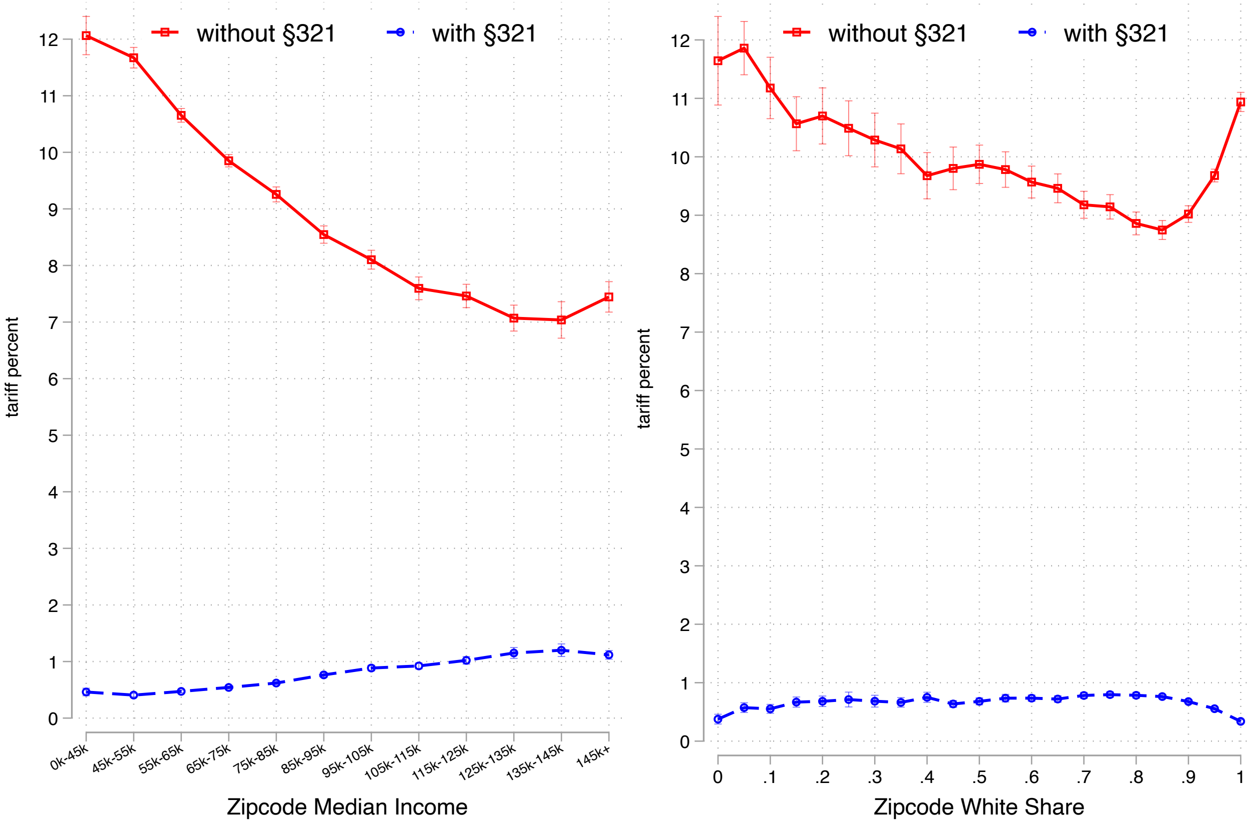
Notes: Figure correlates 2021 per-capita expenditures on shipments below $ 5,000(red series) and de minimis shipments (blue series). The left panel plots against zipcode median family income and the right panel plots against zipcode share of white households. Recall that the carrier data captures about 36.1% of official §321 imports in 2021. Standard errors of the means reported in brackets.

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 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 1.1% 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 7.4% 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.

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.

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

TABLE 3: 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.

Finally, as mentioned above, CBP provided shipments for one-week from 2017-2021. We can 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, say, 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 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.4 reports tariff incidence by zipcode in the CBP data with the caveat that the sample does not contain HS codes for the above-$800 shipments. We construct a zipcode's tariff using origin shares and assign the average tariff by origin. The figure reveals a similar pattern of a progressive tariff policy becoming a regressive one if §321 was eliminated. Overall, the pattern of de minimis spending in the CBP data is broadly consistent with the carrier data, and if anything, understates the benefits of §321 because the higher shares from China.

5 Impact of De Minimis Thresholds

5.1 Evidence of Bunching

The de minimis threshold in §321 creates a notch at $200 prior to March 2016, and $800 subsequently. 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. Since we observe the density of de minimis shipments under different thresholds, we can estimate the impact of the notch non-parametrically without having to fit 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.[18]

We can 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:

$$\ln c_{bodxt} = \alpha_{xdot} + \beta_b + \epsilon_{bodxt} \tag{25}$$

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

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

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.[19] If there were no tariff 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 customs fee) depending on the threshold.

The left panel for Figure 4 shows estimates of β_b separately for the two periods for the USA shipments: before and after March 2016. The figure reveals a few messages. First, we see spikes in \$50 and \$100s, a common form of round-number bunching (e.g., Best and Kleven, 2017). Second, 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 the notch is difficult to see in this graph. In the pre-period series, the density around \$800 appears smooth. Third, there is evidence of bunching in the post-period density (blue) right below \$800, and a stark drop in shipments above the notch: there are \$17.7% fewer shipments between \$900-950 compared to \$700-750 shipments (comparing shipments closer to the notch is more difficult because of the bunching induced by the notch).

Figure 4B reports the density of shipments to the OECD. We continue to observe round-number bunching, but 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.

Next, a simple difference-in-difference specification allows us to identify the impact of the threshold. The specification becomes:

$$\ln c_{bodxt} = \alpha_{xdot} + \beta_b \times \mathrm{USA}_d \times \mathrm{post}_t + \epsilon_{bodxt} \tag{26}$$

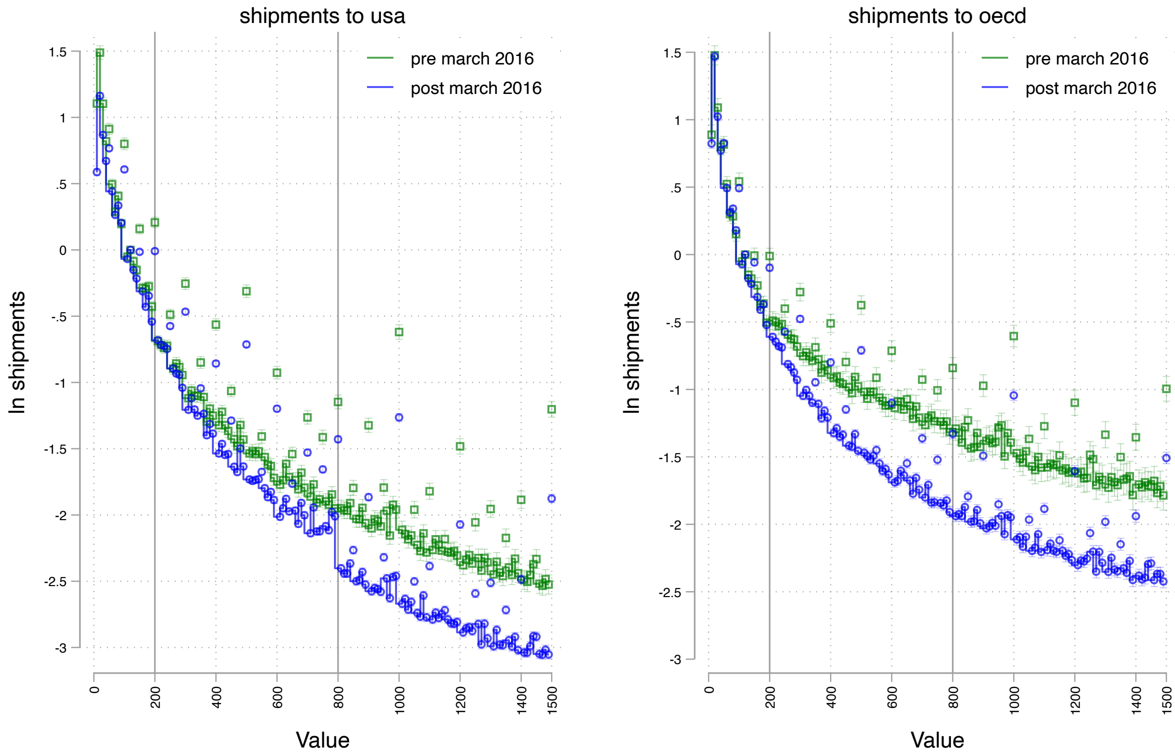
where now β_b is the difference-in-differences estimate of the shipment densities: the difference in the (log) number of US-bound shipments in the post-period relative to the pre-period shipments, relative to that same difference for OECD-bound shipments. The control densities help both to isolate the impacts of the notches on USA shipments in each period, and to neutralize round-number bunching. 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 experienced 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,

[19] We can, of course, choose any bin as the leave-out, and we choose \$120 since it is relatively far from the pre-period threshold and on a slightly flatter part of the density compared to bins below \$100.

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 (25) 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.

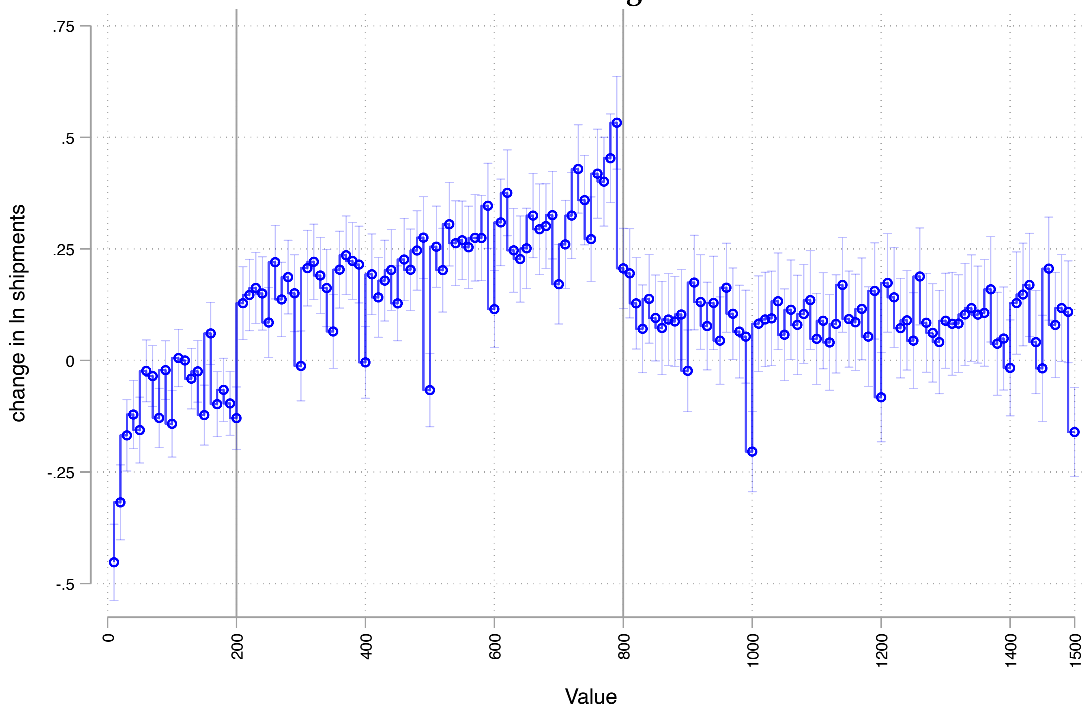
the bunching in the pre-period is not as stark as in the post-period. One potential explanation is that shipping through §321 was less valuable during that time because direct-to-consumer online platforms had not yet taken off and tariff levels were lower. On the other hand, there is bunching at the current \$800 notch: there is an average 10.0% more shipments of \$751-\$800 compared to \$700-\$750. And, the drop in shipments above the notch is also large: there are on average 17.7% fewer shipments of \$900-\$950 compared to \$700-\$750. Second, although we observe bunching, it is not exactly at \$800, nor is there a distinct "hole" right above the notch (in, say, the \$800-\$850 range), as the model with fully rational agents would predict. The lack of bunching exactly at \$800 and the lack of a hole motivates the addition of "naive" exporters who are unaware of the notch when implementing the model (see below).[20]

Figure 5B reports specification (26) separately for shipments from China ($o = CHN$, red) and from the rest of the world ($o = RW$, green). The evidence of bunching from China is much stronger relative to rest of world. We observe sharper (negative) bunching at \$200, and a stark jump up just

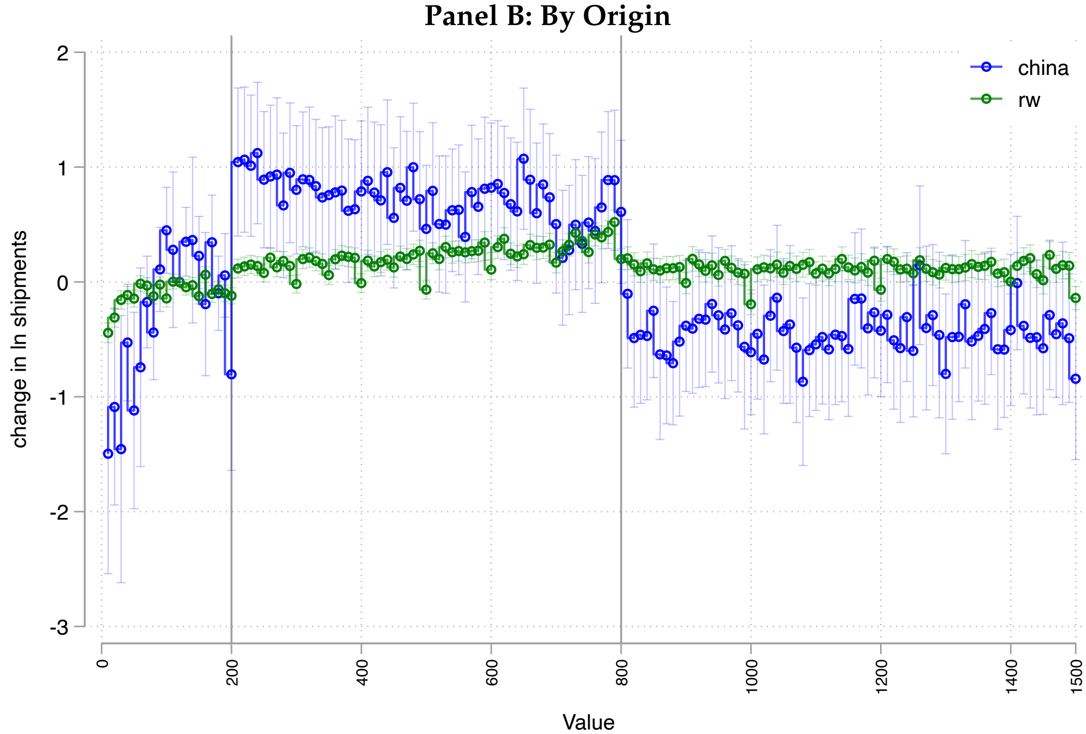
[20]The upward drift across the density suggests destination-bin specific time trends, but since the identification of σ_o rests on local changes in the density, we do not attempt to neutralize this drift in order to keep identifying source of variation in (26) transparent.

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 (26), 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 (26) 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.

above the \$200 notch. Then, as the density approaches \$800, shipments from China of \$751-\$800 are 30.6% larger relative to \$700-\$750. Above the notch there are 74.4% fewer shipments than in the \$700-\$750 range. 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. Since we do not observe data prior to 2016, we plot the analog of (25) and examine the impact of the \$800 notch. It is difficult to assess potential bunching since we do not have a control density to which we can compare; CBP did not provide pre-March 2016 shipments or transshipped items. But, the impact of the notch is evident: there are 55.9% fewer shipments valued between \$900-\$950 than between \$700-\$750. The corresponding drop in shipments from China between these two intervals is even starker, with 154.4% 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 because we do not observe the corresponding control densities from pre-March 2016 or for shipments to OECD.

5.2 Alternative Explanations

This section examines other potential explanations for bunching: freight charges could change at the threshold, and firms or consumers could manipulate the number of items in 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 costs. Appendix Figure A.6 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 into multiple transactions across days, at potentially higher shipping and convenience costs. Thus, firms or consumers could adjust the number of items such that the package value drops below \$800 without any changes in a given item's price.

The top panel of Figure A.7 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, the moment used to pin down the within-origin demand elasticity –the change in package density at the de minimis threshold– should ideally not be contaminated by changes in the number of items per shipment. The cleanest way to do this is to estimate (26) 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.[21] The top panel of Figure A.8 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, which is consistent with item manipulation not being quantitatively important at the threshold.

Finally, while the majority of shipments go to households, it is possible that commercial customers are placing 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. We can examine the share of shipments to households in carrier A's data across the distribution; see Figure A.9. While the share of households importing around the threshold is about 15% lower than at the $120 leave-out, there is no discontinuous change in the household import share, suggesting that the type of importer is not changing around the threshold.

6 Model Implementation

This section parameterizes the model. We discuss how we calibrate the distribution $h(z)$, how obtain the key tariff elasticities, and how we address the missing hole in the shipment density right above the notch. We then examine a policy counterfactual that eliminates §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.

[21] For Chinese imports, single-item shipments are 62.2% of de minimis shipments and 59.2% of de minimis value. For RW imports, single-item shipments are 85.1% of shipments and 82.9% of value.

From now on, we index pricing decisions with an upper-script $j = S, N$ (sophisticated or naive) that indexes the firm type: $v_o^j(z)$. So, naive firms use the simple pricing rules:

$$v_o^N(z) = \begin{cases} v_{L,o}(z) & z < z_{L,o}, \\ v_{H,o}(z) & z \geq z_{L,o}. \end{cases} \tag{27}$$

Similarly, we write $h_o^{\omega,j}(z)$ and index the quality-adjusted distribution defined in (19) by the upper-script $j = S, N$.

6.2 Parametrization

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

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

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

Conditional on σ_o and the post-2016 policies (tariff τ_o^{post}, administrative fee $T^{post} = \$10$, and threshold $v_{DM}^{post} = \$800$), we can compute the thresholds $z_{L,o}$ and $z_{H,o}$ using (13) and (14). 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:

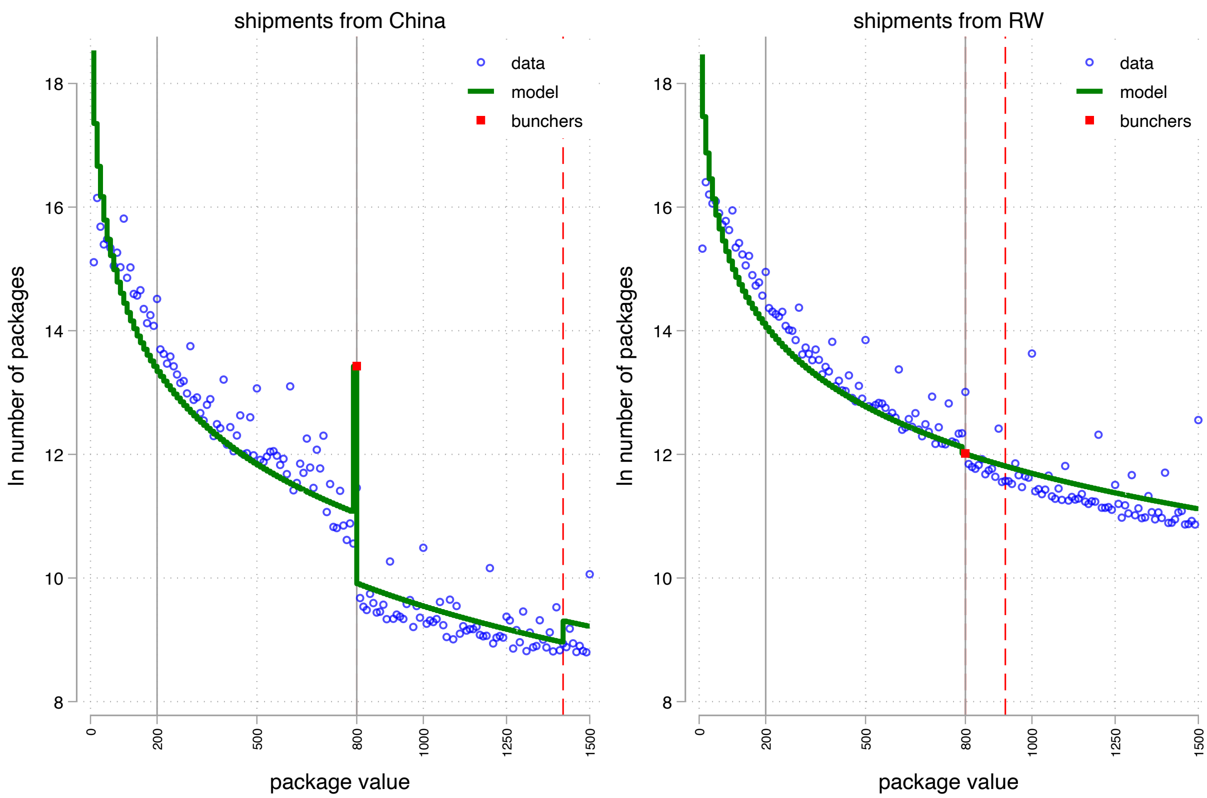
$$\Delta N_o^{US}(v) = \begin{cases} v^{-\sigma_o}\left(1+\delta_o^\omega\right)\left[D_o^{US} h_o^{US,S}\left(z_{L,o}(v)\right)\right]\frac{\sigma_o-1}{\sigma_o}\Delta_v & v < v_{DM}, \\ v_{DM}^{-\sigma_o}\int_{z_L}^{z_H}\left[D_o^{US} h_o^{US,S}(z)\right]dz & v = v_{DM}, \\ v^{-\sigma}\delta_o^\omega\left[D_o^{US}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

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 (10) and (11).

We observe $\Delta N_o^{US}(v)$ over a grid of values $v \in [0, 10, ..., 5000]$ in the post-2016 period. To implement, we assume a power function for $D_o^{US} h_o^{US,S}(z)$. We jointly parameterize δ_o^ω (which regulates the importance of naive firms) to exactly match the observed number of shipments in the excluded region $(v_{DM}, v_{H,o}(z_H)]$, and the power function for $D_o^{US} h_o^{US,S}(z)$ to match the observed $\Delta N_o^{US}(v)$ outside the dominated range ($v \leq v_{DM}$ and and $v > v_{H,o}(z_H)$).[22]

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 31% of packages and 30% of value from China. Outside of this area, the density adds up the exports of both sophisticated and naive firms. Only the former group of firms bunch, with the bunchers shown in the red square in each figure. From China, the model implies a clear discontinuity at \$800. Bunching at \$800 is larger in the model than in the data, as the model lacks a mechanism to make bunching decisions more diffused below the threshold, such as product indivisibilities within shipments. From other origins, where tariffs are much lower, the discontinuity is absent in both model and data.

FIGURE 6: CALIBRATED DISTRIBUTION

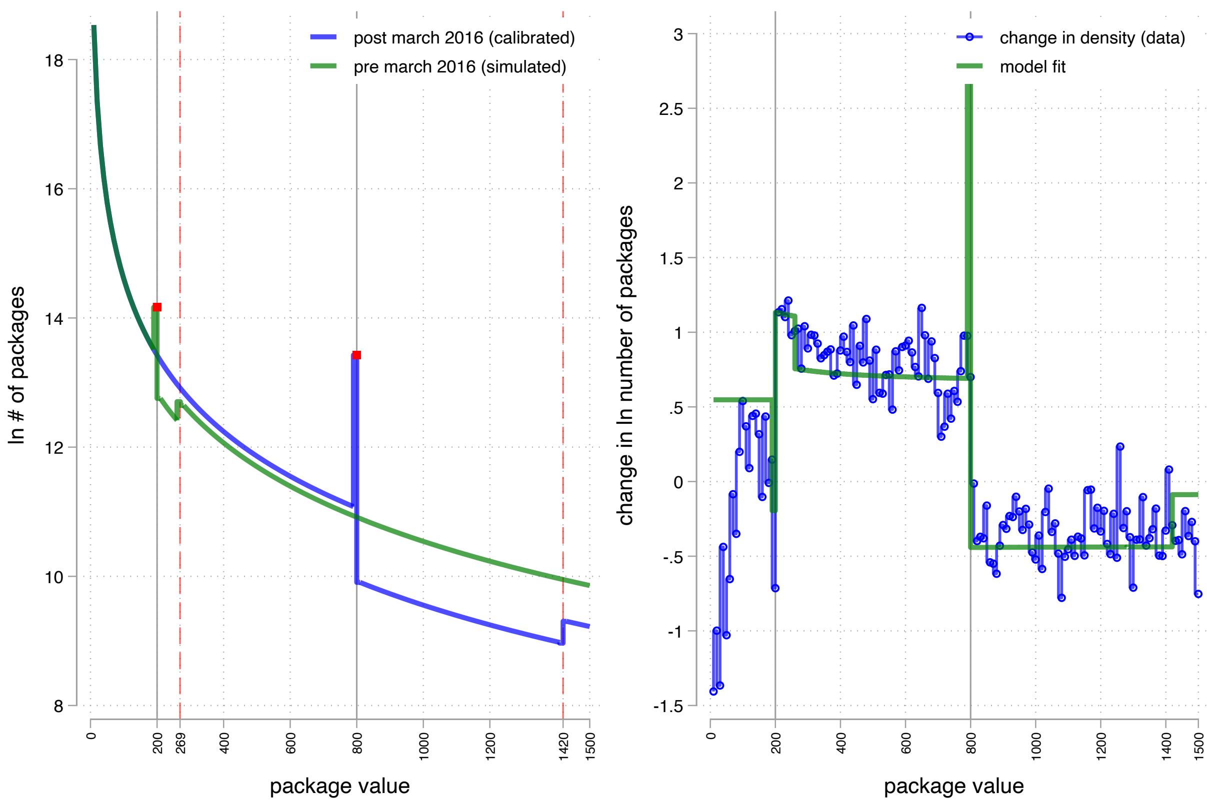


Notes: Figure shows the actual and model-implied histogram at the calibrated values of the elasticities (σ_{CH} = 3.43, σ_{RW} =4.03). The left panel reports the calibration for shipments from China. The right panel reports the calibration for shipments from RW. The red vertical line in each panel indicates 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.

[22]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 (17), 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.

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 (corresponding to the previous step) 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 0.0% to 2.2%; and, we change the threshold from \$800 to \$200. These policy changes mimic the difference-in-differences specification in (26), which estimates changes in the density over time and across origins.

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 (σ_{CH} = 3.43), σ_{RW} =4.03). 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.

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 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 σ_{CH} =3.43 for China, and σ_{RW} =4.03 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:[23]

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

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:

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

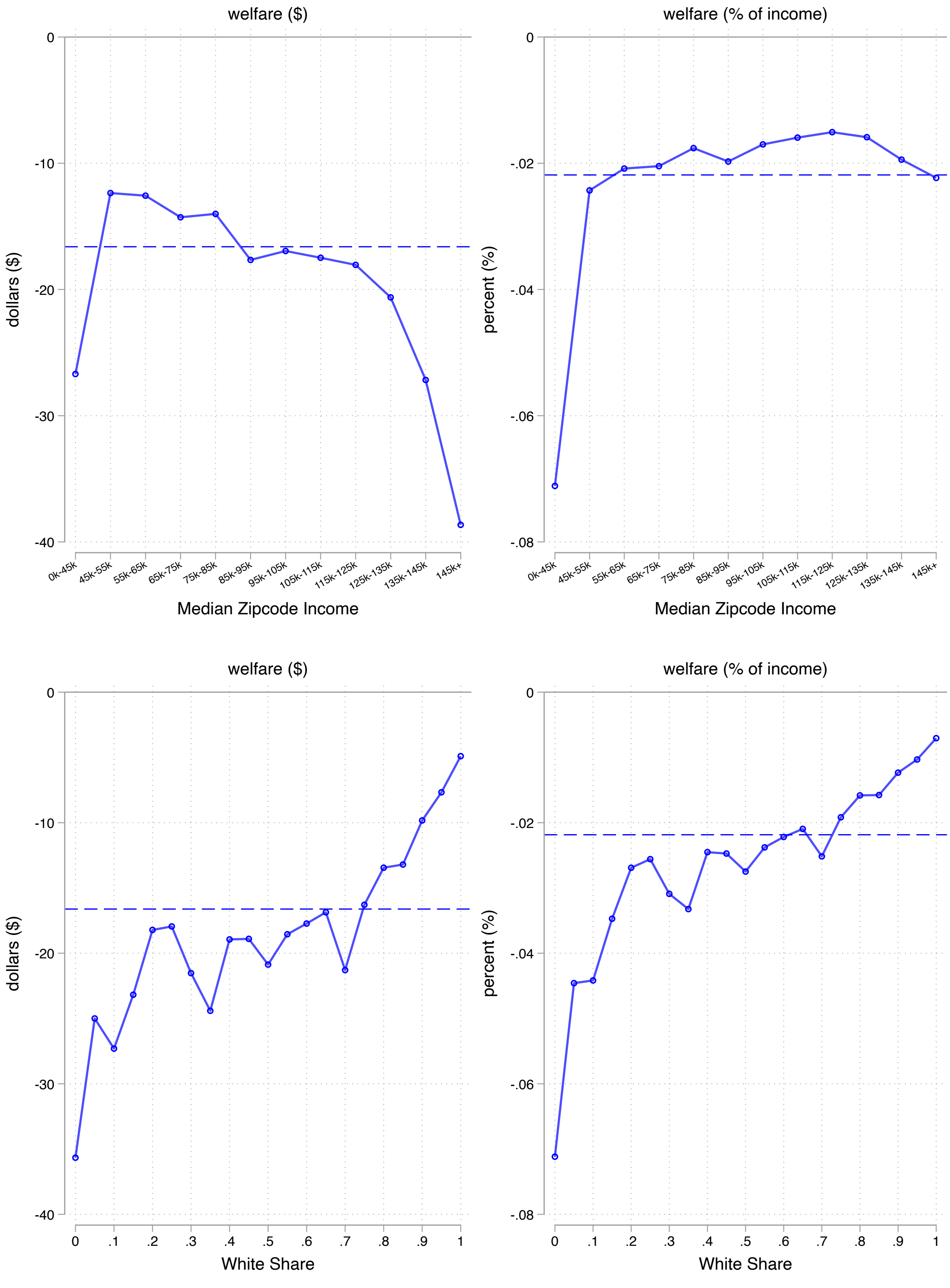
We run this regression in the data, obtaining an estimates for $\hat{\beta}$. We run the same regression in the model for each candidate value of γ, generating coefficients $\beta(\gamma)$, and search in the space of γ such that $\beta_0(\gamma) = \hat{\beta}$. The regression using the data yields β =-0.31 , and we estimate (31) for model-generated densities at different values of gamma. Figure A.10 shows the value of $\hat{\beta}$ and the corresponding $\beta_0(\gamma)$ at each value of gamma. The intersection pins down the choice of γ, which occurs at γ =4.6. As a comparison, Fajgelbaum et al. (2020) estimate a within-product cross-origin elasticity equal to 2.53.

6.3 Welfare Impacts of Eliminating De Minimis

We now assess the 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

[23] 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.

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



Notes: Figure reports ev^w defined in (15) 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=\$10 using parameters $\{\sigma_{CHN}, \sigma_{RW}, \gamma, \kappa\} = \{3.43, 4.03, 4.60, 1.19\}$; the aggregate loss is \$5.3 billion or \$17 per person.

outcomes for both the aggregate US and by consumer group ω as defined in Section 3.5. 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.[24] Given this elasticity, we re-do step 1 from the previous subsection to obtain a quality-adjusted density $h_o^{S,\omega}(z)$ that matches the observed histogram by consumer group ω and origin o, $\Delta N_o^{\omega}(v)$ defined in (29).[25] Second, the impacts defined Section 3.5 are a function of changes in price changes that are independent from demand shifters, and can therefore be computed only once using the results from Proposition 1. To compute changes in price indexes, what varies across groups is the exposure to these price changes, as inferred from the calibrated distributions $h_o^{S,\omega}(z)$. 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 (49).

Figure A.11 shows the change in the price index $\hat{P}^{\omega}$ across income brackets.[26] 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 8 shows the equivalent variation–the welfare impacts of the policy change. We find that the aggregate consumer losses, inclusive of tariff rebates, would be $5.3 billion for low fees, or $17 per person (or $67 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).

The top panel of Figure 8 reports the welfare estimates across zipcode income. Our estimates imply that, in zipcodes with median family income under $45k, per capita welfare would decline by $27 . This compares with a $18 decline for zipcodes with $95k-$105k median family income, and a decline of $39 for the richest zipcodes. As a share of income, the corresponding declines for low, median and high-income zipcodes are 0.07%, 0.02%, and 0.02%. 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

[24]To compute these outcomes, we need values for the elasticities κ (between direct imports and other goods). We use κ =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 formal shipments, not de minimis shipments.

[25]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.

[26]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.

welfare in zipcodes with 0-5% white households would experience a decline of $36 . This compares with a decline of $19 decline for zipcodes with 50-55% white share, and a decline of $5 for the zipcodes with 95-100% white households. As a share of income, the corresponding declines for low, median and high white shares are 0.07%, 0.02%, and 0.007%. Our estimates therefore suggest that eliminating §321 would therefore raise the the cost of living disproportionately more for non-white households.

6.4 Robustness

The losses from eliminating §321 hinge on the customs fee that de minimis packages would face. As discussed above, CBP imposes a merchandise processing fee between $2.22 and $9.99 for informal shipments (shipments valued between $801 and $2500). Additionally, CBP requires a licensed broker to intermediate the informal shipments. Our benchmark scenario assumes a total fee of $10 per package, but the cost of using a licensed broker ranges can considerably (as high as $30 per package). Table 4 reports the aggregate losses with fees ranging from $0–a scenario where de minimis shipments would face only ad valorem tariffs–to $25, a scenario with a high processing and brokerage fee.

Columns 1 and 2 report the losses using the calibrated carrier data. Without customs fees, the aggregate consumer and welfare losses would be $3.5b and $1.4b, respectively. The losses magnify as the fee increases since the per-unit fee considerably raises the cost of low-value shipments. However, the difference between the consumer and welfare losses remains fairly similar at different fees since the fees are not rebated back to consumers.

Columns 3 and 4 repeat the analysis using the calibrated shipment densities from the CBP sample. At each fee structure, the losses from the CBP data are larger. The reason can be seen from comparing the share of shipments from China in the carrier data versus CBP data. In the carrier data, 37.0% of de minimis shipments originate from China. In the CBP sample, the share of de minimis shipments from China is 66.9%. Given the high tariffs currently on shipments from China, with a $10 customs fee, the aggregate welfare loss in the CBP data from eliminating §321 would be $5.7b.

TABLE 4: AGGREGATE IMPACTS OF ELIMINATING §321: ROBUSTNESS

Customs Fee	Carrier Sample		CBP Sample	
	Consumer Loss ($b)	Welfare Loss ($b)	Consumer Loss ($b)	Welfare Loss ($b)
$0/shipment	3.5	1.4	5.1	1.9
$5/shipment	5.4	3.6	6.9	3.9
$10/shipment	6.9	5.3	8.5	5.7
$15/shipment	8.5	7.1	10.2	7.5
$20/shipment	10.1	8.8	11.9	9.4
$25/shipment	13.0	11.7	14.4	11.8

Notes: Table reports the impacts of eliminating §321 at different per-shipment customs fees. Each case assumes parameters: $\{\sigma_{CHN}, \sigma_{RW}, \gamma, \kappa\} = \{3.43, 4.03, 4.60, 1.19\}$.

7 Conclusion

We study §321 section of the 1930 Trade Act, that allows imports to enter the country without paying tariffs or customs 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 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 (15), 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 (24), we start by computing the total differential of u in (20) and using (21), to obtain:

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

From the definition of the price index in (22), and using (13) and (11), 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 (23) 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 (24). These demonstrates part (i).

To derive part (ii), note that, with $v_{DM} = 0$, condition (24) 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 (iii), using (12) and (16), 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. 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.

Implementation of Counterfactuals with Sophisticated and Naive Firms We implement counterfactuals allowing for two groups of firms, $j = S, N$, as discussed in Section 6.1. Compared to the expressions presented in Section 3.5, the only difference is that the price index (3) becomes

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

where

$$\lambda_o^{\omega,j}(z) = \left(\frac{v_o^j(z)}{P_o^{\omega}} \right)^{1-\sigma_o} h_o^{\omega,j}(z), \tag{47}$$

for $j = S, N$. In addition, compute tariff revenue Δtr^{ω}. We have

$$\Delta tr^{\omega} = \sum_o \sum_j \Delta tr_o^{\omega,j}, \tag{48}$$

where tariff revenue collected per consumer in group ω is from firms of type j is:

$$tr_o^{\omega,j} = e_o^j \int_z \tau_o\left(v_o^j(z)\right) \lambda_o^{\omega,j}(z)\, dz. \tag{49}$$

After some manipulations, for $j = S$ firms, we have

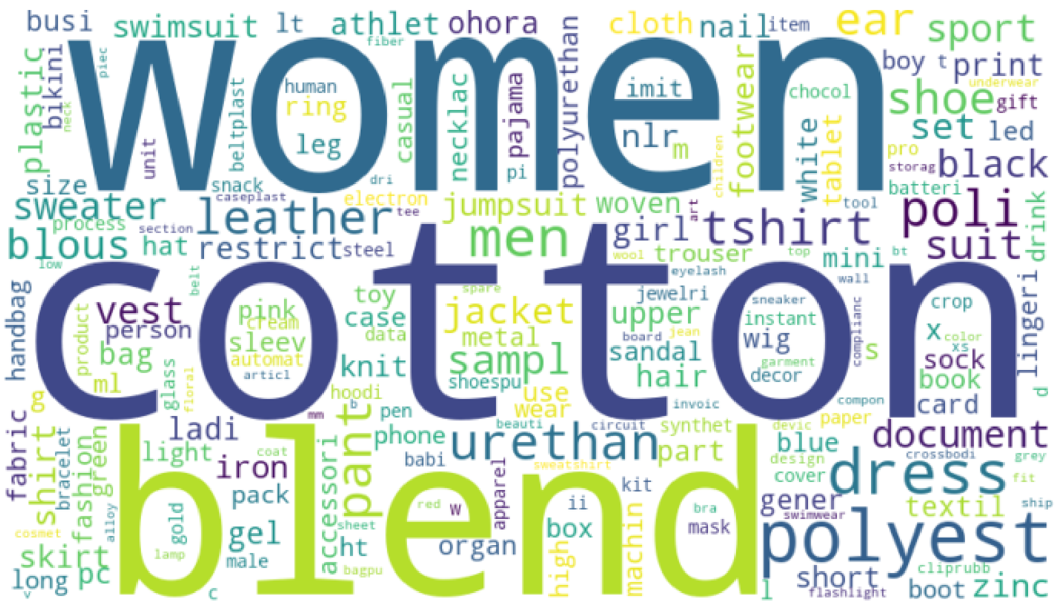
$$\Delta tr_o^{\omega,S} = \tau_o \hat{\tau}_o \frac{e_o^{\omega} \hat{e_o^{\omega}}}{\left(\hat{P}_o^{\omega}\right)^{1-\sigma_o}} \int_{z_{H,o}\hat{z}_{H,o}}^{\infty} \hat{v_o^S}(z)^{1-\sigma_o} \lambda_o^{\omega,S}(z)\, dz - e_o^{\omega} \tau_o \int_{z_{H,o}}^{\infty} \lambda_o^{\omega,S}(z)\, dz;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

while $j = N$ firms we have

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

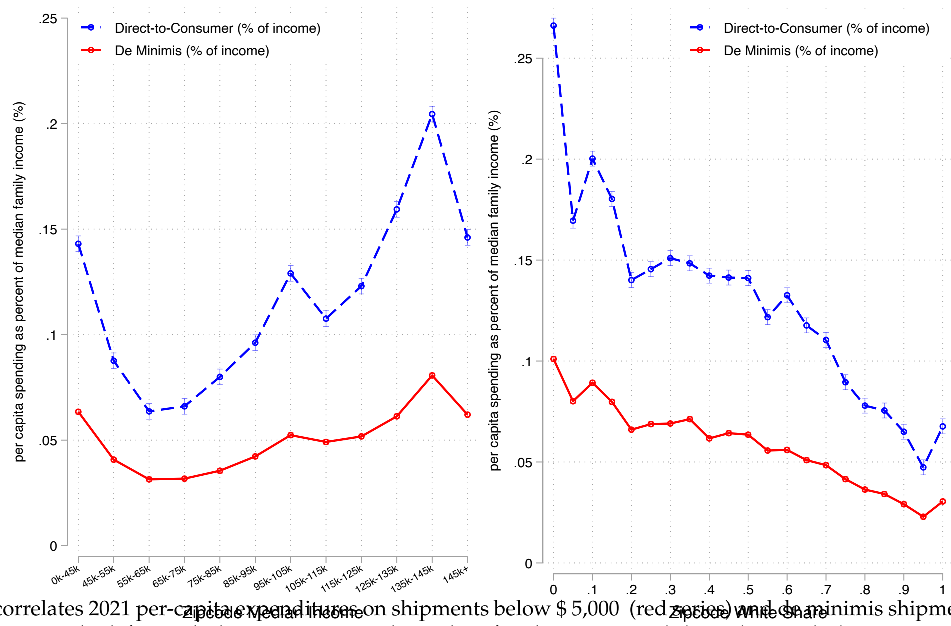
Appendix Tables and Figures

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



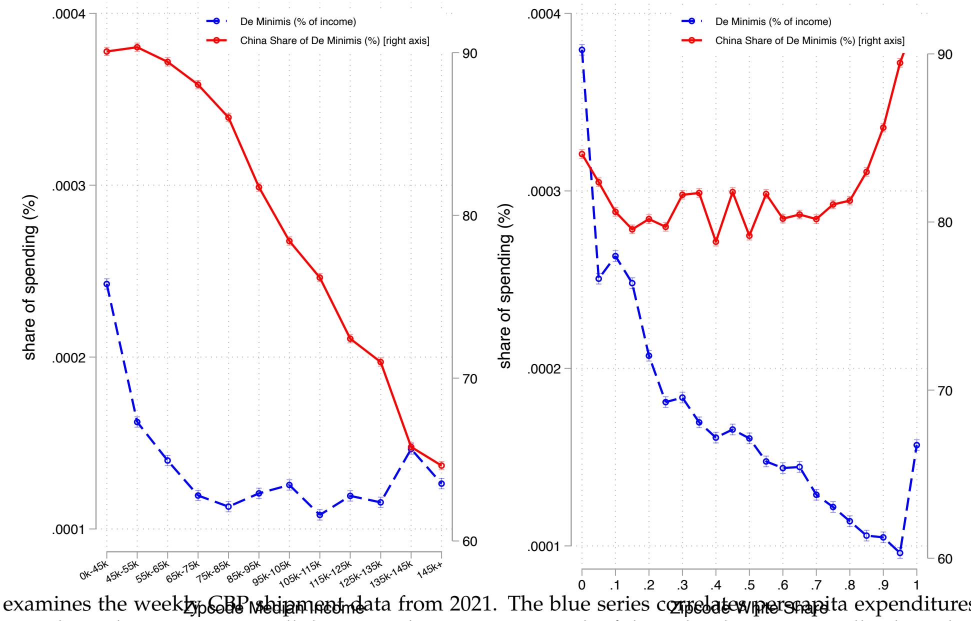
Notes: Figure displays the most common items in direct-to-consumer shipments. The items are reported in carriers A and B shipments, processed using standard text processing (remove stop words, stemming).

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



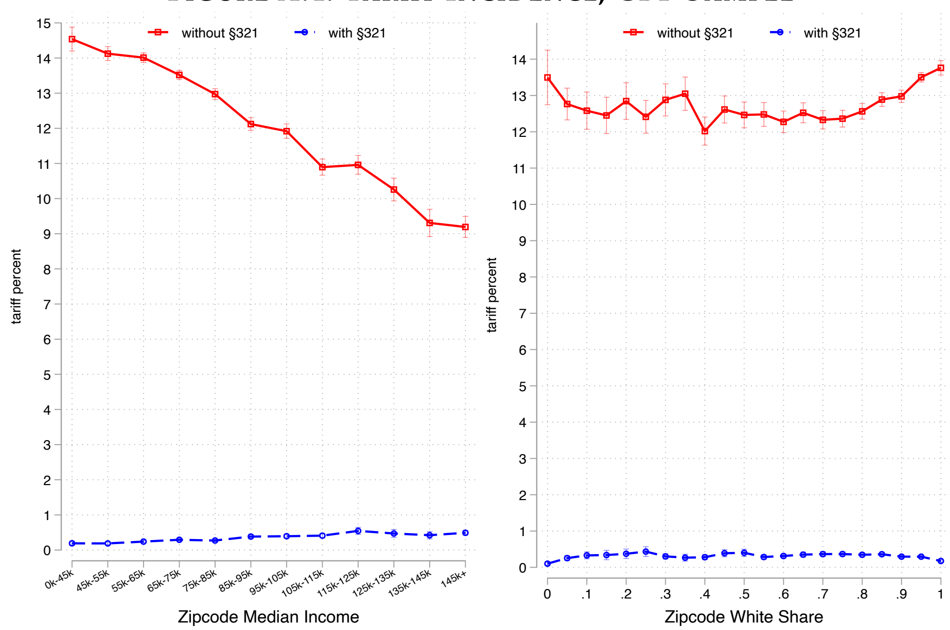
Notes: Figure correlates 2021 per-capita expenditures on shipments below $ 5,000 (red series) and de minimis shipments (blue series), as a share of income. The left panel plots against zipcode median family income and the right panel plots against zipcode share of white households. Standard errors of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

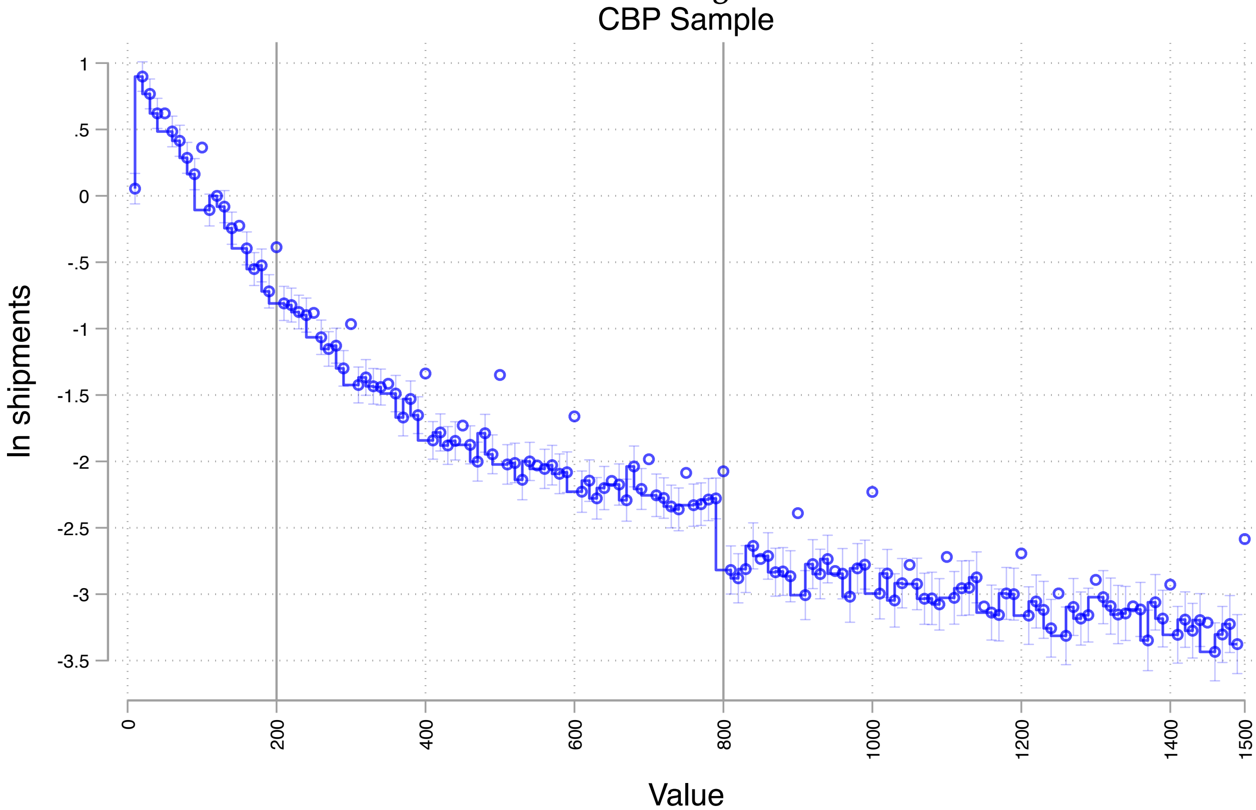
FIGURE A.4: TARIFF INCIDENCE, CBP SAMPLE



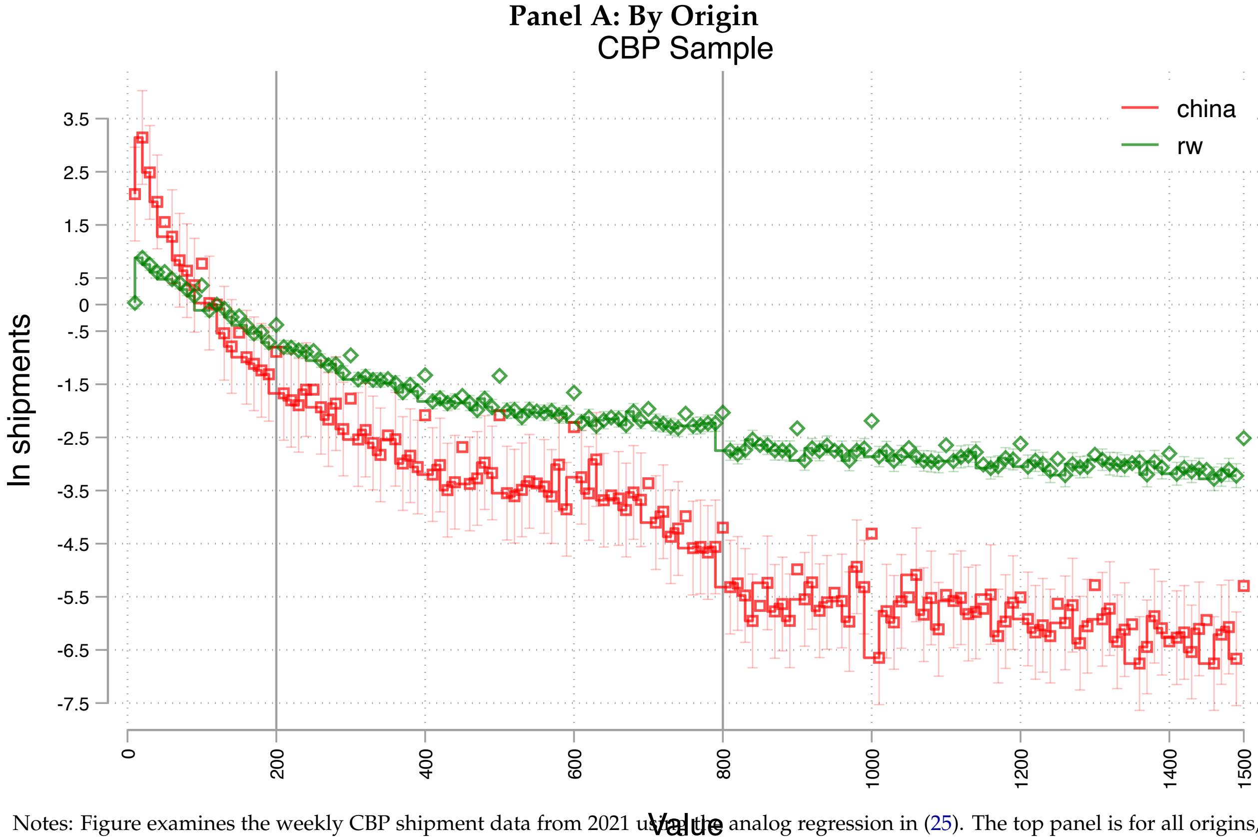
Notes: Figure reports the zipcode-level tariffs from the 2021 CBP data. A zipcode's tariff is the import share weighted average tariff across origins. The blue series is the average tariff with §321. The red series removes the tariff exemption from §321. Standard errors of the means reported in brackets.

FIGURE A.5: CBP SHIPMENT DENSITY

Panel A: All Origins

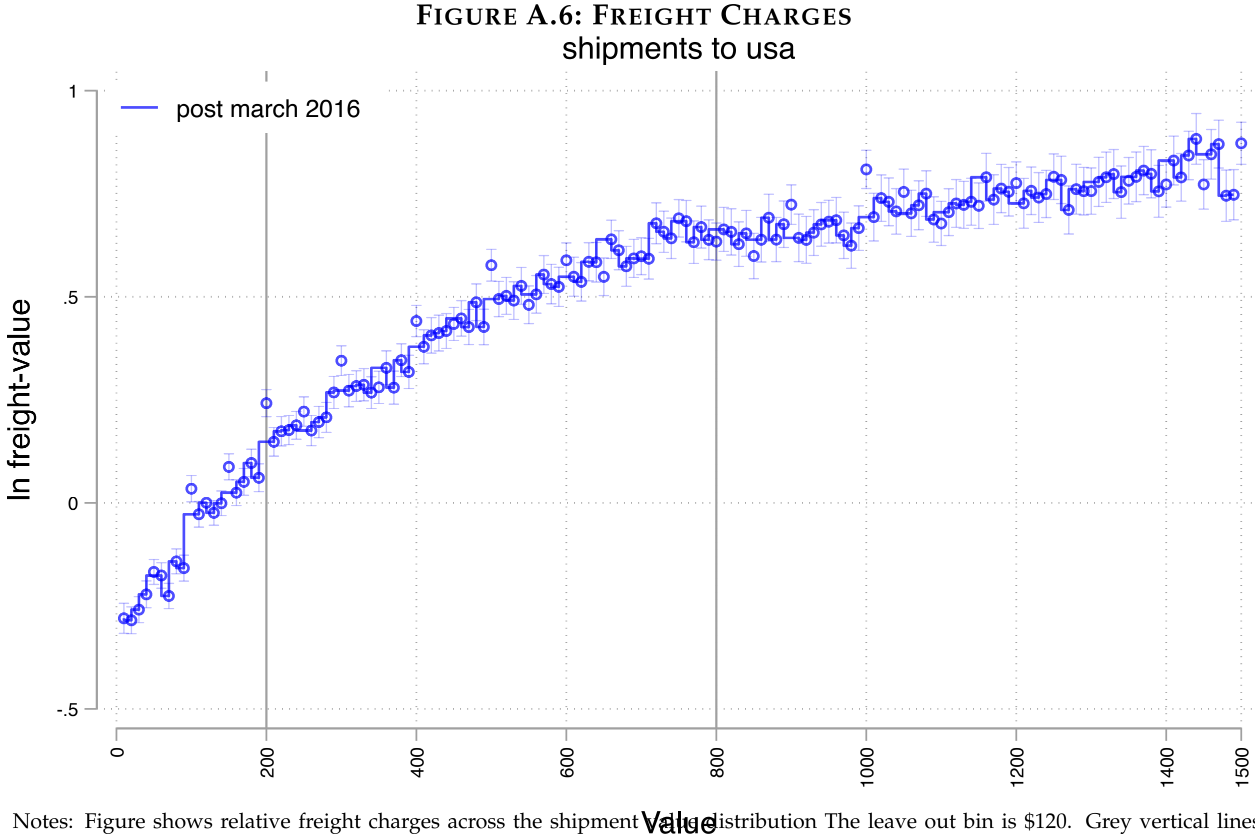


Panel A: By Origin



Notes: Figure examines the weekly CBP shipment data from 2021 using the analog regression in (25). 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.

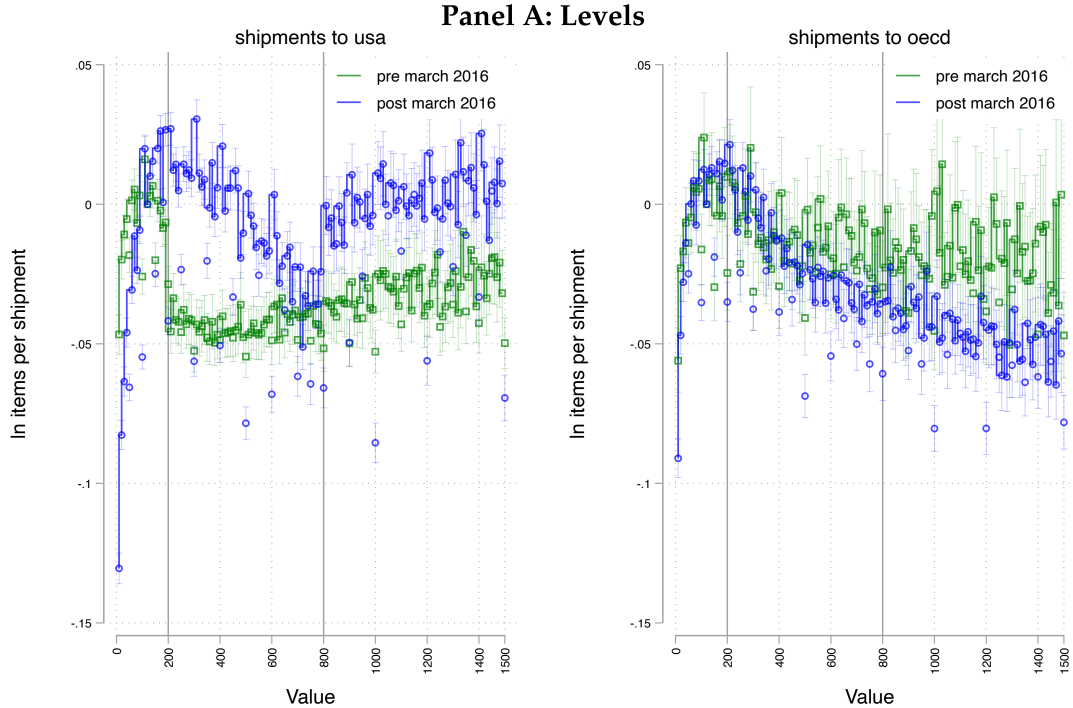
FIGURE A.6: FREIGHT CHARGES



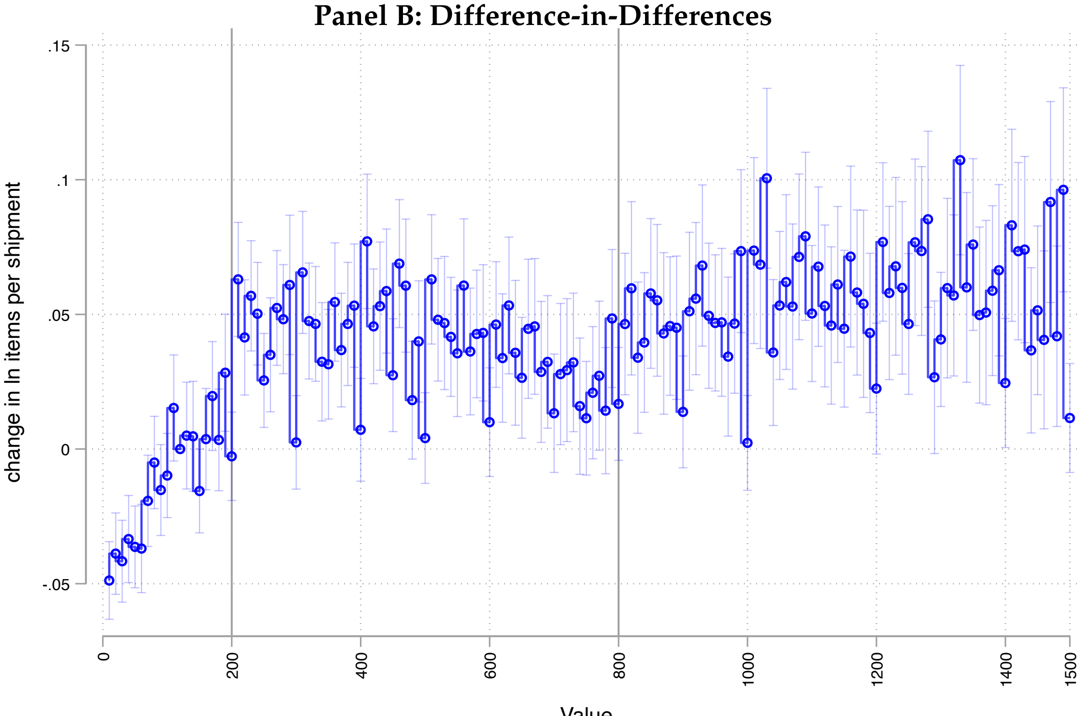
Notes: Figure shows relative freight charges across the shipment value distribution The leave out bin is \$120. Grey vertical lines denote §321 thresholds before and after March 2016. Error bars denote 95% confidence intervals. Data for carrier C, who provided data 2020 onwards and did not provide transshipped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

FIGURE A.7: NUMBER OF ITEMS PER SHIPMENT

Panel A: Levels

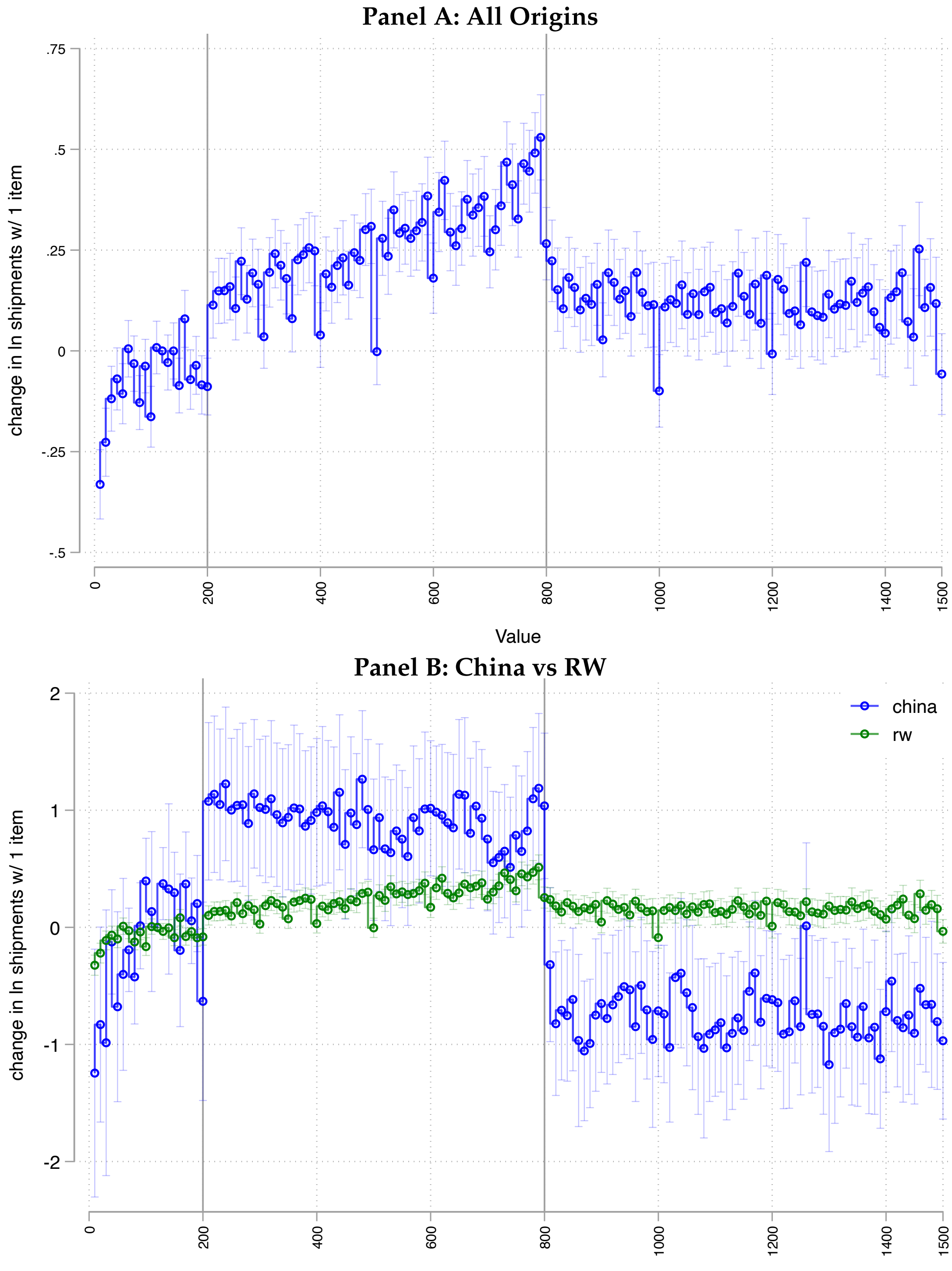


Panel B: Difference-in-Differences



Notes: Figure reports the average number of items per package at each bin. The top panel runs regressions (25) in levels, and the bottom panels reports the difference-in-differences specification (26) 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.

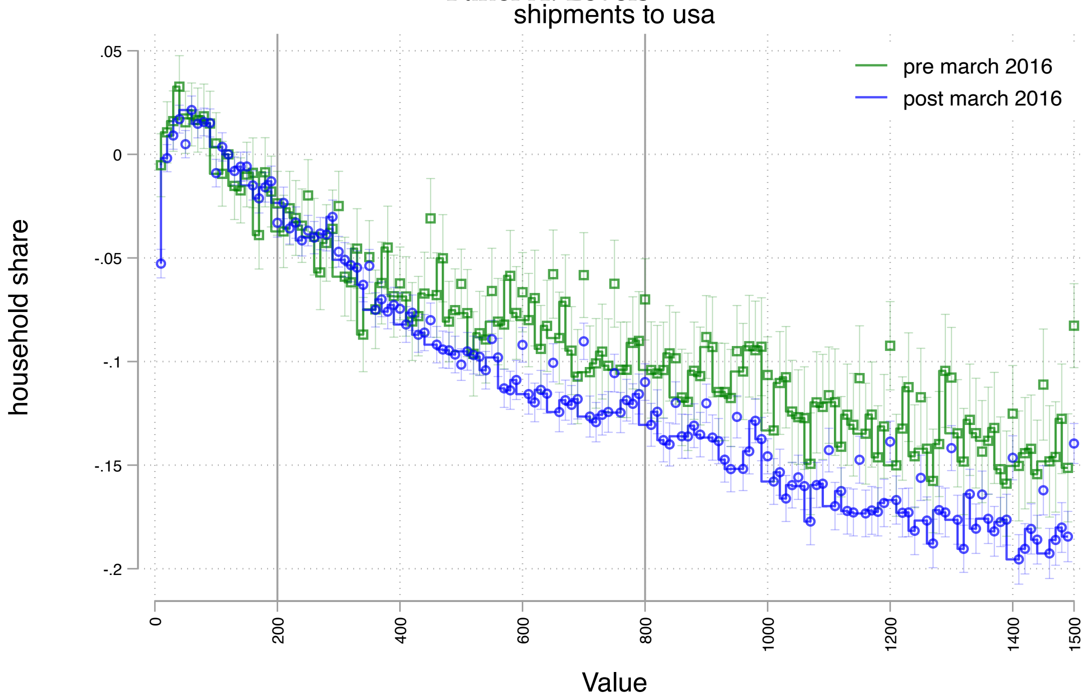
FIGURE A.8: CHANGE IN DENSITY OF ONE-ITEM SHIPMENTS



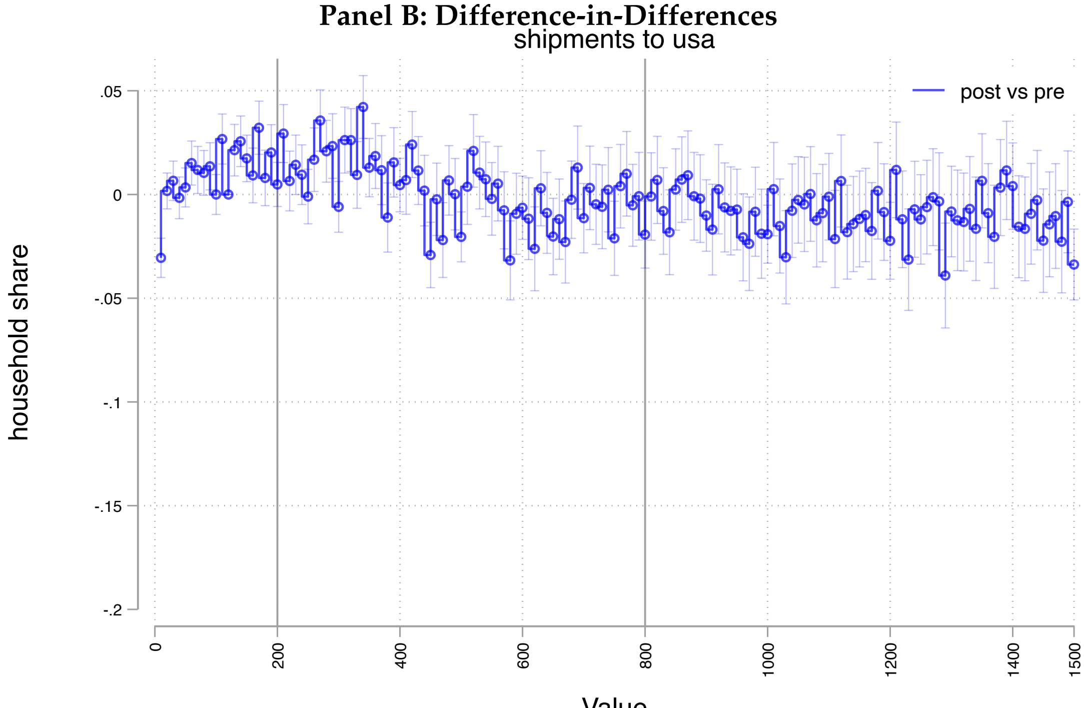
Notes: Figure reports the number of shipments containing one item at each bin. The top panel runs (26) for all origins, and the bottom panels reports results separately for China and RW. Grey vertical lines denote §321 thresholds before and after March 2016. The leave-out bin is $120. Error bars denote 95% confidence intervals. Data is from carriers A and B.

FIGURE A.9: SHARE OF HOUSEHOLDS

Panel A: Levels

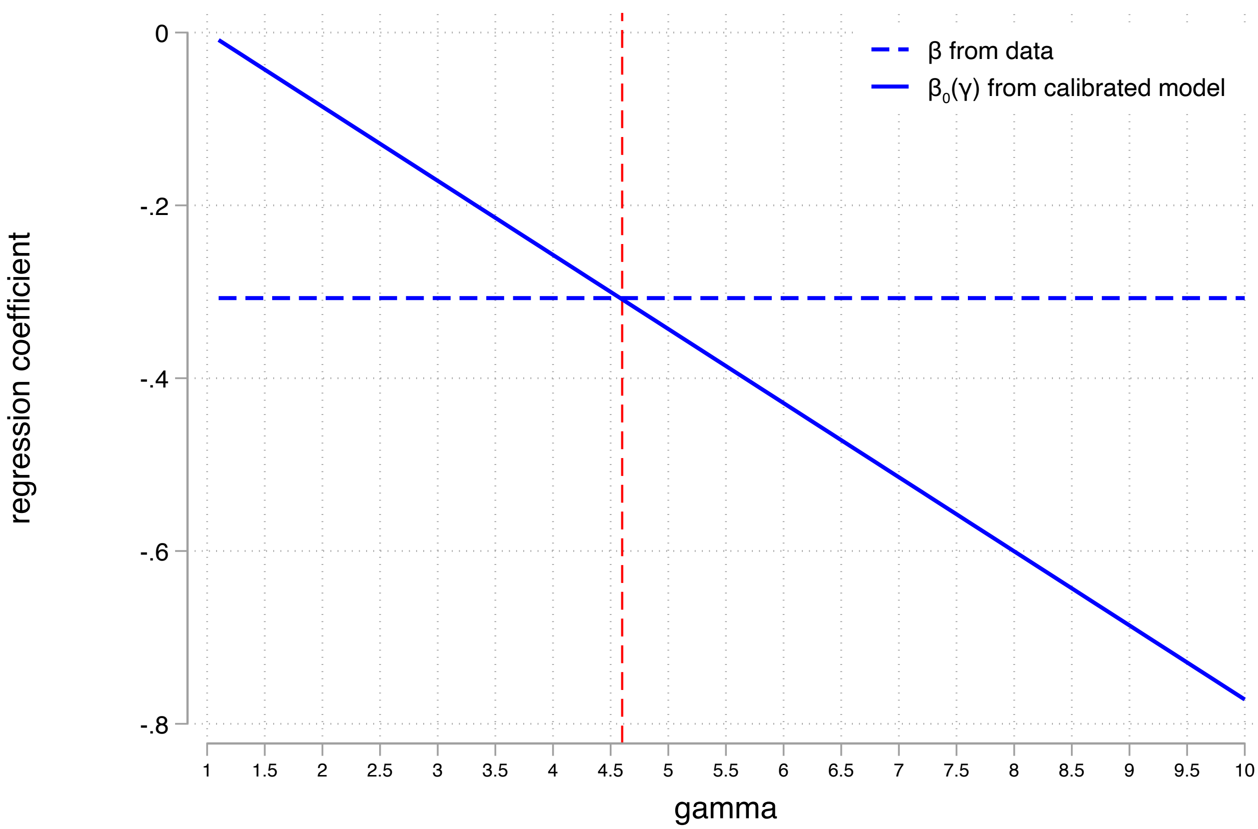


Panel B: Difference-in-Differences



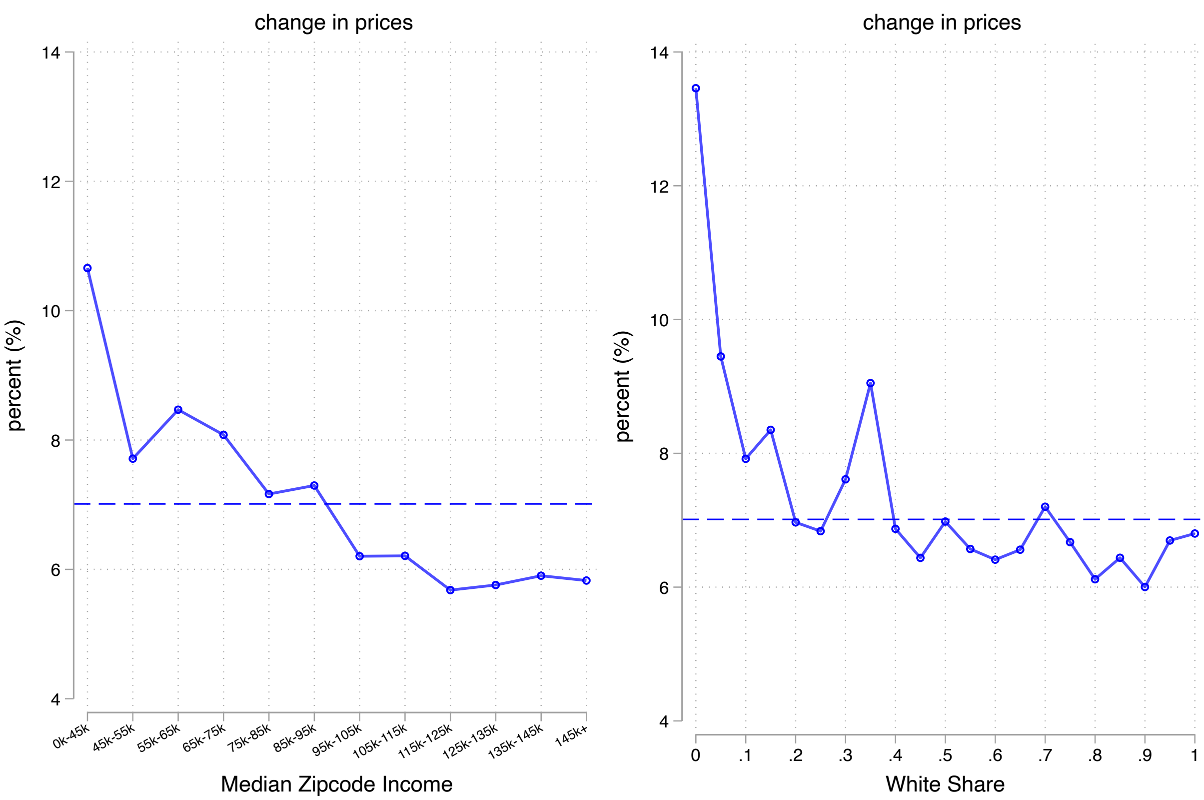
Notes: Figure reports the fraction of shipments in each bin that are sent to addresses matched to US residential zones; see Section 4.1 for details. The regression in the top panel is $hhshare_{bodxt} = \alpha_{odxt} + \beta_b + \epsilon_{bodxt}$, where the green series is run on shipments pre-March 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.10: 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, γ =4.6.

FIGURE A.11: CHANGE IN PRICE INDEX



Notes: Figure reports for defined in 16. 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 7.01%.