Selection into Tariff Avoidance and the Measured Welfare Cost of Tariffs

Jackson Mejia*

Influential studies find U.S. importers bore the full incidence of the 2018 China tariffs. I show this is biased upward by selection: when avoidance is costly, low-passthrough exporters exit customs data through transshipment, leaving only high-passthrough firms in the sample. Measuring transshipment in bilateral trade flows, I find nearly 40% of tariffed products were rerouted, reducing measured passthrough from 100% to 85% and lowering the estimated welfare cost correspondingly. I identify a novel enforcement margin: the corporate tax code. Because firms deduct imported input costs, higher corporate tax rates discourage avoidance. The 2017 tax cut from 35% to 21% reduced tariff revenue by $2–$10 billion through increased avoidance, revealing a quantitatively significant interaction between tax and trade policy.

*Massachusetts Institute of Technology, jpmejia@mit.edu. First Draft: September 2025. This draft: October 2025. I am especially grateful to Steve Miran and Kim Ruhl for extensive discussions and comments on the development of these ideas, as well as to Maxx Cook, Andrew Johnston, Pedro Martinez-Bruera, and Jim Poterba for useful conversations and comments. The views and conclusions contained in this document are mine and should not be interpreted as representing the official policies, either expressed or implied, of any government agency.

1 Introduction

Standard estimates suggest U.S. importers bore the full incidence of the 2018 China tariffs (Amiti, Redding, and Weinstein 2019, 2020; Cavallo et al. 2021; Fajgelbaum et al. 2020; Flaaen, Hortaçsu, and Tintelnot 2020), implying these tariffs were as costly as top income taxes (Finkelstein and Hendren 2020). But this consensus rests on a problematic assumption: that the firms whose transactions we observe in customs data after a tariff increase are representative of all affected firms. They are not. When tariff avoidance is costly, the firms that exit the direct-shipping channel—through transshipment, relocation, or other strategies—are precisely those that would have borne the least incidence. Their selective exit biases standard "border design" estimates upward, overstating both the domestic burden and the welfare cost of tariffs.

The bias arises from a simple sorting mechanism. Exporters with low marginal costs charge high markups and have low tariff passthrough—they must absorb most of the tariff themselves. When costly avoidance options like transshipment become attractive, these high-markup firms have the strongest incentive to pay the fixed cost to reroute through third countries. Higher-cost firms that can pass tariffs through to U.S. buyers continue shipping directly. Standard regressions using customs data therefore average passthrough over a selected sample of "survivors," mechanically yielding estimates that are too high. Given that markups are heterogeneous in practice (Gopinath and Itskhoki 2010; Amiti, Itskhoki, and Konings 2019; De Loecker, Eeckhout, and Unger 2020; Edmond, Midrigan, and Xu 2023), this selection bias is likely empirically important.

Whether this bias affects empirical estimates depends critically on how the sample is constructed. Studies using aggregate customs data, in where imports are classified by their recorded country of origin at the border, are susceptible because transshippers disguise their true origin (Amiti, Redding, and Weinstein 2019; Fajgelbaum et al. 2020; Cavallo et al. 2021). When a Chinese firm reroutes through Vietnam, it exits the China-U.S. sample in customs records and mechanically drops from the analysis. I call this a "border design" because the sample composition is determined by what crosses the customs border. In contrast, studies that track specific products or firms from their true origin to destination, following the same items before and after the tariff regardless of route, avoid this selection problem (Cavallo et al. 2021; Flaaen, Hortaçsu, and Tintelnot 2020). I refer to these as "cohort designs" because they maintain a fixed cohort of goods or firms.

However, even cohort designs may be subject to a different form of selection. For products with high fixed costs of transshipment, such as bulky durables like washing machines or refrigerators, temporary rerouting may be infeasible, but *permanent production relocation* out of China becomes an alternative margin. If a firm moves its assembly operations to Vietnam in response to U.S. tariffs on China, it exits the "Chinese exporter" cohort entirely, removing it from even cohort-based samples that track origin-country firms. This would generate full measured passthrough for the remaining Chinese exporters (those unable or unwilling to relocate) even though the cohort itself is selected. The discrepancy between research designs is revealing: cohort designs find full passthrough primarily for consumption goods—exactly where I detect minimal transshipment—while capital and intermediate goods show evidence of substantial avoidance through both rerouting and potentially relocation.

This paper makes four contributions. First, I develop a tractable model of heterogeneous firms choosing between direct shipping and costly avoidance that formalizes this selection bias and derives a portable correction. The framework features monopolistically competitive firms with Kimball (1995) demand, where the key insight is that low-cost, high-markup firms—those hurt most by tariffs—are the most likely to select into avoidance. Second, I measure transshipment—rerouting through third countries—using novel extensions to the trade flow screens in Freund (2024) and show that nearly 40% of tariffed product codes exhibit evidence of avoidance, with aggregate transshipment reaching 15% of 2017 China-U.S. trade by 2023. Applying my correction implies true tariff passthrough is approximately 85%, meaningfully below the consensus estimate of 100%. Third, I estimate the elasticity of avoidance with respect to the tariff wedge, exploiting within-product variation in exposure. I find a large and robust response concentrated in business inputs: a 10 percentage point increase in the effective tariff raises the probability of transshipment by 20–30 percentage points. Fourth, this elasticity reveals a powerful but overlooked enforcement tool: the corporate tax code. Because firms deduct imported input costs, a higher corporate tax rate makes direct shipping relatively more attractive, reducing avoidance. Using my elasticity estimates, I show that the 2017 Tax Cuts and Jobs Act (TCJA), which cut the corporate rate from 35% to 21%, reduced tariff revenue by \$2–\$10 billion through increased avoidance.

My empirical findings paint a clear picture of selection in action. Transshipment activity was negligible before 2018 but surged after the tariffs, concentrated heavily in capital and intermediate goods where the tax shield from deductibility is strongest. Products with higher transshipment show both lower direct trade volumes and lower unit values, consistent with low-cost, high-value varieties selectively exiting. The elasticity of transshipment with respect to the tariff wedge is large: a 10 percentage point increase in the effective tariff raises the probability of transshipment by 20–30 percentage points. This behavioral response generates a substantial fiscal externality, but the corrected domestic incidence is low enough that the welfare cost of tariffs—properly measured—cannot be rejected as equal to a lump-sum tax.[1]

My findings complement rather than contradict existing cohort-design studies that track specific products or retailers (Flaaen, Hortaçsu, and Tintelnot 2020; Cavallo et al. 2021). Those papers avoid the selection bias I identify by following firms before and after the tariff. Notably, they find full passthrough for consumption goods—exactly the category where I detect minimal transshipment. Recent work confirms the empirical prevalence of rerouting using different methodologies: Do et al. (2025) use proprietary shipment-level data to directly trace transshipment routes, Iyoha et al. (2025) document substantial trade diversion in customs records in Vietnam, and Deng et al. (2025) show that RTAs systematically incentivize circumvention by creating preferential margins, finding that 16.4% of U.S.-Mexico trade growth in 2018 was attributable to transshipment. My estimates, constructed using publicly available bilateral trade flows with conservative screening procedures, are broadly consistent with these independent findings. The convergence across methodologies validates the economic significance of the phenomenon. My contribution is to provide the theoretical framework linking avoidance to passthrough bias, estimate the elasticity needed for policy counterfactuals, and identify the corporate tax channel as an implicit enforcement tool.

The welfare analysis proceeds through the lens of the tariff's marginal cost of public funds (MCPF) (Finkelstein and Hendren 2020), which measures the total welfare cost of raising one dollar of revenue:

$$\text{Tariff MCPF} \approx \frac{\text{Domestic Incidence}}{\text{Fiscal Externality}}$$

This paper contributes to understanding both components. My finding that true incidence is lower than previously thought directly corrects measurement of the numerator. At the same time, the large volume of transshipment constitutes the denominator's fiscal externality. Taken together, they imply that despite tariffs distorting behavior considerably, less than full passthrough means it is difficult to reject them being on par with a lump-sum tax for welfare. That welfare cost could be reduced further by policies which penalize avoidance.

1. Whether heterogeneous foreign markups are good or bad for domestic welfare depends on the welfare components under consideration (consumer surplus, tariff revenue, and terms-of-trade). The selection mechanism here reduces measured border passthrough and increases compliant flows; the net welfare effect is therefore ambiguous ex ante and depends on how these components trade off in the application at hand.

This insight has immediate policy relevance. While the public finance literature focuses on explicit enforcement tools like audits, inspections, and penalties (Allingham and Sandmo 1972; Slemrod and Yitzhaki 2002; Bhandari et al. 2024; Slemrod 2019), I show theoretically that allowing importer firms to fully deduct the cost of imported intermediate and investment goods is isomorphic to such measures. Deductibility lowers the importer's effective burden of the tariff, making them less sensitive to price increases. This allows exporters to pass through more of the tariff on compliant shipments, raising the profitability of direct shipping relative to transshipment and thus reducing avoidance. The TCJA weakened this implicit enforcement mechanism just before the 2018 tariffs were imposed, creating a quantitatively significant policy interaction.

It is important to note the scope of these findings. Transshipment is one salient channel of tariff avoidance, but firms have access to a broader portfolio of strategies, including misreporting value to fall under de minimis thresholds (Fajgelbaum and Khandelwal 2024), breaking up shipments into smaller parcels, or misclassifying goods (Fisman and Wei 2004). My estimates therefore represent a conservative lower bound on total avoidance. Additionally, the welfare analysis is conducted in partial equilibrium and abstracts from general equilibrium effects on wages, prices, and China's terms of trade. These limitations suggest the true correction to measured passthrough could be larger, and the welfare implications more nuanced, than my baseline estimates indicate.

Roadmap. Section 2 discusses the welfare cost of tariffs through the marginal cost of public funds. Section 3 develops the partial equilibrium model of avoidance and passthrough. Section 4 describes the data and methodology used to measure transshipment, which Section 5 uses to present the main empirical results, including the magnitude of avoidance and the elasticity estimates. Section 6 uses these estimates to re-evaluate the tariff's welfare cost and conduct the TCJA counterfactual. Section 7 concludes.

2 An Organizing Framework: The Welfare Cost of Tariffs

This paper's two main contributions, which are correcting the measurement of tariff incidence and analyzing the behavioral response of tariff avoidance, are best understood through the lens of the tariff's welfare cost. I use the Marginal Cost of Public Funds (MCPF) as an organizing framework to connect these two pieces.

The MCPF measures the total welfare cost to society of raising one additional dollar of government revenue through taxation. It provides a welfare-relevant metric for comparing different tax instruments. A natural benchmark is a hypothetical lump-sum tax, which does not distort economic behavior. For such a tax, the welfare cost of raising one dollar is exactly one dollar, yielding an MCPF of one. Real-world taxes like tariffs, by contrast, distort behavior and generate deadweight losses. The MCPF captures these costs through two channels, represented in the numerator and denominator of the following expression:[2]

$$\text{MCPF} = \frac{\beta}{1+\eta}. \tag{1}$$

The numerator, β, represents the *domestic incidence* of the tariff It is the share of the tariff burden borne by domestic consumers and firms rather than foreign exporters. When $\beta = 1$, domestic agents bear the full incidence; when $\beta = 0$, the tariff is effectively a transfer from foreign producers and imposes no direct cost on the home country. The denominator, $1+\eta$, captures the *fiscal externality* from behavioral responses. The elasticity $\eta \leq 0$ reflects how the tax base shrinks as economic agents change their behavior to reduce their tax burden. A larger behavioral response (more negative η) means the government collects less revenue per unit of welfare cost, raising the MCPF.

Existing estimates of the tariff MCPF following the 2018 U.S.-China trade war place it between 1.2 and 1.6 (Finkelstein and Hendren 2020; Jaccard 2021), suggesting tariffs are more costly than lump-sum taxation but comparable to top income taxes. However, these estimates may be biased because they do not account for selection into tariff avoidance. This paper shows that when costly avoidance is possible, low-passthrough firms are the most likely to exit the direct-shipping channel. Their selective exit biases standard estimates of domestic incidence β upward, overstating the burden on U.S. consumers.

At the same time, widespread avoidance erodes the tariff base, generating a fiscal externality that existing estimates may understate. The net effect on the MCPF is *a priori* ambiguous. On one hand, if true domestic incidence is lower than previously measured, the numerator of equation (1) falls, reducing the welfare cost per dollar raised. On the other hand, if avoidance is large, the denominator shrinks (i.e., η becomes more negative), meaning less revenue is collected for each unit of distortion, which *increases* the MCPF. Which effect dominates is an empirical question.

This framework clarifies the paper's contributions. First, I quantify the extent of tariff avoidance to correct the *numerator* (the measured domestic incidence). Second, I estimate the elasticity of avoidance with respect to the tariff wedge to characterize the *denominator* (the fiscal externality). Together, these estimates allow me to evaluate the tariff's true

2. As derived in Appendix A.4. Hendren (2016) and Finkelstein and Hendren (2020) provide a thorough overview of the marginal *value* of public funds. Because I focus on taxes rather than transfers, I refer to it as the marginal *cost* for clarity.

welfare cost and assess policy tools, such as the corporate tax code, that can influence both margins. The model developed in the next section formalizes this intuition and derives testable predictions for how selection into avoidance affects measured passthrough.

3 A Model of Avoidance

This section develops the partial equilibrium model that provides the microfoundations for the two components of the Marginal Cost of Public Funds. I first analyze the numerator by formalizing the selection mechanism, showing how heterogeneous passthrough and costly avoidance combine to generate an upward bias in standard estimates of domestic incidence β. I then use this same framework to analyze the denominator, modeling the avoidance choice as a fiscal externality (η) and showing how domestic tax policy—specifically, the deductibility of inputs—acts as a novel enforcement tool that can mitigate it.

3.1 Environment.

Consider a static partial equilibrium setting with monopolistic competition over differentiated varieties indexed by $i \in \mathcal{J}$. Each exporter sets a price p_i and sells to a Home market that imposes a uniform ad valorem tariff $\tau^d \geq 0$ on direct shipments from the targeted origin. The delivered price paid in home is $\tilde{p}_i^d = (1 + \tau^d)p_i$. The firm may pay a fixed cost $F > 0$ to avoid the tariff. In practice, this may resemble a Chinese exporter shipping through Vietnam to export a good to the United States (transshipment), or it may correspond to relocating production.

Throughout the paper, we focus on a particular kind of avoidance—transshipment—but the idea is more general. With transshipment, the fixed cost F captures the various expenses and risks associated with establishing and using a transshipment route. In reality, this cost is not a single number but is likely determined by several factors. These include the logistical costs tied to the distance and infrastructure of the intermediary country, the characteristics of the product itself (e.g., electronics are easier to reroute than fresh produce or heavy machinery), and the legal or administrative fees required to relabel goods. While F likely varies across firms and products, this model assumes a uniform cost for tractability.[3]

The choice to avoid the direct tariff is not without its own costs. As established in our

3. Acknowledging this heterogeneity, however, suggests that the incentive to tranship is strongest for firms that produce goods that are easy to reroute and have access to efficient transshipment hubs.

organizing framework, the behavioral response of avoidance erodes the tax base and creates a fiscal externality. In our framework, the avoidance channel carries its own (weakly) smaller ad valorem wedge, $\tau^a \in [0, \tau^d)$. Canonically, the public finance literature models this wedge as the result of explicit enforcement actions, such as the expected cost from audits, inspections, or penalties on detected evasion (Allingham and Sandmo 1972; Slemrod 2019). In this case, it would correspond directly to the proposed penalty audits on transshipment from the August 2025 Executive Order 14326. However, this paper argues that other, less direct features of the tax system can have a similar effect. Specifically, we will show later that domestic tax policies, such as the deductibility of imported business inputs, are isomorphic to imposing a positive wedge on the avoidance channel ($\tau^a > 0$), acting as a powerful, built-in enforcement mechanism. For the initial development of the model, we remain agnostic about the source of this wedge.

For any channel $r \in \{d, a\}$, the tax τ^r creates a wedge between the price received by the exporter and the delivered price paid in the home market, denoted as $\tilde{p}_i^r = (1 + \tau^r) p_i$. d denotes direct shipping and a denotes avoidance.

Generalized demand. We impose minimal assumptions on Home demand to nest several important cases. Demand for each variety depends on its own delivered price and an aggregator summarizing the prices of all other varieties. Formally, the demand for variety i takes the form

$$q_i = D_i\big(\tilde{p}_i \mid \mathbf{P}\big), \qquad \mathbf{P} \equiv \mathbf{P}\big(\mathbf{P}_{-i}; \Theta\big),$$

where $\mathbf{P}$ is a pricing aggregator parameterized by Θ, and a sufficient statistic for the competitive environment reflected by firm i. Importantly, it nests CES and Kimball demand, among others. $\mathbf{P}$ is exogenous at the firm level. This corresponds to a standard monopolistic competition setup in which each firm is small relative to the market and takes the price distribution of rivals as given. Importantly, we index the elasticity of demand for each variety by ε and its superelasticity by κ. Under CES, $\kappa = 0$, while Kimball has $\kappa < 0$. That is, elasticity increases with price. Given that, we impose several regularity conditions on demand:

Assumption 1 (Demand)**.** *The demand for each* variety *i depends on its own delivered price* $\tilde{p}_i$ *and on a price aggregator* $\mathbf{P}$ *summarizing rivals. Fixing* $\mathbf{P}$ *as parametric at the variety level, the primitives satisfy:*

D1. ***Downward sloping own demand and outward shifts in rivals:*** $\dfrac{\partial D_i}{\partial \tilde{p}_i} < 0$ *and* $\dfrac{\partial D_i}{\partial \mathbf{P}} > 0$.

D2. ***Smoothness:*** *$D_i(\cdot \mid \mathbf{P}) \in C^2$ in own price.*

D3. ***Elastic demand:*** $\varepsilon_i(\tilde{p}_i \mid \mathbf{P}) \equiv -\dfrac{\tilde{p}_i}{D_i}\dfrac{\partial D_i}{\partial \tilde{p}_i} > 1$.

D4. ***Profit concavity / local stability:*** *For either channel $c \in \{D, T\}$ with delivered price $\tilde{p}_i^c$,*

$$\varepsilon(\tilde{p}_i^c \mid \mathbf{P}) \;-\; 1 \;-\; \kappa(\tilde{p}_i^c \mid \mathbf{P}) \;>\; 0.$$

D5. ***Kimball curvature:*** $\kappa_i(\tilde{p}_i \mid \mathbf{P}) \equiv -\dfrac{\partial \ln \varepsilon_i(\tilde{p}_i \mid \mathbf{P})}{\partial \ln \tilde{p}_i} \leq 0$ *(equals 0 under CES). We also impose two extra conditions:*

(a) $\dfrac{\partial \kappa(\tilde{p}_i \mid \mathbf{P})}{\partial \ln \tilde{p}_i} \leq 0$.

(b) $\kappa'(\tilde{p}) \;\equiv \partial \kappa(\tilde{p}) / \partial \ln \tilde{p} \geq \; -\frac{\varepsilon(\tilde{p})}{\varepsilon(\tilde{p})-1}\,\kappa(\tilde{p})^2$.

Conditions **D1–D4** are standard and ensure well-behaved monopolistic competition with elastic demand and unique profit-maximizing prices. Condition **D5** introduces Kimball-type demand, where $\kappa \leq 0$ means the demand elasticity ε is weakly increasing in price. Intuitively, consumers become more price-sensitive as prices rise, making high-priced (high-markup) goods face flatter residual demand curves. This is the source of heterogeneous passthrough: when a tariff raises delivered prices, high-markup firms face larger elasticity increases and therefore compress their markups more, leading to lower passthrough. The technical conditions **D5(a)–(b)** ensure that this passthrough is monotone in marginal cost, which is critical for the sorting result in Proposition 1. Without these curvature restrictions, passthrough could be non-monotone, and the selection mechanism would be more complex. Empirically, **D5** is a weak condition: the literature consistently finds that markups vary across firms (Gopinath and Itskhoki 2010; Amiti, Itskhoki, and Konings 2019; De Loecker, Eeckhout, and Unger 2020; Edmond, Midrigan, and Xu 2023), and Kimball demand is a tractable way to microfound this heterogeneity.

Firm problem. Each firm $i \in \mathcal{J}$ has a constant marginal cost m_i. Exporter marginal costs m_i are independently drawn from a continuous distribution with support $[\underline{m}, \bar{m}] \subset (0, \infty)$ and density $f_m(m) > 0$. The distribution is independent of policy and of the aggregator $\mathbf{P}$, and has no atoms, so any cutoff $\widehat{m}$ is unique and yields smooth comparative statics.

Each firm must choose whether to pay a uniform fixed cost F to avoid the tariff via transshipment or absorb some part of the tariff and ship directly to the home nation.

Given $r \in \{d, a\}$, the firm solves

$$\pi_i(m_i; r) = \max_{p_i \geq m_i} \underbrace{(p_i - m_i)\, D_i(\tilde{p}_i^r \mid \mathbf{P})}_{\equiv\, \Phi_i(p_i; m_i, \tilde{p}_i^r)} - \mathbb{1}\{r = a\}F, \qquad \tilde{p}_i^r = (1 + \tau^r)p_i.$$

Lemma 1 (Lerner condition and monotone comparative statics)**.** *For either channel $r \in \{d, a\}$ and corresponding wedges τ^r, under **D1–D4**, any $p_i^*(m_i; r)$ is interior and satisfies*

$$\frac{p_i^* - m_i}{p_i^*} = \frac{1}{\varepsilon_i(\tilde{p}_i^r \mid \mathbf{P})}, \qquad \tilde{p}_i^r = (1 + \tau^r)p_i^*.$$

Moreover: (i) p_i^* strictly increases in m_i; (ii) p_i^* is weakly decreasing in the wedge τ^r (constant under CES); and (iii) q_i^* strictly decreases in m_i and τ^r.
Proof: Appendix A.1

Lemma 1 establishes two key results. First, it confirms the standard Lerner condition: firms set their markup inversely to the elasticity of demand they face. This makes all comparative statics run through how a given wedge, τ^r, shifts the delivered price and how elasticity varies with that price. Second, the lemma establishes the monotone comparative statics that are essential for the paper's sorting mechanism.

Part (i) shows that a higher marginal cost pushes a firm's optimal pre-wedge price upward, providing the clean ordering in m necessary to derive a unique sorting cutoff. Part (ii) highlights that any wedge acts as a demand shifter. Under CES demand, elasticity is constant and a firm's optimal markup does not change. Under Kimball-type demand, however, elasticity rises with the delivered price, so firms temper the price increase by lowering their own pre-wedge price; this is the source of heterogeneous passthrough. Finally, Part (iii) records the quantity implications: a higher marginal cost or a higher wedge τ^r reduces the quantity sold. This decline in profitability within a channel is what ultimately drives selection when wedges differ, a mechanism we formalize next.

3.2 The Routing Choice

Before formalizing the cutoff, it is helpful to lay out the core intuition for why certain firms select into avoidance. The model features two key elements: firms have heterogeneous marginal costs, and under Kimball demand, tariff passthrough rises with marginal cost. This means that low-cost firms, which operate with higher markups, have low passthrough. A low passthrough rate means these high-markup firms must absorb a larger share of the tariff themselves, cutting directly into their profit margins. This "price effect" hurts their operating profits more severely than the simple "quantity effect" (lost sales volume) faced by firms that can fully pass on the tariff. Therefore, it is precisely these low-cost, high-markup firms, the ones who would otherwise have to absorb the tariff, that have the strongest incentive to pay the fixed cost to avoid it altogether. Higher-cost firms, which can pass on most of the tariff, find it more profitable to continue shipping directly. This selection process is the key mechanism driving the paper's results.

Given that intuition, we now formally characterize how firms sort between direct shipment and avoidance. The only asymmetry across channels is that the tariff enters the delivered price in the direct channel. Given our primitives **D1–D4**, the direct and avoidance pricing problems are well behaved, so we can study routing by comparing their optimized values as functions of marginal cost m and the tariff.

For any marginal cost m, define the optimized value in a channel r with delivered-price multiplier $1+\tau^r$:

$$V(m,1+\tau^r) \;\equiv\; \max_{p\geq m}\,(p-m)\,D\big((1+\tau^r)p\big), \qquad \pi_d(m)=V(m,1+\tau^d), \quad \pi_a(m)=V(m,1+\tau^a)-F,$$

and the avoid–direct difference

$$\Delta(m;\tau^d,\tau^a) \;\equiv\; \pi_a(m)-\pi_d(m) \;=\; V(m,1+\tau^a)-V(m,1+\tau^d)-F.$$

Proposition 1 (Cutoff routing and wedge comparative statics)**.** *Under* D1–D4*, there exists a unique cutoff* $\widehat{m}(\tau^d,\tau^a)\in[\underline{m},\bar{m}]$ *such that*

$$m<\widehat{m}(\tau^d,\tau^a)\Rightarrow \textit{Avoid}, \qquad m\geq\widehat{m}(\tau^d,\tau^a)\Rightarrow \textit{Direct}.$$

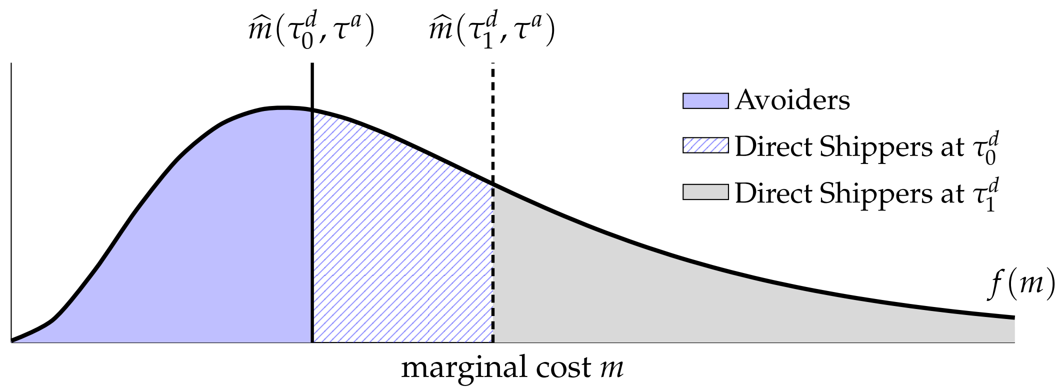
If the cutoff is interior, then

$$\frac{\partial\widehat{m}}{\partial\tau^d}>0 \qquad \textit{and} \qquad \frac{\partial\widehat{m}}{\partial\tau^a}<0.$$

Proof: See Appendix A.2.

Let $\theta(\tau^d,\tau^a)\equiv\Pr(m<\widehat{m}(\tau^d,\tau^a))$. By the signs in Proposition 1, $\partial\theta/\partial\tau^d>0$ and $\partial\theta/\partial\tau^a<0$: compressing the direct–avoidance wedge reduces avoidance.

Figure 1: An increase in tariffs raises the cutoff



Note: Distribution of marginal costs and wedge-induced selection. The cutoff $\widehat{m}(\tau^d, \tau^a)$ partitions the cohort: firms with $m < \widehat{m}$ avoid tariffs, while $m \geq \widehat{m}$ ship direct. A wider wedge gap (e.g., a higher τ^d or a lower τ^a shifts the cutoff right, increasing the avoidance share θ and shrinking the survivor set.

The threshold $\widehat{m}(\tau^d, \tau^a)$ partitions the cohort into two routing groups: firms with $m < \widehat{m}(\tau^d, \tau^a)$ optimally pay F and choose the avoidance channel, while firms with $m \geq \widehat{m}(\tau^d, \tau^a)$ continue to ship direct. The reason is straightforward. As a firm's marginal cost m rises, its per-unit margin $(p^* - m)$ shrinks, equilibrium quantity falls, and overall operating profits decline in both channels.

The decline, however, is not symmetric. The direct channel's value, $V(m, 1+\tau^d)$, is diminished more severely than the avoidance channel's value, $V(m, 1+\tau^a)$, because the direct wedge is larger ($\tau^d > \tau^a$). For low-cost, high-volume firms, the absolute profit loss from facing the higher direct wedge is substantial, making it worthwhile to pay the fixed cost F to access the lower-wedge avoidance channel. For higher-cost firms, volumes and margins are smaller, so the incremental gain from avoiding the higher wedge is not large enough to justify the fixed cost. This monotone ordering in m generates the unique cutoff. As Proposition 1 shows, widening the gap between the wedges—by increasing τ^d or decreasing τ^a—shifts the cutoff $\widehat{m}$ to the right, increasing the share of firms that choose to avoid.

Since a wider wedge gap pushes low-cost firms into the avoidance channel, the average characteristics of the remaining firms that ship direct are altered. I now turn to examining the corresponding pricing response.

Tax Deductibility and the Avoidance Wedge.

A key determinant of the avoidance wedge, τ^a, is the domestic tax treatment of imported inputs. Suppose the buyer is a domestic firm facing a corporate tax rate $\tau^c \in [0, 1)$ with partial deductibility $z \in [0,1]$ of tariff-inclusive input costs. Here z is net present value of a dollar of tax deductions. For inputs which must be expensed over time like some types of capital, $z < 1$. Otherwise, for intermediate inputs, $z = 1$. The factor $(1 - z\tau^c)$ multiplies all input costs, but the key difference between channels arises from the direct tariff wedge, τ^d. After-tax unit costs in each channel are

$$C_d = (1 - \tau^c z)(1 + \tau^d)p, \qquad C_a = (1 - \tau^c z)p,$$

so the direct–avoidance cost gap under deductibility is

$$\Delta C_{\text{ded}} \;=\; C_d - C_a \;=\; (1 - \tau^c z)\,\tau^d\,p.$$

In the general two–wedge model, the corresponding gap is

$$\Delta C_{\text{wedge}} \;=\; \big[(1 + \tau^d) - (1 + \tau^a)\big]\,p \;=\; (\tau^d - \tau^a)p.$$

Equating these gaps yields a simple isomorphism.

Corollary 1 (Deductibility–Wedge Isomorphism)**.** *When imported inputs are deductible, the routing problem is behaviorally equivalent to a two–wedge problem with an effective avoidance wedge of*

$$\tau^a = z\tau^c\,\tau^d.$$

With no deductibility, the benchmark case is $\tau^a = 0$.

Combining Corollary 1 with Proposition 1 turns domestic tax policy into a clean comparative static on the sorting cutoff:

$$\frac{d\widehat{m}}{d\tau^c} \;<\; 0 \quad \text{and} \quad \frac{d\widehat{m}}{dz} \;<\; 0.$$

A higher corporate tax rate (τ^c) or a larger deductibility fraction (z) reduces avoidance. The cutoff $\widehat{m}$ moves left, the survivor set expands, and the marginal firm is less inclined to avoid because deductibility effectively loads a share $z\tau^c$ of the direct tariff into the avoidance channel. Since avoidance is one source of the fiscal externality in the MCPF denominator, tax deductibility acts as a powerful, built-in policy lever that can directly reduce this component of the tariff's welfare cost.

The model's comparative statics show that the incentive to avoid the direct tariff is increasing in the gap between the wedges, $\tau^d - \tau^a$. In practice, the size of this wedge gap depends critically on the domestic tax treatment of the imported good, which varies by its end use. For consumption goods, which are not deductible business expenses, the avoidance wedge is effectively zero ($\tau^a = 0$), and the firm faces the full incentive created by the statutory tariff. For intermediate and capital goods, however, the deductibility of import costs creates a positive avoidance wedge, $\tau^a = z_k \tau^c \tau^d_k$, where k denotes the imported good type. This compresses the gap and reduces the incentive to avoid. To capture this variation across goods and over time in our empirical analysis, we define our main explanatory variable, the wedge Δ_k, as the log difference of the gross tariff factors:

$$\Delta_k \equiv \log \frac{1+\tau^d_k}{1+\tau^a_k}.$$

This wedge, which varies across goods and over time based on domestic tax policy, is the key empirical proxy for the incentive that drives selection into avoidance. The model predicts that a larger wedge will induce more low-cost firms to exit the direct channel. This selection process necessarily alters the composition of the firms that remain. We now turn to analyzing the pricing behavior of these "survivor" firms to understand how this selection affects measured tariff passthrough.

3.3 Passthrough

We now characterize the pricing response to the direct wedge for firms that continue to ship direct. For a survivor i, holding $\mathbf{P}$ fixed,

$$\beta_i \;\equiv\; \frac{d \ln \tilde{p}^d_i}{d\tau^d}, \qquad \tilde{p}^d_i = (1+\tau^d)\, p^*_i(m_i; d).$$

Writing the Lerner condition at the delivered price and differentiating with respect to $\ln(1+\tau^d)$ yields the expression

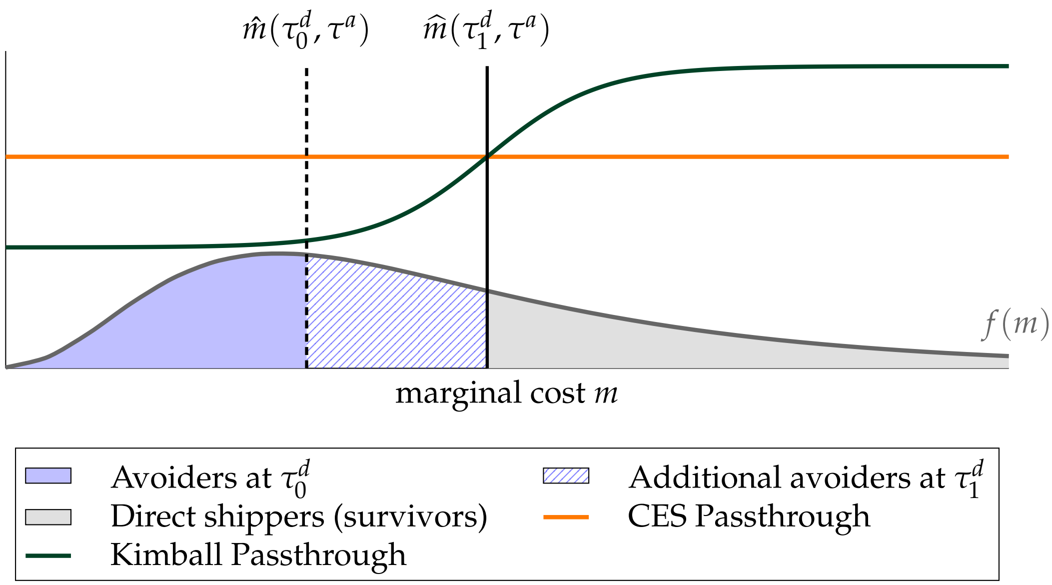
$$\beta_i \;=\; \frac{1}{1+\tau^d} \cdot \frac{\varepsilon\big((1+\tau^d)p^*_i\big) - 1}{\varepsilon\big((1+\tau^d)p^*_i\big) - 1 - \kappa\big((1+\tau^d)p^*_i\big)}, \tag{2}$$

where $\varepsilon(\cdot)$ is the own-price elasticity and $\kappa(\cdot) \equiv -\partial \ln \varepsilon(\cdot)/\partial \ln(\cdot)$ is the superelasticity, both evaluated at the delivered price $(1+\tau^d)p^*_i$. The denominator is positive under **D4**. In the CES benchmark ($\kappa \equiv 0$), passthrough is homogeneous: $\beta_i = (1+\tau^d)^{-1}$ for all survivors.

Proposition 2 (CES vs. Kimball among survivors)**.** *Fix P and assume D1–D4. (i)* CES: *If demand is CES ($\kappa \equiv 0$), then $\partial p^*_i/\partial\tau = 0$ and $\beta_i = (1+\tau)^{-1}$ for every survivor i. (ii) Kimball* *demand: If, in addition, D5a-b holds, then $\partial p_i^*/\partial\tau \leq 0$ and β_i is (weakly) increasing in m_i within the survivor set.*

Equation (2) shows that passthrough is the product of a mechanical factor $1/(1+\tau^d)$ and a curvature factor $(\varepsilon-1)/(\varepsilon-1-\kappa)$. Under CES, elasticity is constant, the optimal markup does not change with the direct wedge τ^d, and all survivors load the same fraction of the wedge into the delivered price. With Kimball demand, that is not the case. Heterogeneous markups imply that passthrough rises with marginal cost. Low-cost firms are less able to pass costs on to domestic consumers, so they are the ones who select into the avoidance channel. From Proposition 1, this means when the direct wedge τ^d rises, the cutoff shifts right and low-m firms exit. Under Kimball demand, the Lerner markup falls with the delivered price, so the average markup of survivors falls, even as their average passthrough rises.

Figure 2: Passthrough $\beta(m)$ under CES and Kimball



Note: The density $f(m)$ is split by the routing cutoffs $\widehat{m}(\tau_0^d, \tau^a)$ (dashed) and $\widehat{m}(\tau_1^d, \tau^a)$ (solid): avoiders are blue, additional avoiders are hatched, and survivors are gray. Overlaid are $\beta(m)$ under CES (flat, tangerine) and Kimball (increasing, green). With Kimball demand, the survivor mean passthrough, $\bar{\beta}$, shifts up when the direct wedge τ^d rises because the cutoff prunes low-β types from the direct channel.

Figure 2 illustrates the mechanism. We take the same distribution as in Figure 1 and overlay two lines: a flat tangerine line corresponding to homogeneous markups under CES demand, and an upward-sloping green line corresponding to heterogeneous markups under Kimball demand. At any given wedge gap, survivors are the high-m types with (weakly) higher passthrough. As the direct wedge τ^d rises, selection tilts the survivor set toward these high-β types, even though each individual firm's passthrough, β_i, can fall mechanically with τ^d. This selection has a first-order effect on measured passthrough.

3.4 Selection in Passthrough Regressions

The model has so far established two key results that, when combined, have direct implications for empirical work. First, the sorting mechanism (Proposition 1) shows that low-cost, high-markup firms are the most likely to select into the avoidance channel. Second, the passthrough analysis shows that under Kimball demand, these same low-cost firms have the lowest passthrough rates. The immediate consequence is that the group of firms that exits the direct-shipping sample is not random; it is disproportionately composed of low-passthrough firms. This section formalizes how this selection process generates an upward bias in standard passthrough regressions that rely on data from the remaining "survivor" firms.

Many influential studies estimate passthrough using so-called "border designs," which rely on customs unit values or aggregate import price indices constructed from direct shipments. The central issue with this approach is that the data-generating process itself is subject to the selection mechanism. By construction, these datasets only capture transactions from firms that continue to ship directly after the tariff change. The firms that select into avoidance are unobserved and mechanically drop out of the estimating sample. This creates a gap between the estimand from the regression and the true cohort-level parameter of interest.

To formalize the resulting bias, let $S_i \in \{0, 1\}$ be the survivor indicator in the post-period ($S_i = 1$ if i ships direct, 0 if i avoids), and let β_i denote firm i's direct-channel passthrough. Consider a regression run on data on imported goods from the targeted country:

$$\Delta \ln \tilde{p}_i \;=\; \alpha \;+\; \beta\,\Delta\tau^d \;+\; \varepsilon_i, \tag{3}$$

where $\tilde{p}_i = (1 + \tau^d)p_i$ is the delivered price and $\Delta\tau^d$ is the policy change.[4] Since $\Delta \ln \tilde{p}_i = \beta_i\,\Delta\tau^d$ for a direct shipper i, the OLS coefficient in (3) run on survivors identifies the survivor average:

$$\widehat{\beta}_{\text{border}} \;=\; \mathbb{E}[\beta_i \mid S_i = 1].$$

Our cohort object of interest is $\beta_{\text{cohort}} \equiv \mathbb{E}[\beta_i]$, the average direct-channel passthrough for

4. In practice, most empirical work relies on much richer specifications, with variation across units in a number of dimensions. That is irrelevant for the broader point about selection.

the pre-tariff cohort. The following identity makes the selection bias transparent.

Proposition 3 (Border vs. cohort bias)**.** *Let* $\Pr(S_i = 1)$ *be the survivor share. Then*

$$\beta_{border} \equiv \mathbb{E}[\beta_i \mid S_i = 1] = \underbrace{\mathbb{E}[\beta_i]}_{\beta_{cohort}} + \frac{\mathrm{Cov}(\beta_i, S_i)}{Pr(S_i = 1)}. \tag{4}$$

Proof. $\mathbb{E}[\beta_i \mid S_i = 1] = \mathbb{E}[\beta_i S_i]/\mathbb{E}[S_i] = \big(\mathbb{E}[\beta_i]\mathbb{E}[S_i] + \mathrm{Cov}(\beta_i, S_i)\big)/Pr(S_i = 1)$. □

Under **D5** and Proposition 1, β_i and S_i are both increasing in m, so $\mathbb{E}[\beta_i \mid S_i = 1] \geq \mathbb{E}[\beta_i \mid S_i = 0]$ and $\beta_{\text{border}} \geq \beta_{\text{cohort}}$. Two immediate corollaries follow. First, under CES ($\kappa \equiv 0$), all survivors have the same firm-level passthrough $\beta_i = (1 + \tau^d)^{-1}$, so $\mathrm{Cov}(\beta_i, S_i) = 0$ and $\beta_{\text{border}} = \beta_{\text{cohort}}$, resulting in no selection bias. By contrast, under Kimball-type demand with **D5** and the single-crossing routing result (Proposition 1), β_i is increasing in m_i and the survivor indicator S_i is also increasing in m_i; hence $\mathrm{Cov}(\beta_i, S_i) > 0$ and $\beta_{\text{border}} > \beta_{\text{cohort}}$. Intuitively, the border regression averages passthrough over the *selected* survivor set; curvature makes β_i rise with cost, the cutoff prunes low-m (low-β) firms, and the survivor mean shifts up. On the other hand, with CES homogeneity, selection does not tilt the average. This is simply an empirical description of what we visualized in Figure 2. Since markups are heterogeneous in practice (Edmond, Midrigan, and Xu 2023), that means standard passthrough regressions likely overstate the degree to which incidence is borne by domestic consumers.

The magnitude of this bias can be expressed directly. By the law of total expectation, the true cohort passthrough is a weighted average of the passthrough of survivors and avoiders:

$$\beta_{\text{cohort}} = (1 - \theta)\mathbb{E}[\beta_i | S_i = 1] + \theta\mathbb{E}[\beta_i | S_i = 0].$$

Using the border estimand, $\beta_{\text{border}} \approx \mathbb{E}[\beta_i | S_i = 1]$, and the fact that passthrough must be non-negative, this implies that the true cohort passthrough is bounded within the range $[(1 - \theta)\beta_{\text{border}}, \beta_{\text{border}}]$. This provides a direct, portable correction for the bias using an estimate of the avoidance share, θ.

When is there selection bias? The selection term in (4) applies whenever the outcome used in the regression is observed only for *direct shippers* or is an aggregate constructed from their transactions. In those designs the estimating sample is $S_i = 1$ by construction, so the OLS estimand is $\beta_{\text{border}} = \mathbb{E}[\beta_i \mid S_i = 1]$ and the gap to the cohort object $\beta_{\text{cohort}} = \mathbb{E}[\beta_i]$ equals $\mathrm{Cov}(\beta_i, S_i) / \Pr(S_i = 1)$.

When firm–product transactions are followed across routing so the *cohort is fixed* at the micro level, there is no selection bias in estimating the cohort passthrough. This requires observing the same exporter–importer (or firm–product–destination) unit before and after the tariff and keeping it in the sample whether it ships direct or avoids. Parts of Cavallo et al. (2021) implement this item-level tracking. Similarly, Flaaen, Hortaçsu, and Tintelnot (2020) avoid this bias by focusing solely on the retail prices of specific goods like washing machines.

One potential puzzle, however, is that some cohort-design studies, such as the Flaaen, Hortaçsu, and Tintelnot (2020) analysis of washing machines, also find near-complete passthrough. This does not necessarily contradict the selection mechanism but suggests its scope may be product- or industry-dependent. There are several potential reasons. First, the firms in that specific market may not have had an incentive to transship in the first place. If the washing machine industry is characterized by a distribution of marginal costs that lies mostly above the avoidance cutoff, then few firms would select into avoidance regardless of the research design. Second, for certain goods, the fixed cost of avoidance may be prohibitively high; large, durable goods like washing machines are difficult to ship discreetly and may require significant, specialized investment to reroute. Finally, passthrough for durable goods, which have complex pricing and supply chains, may be governed by different dynamics than the broader basket of goods driving the aggregate result.

On the other hand, border-level regressions that use customs unit values or aggregate import price indices for targeted product–origin cells estimate β_{border} by construction, since transshippers drop out or are reweighted when the tariff induces origin switching. This is the estimand in the border specifications of Amiti, Redding, and Weinstein (2019), Fajgelbaum et al. (2020), and the unit-value components of Cavallo et al. (2021).[5]

5. The selection logic may also help reconcile the puzzle of why measured tariff passthrough is near unity, while exchange rate passthrough is considerably lower (Cavallo et al. 2021; Gertler 2025). The key difference is the nature of the shock. Tariffs are persistent, so it is worthwhile for firms to invest in costly avoidance infrastructure, such as new transshipment routes. In contrast, exchange rate movements are often transitory and affect all origins, making such large, fixed investments in avoidance unlikely to pay off. The empirical importance of these adjustment costs may be substantial; recent evidence from Boehm, Levchenko, and Pandalai-Nayar (2023) shows that the full response of trade to tariff shocks can take nearly a decade to materialize. Therefore, the low passthrough firms pruned from the tariff sample may remain present in the exchange rate sample, explaining why measured passthrough is high in the former and low in the latter.

3.5 Taking Stock: The MCPF Revisited

The theoretical results now allow us to express the tariff's welfare cost, as captured by the Marginal Cost of Public Funds, directly in terms of our model's key parameters. The avoidance-basedMCPF for a tariff can be written as:

$$\text{MCPF} \approx \frac{\beta_{\text{border}}(1-\theta)}{1+\frac{\theta}{1-\theta}\varepsilon_{\theta}},$$

where θ is the share of avoiding firms and $\varepsilon_{\theta} \equiv \frac{\partial\theta}{\partial\tau^d}\frac{\tau^d}{\theta}$ is the avoidance elasticity.[6]

This expression makes the paper's empirical task clear. The numerator—the corrected domestic incidence—depends on the level of avoidance θ. The denominator—the fiscal externality—is driven by the avoidance elasticity ε_{θ}. To evaluate a tariff's true welfare cost, we must quantify both. The empirical analysis that follows is designed to measure the level of transshipment to correct the numerator, and then estimate its elasticity to analyze the policy levers that can shrink the denominator.

4 A Methodology for Identifying Transshipment

The theoretical framework established two empirical tasks required to evaluate the tariff's true welfare cost: measuring the level of avoidance θ to correct the bias in the MCPF's numerator, and estimating the elasticity of avoidance to analyze the denominator's fiscal externality. This section and the next are dedicated to these two tasks, focusing on transshipment as a key, measurable channel of avoidance. We begin by developing a methodology to identify the level of transshipment in the data.

I use the 2018 tariffs applied on China by the United States to identify transshipment by extending the methodology of Freund (2024) to construct a bounded measure of the share of goods originating from China but transshipped through third countries to the United States over the period 2012-2023.

4.1 Data

I use annual data on bilateral trade flows from CEPII's BACI HS-12 vintage from 2012-2023 at the 6-digit product (HS6) level. For each year y, country pair (i, j), and HS6 code

6. The fiscal externality is the elasticity of the tax base (the survivor share $1-\theta$) with respect to the wedge, $\eta \approx \frac{\partial(1-\theta)}{\partial\tau^d}\frac{\tau^d}{1-\theta}$. The avoidance elasticity is defined as $\varepsilon_{\theta} \equiv \frac{\partial\theta}{\partial\tau^d}\frac{\tau^d}{\theta}$. Substituting this definition simplifies the fiscal externality to $\eta \approx -\frac{\theta}{1-\theta}\varepsilon_{\theta}$.

k, we observe the customs value of shipments $v_{i \to j,k,t}$. Our goal is to discern when goods originate in China and go to another country j on the first leg, and then arrive in the United States as the destination in the second leg. We restrict the intermediate countries i on the second leg to a list of forty potential transshipment hubs. The hubs are selected for geographic plausibility and the mutual importance for them in trade between the US and China before the trade war. I deflate the value of shipments to 2017 dollars using the end-use import price index for all commodities from the Bureau of Labor Statistics.

Our theory identifies the log difference of the gross tariff factors, $\Delta_{k,t}$, as the key explanatory variable capturing the incentive to avoid. To construct this wedge, we need data on its two components: the direct tariff wedge, τ^d, and the avoidance wedge, $\tau^a = z\tau^c\tau^d$, which Corollary 1 shows is a function of domestic tax policy:

I rely on Amiti, Redding, and Weinstein (2020) for a panel of monthly HS10-by-product China-specific tariff rates to construct the direct wedge, $1 + \tau^d_{k,t}$. I aggregate these to the annual, HS6-product level by computing a weighted average, using 2017 import shares as weights. As the model shows, however, the direct tariff is only one piece of the puzzle; the avoidance wedge, τ^a, requires inputs from domestic tax policy and varies by the good's end use.

I use the UN's classification by broad economic categories to determine whether each import is a consumption, intermediate, or capital good. For consumption goods, which are not deductible business expenses, the avoidance wedge is zero ($\tau^a_{k,t} = 0$). For intermediate goods, which can be fully expensed, Corollary 1 implies the avoidance wedge is $\tau^a_{k,t} = \tau^c_t \times \tau^d_{k,t}$, where τ^c_t is the corporate income tax rate in year t.

The case for imported capital goods is different because they are expensed over time. The Internal Revenue Service places most capital goods into one of several tax lives according to the Modified Accelerated Cost Recovery System (MACRS). Let $z_{k,t}$ denote the net present value of statutory depreciation deductions for an imported capital good k in year t.[7] For these goods, the avoidance wedge is $\tau^a_{k,t} = z_{k,t}\tau^c_t\tau^d_{k,t}$. I map each capital good into its corresponding IRS tax life and calculate $z_{k,t}$ accordingly. Figure B.1 plots the interquartile range of the resulting tariff wedge, $\Delta_{k,t}$, for each end-use category.

7. Suppose a firm discounts the future at rate r, an asset has a tax life of T years, and a share d_s of it can be deducted in year $s = 0, \ldots, T$. The present value of one dollar of deductions is $z = \sum_{s=0}^{T} \left(\frac{1}{1+r}\right)^s d_s$. With bonus depreciation, firms can deduct an extra fraction γ upon purchase, so the NPV of deductions becomes $z_{\text{bonus}} = \gamma + (1-\gamma)z$. With 100% bonus depreciation, as was the case after the TCJA, $\gamma = 1$.

4.2 Methodology

Measuring transshipment is a non-trivial task, as international trade avoidance is inherently difficult to detect. Rather than relying on audit data, I infer the degree of transshipment by extending a methodology from Freund (2024). The core idea is to identify a specific "trade footprint" of tariff avoidance by setting rigorous screens on bilateral trade data. To be flagged as transshipment, a trade flow must simultaneously satisfy four conditions that, together, paint a compelling picture of rerouting. Intuitively, we are looking for products where (1) the U.S. tariff on China increased; (2) China's market share in the U.S. subsequently fell while a specific hub country's share rose; (3) China's global competitiveness in that product remained stable; and (4) the new trade flows are quantitatively large enough for the China-to-hub shipments to plausibly supply the hub-to-U.S. shipments.

My approach makes three key improvements to the baseline methodology in Freund (2024). I (i) measure deviations relative to pre-period trends rather than in levels, (ii) impose a within-product cap to prevent double-counting across hubs, and (iii) calibrate quantitative thresholds on placebo products to control the false positive rate.

Preliminaries. To start, I characterize potential two-leg diversions for each HS6 product k and hub i in year t as:

- First leg (China $\to$ hub): $m_{k,i,t} \equiv v_{\mathrm{CHN}\to i,k,t}$
- Second leg (hub $\to$ United States): $x_{k,i,t} \equiv v_{i\to\mathrm{USA},k,t}$.

To disentangle unusual growth from underlying trends, I estimate product- and partner-specific trends in the pre-tariff period (2012-2017) and use them to form counterfactuals. This involves estimating trends for China's and each hub's share of U.S. imports, their respective shares of exports to the rest of the world, and the levels of the two trade legs, $m_{k,i,t}$ and $x_{k,i,t}$. This allows us to compute "surprises" relative to trend for each product and hub:

$$\Delta m_{k,i,t} \equiv \max\{m_{k,i,t} - \widehat{m}_{k,i,t}, 0\} \quad \text{and} \quad \Delta x_{k,i,t} \equiv \max\{x_{k,i,t} - \widehat{x}_{k,i,t}, 0\}.$$

Screening Criteria. With these preliminaries, I impose four screens to detect transshipment.

1. **Tariff Exposure.** The product must have been exposed to U.S. tariff increases on China in 2018 or 2019.

2. **U.S. Reallocation.** China's share of U.S. imports for the product must fall below its pre-trend while the hub's share rises above its pre-trend.

3. **Rest-of-World Specificity.** China's export share to the rest of the world must not fall relative to the hub's, ensuring the pattern is specific to the U.S. market.

4. **Quantitative Consistency.** Using non-treated products as a calibration target, I set a final *low* (conservative) and a *high* (liberal) condition to ensure the China-to-hub flow is large enough to supply the hub-to-U.S. flow.

   (a) **Low (growth-based):** The above-trend increase in China's exports to the hub must be sufficiently proportional to the above-trend increase in the hub's exports to the U.S.: $\Delta m_{k,i,t} \geq c_L \Delta x_{k,i,t}$. The flagged quantity is the bottleneck, $\min(\Delta m_{k,i,t}, \Delta x_{k,i,t})$.

   (b) **High (levels-based):** Both legs must be proportional in levels, analogous to the rule in Freund (2024): $m_{k,i,t} \geq c_H x_{k,i,t}$.

The thresholds c_L and c_H are calibrated such that the implied transshipment share for a placebo group of never-treated products does not exceed 1% in any pre-tariff year. The levels-based rule (4b) is more liberal because it can flag pre-existing trade routes, while the growth-based rule (4a) only captures newly formed or sharply expanding routes. I use these two rules to compute bounds on transshipment, denoted θ_s, for $s \in \{\text{Low}, \text{High}\}$. The final measure is constructed by aggregating the flagged flow mass across all hubs for each product-year, normalizing by the product's 2017 direct China-US import value, and capping the total at that 2017 baseline to prevent over-counting. Summary statistics are in Table B.1.

Scope and Interpretation. It is important to emphasize the scope of this measurement exercise. The screening methodology identifies *transshipment*—the physical rerouting of goods through third countries—as one channel within a broader portfolio of tariff avoidance strategies. Firms facing tariffs can respond through multiple margins: misreporting value to qualify for de minimis treatment (Fajgelbaum and Khandelwal 2024), breaking shipments into smaller parcels, misclassifying products into lower-tariff categories (Fisman and Wei 2004), quality downgrading, or permanently relocating production. Each strategy involves different fixed and variable costs, and firms may substitute across them in response to enforcement intensity or relative prices.

My estimates therefore represent a *conservative lower bound* on total avoidance for two reasons. First, transshipment is only one channel, and I do not observe other forms of evasion. If firms substitute toward undervaluation or misclassification when transshipment becomes more costly or risky, the measured elasticity of transshipment with respect to the tariff wedge understates the true elasticity of total avoidance. Second, within the transshipment channel itself, the screens are deliberately conservative to minimize false positives. The growth-based quantitative rule (Screen 4a) flags only newly formed or sharply expanding routes, missing pre-existing transshipment infrastructure that scales up gradually, which is why I end up with much lower estimates of transshipment than Do et al. (2025).

5 Measured Transshipment

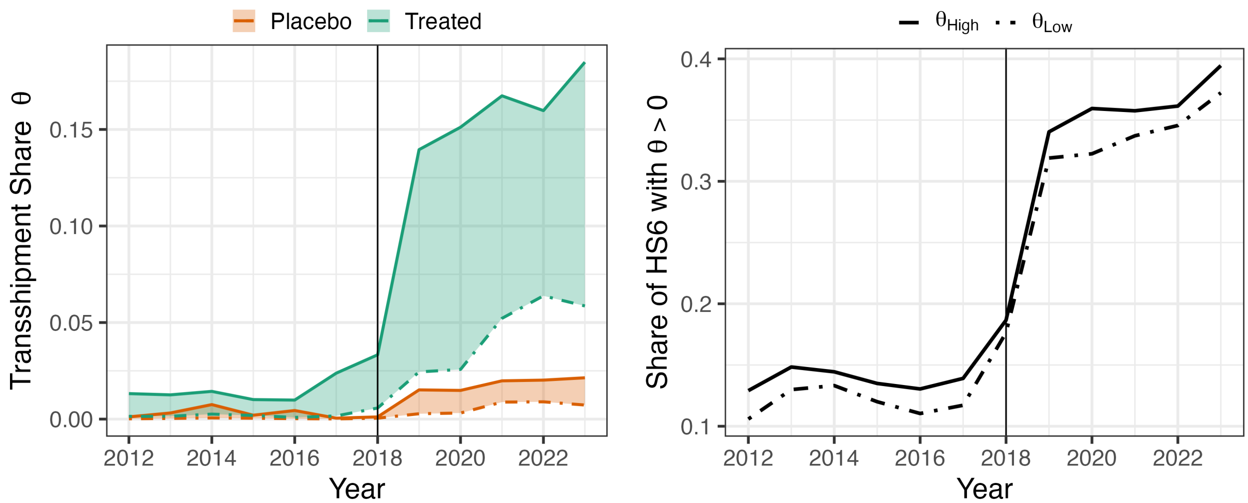
The theoretical framework established the two key parameters needed to evaluate the welfare cost of tariffs: the level of avoidance θ and the avoidance elasticity. This section provides empirical estimates for both. I first quantify the magnitude of transshipment to correct the passthrough bias, then estimate its elasticity with respect to the tariff wedge.

5.1 The Magnitude of Transshipment and Passthrough Incidence

Figure 3 plots the aggregate quantity of transshipment. Prior to the 2018 tariffs, our measure shows that the identified share of transshipment is low. Both the conservative (low) and liberal (high) bands identify that around 1-2 percent of the volume of shipments came to the US from China via transshipment, and only around 10-15 percent of HS6 codes identified any transshipment. Following the onset of tariffs, both numbers spiked. Under the levels-based liberal screen, transshipment became as high as 15 percent of the total volume of 2017 trade with China, while the conservative screen only identifies about a third as much. However, both screens identify that nearly 40 percent of HS6 codes have some positive transshipment.

As a falsification exercise, we apply our transshipment screens to HS6 products that were never subject to Section 301 tariff increases. We define the placebo set as the complement of the tariffed list—all HS6 where China's tariff did *not* rise between December 2017 and December 2018. For this untreated set, we compute transshipment bands using the same procedures as for the treated set. The numerator is the sum of flagged flows, and the denominator is China's direct exports to the U.S. in 2017 on the untreated HS6 set, deflated to 2017 dollars. Figure 3a shows that the placebo transshipment shares remain close to zero throughout 2018–2023, with narrow bands under both the conservative and liberal definitions. This contrasts with the treated HS6 set, which displays steadily rising transshipment bands following the tariff shocks. The placebo test confirms that our screening procedure does not spuriously generate transshipment where no tariff-induced transshipment margin exists. I conduct a series of additional robustness tests for the measure itself, which I discuss later in the section.

Figure 3: Aggregate Transshipment on the Intensive and Extensive Margins



(a) Intensive Margin

(b) Extensive Margin

Notes: Panel (a) shows the intensive margin of transshipment for both treated and untreated HS6 codes following the construction as described in the text. Panel (b) plots the share of HS6 codes which exhibit positive transshipment (extensive margin) according to the screening conditions. The low and high bands come from the low (growth-based) and high (level-based) screening conditions.

Appendix Figure B.2 plots the compositional variant of Figure 3. The upper panels show the share of HS6 codes with positive diversion ($\mathbb{1}\{\theta > 0\}$), while the lower panels show the aggregate diversion share (θ) within each category, both relative to 2017 China–U.S. imports. The vertical line marks 2018, the onset of the Section 301 tariffs. Transshipment activity remains near zero before 2018 across all categories, then rises sharply following the tariff increases, with particularly large and persistent gains for all goods. However, the volume of transshipment rose most for both capital and intermediate goods, with a far lower magnitude of diversion for consumption goods. Both the measures point to a clear structural break after the tariff shocks, consistent with large-scale rerouting of Chinese exports through third-country hubs rather than new entry or global trade growth.[8]

8. By construction, our measure of transshipment is systematically smaller than that in Do et al. (2025)

Following Proposition 3, the identified share of tariff-induced transshipment has immediate implications for the measured passthrough of tariffs. Under the assumption that measured passthrough is the border estimand, our estimate of the transshipment share θ delivers a portable correction for the cohort object. Using the results from Section 3.4, the cohort object satisfies

$$\beta_{\text{cohort}} \in \left[(1-\theta_{\text{high}})\beta_{\text{border}},\ \beta_{\text{border}}\right].$$

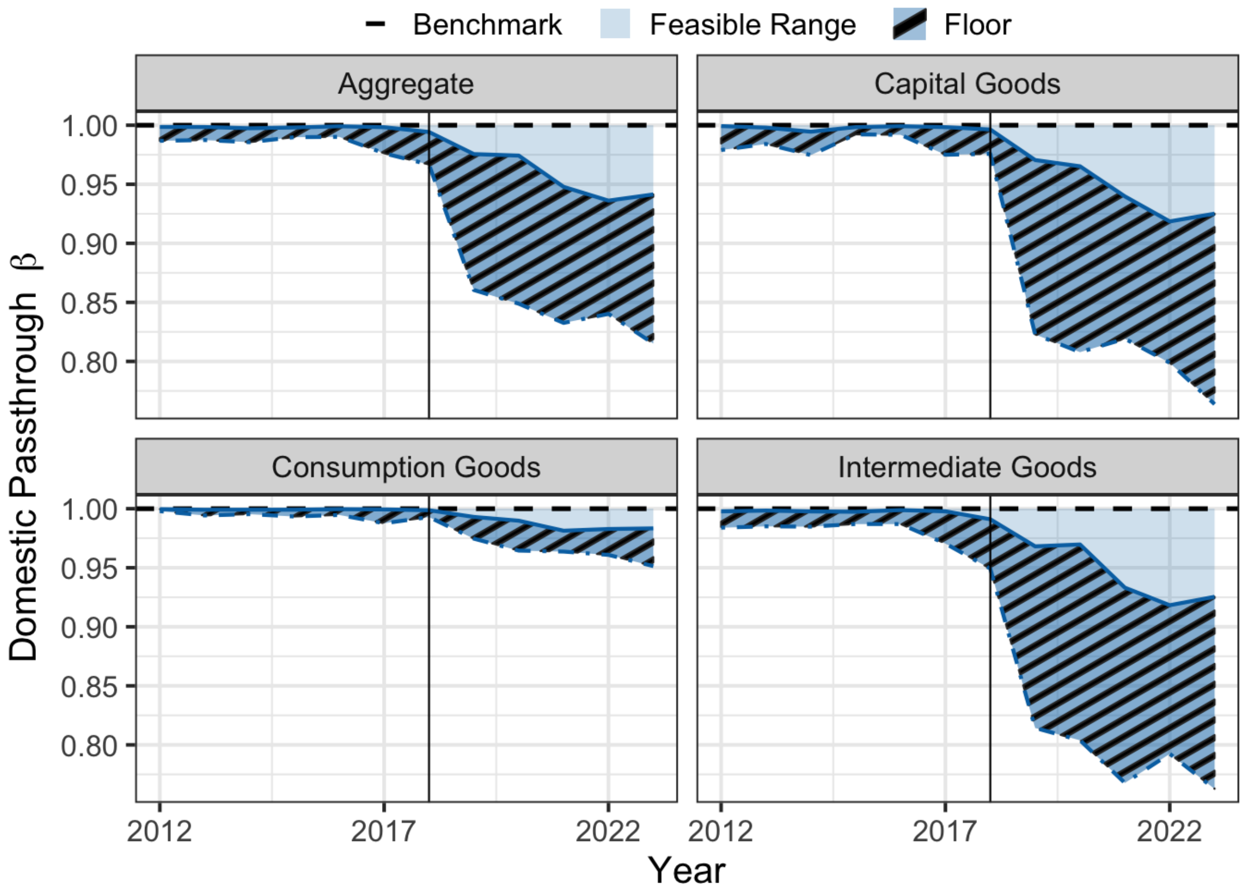
A large number of studies estimate that $\beta_{\text{border}} = 1$. I plot the aggregate estimate of that band in Figure 4. The implied aggregate passthrough remains high in 2018—reflecting the fact that tariffs were only effective part of the year—but it is stably around 85 percent from 2019 onward. Note, however, that this correction only applies to one type of tariff avoidance, so the actual degree of incidence could be lower.

Our bounds also imply a significant degree of passthrough heterogeneity. Amiti, Redding, and Weinstein (2020) reports passthrough coefficients on imported intermediates, capital, and consumption goods around unity. I therefore use that as my benchmark once more. Figure 4 plots corrected passthrough for consumption, capital, and intermediate goods. Corrected passthrough is essentially unity for consumption goods, while it is plausibly around 80% for imported capital and intermediates. This distinction clarifies the relationship between our estimates and the unbiased prior estimates from Flaaen, Hortaçsu, and Tintelnot (2020) and Cavallo et al. (2021). Both papers track consumption goods directly from Chinese exporters to the US, so they have no bias due to transshipment. However, the fact that there is very little transshipment of consumption goods also explains why their estimates of incidence on domestic consumers is so high.

While these heterogeneities reveal where transshipment matters most, the model also predicts how it should reshape observable outcomes. If selection operates as in Proposition 1, products experiencing greater diversion should exhibit weaker direct trade along both the quantity and price margins. Table 1 reports these relationships using deviations from pre-2018 trends in direct China–U.S. imports and export prices as outcomes, with HS6 and year fixed effects and standard errors clustered by HS4. The regressions exploit within-product, over-time variation, comparing for a given HS6 code the years with high diversion to years with little or none, controlling for common shocks.

because we count only policy-induced diversion consistent with tariff avoidance. In contrast, they tally all physical transshipment observed in shipment data (including ordinary logistics, processing, consolidation, and non-policy re-routing), so their benchmark necessarily encompasses a much larger universe than the evasion-focused flows identified here. In that sense, our measurement is conservative.

Figure 4: Corrected Passthrough Coefficient by End Use



Note: Shaded regions show corrected domestic passthrough relative to the border benchmark. The light blue area indicates the full feasible range implied by the model, $\beta_{\text{cohort}} \in [(1-\theta_{\text{high}})\beta_{\text{border}}, \beta_{\text{border}}]$. The hatched band marks the conservative floor using our two transshipment screens, $[(1-\theta_{\text{high}})\beta_{\text{border}}, (1-\theta_{\text{low}})\beta_{\text{border}}]$. The dashed line shows the border benchmark $\beta_{\text{border}} = 1$.

Diversion intensity is strongly negatively correlated with both trade quantities and prices. In columns (1)–(2), higher θ coincides with a steep decline in direct import volumes relative to trend, indicating that transshipment substitutes nearly one-for-one for direct China–U.S. trade. In columns (3)–(4), higher θ is also associated with lower observed China export prices within the same HS6 and year. This negative θ–price relationship does not imply that individual firms cut prices when tariffs rise. Rather, it reflects a change in the composition of surviving direct shipments: when avoidance intensifies, high-value and high-markup varieties are most likely to reroute through hubs, while lower-value, standardized goods continue to ship directly. The average unit value of direct exports therefore falls, even if surviving firms raise their own prices.[9]

9. The negative correlation may also reflect within-firm quality downgrading, where surviving exporters

Together, these results show that greater diversion compresses direct trade flows along both margins: quantities fall and the composition of surviving exports shifts toward lower-value goods. This is the empirical signature of the selection mechanism in the model: as tariffs increase the incentive to avoid, low-pass-through exporters exit the direct channel, reducing the scale and raising the apparent border pass-through of surviving trade flows. Having established that diversion affects both the scale and composition of direct trade, the next section quantifies how tariffs themselves drive θ and the resulting magnitude of this adjustment.

Table 1: Regression of Deviations in Direct China–US Imports on Diversion Intensity

	$\Delta^{\text{trend}}(\text{CN} \to \text{US})_{k,t}$			
	Quantities		Prices	
	(1)	(2)	(3)	(4)
$\sinh^{-1}(\theta_{\text{low}})$	-0.665***		-0.812**	
	(0.234)		(0.328)	
$\sinh^{-1}(\theta_{\text{high}})$		-0.516***		-0.486***
		(0.103)		(0.129)
R^2	0.49	0.50	0.36	0.37
Observations	49,209	49,171	48,922	48,887
Two-way FE	✓	✓	✓	✓

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table reports two–way fixed–effects regressions of $\Delta^{\text{trend}}_{\text{CN}\to\text{US}}$, the deviation of HS6-level direct China$\to$US import values from their pre-2012–2017 linear trend (in log units), on the inverse hyperbolic sine of the diversion measure θ. The dependent variable is constructed by fitting HS6-specific pre-trends in the value of shipments $\log(1 + v_{k,t})$ using BACI bilateral trade data and taking the residuals from these fitted trends for 2012–2023. All specifications include HS6 (i) and year (t) fixed effects, with standard errors clustered at the HS4 level. Columns (1)–(2) correspond to alternative specifications around the two diversion bounds. I use the same procedure to analyze FOB prices from Chinese exporters (Columns (3)–(4)).

cut quality or simplify products to offset higher costs. A third possibility is that transshippers preferentially reroute higher-value varieties to reduce detection risk. Distinguishing among these channels would require firm-level panel data linking products to producers, which is unavailable in the bilateral trade flows used here. All interpretations are consistent with the central claim that avoidance reshapes observed trade flows in ways that bias standard pass-through estimates upward.

5.2 The Tariff Elasticity of Transshipment

Having quantified the level of avoidance needed to correct the numerator of the MCPF, I now turn to the denominator. To analyze the fiscal externality and evaluate counterfactuals related to punishing avoidance, we must estimate the elasticity of avoidance with respect to the tariff wedge.

Transshipment is large, and Figure 3 indicates that it seemed to grow considerably after the 2018 tariffs were imposed by the US on China. I study the intensive and extensive margins of transshipment by leveraging within-HS6 code variation in exposure to the tariff wedge $\Delta_{k,t}$

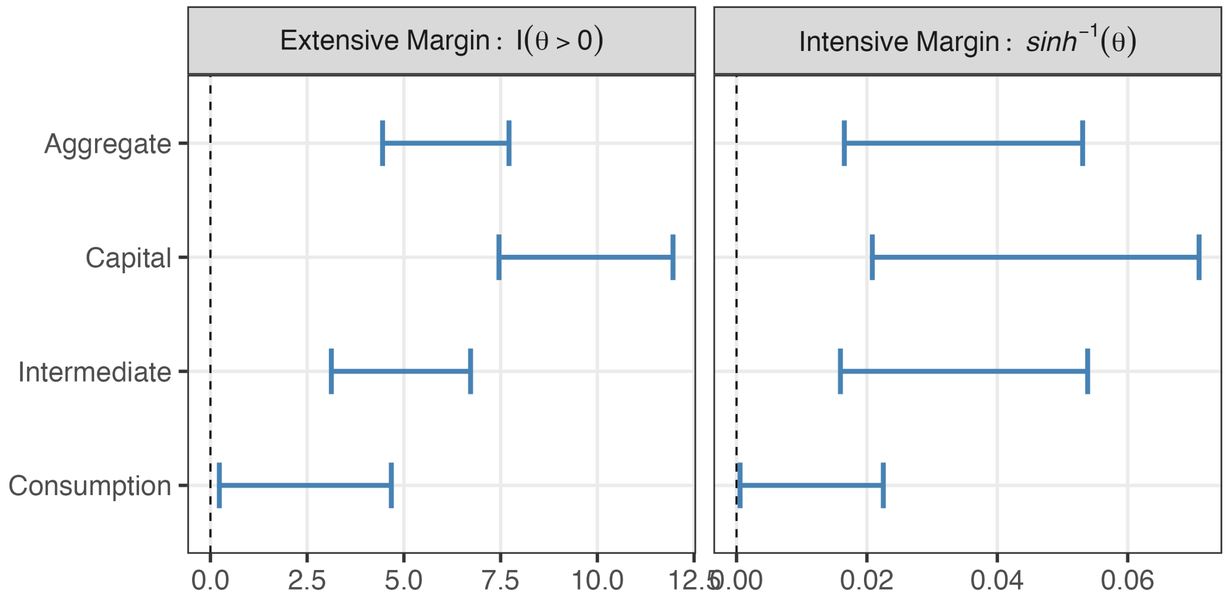
$$f(\theta_{s,k,t}) = \alpha_k + \delta_t + \psi_s \Delta_{k,t} + \varepsilon_{s,k,t}, \tag{5}$$

where $s \in \{\text{Low, High}\}$. $f(\theta_{s,k,t})$ corresponds to either an extensive margin, which I simply estimate with a linear probability model in which the dependent variable is $\mathbf{1}\{\theta_{s,k,t} > 0\}$, or an intensive margin in which the dependent variable is $\sinh^{-1}(\theta_{s,k,t})$.

Identification comes from within–HS6 code changes in the policy wedge $\Delta_{k,t}$ induced by the 2018–2019 tariffs. The cross-sectional variation arises because effective U.S. tariffs differ across HS6 k (constructed from monthly HS10 rates aggregated with fixed 2017 China weights), while the time variation is a discrete pre/post shift. The product fixed effect α_k absorbs all time-invariant product attributes and δ_t absorbs common shocks like the Covid-19 pandemic. Under the assumption that, conditional on α_k and δ_t, no unobserved HS6-by-year shock both moves the two-leg diversion measure $f(\theta_{s,k,t})$ and the tariff wedge except the tariff itself (a parallel-trends condition in θ), the coefficient ψ captures the causal effect of incentives on transshipment along both margins.

I report a joint estimate of ψ_s by constructing Imbens and Manski (2004) bounds for aggregate transshipment and broken down by end-use. I construct the smallest joint 95% confidence set that is guaranteed to contain the true effect under either specification, while allowing for correlation between them. Intuitively, the left whisker of the band reflects the conservative estimate pushed down by its uncertainty, the right whisker the liberal estimate pushed up by its uncertainty, and the resulting interval is the identified set with sampling error—that is, the range of effects consistent with both bounding assumptions at the 95% confidence level. The estimated effects are then scaled to represent the impact of a 10 p.p. increase in the tariff wedge. For the extensive margin, the band shows percentage-point changes in the probability that $\theta > 0$; for the intensive margin, it shows changes in $\sinh^{-1}(\theta)$.

Figure 5: The Tariff Elasticity of Transshipment



Note: This figure reports Imbens and Manski (2004) bounds for (5). The bounds takes the form:

$$\left[\hat{\beta}_{\text{Low}} - c^{\star}\,\text{se}(\hat{\beta}_{\text{Low}}),\ \hat{\beta}_{\text{High}} + c^{\star}\,\text{se}(\hat{\beta}_{\text{High}})\right],$$

where $c^{\star}$ is an adjusted critical value that depends on the estimated correlation $\rho \in (-1, 1)$ between the two slopes. The constant $c^{\star}$ is obtained by integrating the bivariate normal distribution to achieve joint coverage of $1 - \alpha$.

Across both margins, Figure 5 shows that the bands lie strictly to the right of zero, indicating that tariff exposure robustly raises diversion. The extensive margin implies that a 10 pp tariff increase activates diversion for roughly 20–30 percent of HS6 codes, while the intensive margin suggests that conditional diversion rises by 5–15 percent in $\sinh^{-1}(\theta)$. The effects are largest for capital and intermediate goods, consistent with greater rerouting flexibility in production networks, and smallest for consumption goods. Together, these estimates indicate economically meaningful and statistically robust transshipment responses concentrated in capital and intermediate categories. Results for θ_{low} and θ_{high} are reported separately in Table S1.

5.3 Robustness and Identification

The identifying assumption, namely that transshipment moves solely due to exogenous variation in tariff policy, is plausible for several reasons.

Identification by Construction. By construction, θ removes the main sources of confounding that could otherwise masquerade as diversion. Each HS6–hub pair must (i) show U.S.-specific reallocation (China's U.S. import share falls while the hub's rises relative to pre-2018 trends) and (ii) pass a rest-of-world specificity screen ensuring that China's global share remains stable. These filters rule out global shocks and isolate U.S.-specific rerouting. The quantitative consistency rules then tie China$\rightarrow$hub and hub$\rightarrow$U.S. flows together through growth-based and levels-based thresholds calibrated on pre-period placebo HS6s, such that implied diversion shares never exceed one percent in any pre-year. The within-HS6 cap further prevents over-attribution by limiting flagged diversion mass to the 2017 China–U.S. base flow.

Validation Tests. The Supplemental Appendix documents a broad set of checks that support a causal interpretation of the regression results.

First, I test for the presence of pre-trends. Visually, Figure 3 indicates that they are not. Regression analysis confirms this by showing that the coefficient on an interaction between the tariff wedge and an indicator for pre-2018 years is zero (Table S3). Furthermore, block-permutatation tests verify that treated HS6 codes do not differ systematically from the placebo set before 2018, indicating that the construction of θ does not mechanically generate pre-shock differences.

Third, I test whether the estimated elasticities reflect genuine transshipment rather than mechanical covariance using a permutation placebo that preserves marginal flows but breaks network linkages. For each year, I aggregate the China$\rightarrow$hub and hub$\rightarrow$US legs at the HS6–hub level and randomly reassign the hub–US leg across HS6 codes within the same HS4 block. This preserves each HS6's total exports from China, each hub's total US-bound shipments, the exposure wedge, and year and HS6 fixed effects, while eliminating the directional China$\rightarrow$hub$\rightarrow$US match required for transshipment. I repeat this 5,000 times, reconstruct θ for each draw, and re-estimate the intensive margin $\sinh^{-1}(\theta)$ and extensive margin $\mathbf{1}\{\theta > 0\}$ regressions on the wedge. The null distribution of $\beta(\text{wedge})$ in Figure S1 centers slightly above zero but far below the observed coefficients, reflecting residual scale-driven covariance. The true network's coefficients lie deep in the right tail, confirming that only the intact China$\rightarrow$hub$\rightarrow$US linkage generates the large elasticities observed, while background covariance is economically negligible.

Finally, the results are robust to several other sensitivity checks. Table S2 shows that the estimated elasticities remain stable when re-estimating the regressions while excluding one hub at a time, demonstrating that the pattern is not driven by any single country. Re-estimating the same screens and regressions with the European Union or Canada as the destination yields coefficients that are small and statistically indistinguishable from zero, indicating that the observed pattern is specific to the U.S. market (see Table S4). Additionally, The results remain significant when using the partial tariff wedge $1 + \tau^{D}_{k,t}$ rather than the full wedge $\Delta_{k,s,t}$ (Table S2).

Any remaining threats are conceptually limited. Common product-level shocks are absorbed by α_k, and global or macroeconomic shocks by δ_t. Any residual HS6-by-year disturbance would have to be (i) U.S.-specific, (ii) shift China's and the hub's relative U.S. shares in line with our pre-trend screens, (iii) produce quantitatively consistent two-leg growth, (iv) leave no trace in EU or Canada outcomes, and (v) survive the network-shuffling placebo. This joint pattern is highly implausible. Thus, it is reasonable to conclude that (a) the magnitude of transshipment is large and (b) the tariff elasticity of transshipment is large on both the intensive and extensive margins.

6 Re-evaluating the Welfare and Revenue Effects of Tariffs

Given the parameters estimated in the previous section, we are now ready to compute the marginal cost of public funds for tariffs. Since our focus is on avoidance, this section isolates that channel to clearly elucidate the welfare and revenue trade-offs inherent in the policy response.

6.1 Correcting the Measured MCPF of Tariffs

Our empirical findings allow us to directly correct existing estimates of the tariff's welfare cost. The literature, which does not account for the selection bias in incidence, places the Marginal Cost of Public Funds (MCPF) for the 2018 tariffs in the range of 1.2–1.6 (Finkelstein and Hendren 2020; Jaccard 2021). As shown in Section 3.4, the true domestic incidence can be approximated by scaling the biased border estimate by $(1 - \theta)$. Applying our aggregate estimate for the level of avoidance ($\theta_{\text{high}} \approx 0.15$), the corrected scaling factor is approximately 0.85. This implies a new, lower range for the MCPF of roughly 1.0–1.6. This is a notable result: after correcting for selection bias in the numerator, we cannot reject that the welfare cost of the 2018 tariffs is on par with a distortion-free lump-sum tax.

This aggregate correction, however, is incomplete because the fiscal externality (η) in these prior studies includes other behavioral responses, like substitution. To isolate the welfare cost of the specific mechanism studied in this paper, we can construct an "avoidance-based" MCPF using our estimated parameters for both the numerator and the denominator. We use our estimate of the avoidance level (θ) to correct the incidence term and our estimate of the avoidance elasticity (ε_θ) to construct the fiscal externality term, $\eta \approx -\frac{\theta}{1-\theta}\varepsilon_\theta$. Using these components, we compute bounds for the avoidance-based MCPF, propagating the uncertainty from our elasticity estimates.

Figure B.3 plots the resulting time series. Before the 2018 trade war, with little avoidance, the MCPF for all goods is approximately one. After 2018, the story diverges by end-use. For consumption goods, where avoidance is minimal, the MCPF remains near one. For capital and intermediate goods, however, the high elasticity of avoidance leads to a significant fiscal externality, pushing the upper bound of the avoidance-based MCPF to around 1.5. This demonstrates that the welfare cost of tariffs is driven almost entirely by the behavioral response in production-related goods.

The concentration of the welfare cost in capital and intermediate goods is consistent with the findings in Alessandria et al. (2025). In their dynamic general equilibrium model, they show that tariffs are especially distortionary for investment, as capital goods have a high import share. Our paper provides a complementary mechanism: these are precisely the goods where the fiscal externality from avoidance is largest. Both papers thus underscore the critical interaction between trade and fiscal policy. While Alessandria et al. (2025) focus on how tariff revenue is spent to offset other distortions, our mechanism highlights how the domestic tax system itself—through deductibility—is isomorphic to an enforcement penalty that alters the incentive to pay the tariff in the first place. This interaction was altered by the 2017 Tax Cuts and Jobs Act (TCJA), which cut the corporate tax rate just before the 2018 tariffs were imposed. A natural question, which we explore next, is how much lower avoidance would have been had this tax cut not occurred.

6.2 Policy Counterfactual: The Role of the TCJA

The theoretical link between domestic tax policy and tariff avoidance was altered by the 2017 Tax Cuts and Jobs Act (TCJA), which cut the corporate tax rate from 35% to 21% just before the 2018 tariffs were imposed while simultaneously making all imported capital and intermediates fully tax deductible. A natural counterfactual, therefore, is to ask how much lower avoidance would have been had the income tax cut not occurred, but capital became fully deductible. Our estimated avoidance elasticities allow us to directly quantify this effect. Since the tax shield from deductibility only applies to business inputs, we focus on capital and intermediate goods, which our results show have the largest avoidance responses.

Table 2 reports the results of this counterfactual exercise, showing the average change in transshipment (θ) over the 2018–2023 period. Had the corporate tax rate remained at 35%, the share of transshipped goods would have been between 0.3 and 2.3 percentage points lower for capital goods and between 0.6 and 2.8 percentage points lower for intermediates. This reduction in avoidance would have directly translated into higher government revenue, increasing total tariff collections by 0.7% to 4.2%, or an estimated $2 billion to $10 billion. Consequently, the measured welfare cost of the tariff would also fall, with the estimated range for the MCPF declining by about 5%. This demonstrates a meaningful and quantitatively significant interaction between the corporate tax base and tariff revenue, highlighting how domestic tax policy can serve as a powerful, if unintentional, trade enforcement tool.

Table 2: Counterfactual Changes in Diversion, Revenue, and Welfare under a 35% Corporate Tax Rate

Category	$\Delta\theta$ (level)	ΔR (%)	ΔMCPF (%)
Capital	-0.003—0.023	[0.5, 3.6]	[-5.2, -5.2]
Intermediate	-0.006—0.028	[1.0, 5.0]	[-4.6, -3.9]
Capital + Intermediate	-0.004—0.025	[0.7, 4.2]	[-5.1, -5.0]

Thus, there is meaningful interaction between the two tax bases, with a higher corporate rate pushing up tariff revenue on the margin.

7 Conclusion

This paper shows that tariff avoidance has first-order implications for both the measurement of tariff incidence and the design of trade-related policy. The core of the argument is a selection mechanism: when costly avoidance is possible, low-cost, low-passthrough firms are the most likely to exit the direct-shipping channel, biasing standard "border design" estimates of passthrough upward. We provide a portable correction for this bias and show that accounting for transshipment, which is a key avoidance channel, materially lowers the measured incidence of the 2018 U.S. tariffs.

This behavioral response also constitutes a significant fiscal externality, which erodes the tariff base and raises the tariff's welfare cost. Our theoretical and empirical analysis reveals a novel, built-in enforcement tool within the domestic tax system that can mitigate this externality. The tax deductibility of imported business inputs is isomorphic to an explicit penalty on avoidance. Our elasticity estimates allow us to quantify the impact of this channel, showing that the 2017 corporate tax cut resulted in billions of dollars in lost tariff revenue.

Several caveats merit emphasis. First, the analysis focuses on transshipment as the primary avoidance margin because it is observable in bilateral trade flows, but firms have access to a richer set of strategies including undervaluation, misclassification, and permanent relocation. To the extent that firms substitute across these margins, my elasticity estimates represent lower bounds on the responsiveness of total avoidance. This substitution also implies that policies targeting one channel (e.g., stricter rules-of-origin enforcement against transshipment) may simply induce reallocation to other channels, limiting their effectiveness. A complete welfare analysis would require measuring the full avoidance portfolio and the elasticity of substitution across margins, which is an important direction for future research.

While the analysis here is static and partial-equilibrium, the framework is sufficient to establish the core selection mechanism and its implications. Future work should examine how the persistence of tariffs shapes firms' dynamic investment in avoidance—such as the choice between short-run transshipment and long-run production relocation—and how large-scale rerouting affects wages and prices in a general equilibrium setting. These extensions would enrich the welfare analysis, but the central conclusion remains: accounting for selection into avoidance is critical for correctly evaluating the welfare and revenue effects of tariffs.

References

Alessandria, George, Jiaxiaomei Ding, Shafaat Khan, and Carter Mix. 2025. *The Tariff Tax Cut: Tariffs as Revenue.* Technical report. Cambridge, MA: National Bureau of Economic Research, May. https://doi.org/10.3386/w33784.

Allingham, Michael G., and Agnar Sandmo. 1972. "Income tax evasion: a theoretical analysis." *Journal of Public Economics* 1, nos. 3-4 (November): 323–338. ISSN: 00472727. https://doi.org/10.1016/0047-2727(72)90010-2.

Amiti, Mary, Oleg Itskhoki, and Jozef Konings. 2019. "International Shocks, Variable Markups, and Domestic Prices." *The Review of Economic Studies* 86, no. 6 (November): 2356–2402. ISSN: 0034-6527. https://doi.org/10.1093/restud/rdz005.

Amiti, Mary, Stephen J. Redding, and David E. Weinstein. 2019. "The Impact of the 2018 Tariffs on Prices and Welfare." *Journal of Economic Perspectives* 33, no. 4 (November): 187–210. ISSN: 0895-3309. https://doi.org/10.1257/jep.33.4.187.

———. 2020. "Who's Paying for the US Tariffs? A Longer-Term Perspective." *AEA Papers and Proceedings* 110. ISSN: 2574-0768. https://doi.org/10.1257/pandp.20201018.

Bhandari, Anmol, David Evans, Ellen R Mcgrattan, and Yuki Yao. 2024. *Business Income Underreporting and Public Finance*.* Technical report.

Boehm, Christoph E., Andrei A. Levchenko, and Nitya Pandalai-Nayar. 2023. "The Long and Short (Run) of Trade Elasticities." *American Economic Review* 113, no. 4 (April): 861–905. ISSN: 0002-8282. https://doi.org/10.1257/aer.20210225.

Cavallo, Alberto, Gita Gopinath, Brent Neiman, and Jenny Tang. 2021. "Tariff Pass-Through at the Border and at the Store: Evidence from US Trade Policy." *American Economic Review: Insights* 3, no. 1 (March): 19–34. ISSN: 2640-205X. https://doi.org/10.1257/aeri.20190536.

De Loecker, Jan, Jan Eeckhout, and Gabriel Unger. 2020. "The Rise of Market Power and the Macroeconomic Implications*." *The Quarterly Journal of Economics* 135, no. 2 (May): 561–644. ISSN: 0033-5533. https://doi.org/10.1093/qje/qjz041.

Deng, Jianpeng, Jialin Li, Joseph Mai, Yanmin Shi, and Linke Zhu. 2025. "Trade circumvention in free trade areas." *Journal of International Money and Finance* 150 (February): 103232. ISSN: 02615606. https://doi.org/10.1016/j.jimonfin.2024.103232.

Do, Anh D., Sharat Ganapati, Woan Foong Wong, and Oren Ziv. 2025. "Transshipment Hubs, Trade, and Supply Chains."

Edmond, Chris, Virgiliu Midrigan, and Daniel Yi Xu. 2023. "How Costly Are Markups?" *Journal of Political Economy* 131, no. 7 (July): 1619–1675. ISSN: 0022-3808. https://doi.org/10.1086/722986.

Fajgelbaum, Pablo, and Amit Khandelwal. 2024. *The Value of De Minimis Imports.* Technical report. Cambridge, MA: National Bureau of Economic Research, June. https://doi.org/10.3386/w32607.

Fajgelbaum, Pablo D, Pinelopi K Goldberg, Patrick J Kennedy, and Amit K Khandelwal. 2020. "The Return to Protectionism*." *The Quarterly Journal of Economics* 135, no. 1 (February): 1–55. ISSN: 0033-5533. https://doi.org/10.1093/qje/qjz036.

Finkelstein, Amy, and Nathaniel Hendren. 2020. "Welfare Analysis Meets Causal Inference." *Journal of Economic Perspectives* 34, no. 4 (November): 146–167. ISSN: 0895-3309. https://doi.org/10.1257/jep.34.4.146.

Fisman, Raymond, and Shang-Jin Wei. 2004. "Tax Rates and Tax Evasion: Evidence from "Missing Imports" in China." *Journal of Political Economy* 112, no. 2 (April): 471–496. ISSN: 0022-3808. https://doi.org/10.1086/381476.

Flaaen, Aaron, Ali Hortaçsu, and Felix Tintelnot. 2020. "The Production Relocation and Price Effects of US Trade Policy: The Case of Washing Machines." *American Economic Review* 110, no. 7 (July): 2103–2127. ISSN: 0002-8282. https://doi.org/10.1257/aer.20190611.

Freund, Caroline. 2024. *The China Wash: Tracking Products To Identify Tariff Evasion Through Transshipment.* Technical report.

Gertler, Sarah M. 2025. "Exchange Rate Pass-through and Expenditure-Switching Revisited."

Gopinath, Gita, and Oleg Itskhoki. 2010. "Frequency of Price Adjustment and Pass-Through." *Quarterly Journal of Economics* 125, no. 2 (May): 675–727. ISSN: 0033-5533. https://doi.org/10.1162/qjec.2010.125.2.675.

Hendren, Nathaniel. 2016. "The Policy Elasticity." *Tax Policy and the Economy* 30, no. 1 (January): 51–89. ISSN: 0892-8649. https://doi.org/10.1086/685593.

Imbens, Guido W., and Charles F. Manski. 2004. "Confidence Intervals for Partially Identified Parameters." *Econometrica* 72, no. 6 (November): 1845–1857. ISSN: 0012-9682. https://doi.org/10.1111/j.1468-0262.2004.00555.x.

Iyoha, Ebehi, Edmund Malesky, Jaya Wen, and Sung-Ju Wu. 2025. *Exports in Disguise? Trade Rerouting during the US-China Trade War.* Technical report.

Jaccard, Torsten. 2021. "Who Pays for Protectionism? The Welfare and Substitution Effects of Tariffs." *SSRN Electronic Journal,* ISSN: 1556-5068. https://doi.org/10.2139/ssrn.3967700.

Kimball, Miles S. 1995. "The Quantitative Analytics of the Basic Neomonetarist Model." *Journal of Money, Credit and Banking* 27, no. 4 (November): 1241. ISSN: 00222879. https://doi.org/10.2307/2078048.

Slemrod, Joel. 2019. "Tax Compliance and Enforcement." *Journal of Economic Literature* 57, no. 4 (December): 904–954. ISSN: 0022-0515. https://doi.org/10.1257/jel.20181437.

Slemrod, Joel, and Shlomo Yitzhaki. 2002. "Tax Avoidance, Evasion, and Administration," 1423–1470. https://doi.org/10.1016/S1573-4420(02)80026-X.

A Proofs

A.1 Proof of Lemma 1.

Proof. Interior and FOC. By **D2–D4**, $\Phi_i(\cdot)$ is strictly concave in p_i; the unique maximizer is interior and characterized by the FOC. Let the delivered price be

$$\tilde{p}_i \equiv \tilde{p}_i(p_i, \tau^r) = \begin{cases} (1+\tau^a)p_i & \text{(avoid channel)} \\ (1+\tau^d)\, p_i & \text{(direct channel).} \end{cases}$$

Then $\partial \tilde{p}_i / \partial p_i \in \{1+\tau^a,\ 1+\tau^d\}$, and the FOC is

$$0 = \frac{\partial \Phi_i}{\partial p_i} = D_i(\tilde{p}_i) + (p_i - m_i)\, D_i'(\tilde{p}_i)\, \frac{\partial \tilde{p}_i}{\partial p_i}.$$

With $\varepsilon_i(\tilde{p}_i) \equiv -\, \tilde{p}_i D_i'(\tilde{p}_i)/D_i(\tilde{p}_i)$,

$$\frac{p_i^* - m_i}{p_i^*} = \frac{\tilde{p}_i}{(\partial \tilde{p}_i/\partial p_i)\, p_i^*} \cdot \frac{-D_i(\tilde{p}_i)}{\tilde{p}_i D_i'(\tilde{p}_i)} = \frac{1}{\varepsilon_i(\tilde{p}_i)}.$$

This is the Lerner condition.

Monotonicity in m_i. Define

$$g(p, m; \tau^r) \equiv D(\tilde{p}) + (p - m)\, D'(\tilde{p})\, \frac{\partial \tilde{p}}{\partial p}, \qquad \tilde{p} = \tilde{p}(p, \tau^r).$$

At the optimum, $g(p^*, m; \tau^r) = 0$. Partials:

$$\frac{\partial g}{\partial m} = -\, D'(\tilde{p})\, \frac{\partial \tilde{p}}{\partial p} > 0 \quad (\mathbf{D1}), \qquad \frac{\partial g}{\partial p} = 2\, D'(\tilde{p})\, \frac{\partial \tilde{p}}{\partial p} + (p - m)\, D''(\tilde{p}) \Big(\frac{\partial \tilde{p}}{\partial p}\Big)^2.$$

Strict concavity of profits (**D4**) implies $\partial g/\partial p < 0$ at p^*. By the implicit function theorem, $\partial p^*/\partial m = -(\partial g/\partial m)/(\partial g/\partial p) > 0$.

Monotonicity in τ^r. For the direct channel, $\tilde{p} = (1+\tau^r)p$. Write

$$G(p, \tau^r) \ \equiv\ \frac{p - m}{p} - \frac{1}{\varepsilon((1+\tau^r)p)} \ =\ 0.$$

Then

$$\frac{\partial G}{\partial \tau^r} = \frac{\varepsilon'((1+\tau^r)p)}{\varepsilon((1+\tau^r)p)^2}\, p \ \geq 0, \qquad \frac{\partial G}{\partial p} = \frac{m}{p^2} + \frac{\varepsilon'((1+\tau^r)p)}{\varepsilon((1+\tau^r)p)^2}\, (1+\tau^r).$$

Under Kimball demand, $\varepsilon'(\cdot) \geq 0$, so $\partial G/\partial \tau^r \geq 0$. Profit concavity (D4, equivalently $\varepsilon - 1 - \kappa > 0$ at the optimum) implies $\partial G/\partial p > 0$. Hence, by the IFT,

$$\frac{\partial p^*}{\partial \tau^r} = -\frac{\partial G/\partial \tau^r}{\partial G/\partial p} \leq 0,$$

with equality under CES ($\varepsilon' \equiv 0$).

Quantities. In either channel $\tilde{p} = (1+\tau^r)p^*$ and

$$\frac{d\big((1+\tau^r)p^*\big)}{d\tau^r} = p^* + (1+\tau^r)\frac{dp^*}{d\tau^r} = p^*\left(1 + \frac{\kappa(\tilde{p})}{\varepsilon(\tilde{p}) - 1 - \kappa(\tilde{p})}\right) = p^* \frac{\varepsilon(\tilde{p}) - 1}{\varepsilon(\tilde{p}) - 1 - \kappa(\tilde{p})} > 0,$$

since $\varepsilon(\tilde{p}) > 1$ and the denominator is positive by D4. With $D'(\cdot) < 0$, $q_i^* = D(\tilde{p})$ strictly falls in τ^r; similarly, q_i^* strictly falls in m because p^* rises in m and demand slopes down. This proves (i)–(iii). □

A.2 Proof of Proposition 1

Proof. By **D2–D4**, the maximizer in $V(m, 1+\tau^r)$ is interior and unique; envelope arguments apply. The primitive $(p-m)D((1+\tau^r)p)$ has increasing differences in $(m, 1+\tau^r)$ because $\partial^2[(p-m)D((1+\tau^r)p)]/\partial m\, \partial(1+\tau^r) = -pD'((1+\tau^r)p) > 0$ by **D1**. Hence V inherits increasing differences in $(m, 1+\tau^r)$ by Topkis. Fix (τ^d, τ^a). Then

$$\frac{\partial \Delta}{\partial m} = V_m(m, 1+\tau^a) - V_m(m, 1+\tau^d) < 0$$

since $1+\tau^a < 1+\tau^d$ and V has increasing differences; continuity of V yields a unique threshold $\hat{m}$ solving $\Delta(\hat{m}; \tau^d, \tau^a) = 0$. For the comparative statics, differentiate the indifference condition:

$$\frac{d\hat{m}}{d\tau^d} = -\frac{\partial \Delta/\partial \tau^d}{\partial \Delta/\partial m}, \qquad \frac{d\hat{m}}{d\tau^a} = -\frac{\partial \Delta/\partial \tau^a}{\partial \Delta/\partial m}.$$

By the envelope theorem at the direct and avoidance optima p_d^* and p_a^*,

$$\frac{\partial V(m, 1+\tau^r)}{\partial(1+\tau^r)} = (p^* - m)\, p^*\, D'\big((1+\tau^r)p^*\big) \leq 0,$$

so $\partial V(m, 1+\tau^d)/\partial \tau^d \leq 0$ and $\partial V(m, 1+\tau^a)/\partial \tau^a \leq 0$. Hence

$$\frac{\partial \Delta}{\partial \tau^d} = -\frac{\partial V(m, 1+\tau^d)}{\partial \tau^d} \geq 0, \qquad \frac{\partial \Delta}{\partial \tau^a} = \frac{\partial V(m, 1+\tau^a)}{\partial \tau^a} \leq 0.$$

Since $\partial\Delta/\partial m < 0$ at an interior cutoff, the stated signs follow. $\square$

A.3 Proof of Proposition 2

Proof. Write the first-order condition for a firm in the direct channel as $G(p, \tau^d) \equiv (p - m)/p - 1/\varepsilon((1+\tau^d)p) = 0$. Totally differentiate and use

$$\frac{\partial G}{\partial \tau^d} = \frac{\varepsilon'((1+\tau^d)p)}{\varepsilon((1+\tau^d)p)^2}\, p, \qquad \frac{\partial G}{\partial p} = \frac{m}{p^2} + \frac{\varepsilon'((1+\tau^d)p)}{\varepsilon((1+\tau^d)p)^2}\,(1+\tau^d).$$

Using $\kappa(u) = -u\,\varepsilon'(u)/\varepsilon(u)$ and the Lerner condition $m = p^*(\varepsilon - 1)/\varepsilon$,

$$\frac{dp^*}{d\tau^d} = -\frac{\partial G/\partial \tau^d}{\partial G/\partial p} = \frac{\kappa(\tilde{p}^d)}{1+\tau^d} \cdot \frac{p^*}{\varepsilon(\tilde{p}^d) - 1 - \kappa(\tilde{p}^d)}.$$

Finally, the passthrough elasticity is

$$\beta_i = \frac{d\ln\big((1+\tau^d)p^*\big)}{d\tau^d} = \frac{1}{1+\tau^d} + \frac{1}{p^*}\frac{dp^*}{d\tau^d} = \frac{1}{1+\tau^d} \cdot \frac{\varepsilon(\tilde{p}^d) - 1}{\varepsilon(\tilde{p}^d) - 1 - \kappa(\tilde{p}^d)}.$$

Under Assumption **D4**, strict profit concavity at the optimum is equivalent to $\varepsilon - 1 - \kappa > 0$, which ensures the denominator is positive. $\square$

A.4 MCPF Derivation

Suppose a planner has access to a vector of linear tax instruments τ (with individual elements τ_i). Each tax instrument has a corresponding base $B_i(\boldsymbol{\tau})$. For simplicity, I assume no spillovers between them. The government chooses instruments to maximize a well-behaved welfare function $W(\boldsymbol{\tau})$ subject to a revenue constraint:

$$\max_{\boldsymbol{\tau}} W(\boldsymbol{\tau}) \quad \text{subject to} \quad G = R(\boldsymbol{\tau}) \equiv \sum_{i=1}^{N} \tau_i B_i(\tau) \tag{SPP}$$

Denote λ as the shadow value of public funds:

$$\lambda = -\frac{W'(\tau_i)}{R'(\tau_i)} \iff \frac{W'(\tau_i)}{R'(\tau_i)} = \frac{W'(\tau_j)}{R'(\tau_j)}.$$

With no spillovers,

$$R'(\tau_i) = B_i(\tau_i) + \tau_i \frac{\partial B_i}{\partial \tau_i} = B_i(\tau_i) \times \underbrace{\left(1 + \tau_i \frac{B_i'(\tau_i)}{B_i(\tau_i)}\right)}_{1+\eta_i}$$

By the envelope theorem, the marginal welfare cost of nudging each instrument is the domestic willingness to pay to avoid it, i.e., $-\partial W / \partial \tau_i = \beta_i B_i$, so

$$\text{MCPF}_{\tau_i} = \frac{\beta_i B_i(\tau_i)}{B_i(\tau_i)(1+\eta_i)} = \frac{\beta_i}{1+\eta_i}.$$

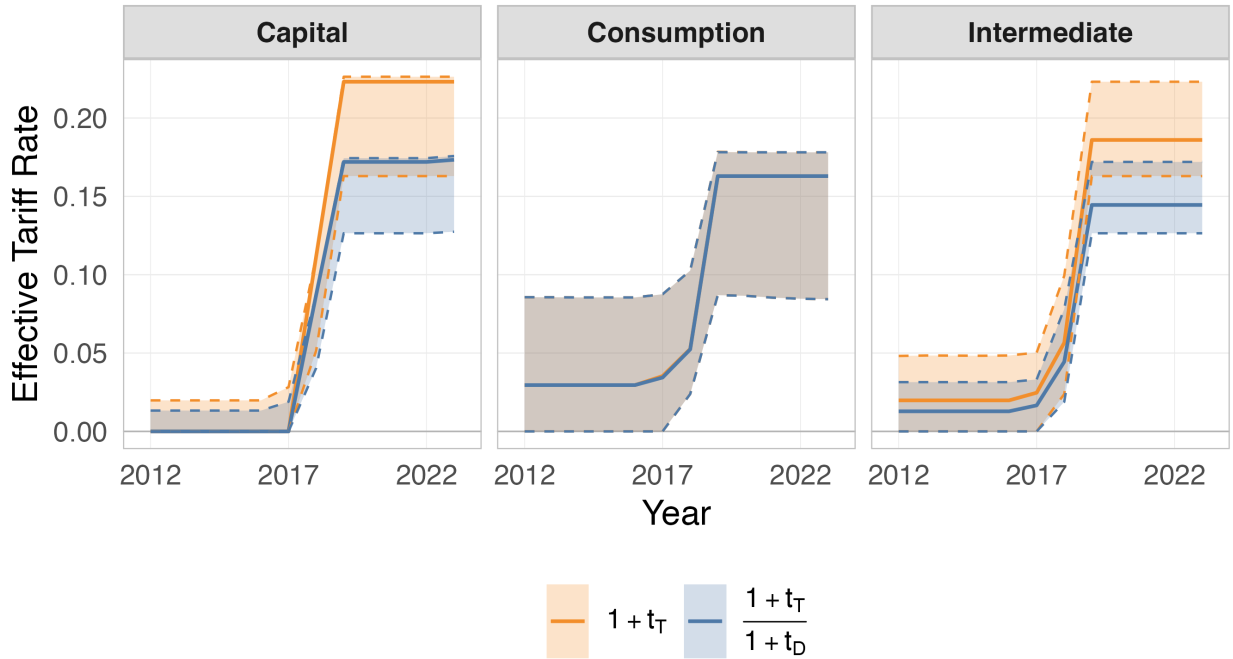
B Empirical Results

Table B.1: Summary Statistics

	Pre		Post			N		
Variable	Mean	SD	Mean	SD	Δ (Post–Pre)	$HS6_{\text{Pre}}$	$HS6_{\text{Post}}$	$HS6_{\cap}$
$\log \frac{1+t_D}{1+t_T}$	0.025	0.038	0.129	0.058	0.105	4328	4328	4272
θ_{low}	0.021	0.115	0.050	0.157	0.029	4325	4327	4272
θ_{high}	0.054	0.195	0.105	0.243	0.051	4320	4317	4265
Share($\theta_{\text{low}} > 0$)	0.119	0.324	0.314	0.464	0.194	4325	4327	4272
Share($\theta_{\text{high}} > 0$)	0.138	0.345	0.335	0.472	0.197	4320	4317	4265
Consumption share	0.207	0.405	0.206	0.404	-0.001	4328	4328	4272
Capital share	0.134	0.341	0.133	0.340	-0.001	4328	4328	4272
Intermediate share	0.592	0.491	0.593	0.491	0.001	4328	4328	4272

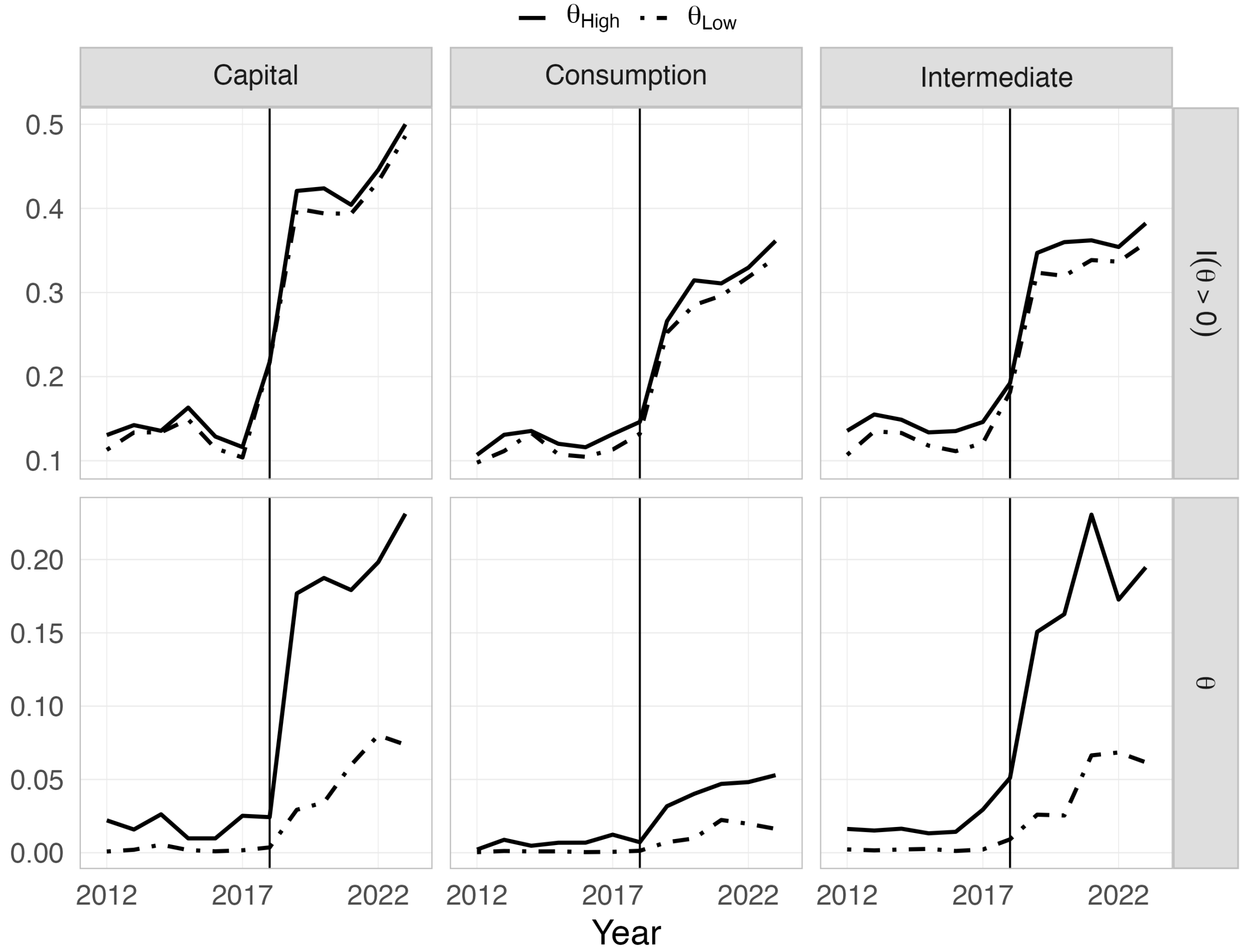
Notes: Variable construction is described in the main text. t_D is the tariff rate and $t_T = \tau z \times t_D$.

Figure B.1: Interquartile Range of the Tariff Wedge by End Use



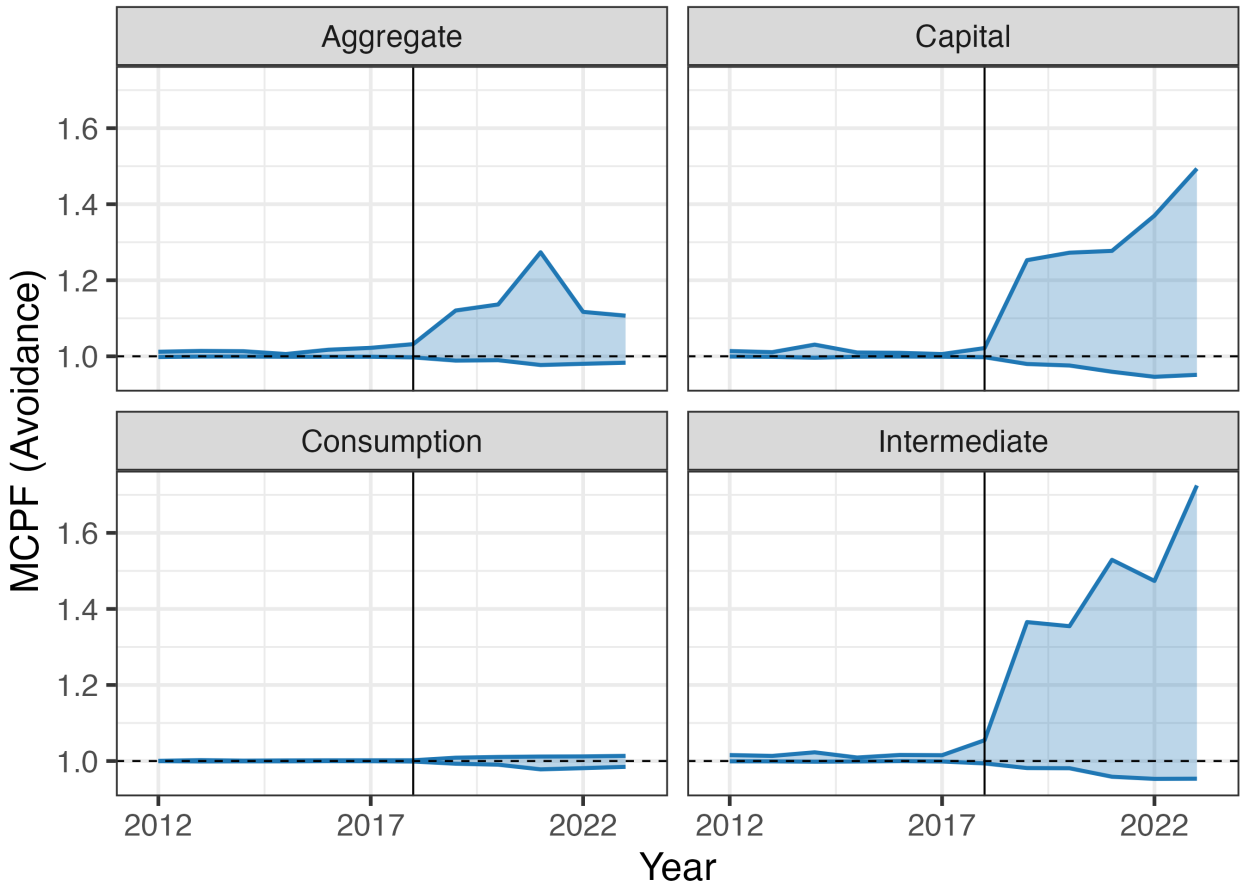
Note: Each panel displays the interquartile range of effective tariff rates for imported goods categorized by end use. The orange line plots the uncorrected effective tariff rate $1 + t_D$, while the blue line plots the tariff rate corrected for import deductibility: $(1 + t_D)/(1 + t_T)$. Since intermediates are fully tax-deductible, $t_T = \tau_t^c \times t_{D,t}$. Prior to the 2017 Tax Cuts and Jobs Act, $\tau_t^c = 0.35$; after TCJA $\tau_t^c = 0.21$. Capital goods are expensed over time. Denoting the present-value of such deductions as z_t, the effective tariff wedge for capital goods is $t_T = z\tau^c \times t_D$. After TCJA, $z = 1$. Prior to TCJA, z was slightly less than one for most imported capital goods. I obtain z by mapping the imported capital good HS6 codes into the corresponding IRS tax lives and calculating the present value of deductions with a discount rate of 0.06.

Figure B.2: Transshipment by End Use Category



Note: The top panels plot the share of HS6 codes within each end use category which have detected transshipment. The bottom panels display a weighted average transshipment share by end use. Each HS6 code is weighted by its share of 2017 imports from China.

Figure B.3: The Marginal Cost of Public Funds by End Use



Note: Each figure plots the marginal cost of public funds evaluated in each year given the corresponding regressions. Uncertainty is propagated via the Imbens-Manski bands.

Supplemental Appendix

Table S1: Transshipment Response to Tariffs

	Intensive Margin				Extensive Margin			
	$\sinh^{-1}(\theta_{\text{low}})$		$\sinh^{-1}(\theta_{\text{high}})$		$\mathbb{1}(\theta_{\text{low}} > 0)$		$\mathbb{1}(\theta_{\text{high}} > 0)$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta_{k,t}$	0.389***		1.34***		3.01***		3.04***	
	(0.051)		(0.139)		(0.451)		(0.452)	
$\Delta_{k,t} \times$ Cap		0.369***		1.28***		3.72***		3.71***
		(0.081)		(0.257)		(0.718)		(0.722)
$\Delta_{k,t} \times$ Int		0.498***		1.74***		2.81***		2.85***
		(0.064)		(0.159)		(0.451)		(0.451)
$\Delta_{k,t} \times$ Con		0.049		0.033		1.86***		1.96***
		(0.051)		(0.148)		(0.680)		(0.683)
R^2	0.39	0.41	0.47	0.50	0.61	0.61	0.61	0.62
Observations	50,763	50,763	50,725	50,725	50,763	50,763	50,725	50,725
Two-way FE	✓	✓	✓	✓	✓	✓	✓	✓
Weighted	✓	✓	✓	✓	✓	✓	✓	✓

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table reports the coefficients for regressions of the form

$$f(\theta_{j,i,t}) = \alpha_i + \delta_t + \beta \log \frac{1 + t_{D,i}}{1 + t_{T,i}} + \varepsilon_{i,t},$$

for $j \in \{\text{low}, \text{high}\}$ and where α_i and δ_t correspond to HS6 and year fixed effects, respectively. $f(\theta_{j,i,t})$ corresponds to an intensive margin response (given by an inverse hyperbolic sine transformation of $\theta_{i,j,t}$), or to an extensive margin response. All specifications are weighted by the HS6 code's share of imports from China to the United States.

Table S2: Transshipment Response to Tariffs (No Deductibility)

	$\sinh^{-1}(\theta_{\text{low}})$		$\sinh^{-1}(\theta_{\text{high}})$	
	(1)	(2)	(3)	(4)
$\log(1+t_D)$	0.341***		1.17***	
	(0.041)		(0.110)	
$\log(1+t_D) \times$ cap		0.294***		1.01***
		(0.064)		(0.205)
$\log(1+t_D) \times$ int		0.396***		1.37***
		(0.050)		(0.125)
$\log(1+t_D) \times$ cons		0.064		0.062
		(0.049)		(0.135)
R^2	0.40	0.41	0.48	0.51
Observations	50,763	50,763	50,725	50,725
Two-way FE	✓	✓	✓	✓
Weighted	✓	✓	✓	✓

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table repeats the intensive margin exercise from Table S1, but uses the tariff wedge gross of the deductibility penalty as a regressor.

Table S3: Pre-Period Test

	Intensive Margin		Extensive Margin	
	$\sinh^{-1}(\theta_{\text{low}})$	$\sinh^{-1}(\theta_{\text{high}})$	$\mathbb{1}(\theta_{\text{low}} > 0)$	$\mathbb{1}(\theta_{\text{high}} > 0)$
	(1)	(2)	(3)	(4)
$\log \frac{1+t_D}{1+t_T}$	0.228***	0.452***	0.742***	0.690***
	(0.032)	(0.054)	(0.119)	(0.124)
$\log \frac{1+t_D}{1+t_T}$ × I(year¡2018)	0.002	0.044	-0.288**	-0.355**
	(0.035)	(0.051)	(0.144)	(0.151)
R^2	0.24	0.26	0.32	0.32
Observations	50,763	50,725	50,763	50,725
Two-way FE	✓	✓	✓	✓
Weighted	✓	✓	✓	✓

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Each column repeats the main regression specification for both intensive and extensive margins, but controls for the pre-period with an indicator variable for pre-tariff years.

Table S4: Regression of Deviations in Direct China–US Imports on Diversion Intensity

	EU-27 + UK				Canada			
	$\sinh^{-1}(\theta_{\text{low}})$	$\sinh^{-1}(\theta_{\text{high}})$	$\mathbb{1}(\theta_{\text{low}} > 0)$	$\mathbb{1}(\theta_{\text{high}} > 0)$	$\sinh^{-1}(\theta_{\text{low}})$	$\sinh^{-1}(\theta_{\text{high}})$	$\mathbb{1}(\theta_{\text{low}} > 0)$	$\mathbb{1}(\theta_{\text{high}} > 0)$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\log \frac{1+t_D}{1+t_T}$	0.038*	-0.044	-0.038	-0.038	0.033**	0.015	-0.141*	-0.231**
	(0.021)	(0.028)	(0.088)	(0.088)	(0.013)	(0.019)	(0.081)	(0.092)
R^2	0.19	0.19	0.18	0.18	0.16	0.17	0.20	0.20
N	50,308	50,308	50,308	50,308	50,308	50,308	50,308	50,308
Two-way FE	✓	✓	✓	✓	✓	✓	✓	✓

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Entries report two–way fixed–effects regressions of placebo diversion measures on the U.S. tariff wedge $\log\big((1+t_D)/(1+t_T)\big)$, where the wedge is the same as in the main specification and is constructed from statutory U.S. HS6 tariffs and the tax–shield (see text). Outcomes are diversion measures computed with (i) the EU–27+UK treated as a single destination (left block) and (ii) Canada as the destination (right block). For each destination and year, diversion is built from HS6 flows using the same screening steps as in the main analysis but with the destination replaced by EU–27+UK or Canada. For comparability with the U.S. baseline, the exposure gate uses the U.S. HS6 tariff panel ($t_{k,t} > 0$) and diversion is capped within HS6 by the 2017 China→U.S. base so that $\sum_i \theta_{k,t} \le 1$. Columns (1)–(2) and (5)–(6) use inverse–hyperbolic–sine outcomes $\sinh^{-1}(\theta_{\text{low}})$ and $\sinh^{-1}(\theta_{\text{high}})$; columns (3)–(4) and (7)–(8) use indicators $\mathbb{1}\{\theta_{\text{low}} > 0\}$ and $\mathbb{1}\{\theta_{\text{high}} > 0\}$. All specifications include HS6 and year fixed effects with standard errors clustered by HS6.

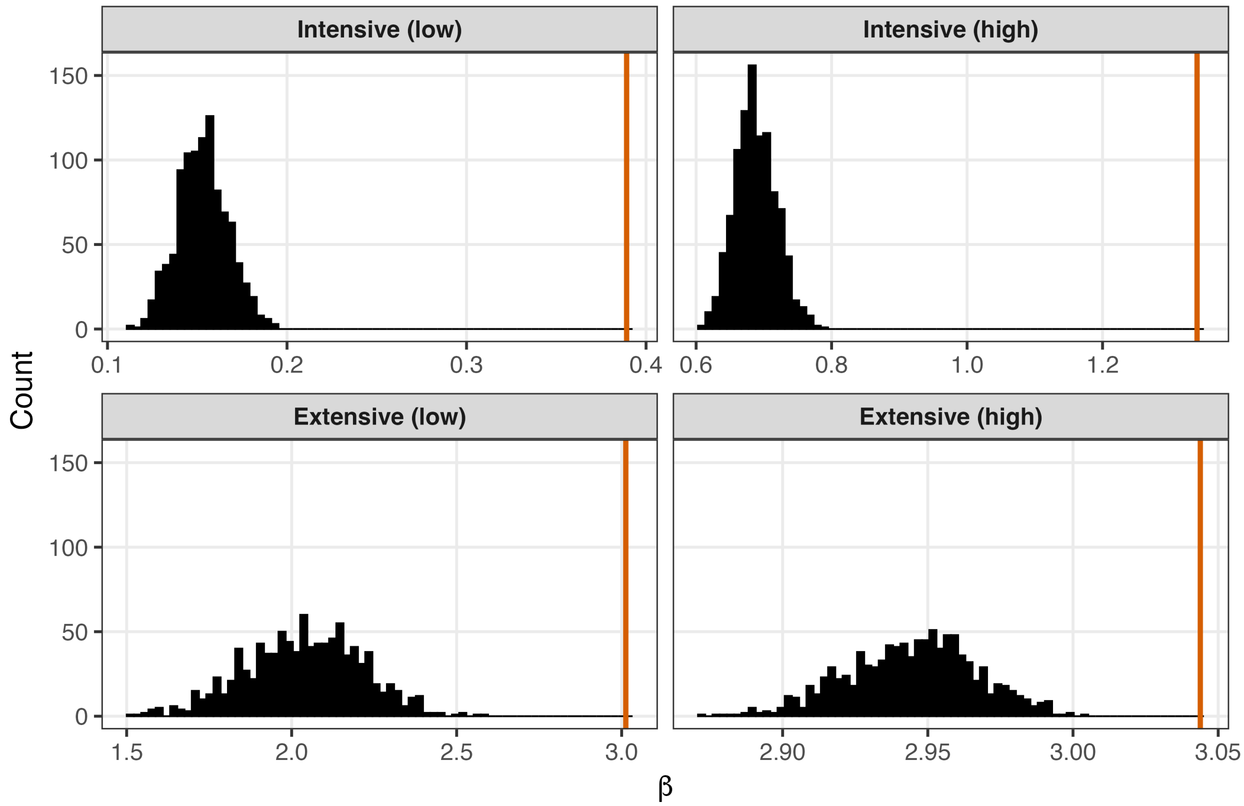
Table S5: Pre- and Post-Period Placebo Results for Canada

	2012–2017				2018–2023			
	$\sinh^{-1}(\theta_{\text{low}})$	$\sinh^{-1}(\theta_{\text{high}})$	$\mathbb{1}(\theta_{\text{low}} > 0)$	$\mathbb{1}(\theta_{\text{high}} > 0)$	$\sinh^{-1}(\theta_{\text{low}})$	$\sinh^{-1}(\theta_{\text{high}})$	$\mathbb{1}(\theta_{\text{low}} > 0)$	$\mathbb{1}(\theta_{\text{high}} > 0)$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\log \frac{1+t_D}{1+t_T}$	0.147*	0.275	1.33	1.48	-0.025	-0.033	-0.308**	-0.200
	(0.077)	(0.217)	(1.14)	(1.33)	(0.019)	(0.029)	(0.152)	(0.169)
R^2	0.18	0.20	0.18	0.17	0.37	0.42	0.51	0.53
N	25,259	25,259	25,259	25,259	25,049	25,049	25,049	25,049
Two-way FE	✓	✓	✓	✓	✓	✓	✓	✓

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table breaks down Columns (5)-(8) in Table S4 into the pre- and post-policy window.

Figure S1: Permutation Null Distributions of β under a Broken China–Hub–US Network Mapping



Note: This figure displays the permutation-based placebo distributions for the estimated elasticity of diversion with respect to the tax wedge, β, under a broken network mapping. For each replication, the pairing between China$\rightarrow$hub and hub$\rightarrow$US shipment legs is randomly deranged within HS4–year product groups while keeping the marginal leg volumes, pre-trend screens, and denominator structure fixed. Each permutation thus preserves the observed scale and composition of trade at the HS4 level but eliminates the structural correspondence between the two legs of the network. The distributions shown in black correspond to the resulting estimates of β from 1,000 such random permutations, re-estimated separately for intensive and extensive outcomes. The vertical orange lines indicate the coefficients obtained under the intact network mapping. The top panels use the inverse-hyperbolic-sine transformations of the diversion measures $\sinh^{-1}(\theta_{\text{low}})$ and $\sinh^{-1}(\theta_{\text{high}})$, while the bottom panels use binary indicators for positive diversion $1\{\theta_{\text{low}} > 0\}$ and $1\{\theta_{\text{high}} > 0\}$. All specifications include HS6 and year fixed effects and are weighted by 2017 China–US import shares.

Table S6: Permutation Tests for Pre-Period Balance

Outcome	Observed Gap	P (left)	P (right)	P (two-sided)	P (Holm)
$\sinh^{-1}(\theta_{\text{high}})$	-0.021	0.001	0.999	0.002	0.004
$\sinh^{-1}(\theta_{\text{low}})$	-0.001	0.105	0.895	0.210	0.210
$\mathbb{1}\{\theta_{\text{high}} > 0\}$	-0.925	0.000	1.000	0.000	0.000
$\mathbb{1}\{\theta_{\text{low}} > 0\}$	-0.878	0.000	1.000	0.000	0.000

Notes: Each row reports the observed weighted mean difference (treated minus placebo) in the specified outcome during the pre-period (2012–2017), along with permutation-based p-values. For each outcome, 5,000 block permutations were performed by reassigning treated HS6 codes within HS4 product groups while preserving the overall number of treated observations. For each permutation draw, the treated–placebo gap in the weighted mean outcome (weighted by 2017 China–US import shares) was recalculated. The empirical p-values are computed as the fraction of permuted gaps that are as or more extreme than the observed gap, with Holm–Bonferroni adjustments applied for multiple outcomes. All outcomes are defined at the HS6–year level and correspond to the conservative and liberal diversion measures in the main text, expressed as either inverse hyperbolic sine or binary indicators.

Table S7: Percent difference between baseline and leave-one-out: $100 \times \frac{\beta_{LOO}-\beta}{\beta}$

Country	Intensive (Low)	Intensive (High)	Extensive (Low)	Extensive (High)
Taiwan	-13.06	-10.30	-0.04	-0.02
Japan	-11.18	-11.01	-0.37	-0.05
Canada	-9.66	-7.81	0.51	0.03
Mexico	-6.71	-8.62	-0.33	-0.07
Cambodia	-8.14	-2.03	-1.91	0.00
Germany	-6.78	-7.86	0.14	-0.28
India	-7.68	-4.14	-0.25	-0.02
Malaysia	-7.24	-4.52	-0.30	-0.00
Thailand	-4.20	-3.60	-0.76	0.06
Indonesia	-3.77	-1.73	-0.12	-0.00
Vietnam	-3.06	-1.94	-0.33	-0.03
Singapore	-3.05	-1.06	-0.31	-0.01
Israel	-1.74	-0.83	0.09	0.06
Poland	-1.56	-1.23	1.05	-0.00
Turkey	-1.32	-0.69	-0.14	-0.03

Notes: For each regression specification, I leave out one hub and recompute the coefficient. After that, I compute the percent difference between the leave-one-out estimate and the baseline regression. For example, the leave-one-out coefficient when excluding Taiwan from the sample is 13 percent smaller than the baseline intensive margin coefficient from Column 1 of Table S1. The table shows the most influential fifteen hubs.