Paying More and Buying Less: 2025 Tariffs and U.S. Household Spending

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Abstract

We estimate the effects of 2025 U.S. tariffs on household spending using transaction-level data from 125,000 households. Tariff exposure raises retail prices modestly but reduces spending substantially, with the decline driven primarily by quantity reductions. Average losses are 3.2 percent of spending on tariff-affected goods. High-income households experience larger proportional losses in discretionary categories. All households mitigate costs by trading down to cheaper products within categories, while high-income households additionally reallocate spending across categories. As a share of income, low-income households bear roughly ten times the burden of high-income households confirming tariffs are regressive.

Keywords: Tariffs, Households, Consumption, Spending, Prices, Welfare

JEL Classification: F13, D12, E31

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1 Introduction

Beginning in February 2025, the United States imposed broad-based tariffs covering virtually all trade partners, marking one of the most substantial shifts in U.S. trade policy in decades. While a growing body of research has documented the price effects of tariffs (e.g., Amiti et al., 2019; Fajgelbaum et al., 2020; Cavallo et al., 2021), understanding how households respond along the quantity margin (how much they buy, where they reallocate spending, and how they substitute across products) remains a central question for assessing the welfare consequences of trade policy. This paper provides new evidence on these dimensions by exploiting granular transaction-level data covering the 2025 tariff episode.

We analyze nearly 125,000 households observed continuously from January 2024 through December 2025, tracking the price, quantity, and product category of each purchase alongside detailed household demographics including income. The data offer comprehensive coverage of frequently purchased physical goods (groceries, health and beauty products, apparel, home goods, and electronics), categories that are both directly exposed to tariffs on traded goods and central to households' consumption decisions. Recent evidence indicates that households form inflation expectations primarily based on the prices of such high-frequency purchases (D'Acunto et al., 2021), and that these expectations causally affect spending decisions (Coibion et al., 2022), making these categories particularly salient for understanding consumption responses to trade shocks. We link household transactions to tariff exposure measures constructed at the 4-digit Harmonized System (HS4) level, combining country-specific import shares with time-varying tariff rates.

The key empirical advantage of our data is the joint observation of prices and quantities at the household-product level. This allows us to estimate the spending response to tariffs: not only whether prices rise, as studied in existing work on the 2025 episode (e.g., Cavallo et al., 2025), but also how households change their spending in response to tariffs. We provide, to our knowledge, the first household-level estimates of quantity and spending responses to the 2025 U.S. tariffs, complementing the small but growing literature that examines consumption adjustments to trade policy shocks (e.g., Waugh, 2019; Ma et al., 2025).

Using a difference-in-differences design that exploits cross-sectional variation in tariff exposure across product categories, we document three main findings. First, tariffs generate modest retail price increases but substantial reductions in household spending, with the adjustment concentrated on the quantity margin. A one percentage point increase in tariff exposure raises retail prices by 0.06 percentage points (implying roughly 6 percent pass-through) but reduces real spending by 0.32 percent and quantities by 0.28 percent. The limited price response is consistent with recent evidence that quantity adjustments attenuate measured pass-through (Ganapati and Hottman, 2026). The spending decline is driven almost entirely by reduced quantities rather than higher prices.

This pattern suggests that the demand response operates through channels beyond direct price effects. The findings align with recent macro evidence showing that tariff-induced uncertainty depresses economic activity and consumption (Barnichon and Singh, 2025; Candia et al., 2026). Our micro-level estimates provide a household consumption foundation for these aggregate patterns: when tariffs increase, households pull back on purchases even when retail prices rise only modestly, consistent with precautionary behavior in the face of policy uncertainty. The quantity responses we document also mirror the import demand contractions observed in prior work on tariff episodes (Fajgelbaum et al., 2020; Amiti et al., 2019).

The effects vary meaningfully across trading partners and product types. China accounts for the bulk of the aggregate response, reflecting substantially higher tariff rates post-February 2025. Canada and Mexico face lower tariffs due to United States-Mexico-Canada Agreement (USMCA) provisions and exemptions, generating smaller consumption effects and evidence of trade diversion as households and retailers shift toward North American suppliers. Essential goods (groceries, household staples, health and beauty products) show no significant price or quantity response, consistent with inelastic demand for necessities and possible retailer margin absorption. Non-essential and durable goods exhibit large spending and quantity declines, reflecting greater postponability and substitutability of discretionary purchases.

Second, we quantify the distributional consequences of these responses by constructing household-specific welfare measures that combine estimated behavioral elasticities with baseline expenditure patterns and tariff exposure. On average, households experience

consumption losses equivalent to 3.2 percent of their pre-tariff spending on tariff-affected goods. However, the incidence varies substantially across the income distribution. High-income households face the largest proportional losses (4.1 percent of affected spending, or approximately $84 per month) driven by their higher baseline expenditure and stronger quantity responses in discretionary categories such as electronics, apparel, and home goods. Low-income households lose 2.7 percent ($27 per month), concentrated in food and necessities where substitution is more constrained. Middle-income households lose 2.6 percent ($32 per month).

When expressed as a share of income, the regressive nature of tariffs is evident: on aggregate, low-income households lose 0.54 percent of income compared to 0.05 percent for high-income households, consistent with prior findings that tariffs function as a regressive consumption tax (Acosta and Cox, 2024; Fajgelbaum and Khandelwal, 2016). We complement these spending-based measures with deadweight loss and CES equivalent variation calculations following standard methods (Fajgelbaum et al., 2020). Both welfare metrics yield substantially smaller magnitudes, reflecting the limited observed price pass-through. The gap between behavioral spending losses and price-anchored welfare measures indicates that households adjust consumption beyond what realized price changes would predict, with uncertainty and anticipation likely playing important roles in the adjustment process.

Third, we examine the margins of substitution through which households mitigate tariff costs. On the intensive margin, we find strong evidence of within-category quality downgrading: in tariff-exposed product categories, cheaper items gain revenue share at the expense of more expensive varieties. This pattern holds across income groups and operates through demand-side behavior rather than differential pricing strategies. On the extensive margin, cross-category reallocation is concentrated among high-income households, who have greater flexibility to shift spending away from tariff-exposed categories entirely. Low- and middle-income households adjust primarily by trading down within the categories they continue to purchase, a more constrained form of substitution with distinct welfare implications. These findings reveal how the capacity to substitute varies with income, contributing to the regressive incidence of tariff-induced consumption losses.

Our findings build on and extend several strands of research. The 2018-19 U.S.-

China trade war generated important evidence on tariff pass-through. Amiti et al. (2019, 2020); Fajgelbaum et al. (2020) establish near-complete pass-through to import prices, while Cavallo et al. (2021) trace the transmission from border to retail prices. The modest percentage pass-through partly reflects the composition of our data toward everyday consumer goods, where retailer margin absorption and competitive pricing may attenuate measured price responses. Additionally, Sangani (2026) shows that incomplete pass-through in percentages can disguise complete pass-through in levels, a dollar-for-dollar transmission of cost increases to prices when a gap exists between price levels and costs. Since our empirical design, like most in the literature, measures pass-through in percentage terms, we may understate the extent to which tariff costs are transmitted to retail prices. Moreover, Ganapati and Hottman (2026) show that accounting for endogenous quantity responses reduces measured pass-through to around 60 percent. For the 2025 episode, Cavallo et al. (2025) documents partial retail price pass-through using online price data. Our retail pass-through estimate of 6 percent falls at the lower end of this range, consistent with quantity-attenuated estimates and the composition of our sample toward high-frequency consumer goods.

A parallel literature examines how trade policy affects household welfare through the consumption basket. Fajgelbaum and Khandelwal (2016) demonstrate that trade liberalization disproportionately benefits lower-income households because they allocate more of their budgets to tradable goods. Acosta and Cox (2024) provide direct evidence that U.S. tariffs act as regressive taxes. Waugh (2019) documents consumption losses in automobile purchases from Chinese retaliatory tariffs, while Ma et al. (2025) estimates household-specific price indexes during the 2018-19 trade war, finding that wealthier households' greater substitution capacity drove distributional differences in welfare losses.[1]

We make three contributions to this literature. First, we provide the first household-level estimates of both price pass-through and quantity responses to the 2025 U.S. tariffs. The joint estimation reveals that the bulk of household adjustment operates through the quantity margin, with spending declines substantially exceeding what observed price

[1]Related work explores broader labor market and welfare effects of trade shocks, including Topalova (2010); Autor et al. (2013); Pierce and Schott (2016); Autor et al. (2021); Caliendo and Parro (2023); Borusyak and Jaravel (2021). Jaravel and Sager (2024) show that U.S.-China trade historically reduced consumer prices, especially for lower-income households. Feng et al. (2023) document price effects of Chinese imports and retaliatory tariffs.

increases would predict. This micro evidence helps rationalize recent macro findings on tariff-induced demand contractions. Second, we construct household-specific welfare measures that account for heterogeneous behavioral responses, baseline spending patterns, and tariff exposure, documenting the regressive incidence of the 2025 tariffs and showing how the composition of losses varies across the income distribution. Third, we characterize the substitution margins households use to cope with tariff shocks, finding that households across income groups engage in within-category quality downgrading but only high-income households have the flexibility to reallocate spending across categories, a finding with direct implications for understanding why tariff burdens fall disproportionately on lower-income households.

The remainder of the paper proceeds as follows. Section 2 describes the data and the construction of key measures. Section 3 outlines the empirical strategy. Section 4 presents the main results on prices, spending, and quantities, and documents heterogeneity across income groups. Section 5 quantifies household-level welfare losses. Section 6 examines substitution behavior. Section 7 concludes.

2 Data and the Construction of Key Measures

This section presents the data and key measures used throughout the paper. We begin with the transaction-level household data and trade data. These two datasets are merged using a crosswalk, which we describe next. Following the data overview, we outline the key measures employed in our analysis: the tariff exposure measure and the Fisher Price Index.

2.1 Transaction-Level Household Data

Our primary data source is the Numerator household panel, which provides comprehensive transaction-level records of consumer purchases combined with detailed demographic information. Panelists submit purchase records through the Receipt Hog mobile app via three channels: uploading photographs of paper receipts, connecting email accounts for automatic digital receipt collection, and linking retail loyalty programs (including Amazon, Walmart, and other major retailers). The only requirement for participation is

ownership of a mobile phone with camera capability. Participants receive approximately $10 monthly compensation through gift cards or direct payment. The dataset includes rich demographic attributes obtained through periodic surveys, such as education levels, age groups, 5-digit zip code, household composition, and race/ethnicity. The dataset provides 16 categorical income brackets derived from panelists' self-reported earnings. Appendix A provides more information on data collection, weighting methodology, and representativeness.

The panel by the end of 2025 comprises 200,000 households selected from a broader pool exceeding one million registered users to ensure demographic and geographic representativeness. Numerator designates households as *static panelists* if they maintain continuous and complete transaction records for a minimum of 12 months, enabling reliable longitudinal analysis. For our analysis, we restrict the sample to the 124,883 static panel households who remained active throughout the entire 24-month period from January 2024 through December 2025, ensuring consistent measurement of tariff responses without compositional changes in the panel. Given that we analyze a subset of the full representative panel, we apply Numerator's demographic weights in all spending analyses. The demographic weights align the panel with U.S. Census benchmarks across eight dimensions: gender, age, ethnicity, household income, household size, presence of children, Census division, and urbanicity as Appendix A demostrates.

The household data contain products that are identified with their unique item identification numbers (item_id). The data structure links three core identifiers: user_id (household), basket_id (shopping trip/transaction), and item_id (product), allowing us to track individual purchase decisions at the household-product-trip level. Within the sample period of 2024-2025, we have 536,913,789 unique products in the data. This high number of products reflects Numerator's product cataloging system, which assigns separate item identifications based on package size and format. For example, a single can of soda receives its own item ID, while a 12-pack of the same soda receives a different item ID, even though the unit price per can may be identical. All products are mapped to a hierarchy of classifications by Numerator. To ensure data quality, we omit items with prices below $1 (as some zero or very low prices reflect buy-one-get-one-free deals or transcription errors), and we remove any product where unit price exceeds $5,000 (or

$500 for grocery items).

Table 1 lists the broader sectoral classification with each sector's expenditure shares in the final data. The dataset primarily captures expenditures on physical goods purchased through traditional (both brick-and-mortar and online) retailers. Several spending categories are systematically excluded or underrepresented: services (restaurants, entertainment, professional services), housing (rent, mortgage, utilities), motor vehicles (purchases and leases, though automotive products such as oil and parts are included), healthcare services (though over-the-counter products are captured), and financial services. The resulting coverage represents approximately 20 percent of the consumption basket captured in the PCE and CPI. However, this subset captures the categories most directly affected by tariffs on traded goods. Moreover, recent research indicates that households form inflation expectations primarily based on prices of frequently purchased items such as groceries rather than expenditure-weighted basket averages (D'Acunto et al., 2021; Weber et al., 2022), suggesting that the categories in our data are particularly salient for understanding consumption responses to price shocks.

2.2 Trade Data

Traded products are classified into the Harmonized System (HS) codes which a standardized international classification system used by customs authorities to identify and categorize traded goods. Every product has a 10-digit HS code which is a very detailed product classification. Trade data, exports or imports, can be aggregated to different levels, such as 6- or 4- digits HS codes. In this paper, we work with 4-digit HS codes (HS4) which provides us with broad product categories the reasons of which we discuss below in the household to trade data crosswalk section.

We obtain import values and duties paid data from the US Census Bureau.[2] We first construct HS4 code and source country level import shares. These shares capture the fraction of U.S. imports in each product category originating from each source country. We also construct monthly tariff rate at the HS4-country level spanning 2024–2025, which allows us to track the evolution of trade policy over our sample period. These tariff rates

[2]Source: Merchandise data - Trade Imports. https://www.census.gov/foreign-trade/data/dataproducts.html.

TABLE 1: Expenditure Shares by Sector

Sector Description	Expenditure Share (%)
Grocery	46.43
Home & Garden	9.59
Health & Beauty	9.58
Apparel	6.54
Household	5.16
Tools & Home Improvement	4.28
Pet	4.17
Electronics	3.80
Party & Occasions	2.64
Toys	1.99
Automotive Products (excludes motor vehicles)	1.41
Baby	1.20
Textiles	1.00
Tobacco Products	0.87
Office	0.83
Books	0.40
Entertainment	0.11

Note: Values in percent. Expenditure shares are calculated by aggregating total expenditure across all households and time periods for each sector for data spanning January 2024 to December 202; total spending over the 24 month period is $3,802,841,523 on 536,913,789 products. Sectors are sorted in descending order by expenditure share.

are constructed as the ratio of total duties collected to the value of total imports for each HS4 product code and source country combination in each month. This approach yields effective tariff rates that reflect the realized tariff burden on imports, rather than announced tariff rates at the Federal Register. Due to delay in implementation of tariffs and exemptions at the county or product level, we use realized tariff rates in our analysis, see Azzimonti (2025); Cavallo et al. (2025); Gopinath and Neiman (2026). Our baseline specification defines tariff start date as February 2025.

2.3 Household to Trade Data Crosswalk

A central challenge in linking retail transaction data to trade-based tariff measures involves mapping retail product classifications in the household data to standardized HS codes used in international trade. To address this challenge, we create a crosswalk that

maps retail product categories in the household data to HS4 codes preserving the full retail hierarchy available in the household data: sector → department → major category → category → HS4 code.

Our approach maps product categories to HS4 codes rather than matching individual Universal Product Codes (UPCs) to 10-digit HS codes as in Cavallo et al. (2025). This methodological choice reflects data constraints, where UPCs are not consistently available across all products in the household data but full retail hierarchy is.[3] In the crosswalk, products are first matched at the most granular category level, if it exists, and unmatched items are successively matched at increasingly aggregate levels (major category, department, then sector).[4] Table 2 presents an example of the hierarchical classification structure, ranging from the broadest (sector) to the most detailed (category) level, showing how household expenditure categories correspond to HS4 codes.

TABLE 2: Example Crosswalk: Sector Hierarchies to HS Codes

Sector	Department	Major Category	Category	HS Code
Apparel	Apparel Accessories	Belts	Leather Belts	4203
Apparel	Baby Apparel	Baby Pajamas	Baby Girl Pajamas	6111
Electronics	Video Games & Acc.	Video Games	PlayStation Games	9504
Entertainment	Movies & TV	Blu-ray	Comedy Blu-ray Movies	8523
Grocery	Beverages	Tea	Earl Grey Tea	0902
Grocery	Dairy	Cheese	Soft Cheese	0406
Grocery	Meat	Sausage	Sausage-Pork	1601
Health & Beauty	Makeup	Eye Makeup	Mascara	3304

Notes: The table demonstrates the four-level hierarchical structure (Sector → Department → Major Category → Category) mapping to standardized HS codes.

[3] Restricting our sample to only UPC-identified products would significantly reduce coverage and compromise the representativeness of household consumption baskets. Moreover, the proprietary nature of the product level data does not allow the use of artificial intelligence tools or alike, as in Cavallo et al. (2025) to classify products into more granular trade codes.

[4] Anthropic Claude 4.5 was used in the construction of the Numerator category to HS4 crosswalk. The accuracy of the crosswalk was manually verified by the authors which was then cross-checked by Anthropic Claude Opus 4.6. This hierarchy match often returns 6-digit HS codes for some categories. But to ensure consistency across the wide range of products, we aggregate them to 4-digit level.

2.4 Tariff Exposure Measure

To use in our empirical specification, we construct a monthly tariff exposure measure at the HS4 code level. For each HS4 code h in month t, tariff exposure to country C is:

$$\text{TariffExposure}_{h,t}^{C} = \text{ImportShare}_{h}^{C} \times \tau_{h,t}^{C} \tag{1}$$

where $\text{ImportShare}_{h}^{C}$ is the share of U.S. imports of HS code h originating from country C (fixed at 2024 values), and $\tau_{h,t}^{C}$ is the tariff rate applied to country C for HS code h in month t. The variation in the tariff exposure measure comes from the changes in tariff rates at the HS4 level which is key for the identification of tariff effects on retail prices and household spending. Total tariff exposure sums across all source countries:

$$\text{TariffExposure}_{h,t}^{\text{Total}} = \sum_{C} \text{TariffExposure}_{h,t}^{C}. \tag{2}$$

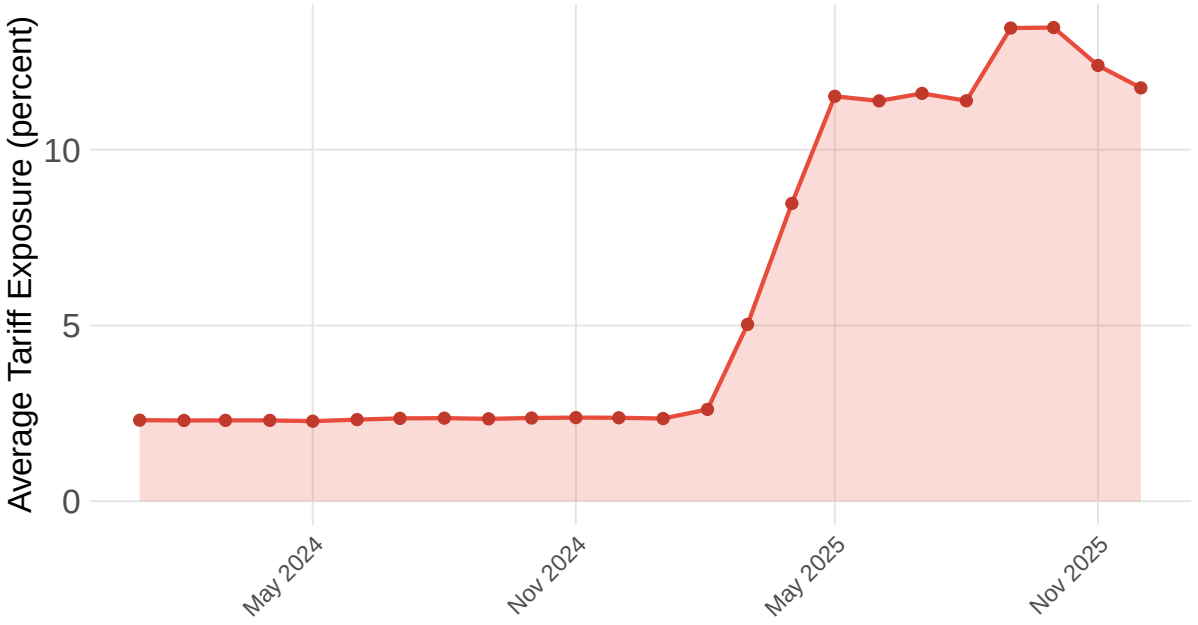
The tariff exposure captures the effective tariff rates faced by consumers of each HS4 code, accounting for the origin composition of imports. In other words, tariff exposure is the probability-weighted average across origins when source-country is not known. Since our panel is constructed at the product-hierarchy × HS4 code level , each panel unit maps directly to a single HS4 code, and no within-category aggregation across HS codes is required. As shown in Figure 1, average total tariff exposure is low in the pre-tariff period and starts increasing after tariffs are imposed in February 2025.

Appendix D shows tariff exposure by sector, country, durability and essentiality whose definitions we provide in Section 4. Moreover, in Appendix C, we construct a tariff measure for a smaller set of products for which we know the country of origin information, through another dataset matched with the household panel, to validate the accuracy of our main tariff exposure measure.

2.5 Fisher Price Index

For our empirical model, we leverage product-level prices and quantities from the household panel and compute a monthly Fisher Price Index (FPI) beginning in January 2024 at the HS4 level. The FPI accounts for both base- and current-period quantity weights,

FIGURE 1: Average Total Tariff Exposure



Notes: This figure shows the monthly average tariff exposure over the sample period. For each year-month, we calculate the mean tariff exposure across all observations. Tariff exposure is measured in percentage points.

offering a key advantage over the alternatives that rely solely on prices without quantity weighting. Fixed-base FPI is that it holds the product basket fixed when computing price changes and is therefore immune to within-category composition effects. We relax this assumption and explore composition effects in detail using unit values in Section 6.

For period t relative to base period 0, the FPI for an HS4 code h is:

$$F_{h,t} = \sqrt{L_{h,t} \cdot P_{h,t}} = \sqrt{\frac{\sum_{h,k\in\Omega} p_{hkt} q_{hk0}}{\sum_{h,k\in\Omega} p_{hk0} q_{hk0}} \cdot \frac{\sum_{h,k\in\Omega} p_{hkt} q_{hkt}}{\sum_{h,k\in\Omega} p_{hk0} q_{hkt}}} \tag{3}$$

where for a given h, L_t denotes the Laspeyres index using base-period quantities, P_t the Paasche index using current-period quantities, and p_{kt}, q_{kt} are the price and quantity of product k in period t. The FPI is the geometric mean of the two. This construction parallels that of the Bureau of Economic Analysis's PCE Index, which similarly employs expenditure-weighted aggregation. Appendix B provides a discussion of how the

aggregate Fisher Price Index for a longer time period of January 2018 to December 2025 compares with officially published price indices.

3 Empirical Strategy

Our main specification is a difference-in-differences model that exploits variation in tariff exposure intensity across product categories:

$$\ln(Y_{it}) = \gamma_t + \delta_{i,m(t)} + \beta \left(\text{TariffExposure}_i \times \text{Post}_t\right) + \varepsilon_{it} \tag{4}$$

where i indexes the panel unit (sector × department × major category × category × HS code), t indexes the year-month, and Y_{it} is one of three outcomes: Fisher Price Index, real spending or quantity. The term γ_t is a year-month fixed effect absorbing common macroeconomic shocks. The term $\delta_{i,m(t)}$ denotes panel-unit-by-calendar-month fixed effects, where $m(t) \in \{1, \ldots, 12\}$ maps each year-month to its calendar month; these allow each panel unit to have its own monthly pattern, absorbing unit-specific cyclical demand variation that might otherwise confound the tariff effect. The binary indicator Post_t equals one for months from February 2025 onward. Spending is deflated by the PCE goods price index.[5]

The coefficient β identifies whether categories with higher tariff exposure experience differentially larger changes in the outcome variable after tariffs are imposed, relative to the pre-tariff period and relative to less-exposed categories. In other words, β implies the percentage point price, spending or quantity change per an additional percentage point of tariff exposure. We estimate Equation (4) for total tariff exposure and separately for the US's main trading partners Canada, Mexico, and China, while bundling all other source countries under "Rest of the World (RoW)". To explore household heterogeneity across different dimensions, we apply the same empirical model, tailoring it to each specific analysis throughout the paper, with the appropriate clustering of the standard errors at the treatment level which is generally at the HS4 level.

[5]Data for the PCE goods index is downloaded from FRED. Personal consumption expenditures: Goods (chain-type price index) (DGDSRG3M086SBEA).

4 Results on Price, Quantity and Spending Changes due to Tariffs

This section summarizes the results on price, quantity and spending changes due to tariffs. We first present the aggregate results and then we present the results decomposed by income.

4.1 Aggregate Results

Table 3 presents the price pass-through estimates, and real spending and quantity results for total and by source country. Starting from the top panel, the FPI coefficient is positive and statistically significant, implying that a 1 percentage point increase in tariff exposure raises prices by 0.06 percentage points, in other words 6 percent pass through. The price effect is driven primarily by Rest of World, with 15 percent pass-through, while China and Canada show positive and economically meaningful price effects despite low statistical accuracy.

The second and third panels together reveal the key finding in our analysis: while prices rise slightly, spending and quantity decline significantly in tandem, indicating that the spending decline is primarily driven by the quantity margin. Total real spending declines by 0.32% and quantity declines by 0.28% per percentage point of tariff exposure.[6] The spending and quantity reductions are driven mostly by China tariff exposure which is evidence in the high tariff exposure of China shown in Figure D.1. Notably, Canada exposure shows a significant positive coefficient for both spending and quantity. One potential explanation for the gain in spending on Canadian goods is trade diversion: as tariffs on China and RoW increase, consumers may substitute toward Canadian-sourced goods in overlapping product categories where tariffs are lower, see Figure D.1.

The country-specific decomposition reveals that China is the dominant source of tariff exposure. As it is evident in Figure D.1, average tariff exposure from China rises sharply after February 2025, reaching levels several times higher than those from other trading

[6]Since spending equals price times quantity, we would naturally expect the spending and quantity coefficients to move closely together. The residual divergence between these coefficients reflects two factors: the effect of price increases on nominal spending, and our use of real rather than nominal spending in the estimations.

TABLE 3: Price, Spending, and Quantity Results by Source Country

	(1) Total	(2) China	(3) Canada	(4) Mexico	(5) RoW
Panel A: FPI (Price Index)					
Tariff Exp. × Post	0.06**	0.04*	0.32	−0.06	0.15*
	(0.03)	(0.02)	(0.30)	(0.05)	(0.08)
Adjusted R^2	0.62	0.61	0.61	0.61	0.62
Panel B: Real Spending					
Tariff Exp. × Post	−0.32***	−0.39***	2.4***	0.63	−0.31
	(0.07)	(0.09)	(0.78)	(0.42)	(0.19)
Adjusted R^2	0.95	0.95	0.95	0.95	0.95
Panel C: Quantity					
Tariff Exp. × Post	−0.28***	−0.37***	2.0***	0.52	−0.21
	(0.07)	(0.09)	(0.68)	(0.33)	(0.17)
Adjusted R^2	0.97	0.97	0.97	0.97	0.97
Panel unit FE	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes
Panel unit × month	Yes	Yes	Yes	Yes	Yes
Observations	106,356	106,356	106,356	106,356	106,356

Notes: Each column reports estimates from Equation (4) with the corresponding tariff exposure measure. Coefficients represent the percentage change in the outcome variable associated with a 1 percentage point increase in tariff exposure. Standard errors clustered at the HS4 level are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

partners. By contrast, tariff exposure from Canada and Mexico remains substantially lower throughout the post-tariff period, reflecting the USMCA, and various product and sectoral level exemptions. This asymmetry in tariff exposure across source countries helps explain the concentration of spending and quantity effects in China-specific tariffs documented in Table 3, as well as the positive Canada coefficients that suggest trade diversion toward less-tariffed North American partners.

The main results reported above are robust to alternative specifications that control for household characteristics and regional shocks. Appendix F presents two complementary exercises. First, aggregating transactions to the household-month level and controlling for household size, age, and regional fixed effects, we find that tariff exposure consistently reduces household spending, with single-person and younger households

exhibiting the largest responses. Second, estimating the baseline specification at the disaggregated household-product-month level with demographic controls and region-time fixed effects, the tariff coefficient remains stable across progressively saturated specifications. The directionality and statistical significance of tariff effects are consistent across all specifications, confirming that compositional changes in household characteristics or confounding regional trends do not drive the product-level estimates. These robustness checks support a causal interpretation of the baseline results.

Next, we classify the products in the data under two broad groups: essentials and nonessentials.[7] Table 4 reports the estimates of Equation (4) by essentiality to explore the substantial heterogeneity behind the coefficients documented in Table 3.

Essential goods such as grocery, household, and health and beauty products show no statistically significant response in spending or quantity to any tariff source, consistent with near-inelastic demand for necessities at the product level. Essential goods exhibit no significant price response to total tariff exposure, and China-specific exposure actually reduces essential prices by 0.11 percentage points, possibly reflecting competitive pressure among retailers reluctant to raise prices on high-visibility staple goods. Non-essential goods, by contrast, exhibit large and highly significant declines in both spending and quantity, with China-specific effects of similar magnitude. The Canada and Mexico coefficients provide complementary evidence of trade diversion: they are large and positive for non-essential goods, consistent with retailers and consumers substituting toward USMCA partners as goods purchased from China become more expensive. This diversion does not appear for essential goods, where supply chains, particularly for perishable grocery items and established household product sourcing, are harder to redirect in the short run. RoW coefficient, meanwhile, is statistically insignificant across all outcomes and sector groups, confirming that the aggregate effects are driven primarily by China-specific tariff shocks.

These results suggest that the incidence of tariffs is partially mediated by the retail sector. Event study results presented in Appendix E speak to the gradual and small changes in prices with no detectable pre-trends. As tariffs start in February, prices do not

[7]Essential: Grocery, Household, Health & Beauty. Non-essential: everything else (Automotive, Electronics, Tools & Home Improvement, Home & Garden, Office, Baby, Pet, Tobacco, Apparel/Footwear/Accessories, Sports, Toys, Books, Entertainment, Party & Occasions). For results by durability (durables versus nondurables), see Appendix H.

show a detectable change until around September 2025. Around the same time, spending and quantity start declining significantly, more so than small price adjustments can account for. Given no sign of pre-tariff stockpiling as documented in Appendix G, retailers might be shielding consumers from price increases on essential goods. Nevertheless, the significant quantity reductions across categories imply real welfare losses through reduced consumption. The inelastic demand for essentials means that the consumption-side burden falls disproportionately on discretionary purchases, though the retailer absorption channel partially mitigates regressivity by protecting staple goods prices. We will turn to explore these potential channels in Sections 5 and 6.

TABLE 4: Results by Essentiality

	Essential			Non-essential		
	Price	Spending	Quantity	Price	Spending	Quantity
Total	-0.03	0.00	0.05	0.04	-0.28***	-0.28***
	(0.03)	(0.13)	(0.11)	(0.03)	(0.09)	(0.08)
China	-0.11**	-0.21	-0.08	0.01	-0.34***	-0.36***
	(0.05)	(0.20)	(0.19)	(0.03)	(0.11)	(0.10)
Canada	0.17	0.56	0.82	0.05	4.66***	3.74***
	(0.31)	(0.87)	(0.76)	(0.35)	(1.39)	(1.07)
Mexico	-0.02***	0.20	0.19	-0.41	3.30***	2.45**
	(0.01)	(0.19)	(0.18)	(0.26)	(1.15)	(1.02)
Rest of World	0.03	0.14	0.14	0.15	-0.25	-0.12
	(0.04)	(0.19)	(0.15)	(0.10)	(0.25)	(0.25)
Average Adjusted R^2	0.64	0.97	0.98	0.61	0.93	0.95
Observations		44,430			61,926	
Panel unit FE		Yes			Yes	
Year-month FE		Yes			Yes	
Panel unit × month		Yes			Yes	

Notes: Each cell reports the coefficient β from Equation (4) for each group and outcome variable. Coefficients represent the percentage change in the outcome variable associated with a 1 percentage point increase in tariff exposure. Standard errors clustered at the HS4 code level in parentheses. All specifications include year-month and product × calendar-month fixed effects. Adjusted R^2 averaged across tariff source specifications within each outcome. Essential: Grocery, Household, Health & Beauty. Non-essential: everything else (Automotive, Electronics, Tools & Home Improvement, Home & Garden, Office, Baby, Pet, Tobacco, Apparel/Footwear/Accessories, Sports, Toys, Books, Entertainment, Party & Occasions). For results by durability (durables versus nondurables), see Table H.1 in Appendix H. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

4.2 Income-Specific Results

The aggregate results in the previous section provide a useful overview of tariff impacts but as the analysis by durability and essentiality indicates, there might be significant heterogeneity on how tariffs affect households with different demographics. For instance, the aggregate FPI weights all products equally across the income distribution, and the pooled spending coefficient assumes that households at different income levels respond identically to tariff exposure. However, if consumption baskets and behavioral responses differ systematically by income, these aggregate estimates may obscure distributional consequences. To address this, we construct income-specific FPIs that reflect each income group's actual consumption weights and re-estimate the model separately for each group. For this analysis, we define three income groups from households' reported income brackets: low-income households earning \$0–\$40,000, middle-income households earning \$40,000–\$125,000, and high-income households earning above \$125,000, all annual and gross.[8]

We run the same empirical specification as in Equation (4) for each income group. Table 5 presents the price pass-through estimates using income-specific FPIs. Low-income households experience a price pass-through of 8%, middle-income households face the smallest price increase at 5%, and high-income households experience 9% pass-through. Note that the aggregate and income-specific regressions use different samples due to income-specific FPI availability at HS4 level, which accounts for differences in the estimated coefficients between Table 3 and the income-group-specific estimates.

Table 6 reports the spending and quantity coefficients by income group. The results reveal important heterogeneity. High-income households exhibit the largest quantity and hence spending decline around 0.3% per 1 percentage point increase in tariff exposure. Low- and middle-income households display responses similar in magnitude to low-income households, with spending and quantity declining around 0.2%.

These findings hint at different adjustment mechanisms across the income distribution.

[8]Based on the 2024 Current Population Survey published in September 2025 by the U.S. Census Bureau, low-income households with \$40,000 in annual income would fall between the 20th and 30th percentile of household income, and high-income households with \$125,000 annual income would fall between the 60th and 70th percentile. See https://www.census.gov/library/publications/2025/demo/p60-286.html.

TABLE 5: Price Changes by Income Group

	(1) Low	(2) Middle	(3) High
Tariff Exp. × Post	0.08**	0.05**	0.09*
	(0.04)	(0.03)	(0.05)
Panel unit FE	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes
Panel unit × month	Yes	Yes	Yes
Observations	101,309	104,932	103,545
Adjusted R^2	0.44	0.53	0.49

Notes: Each column reports estimates from Equation (4) using income-group-specific Fisher Price Indices as the dependent variable. Standard errors clustered at the HS4 level are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

TABLE 6: Spending and Quantity Changes by Income Group

	Real Spending			Quantity		
	(1) Low	(2) Middle	(3) High	(4) Low	(5) Middle	(6) High
Tariff Exp. × Post	-0.23***	-0.22***	-0.33***	-0.20***	-0.21***	-0.32***
	(0.05)	(0.05)	(0.08)	(0.06)	(0.07)	(0.07)
Panel unit FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Panel unit × month	Yes	Yes	Yes	Yes	Yes	Yes
Observation	101,309	104,932	103,545	101,309	104,932	103,545
R^2	0.92	0.94	0.93	0.96	0.96	0.96

Notes: Each column reports estimates from Equation (4) estimated separately by income group. All specifications include panel-unit-by-calendar-month fixed effects. Standard errors clustered at the HS4 level are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

High-income households exhibit the largest and most significant quantity decline, indicating active adjustment in purchasing behavior, potentially reflecting greater flexibility to substitute away from tariff-affected products or to reduce discretionary consumption. Low- and middle-income households show significant responses in both spending and quantity but to a smaller extent, suggesting a relatively limited adjustment to tariff exposure compared to high-income households. The heterogeneity analysis by essentiality and income shown in Table 7 reveals patterns that support these results.

For essential goods (grocery, household, health and beauty), no coefficient reaches conventional significance for any income group, consistent with low demand elasticity for

necessities regardless of income. The non-essential results show significant spending and quantity declines across the income distribution, with high-income households exhibiting the strongest responses. The significant price increase in non-essentials for low-income households is consistent with the mechanism documented by Orchard (2025), who shows that adverse macroeconomic shocks shift aggregate demand toward products disproportionately purchased by low-income households, raising their relative prices. Relatedly, Cavallo and Kryvtsov (2024) document that cheaper product varieties experienced disproportionately larger price increases during the post-pandemic inflation surge, a pattern that would particularly burden households relying on lower-priced goods. These price increases may also reflect a demand-driven channel: as higher-income households trade down to lower-priced non-essentials more commonly purchased by low-income households, the resulting demand pressure pushes prices upward. The following sections investigate these mechanisms in more detail. The following sections investigate these mechanisms in more detail.

TABLE 7: Results by Essentiality and Income Group

	Low Income			Middle Income			High Income		
	Price	Spending	Quantity	Price	Spending	Quantity	Price	Spending	Quantity
Essential	-0.02	0.03	0.06	-0.04	-0.01	0.06	-0.03	-0.04	-0.04
	(0.04)	(0.12)	(0.10)	(0.04)	(0.11)	(0.10)	(0.03)	(0.17)	(0.15)
Non-essential	0.08**	-0.20*	-0.20*	0.03	-0.26***	-0.28***	0.07	-0.22**	-0.25***
	(0.04)	(0.11)	(0.11)	(0.04)	(0.08)	(0.08)	(0.06)	(0.10)	(0.09)
Observations		43,846			44,248			44,052	
Panel unit FE		Yes			Yes			Yes	
Year-month FE		Yes			Yes			Yes	
Panel unit × month		Yes			Yes			Yes	

Notes: Each cell reports the coefficient on Tariff Exposure (Total) × Post from a separate regression estimated on the indicated sector group × income group subsample. Coefficients represent the percentage change in the outcome variable associated with a 1 percentage point increase in tariff exposure. Standard errors clustered at the HS4 code level in parentheses. All specifications include year-month and product × calendar-month fixed effects. Income groups: Low (<$40k), Middle ($40k–$125k), High (>$125k). Essential: Grocery, Household, Health & Beauty. Non-essential: all remaining sectors. For results by durability (durables versus nondurables) and income group, see Table H.2 in Appendix H. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

5 Welfare Analysis

Having established that tariffs generate heterogeneous price and quantity responses across income groups, we now quantify the welfare costs experienced by households.

1. Net Spending Effect: Our first measure captures the total observed change in household expenditure on tariff-affected goods. For each household i in income group g and HS4 code h:

$$\text{NetSpendingEffect}_{i,h} = \text{Spend}_{i,h}^{\text{pre}} \times \hat{\beta}_{\text{spend}}^{g(i)} \times \text{TariffExposure}_{h}^{\text{post}} \tag{5}$$

where $\text{Spend}_{i,h}^{\text{pre}}$ is household i's annualized 2024 pre-tariff spending on HS4 code h, $\hat{\beta}_{\text{spend}}^{g(i)}$ is the income-group-specific spending coefficient from Table 6, and $\text{TariffExposure}_{h}^{\text{post}}$ is the average post-period tariff exposure for HS code h. This measure reflects the behavioral outcome on how much households actually changed their spending and is appropriate for gauging the scale of consumption changes. However, it is not a welfare measure per se: it nets the quantity reduction against the price increase, treating the decline in purchased quantities as though it were costless.

A key challenge in measuring welfare, however, is that the observed change in total household expenditure conflates two distinct mechanisms: higher prices on goods that households continue to buy, and reduced consumption of goods that households cut back on or stop purchasing. The net spending effect treats the quantity reduction as an offset to the price burden, implicitly understating the true welfare cost because foregone consumption is itself a loss of consumer surplus, not a costless adjustment. We therefore present two other complementary welfare measures that progressively account for this distinction.

2. Deadweight Loss: To account for the welfare cost of foregone consumption, we decompose the spending response into a price burden and a deadweight loss. The price burden captures how much more households pay for goods they continue to buy:

$$\text{PriceBurden}_{i,h} = \text{Spend}_{i,h}^{\text{pre}} \times |\hat{\beta}_{\text{price}}^{g(i)}| \times \text{TariffExposure}_{h}^{\text{post}} \tag{6}$$

The deadweight loss captures the consumer surplus lost from units no longer purchased:

$$\text{DWL}_{i,h} = \frac{1}{2} \times \text{Spend}_{i,h}^{\text{pre}} \times |\hat{\beta}_{\text{price}}^{g(i)} \times \text{TariffExposure}_{h}^{\text{post}}| \times |\hat{\beta}_{\text{qty}}^{g(i)} \times \text{TariffExposure}_{h}^{\text{post}}| \quad (7)$$

where $\hat{\beta}_{\text{qty}}^{g(i)}$ is the income-group-specific quantity coefficient. The total deadweight loss is:

$$\text{WelfareLoss}_{i,h}^{\text{DWL}} = \text{PriceBurden}_{i,h} + \text{DWL}_{i,h} \quad (8)$$

This approximation is valid under the assumption that foreign supply is perfectly elastic, i.e., foreign exporters do not absorb any of the tariff cost so that the welfare is purely a consumer-side object. This assumption is supported by recent evidence on 2025 tariffs that 90–96% of tariff-induced price changes are absorbed domestically, see Amiti et al. (2026); Hinz et al. (2026).[9]

3. Constant Elasticity of Substitution (CES) Equivalent Variation: As a robustness check, we compute the equivalent variation under a CES demand structure, following the sufficient-statistics approach of Fajgelbaum et al. (2020):

$$\text{EV}_{i,h} = \text{Spend}_{i,h}^{\text{pre}} \times \left[(1 + \hat{\tau}_h)^{\frac{1}{1-\sigma_g}} - 1 \right] \quad (9)$$

where $\hat{\tau}_h = \exp(\hat{\beta}_{\text{price}}^{g(i)} \times \text{TariffExposure}_{h}^{\text{post}}) - 1$ is the tariff-induced price change in levels, and $\sigma_g = |\hat{\beta}_{\text{qty}}^{g(i)} / \hat{\beta}_{\text{price}}^{g(i)}|$ is the elasticity of substitution backed out from the ratio of the income-specific quantity and price coefficients. This measure requires only the observed price change and the demand elasticity without any supply-side assumptions beyond the observed price change and captures higher-order welfare effects that the linear deadweight loss approximation might miss.

For all three measures, household-level welfare is obtained by summing across all HS4 codes: $\text{WelfareLoss}_i = \sum_h \text{WelfareLoss}_{i,h}$. This approach implicitly weights tariff exposure by each household's spending pattern and allows behavioral responses to vary by income group.

Each measure answers a different question. The net spending effect (Equation 5)

[9]Note that the deadweight loss measure captures consumer welfare losses only and understates the total domestic welfare cost, which additionally includes reduced intermediary profits.

measures total behavioral disruption on how much households actually changed their expenditure. This is our headline empirical finding: consumers are actively adjusting their consumption in response to tariffs, and the adjustment is large and heterogeneous by income. The deadweight loss approximation (Equation 8) and the CES equivalent variation (Equation 9) are welfare measures anchored to the realized price change. Given the limited pass-through documented in Tables 3 and 5, we expect that the deadweight loss and the CES EV are smaller than the net spending effect.

We first present the net spending effect by income group in Table 8. High-income households bear the largest absolute effects at $84 per month, reflecting both higher baseline spending and stronger behavioral responses to tariffs. Low-income households experience monthly effects of $27, while middle-income households face effects of $32 per month. Mean effects consistently exceed median effects across all income groups, indicating right-skewed distributions with some households experiencing particularly large impacts. Overall, these estimates translate to an average annual net spending change of approximately $529.

TABLE 8: Net Spending Loss from Tariffs by Income Group

Income Group	N HHs	Mean ($/month)	Median ($/month)	Mean ($/year)	Percent (% of Mean Spend)
Low	28,151	27.04	18.22	324.46	2.68
Middle	64,943	31.84	24.27	382.07	2.64
High	31,739	84.24	61.30	1,010.83	4.12
Overall	124,833	44.07	32.32	528.90	3.24

Notes: Net spending effects are calculated using Equation (5) with income-group-specific spending coefficients from Table 6. "% of Mean Spend" is the ratio of mean annual net spending effect to mean annual spending on tariff-affected goods. Mean annual spending of households are: Low ($12,090.61); Middle ($14,153.76); High ($24,553.85); Overall ($16,334.54). Overall row shows weighted averages using household counts as weights.

The distributional pattern reveals that when expressed as a share of spending, high-income households face the largest proportional burden at 4.1%, followed by low-income households at 2.7%, with middle-income households bearing the smallest share at 2.6%. This pattern reflects the combination of two forces. First, price pass-through is highest for low- and high-income groups compared to middle-income households. Second,

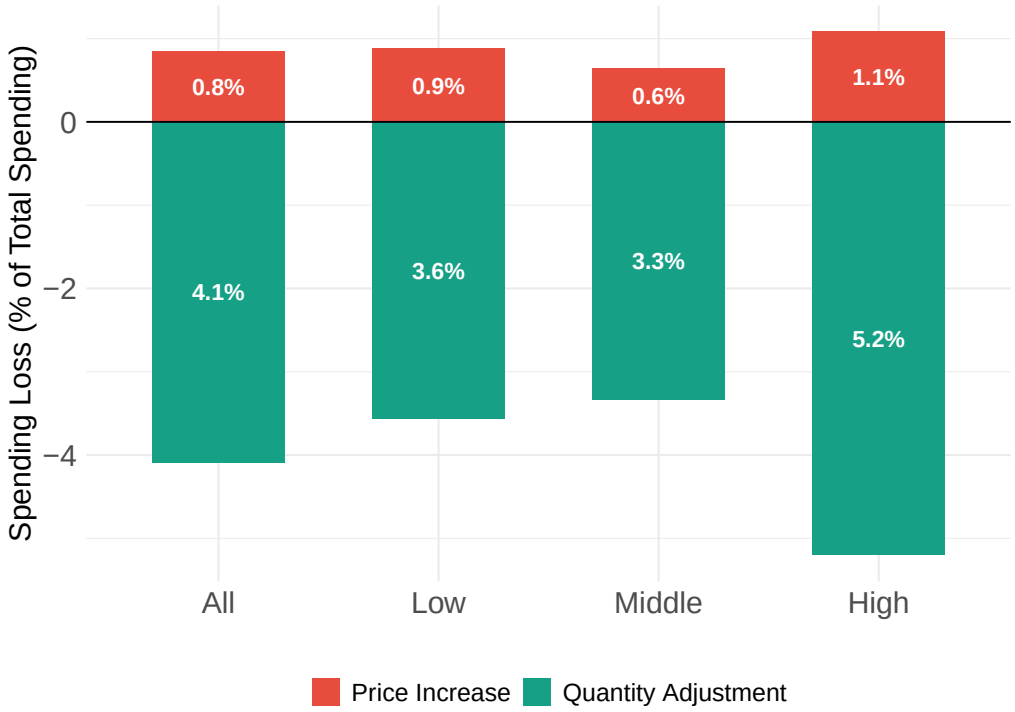
quantity responses are strongest for high-income households, intermediate for low-income households, and weakest for middle-income households. These results imply that middle-income households, who face moderate price increases but adjust quantities least, bear the smallest proportional net spending effect.

Figure 2 decomposes the net spending effect into its price burden and quantity offset components. The price burden accounts for approximately 0.6–1.1% of annual spending across income groups. A noteworthy point is that low-income households' price burden is close to high-income households, which was evident in the price pass-through results presented in Tables 5 and 7. Households substantially offset this cost through quantity adjustment, reducing purchases by 3.3–5.2% of annual spending. The quantity offset exceeds the price burden for all income groups, meaning that on net, household expenditure on tariff-affected goods declines. High-income households exhibit both the largest price burden and the largest quantity offset, consistent with their stronger behavioral responses documented in Section 4.2. Importantly, this quantity offset should not be interpreted as a welfare gain: as the deadweight loss and CES EV calculations show below, households are substituting away from preferred goods precisely because tariffs have made them more expensive, and this substitution entails a loss of consumer surplus.

The finding that the quantity offset substantially exceeds the price burden across all income groups is consistent with evidence from Barnichon and Singh (2025), who show that large tariff increases in pre-World War II episodes depressed economic activity and lowered inflation rather than raising it. Their interpretation emphasizes the demand-depressing role of tariff-induced uncertainty, which can curtail consumption beyond what realized price changes alone would predict. Our household-level evidence provides a micro-foundation for this pattern: the price burden from tariff pass-through accounts for only 0.6–1.1% of spending, yet total spending reductions reach 3.3–5.2%, implying that the bulk of the consumption adjustment operates through channels other than realized price increases.

To understand which types of goods drive the net spending effects, we decompose total welfare effects by essentiality: essentials and nonessentials. To allow the behavioral response to vary by both income group and product category, we estimate separate regressions, in the spirit of Equation (4), for each of the six income × essentiality cells, each

FIGURE 2: Welfare Decomposition: Price Burden and Quantity Offset



Notes: The figure decomposes the net spending effect into the price burden and the quantity offset (Equation (5)), expressed as a percentage of mean annual spending on tariff-affected goods. The price burden (below zero) represents the additional cost from tariff-induced price increases. The quantity offset (above zero) represents the expenditure reduction from behavioral adjustment. Values are computed using income-specific coefficients from Tables 5 and 6.

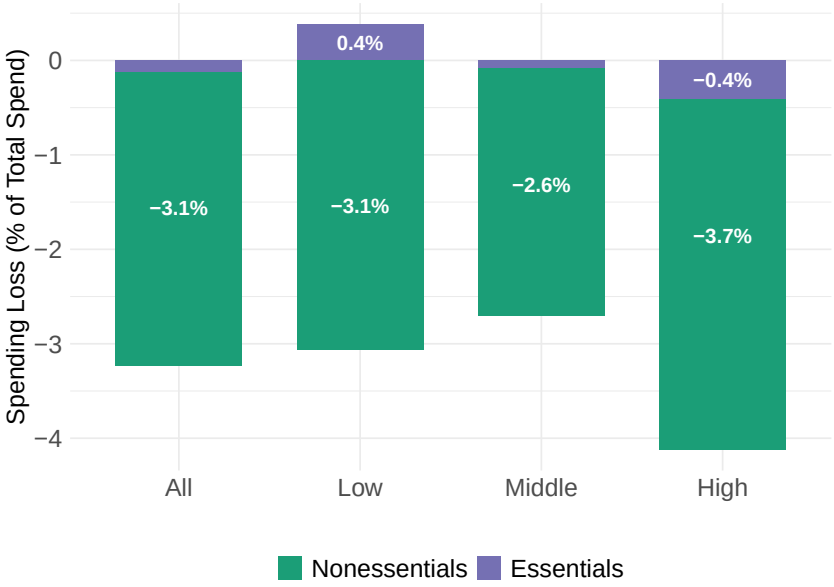
with its own set of time and panel fixed effects. This avoids imposing a common time trend across income groups within a sector and ensures that the decomposition reflects actual differential responses rather than assumed pre-tariff spending shares.[10] The sector shares from these regressions are then applied to the headline welfare totals from Table 8, so that the decomposition sums exactly to the main specification.

Figure 3 presents the decomposition of the mean monthly net spending effect by income group. Nonessentials account for the dominant share of spending reductions across all income groups. This asymmetry reflects both differential tariff exposure and differ-

[10] An alternative approach would be to estimate a single regression with full interactions between tariff exposure, the post indicator, income group, and sector type. However, this forces all cells to share time fixed effects, which we show in robustness checks can generate substantial bias when income groups have different secular spending trends. The separate regressions avoid this contamination at the cost of estimating each cell with fewer observations.

ential behavioral responses. Nonessential goods face average tariff exposure of approximately 13.8 percentage points, compared to 9.25 percentage points for essentials, a gap of roughly 4.5 percentage points. Beyond this difference in tariff exposure, the behavioral responses documented in Table 4 differ sharply across the two categories: essential goods show no statistically significant spending or quantity response to tariff exposure, whereas nonessential goods exhibit spending and quantity declines of approximately 0.28 percent per percentage point of tariff exposure. The composition of effects is therefore similar across income groups, as confirmed by Table 7: nonessentials drive the bulk of spending losses at every income level, while essentials contribute modestly at most.

FIGURE 3: Decomposition of Average Monthly Net Spending Change by Essentiality



Notes: The figure decomposes the mean monthly net spending effect into essentials (Grocery, Household, Health & Beauty) and nonessentials (all other sectors). Sector shares are estimated from separate regressions for each income group × essentiality cell and applied to the headline totals from Table 8. Percent values in each bar indicate total mean percent monthly net spending effect for the respective income group. The combined effects equal the values presented in Table 8. For decomposition by durability (durables versus nondurables), see Figure H.1 in Appendix H.

Table 9 compares the three welfare measures. The net spending effect substantially exceeds both the deadweight loss approximation and the CES equivalent variation across all income groups. For low-income households, the net spending effect is \$27 per month, while the deadweight loss measure is \$9 and the CES EV is \$5.31. For high-income

households, the corresponding figures are $84, $23, and $8. The pattern is similar for middle-income households. The gap reflects the fact that consumer price pass-through is limited so welfare measures anchored to realized price changes are correspondingly small. However, spending and quantity responses are large, indicating that households are adjusting consumption well beyond what realized price changes alone would predict.

TABLE 9: Comparison of Welfare Losses Income Group

	Monthly ($)			% of Spending		
Income Group	Net Spend	DWL	CES EV	Net Spend	DWL	CES EV
Low	27.04	9.02	5.31	2.68	0.90	0.53
Middle	31.84	7.69	2.52	2.70	0.65	0.21
High	84.24	22.87	8.12	4.12	1.12	0.40
All	44.08	11.85	4.57	3.24	0.87	0.34

Notes: Net spending effect computed using Equation (5); deadweight loss (DWL) computed using Equations (6)–(8); CES equivalent variation (EV) computed using Equation (9). All measures use income-specific coefficients from Tables 5 and 6. "% of Spending" is the ratio of mean annual welfare loss to mean annual spending on tariff-affected goods.

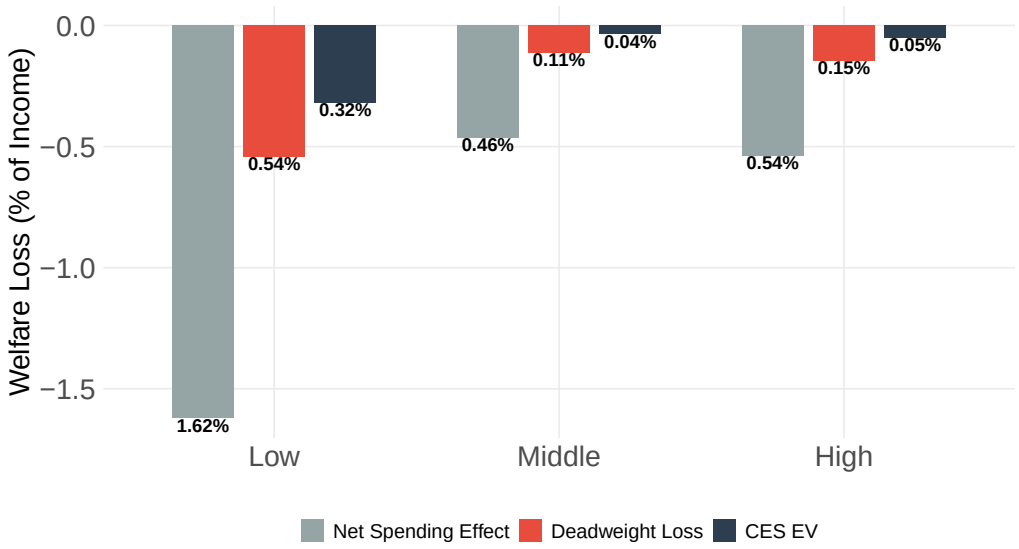
The divergence between the net spending effect and the price-anchored welfare measures has a natural interpretation. The deadweight loss and CES EV measure the consumer surplus cost attributable to price increases that have already materialized. The net spending effect captures the full behavioral response, including quantity adjustments driven by anticipated future price increases or uncertainty about tariff policy. This result is in line with the findings of the Candia et al. (2026) that tariff uncertainty curbs household purchases. The fact that quantity reductions substantially exceed what realized price increases would predict is consistent with consumers responding to the *expected* rather than the *realized* tariff burden. This interpretation is reinforced by the substitution analysis in Section 6, which documents active trading down and cross-category reallocation even in product groups where measured price pass-through is modest. In this sense, the deadweight loss and CES EV provide a lower bound on consumer welfare costs attributable to realized price changes, while the net spending effect captures the broader consumption disruption that tariff policy induces.

Although high-income households appear to bear the largest burden when welfare losses are expressed as a share of spending, the picture reverses when losses are measured

relative to *income*. Figure 4 presents the three welfare measures as a share of approximate household income, using bracket midpoints: $20,000 for low-income, $82,500 for middle-income, and $187,500 for high-income.[11]

Under the net spending measure, low-income households lose 0.54% of income, compared to 0.15% for middle-income and 0.05% for high-income households. Even the price-anchored measures exhibit a regressive pattern: the deadweight loss represents 0.36% of low-income households' income versus 0.15% for middle-income and 0.05% for high-income households. In other words, while high-income households reduce their spending by more in dollar terms, they can readily afford to do so; low-income households adjust by less but bear a proportionally larger cost relative to their resources. This regressive nature of the tariffs is in line with the findings of Acosta and Cox (2024).

FIGURE 4: Welfare Losses as Share of Approximate Income



Notes: The figure presents three welfare measures: net spending effect, deadweight loss approximation, and CES equivalent variation as a percentage of approximate household income. Income is approximated using bracket midpoints: $20,000 (low), $82,500 (middle), $187,500 (high). The high-income midpoint is a lower bound on mean income in this group, as the top bracket ($250,000+) has no upper bound. See Equations (5)–(9) for measure definitions.

[11] The high-income midpoint of $187,500 is imprecise because this group includes all households earning above $125,000, with the top bracket capturing $250,000 and above with no upper bound. If actual mean incomes in this group are substantially higher than $187,500, the high-income burden as a share of income would be even smaller, further reinforcing the regressive pattern.

6 Substitution

The previous section established the large quantity and hence adjustments by households as a response to tariffs, despite small price pass-through. This section examines how households adjust their spending in response to tariffs, and whether these adjustment margins differ across the income distribution. We consider two margins of adjustment: an extensive margin, where households shift spending away from tariff-exposed product categories, and an intensive margin, where households substitute toward cheaper items within the same category.

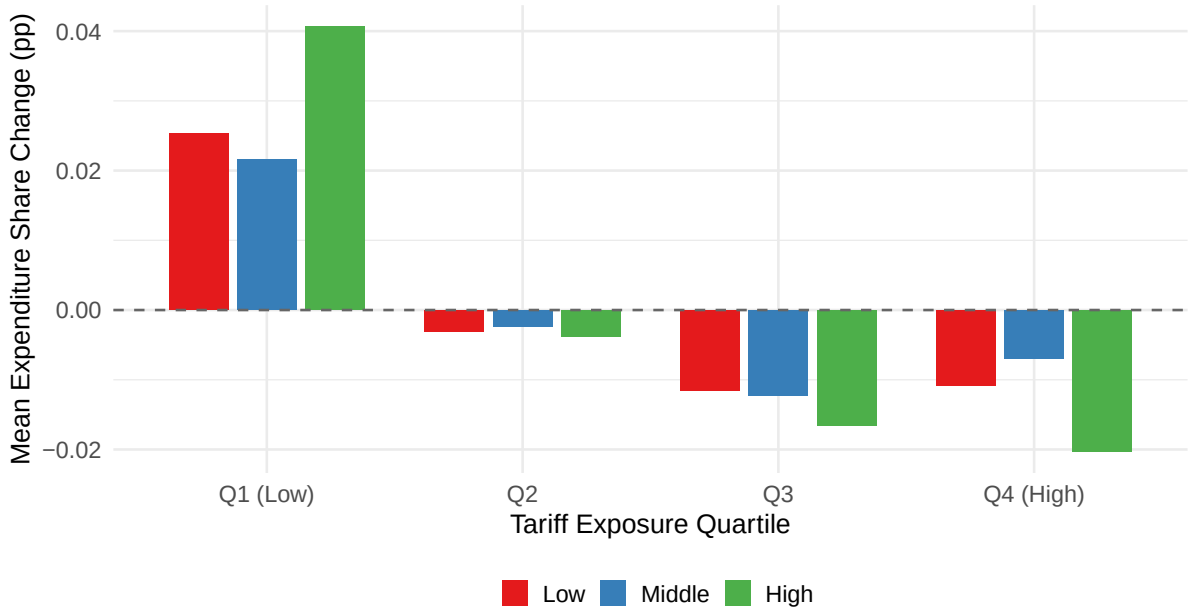
The results indicate that both margins are active, but their relative importance varies systematically with household income. Namely, although all income groups exhibit similar aggregate spending reductions per unit of tariff exposure, the underlying behavioral mechanisms are distinct. While low-income households primarily trade down to cheaper items within the categories they continue to purchase (intensive margin), high-income households significantly reallocate spending across product categories (extensive margin) in addition to adjusting in the intensive margin. The welfare implications of these different adjustment margins also differ: exiting a discretionary category is a qualitatively less costly adjustment than trading down within essentials, where substitution options are more constrained.

6.1 Cross-Category Substitution (Extensive Margin)

First, we test whether households shifted spending away from tariff-exposed product categories, and whether the magnitude of reallocation differs by income. As a start, Figure 5 provides descriptive evidence of cross-category substitution by comparing expenditure shares before and after the tariff shock. For each HS4 product code, we compute the change in its expenditure share between the pre- and post-tariff periods, then group products into quartiles of tariff exposure and average these share changes within each income group. Across all income groups, expenditure shares increase for low-tariff goods in the first quartile and decline for high-tariff goods in the third and fourth quartiles, consistent with households reallocating spending away from tariff-exposed categories. The pattern of declining shares in higher quartiles is broadly similar across income groups.

The most notable finding is that high-income households exhibit larger share gains in the first quartile compared to their lower-income counterparts.

FIGURE 5: Expenditure Share Changes by Tariff Exposure Quartile



Notes: The figure plots mean expenditure share changes (in percentage points) from the pre- to post-tariff period, by tariff exposure quartile and income group. Q1 corresponds to HS codes with the lowest tariff exposure; Q4 corresponds to the highest. Negative values indicate households shifted spending away from those categories.

To approach the question at hand more rigorously, we estimate the following regression by defining $s_{h,g,t}$ as the expenditure share of HS4 code h in income group g's total spending in month t:

$$\ln s_{h,g,t} = \alpha_{h\times g} + \delta_{h\times g,m(t)} + \gamma_t + \beta_g \left(\tau_h^{\text{post}} \times \text{Post}_t\right) + \varepsilon_{h,g,t}. \tag{10}$$

separately for each income group g. The HS-by-income fixed effects $\alpha_{h\times g}$ absorb time-invariant differences in baseline expenditure shares across income groups for the same product, and $\delta_{h\times g,m(t)}$ are HS4-by-income-by-calendar-month fixed effects. The term τ_h^{post} denotes the post-tariff tariff exposure of HS4 code h. The coefficient $\hat{\beta}_g$ identifies the differential change in spending shares for high- versus low-tariff goods within income group g after the tariff shock. A negative coefficient implies households shifted spending

away from tariff-exposed categories.

TABLE 10: Cross-Category Substitution by Income Group

	(1) Low	(2) Middle	(3) High
Tariff Exp. × Post	−0.10	−0.09	−0.20**
	(0.08)	(0.08)	(0.09)
HS × Income FE	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes
HS × Income × month	Yes	Yes	Yes
Observations	4,123	4,127	4,128
Adjusted R^2	0.98	0.98	0.98

Notes: The dependent variable is the log expenditure share of HS code h in income group g's total spending in month t. Coefficients are multiplied by 100 for readability. The specification follows Equation (10), estimated separately by income group. Standard errors clustered at the HS4 code level are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 10 presents the regression results from Equation (10). High-income households exhibit the only economically and statistically significant reallocation away from tariff-exposed categories. This result indicates that high-income households respond to tariffs in part by reallocating spending across product categories, consistent with greater flexibility to substitute toward lower-tariffed or untariffed alternatives. The insignificant coefficient for low-income households suggests they have limited scope to shift spending across categories, potentially because their consumption is more concentrated in essential goods with fewer substitutes, a well-documented pattern in the consumption inequality literature (Attanasio and Pistaferri, 2016; Aguiar and Bils, 2015). To summarize, while all income groups reduce spending within tariff-affected categories, as documented in Table 6, only high-income households exhibit statistically significant reallocation across categories, i.e. in the extensive margin.

6.2 Within-Category Item Substitution (Intensive Margin)

The previous subsection explores the extensive margin adjustments by households as a response to tariffs and shows that only high-income households change spending behavior in the extensive margin. We now ask a different question: conditional on continuing to purchase within a given category, do households substitute toward cheaper items?

Because the item-level data are aggregated across households, the within-category tests in this subsection capture market-level substitution patterns rather than income-group-specific behavior.

For each item j within HS4 code h, we classify items into price tiers based on their pre-tariff (pre-February 2025) average price relative to other items in the same HS4 code. Let p_j^{pre} denote item j's mean pre-tariff price and define its within-HS4 price percentile as

$$\pi_j = \frac{\text{rank}(p_j^{\text{pre}} \mid j \in h)}{N_h}, \tag{11}$$

where N_h is the number of distinct items in HS code h. We restrict the sample to HS4 codes with at least five categories, ensuring meaningful within-category variation.

First, we assign items to tercile-based price tiers with cheap ($\pi_j \leq 1/3$), middle, and expensive ($\pi_j > 2/3$), and compute the revenue share of each tier k within HS code h in month t:

$$s_{h,k,t}^{\text{tier}} = \frac{\sum_{j \in (h,k)} r_{j,t}}{\sum_{j \in h} r_{j,t}}, \tag{12}$$

where $r_{j,t}$ is item j's revenue (transactions × price). We then estimate

$$\ln s_{h,k,t}^{\text{tier}} = \alpha_{h \times k} + \gamma_t + \delta_{h,m(t)} + \sum_k \beta_k \left(\tau_h^{\text{post}} \times \text{Post}_t \times \mathbf{1}[\text{Tier}_j = k] \right) + \varepsilon_{h,k,t}, \tag{13}$$

with HS-by-tier fixed effects, month fixed effects, and HS-by-calendar-month effects. A positive $\hat{\beta}_{\text{Cheap}}$ (negative $\hat{\beta}_{\text{Expensive}}$) indicates that cheap items gained (expensive items lost) revenue share within high-tariff HS4 codes after the tariff shock, providing direct evidence of within-category substitution toward cheaper varieties.

Table 11 reports the results. Cheap items gained significant revenue share within tariff-exposed HS4 codes, with a coefficient of 0.66, while expensive items lost share by a nearly symmetric magnitude (−0.62). Middle-tier items also gained share, though by less than cheap items. The near-symmetry between cheap-tier gains and expensive-tier losses is consistent with a zero-sum reallocation of revenue shares within HS codes: tariffs induced consumers to substitute away from expensive varieties toward cheaper alternatives within the same product category.

Next, to avoid arbitrary tercile cutoffs, we also estimate the substitution pattern

TABLE 11: Within-HS Substitution: Revenue Share Response by Price Tier

	$\ln s^{\text{tier}}_{h,k,t}$
Tariff Exp. × Post × Cheap	0.66***
	(0.08)
Tariff Exp. × Post × Middle	0.24***
	(0.05)
Tariff Exp. × Post × Expensive	−0.62***
	(0.06)
HS × Tier FE	Yes
Year-Month FE	Yes
HS × month	Yes
Observations	12,362
Adjusted R^2	0.96

Notes: The dependent variable is the log revenue share of each price tier within HS code × month. The specification follows Equation (13). Items are classified into tercile-based price tiers using pre-tariff (pre February 2025) average prices. Standard errors clustered at the HS4 code level are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

continuously at the item level. Let $s_{j,t}$ denote item j's revenue share within its HS4 code in month t. We estimate

$$\ln s_{j,t} = \alpha_j + \gamma_t + \delta_{j,m(t)} + \beta_1 \left(\tau_h^{\text{post}} \times \text{Post}_t\right) + \beta_2 \left(\tau_h^{\text{post}} \times \text{Post}_t \times \pi_j\right) + \varepsilon_{j,t}, \tag{14}$$

where α_j are item fixed effects and $\delta_{j,m(t)}$ are item-by-calendar-month effects. The coefficient $\hat{\beta}_2$ traces how the tariff-induced share reallocation varies across the within-HS price distribution. A negative $\hat{\beta}_2$ implies that, within high-tariff categories, cheaper items (low π_j) gained market share at the expense of more expensive items.

Table 12 reports the results from over 63.5 million item-month observations. The coefficient of 1.40 on Tariff Exp. × Post captures the baseline tariff-induced share gain for the cheapest items ($\pi_j = 0$). For example, in an HS4 code facing a 10 percentage point tariff, the cheapest items' revenue share increases by approximately $1.40 \times 10 = 14$ log points *more* than similarly cheap items in non-exposed categories.

The interaction coefficient of −0.56 shows that this advantage diminishes linearly with price. For each step up in the within-category price distribution, the tariff-induced gain in market share falls by 0.56 log points per unit of tariff exposure. In an HS4 code

TABLE 12: Within-HS Item Substitution: Continuous Specification

	$\ln s_{j,t}$
Tariff Exp. × Post	1.40^{***}
	(0.33)
Tariff Exp. × Post × Price Percentile	-0.56^{***}
	(0.10)
Item FE	Yes
Year-month FE	Yes
Item × month FE	Yes
Observations	63,573,069
Adjusted R^2	0.83

Notes: The dependent variable is the log revenue share of item j within its HS code in month t. The specification follows Equation (14). Price percentile π_j is defined in Equation (11) and ranges from 0 (cheapest) to 1 (most expensive). All specifications include item-by-calendar-month fixed effects. Standard errors clustered at the HS4 code level are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

facing a 10 percentage point tariff, moving from the cheapest to the most expensive item reduces the tariff-induced share gain by $0.56 \times 10 = 5.6$ log points. The most expensive items ($\pi_j = 1$) see a differential effect of $(1.40 - 0.56) \times 10 = 8.4$ log points for the same 10 percentage point tariff, compared to 14 log points for the cheapest items. Overall, since shares within an HS4 code must sum to 100%, this wedge represents a reallocation from expensive to cheap items within tariff-exposed categories, relative to the control group. This finding is consistent with consumers trading down to save money.

The within-category (intensive margin) substitution documented above is estimated at the market level, pooling across all households. To examine whether the intensity of within-category trading down varies by income, we exploit the wedge between unit values and fixed-basket price indices. The Fisher Price Indices used in Section 4 hold the item basket fixed, while unit values reflect actual purchasing behavior including item switching within HS codes. The wedge between the two measures therefore captures within-category quality adjustment. For each HS4 code h, income group g, and month t, we compute

$$Q_{h,g,t} = \ln\left(\frac{\text{UV}_{h,g,t}}{\text{UV}_{h,g,0}}\right) - \ln\left(\frac{\text{FPI}_{h,g,t}}{\text{FPI}_{h,g,0}}\right), \tag{15}$$

where $\text{UV}_{h,g,t}$ is the unit value (total expenditure divided by total quantity) and $\text{FPI}_{h,g,t}$

is the income-specific Fisher Price Index, both indexed to the base period $t = 0$ (January 2024). A negative quality wedge indicates that unit values grew less than the fixed-basket price index, meaning that households switched to cheaper items within the category. We estimate

$$Q_{h,g,t} = \alpha_{h,g,m} + \sum_{g} \beta_g \left(\tau_h \times \text{Post}_t \times \mathbf{1}[G = g]\right) + \varepsilon_{h,g,t}, \tag{16}$$

where $Q_{h,g,t}$ is the quality wedge measuring within-category item substitution; $\alpha_{h,g,m}$ are HS4 × income group × month-of-year fixed effects that control for seasonal purchasing patterns specific to each product-income cell; τ_h is the post-period tariff exposure (February 2025 onward) for HS4 code h; Post_t is an indicator for months after February 2025; and $\mathbf{1}[G = g]$ indicates income group $g \in \{\text{Low, Middle, High}\}$. The coefficients β_g capture the differential quality downgrading response to tariffs across income groups, with standard errors clustered at the HS4 level. Negative values of β_g indicate that higher tariff exposure led to greater within-category trading down to cheaper items.

TABLE 13: Quality Wedge Regression Results by Income Group

	Quality Wedge ($Q_{h,g,t}$)
Tariff Exposure × Post × Low Income	−0.124***
	(0.045)
Tariff Exposure × Post × Middle Income	−0.131***
	(0.039)
Tariff Exposure × Post × High Income	−0.132***
	(0.040)
HS × Income FE	Yes
Year-month FE	Yes
HS × month FE	Yes
Observations	11,737
Adjusted R^2	0.48

Notes: The dependent variable is the quality wedge defined in Equation (15). Coefficients are multiplied by 100 for readability. The specification follows Equation (16). Standard errors clustered at the HS4 code level are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 13 reports the regression results from Equation (16). All three income groups exhibit negative and statistically significant coefficients, confirming that tariff exposure is associated with quality downgrading across the income distribution. These results suggest that, for example, if an HS code faced a 10 percentage point increase in tariffs,

the high-income coefficient implies that the quality wedge decreases by approximately 1.3 percentage points, meaning their unit values grow around 1.3 percentage points less than the fixed-basket prices, indicating they shift toward cheaper items. The coefficients are similar across income groups, with all three showing quality downgrading of comparable magnitude. All in all, the consistency of the negative quality wedge across all three groups, combined with the strongly significant market-level results in Tables 11 and 12, provides robust evidence that quality downgrading is a pervasive response to tariffs across the income distribution.

Comparing the cross-category results in Table 10 with the within-category quality wedge in Table 13 reveals distinct adjustment margins across the income distribution. High-income households respond to tariffs on both margins: they significantly reallocate spending away from tariff-exposed categories (significant extensive margin in Table 10) and engage in significant within-category adjustment (Tables 11 and 12) and quality downgrading (Table 13). This pattern is consistent with high-income households having the flexibility both to exit affected categories and to trade down within them. Low-income households, by contrast, show no significant cross-category reallocation but do exhibit significant quality downgrading, suggesting that their primary adjustment channel is trading down to cheaper items within the categories they continue to purchase. Middle-income households display a similar pattern to low-income households.

7 Conclusion

This paper uses transaction-level household data to estimate how U.S. tariffs in 2025 affected consumer prices, quantities, and welfare. While our data capture everyday retail purchases rather than the full consumption basket, they provide a granular view of how tariffs reshape household spending on the goods most directly affected by trade policy.

The central finding is that tariffs reduce consumption primarily through quantities. Retail price pass-through is modest at 6 percent, yet spending and quantities decline significantly, by 0.32% and 0.28% per percentage point of tariff exposure, respectively, some of which is driven by large China-specific tariff shocks. This pattern is consistent with the existing evidence that tariffs increase retail prices and dampen economic activity,

in our case through household spending, such that large tariff increases depress demand through uncertainty channels rather than raising prices.

The distributional consequences are substantial. High-income households cut spending the most in dollar terms, concentrated in discretionary categories. Low-income households lose less in absolute terms, but bear a disproportionate burden on food and essentials, and face sharper costs relative to income. The adjustment mechanisms also differ: while all households trade down to cheaper items within the categories they continue to purchase, low- and middle-income households rely primarily on this intensive-margin adjustment, whereas high-income households also reallocate spending across categories. This means that while all households find ways to cope with tariffs, the options available to lower-income households (buying cheaper versions of the same goods rather than cutting discretionary spending) represent a more constrained form of adjustment.

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Online Appendix

A More Detail on the Numerator Household Panel

This section provides technical details on the Numerator data collection, panel composition, weighting methodology, and data structure.

A.1 Data Collection and Panel Composition

Numerator collects purchase data through a mobile app called Receipt Hog, which enables consumers to upload photographs of paper receipts, connect email accounts for automatic digital receipt collection, and link retail loyalty programs (including Amazon, Walmart, and similar platforms). The only requirement from panelists is to own a mobile phone with a camera. Participants receive approximately $10 monthly in compensation through gift cards or direct payment. The panel has grown to include up to 200,000 panelists as of 2025, up from approximately 150,000 in 2024.

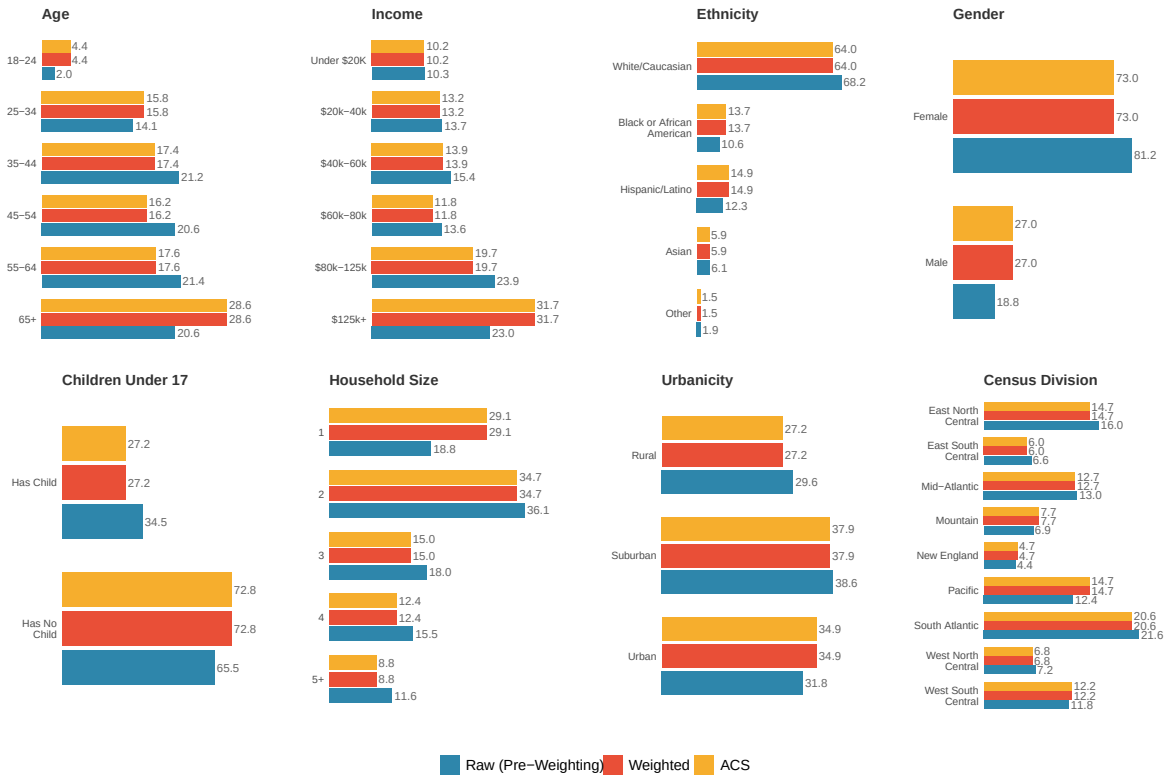
Our analysis uses Numerator's "Static Panel" households, a subset of the broader panel selected for consistent reporting behavior. Static Panelists must meet the following criteria: (1) maintain active status for a minimum of 12 consecutive months, (2) submit purchases consistently across the period with no extended gaps in reporting, and (3) meet Numerator's internal quality thresholds for transaction completeness. The Static Panel designation is important because it enables accurate longitudinal tracking of household behavior without compositional changes that could confound difference-in-differences estimates. As of 2025, approximately 200,000 households qualify as Static Panelists, selected from a pool exceeding one million registered Receipt Hog users. Our analysis further restricts to the 124,883 households with complete data coverage from January 2024 through December 2025, ensuring balanced panel composition throughout the tariff implementation period.

A.2 Weighting and Calibration Methodology

Numerator applies a two-stage weighting procedure to ensure representativeness. The first stage applies demographic weights to align the sample with U.S. Census benchmarks

using raking (iterative proportional fitting) across eight demographic dimensions simultaneously: gender of head of household, age, ethnicity, household income, household size, presence of children under 18 living at home, Census division, and urbanicity. Figure A.1 compares the Numerator panel to American Community Survey (ACS) targets across these eight dimensions as of March 2025. The weighted panel matches ACS benchmarks within 2 percentage points for all dimensions. The close alignment between the weighted panel and ACS targets validates our spending measures as representative of the broader population.

FIGURE A.1: Numerator Panel Demographics



Note: Numerator Total Commerce Static Panel weighted as of March 2025. Values shown as percentages. Blue bars show Numerator panelists before applying demographic weights; red bars show the panel after demographic weights are applied; yellow bars shows the American Community Survey (ACS) implied demographics in 2024.

The second stage applies calibration weights (national_factor) to scale aggregate spending to match external benchmarks. Numerator calibrates total dollar spend to the following sources: (1) Census Bureau Retail Sales (excluding motor vehicles and parts), (2)

public company filings (10-K and 10-Q reports from major retailers), (3) direct retail relationships and partnerships, and (4) third-party data partnerships (e.g., location data providers). Additionally, for Static Panel households, Numerator applies a trend factor adjustment to account for missing buyers within product categories, ensuring that the panel represents not just frequent purchasers but also occasional buyers in each category. All weights are updated quarterly to reflect changes in panel composition and external benchmark data.

A.3 Data Structure and Core Identifiers

The Numerator disaggregated data feed is structured around three core identifiers: (1) user_id: anonymized household identifier linking all purchases by a given household across time, (2) basket_id: shopping trip/transaction identifier representing a single receipt or online order, and (3) item_id: product identifier at the most granular level, where different package sizes and formats receive distinct IDs (e.g., a single can versus a 12-pack of the same beverage). The data are delivered in six primary tables that can be joined using these identifiers: fact_table (transaction and trip details), item_table (product dimension with brand, category, department, sector hierarchy), static_table (Static household roster), people_table (core demographics), people_attributes_table (extended attributes such as psychographics), and banner_table (retailer information). This relational structure allows flexible aggregation from the transaction-item level to household-month or category-month panels while preserving the underlying granularity for detailed analysis.

A.4 Income Measurement

Numerator panelists self-report their annual household income in categorical brackets rather than exact dollar amounts. The categories are: less than $20,000 through $100,000 in $10,000 increments, and $100,000 through $250,000 in $25,000 increments, with a top-coded category for $250,000 and above. This categorical approach minimizes measurement error from inaccurate reporting of exact earnings while retaining sufficient variation for distributional analysis. Household income information is updated through annual resurveys, with additional triggered updates when panelists indicate significant life

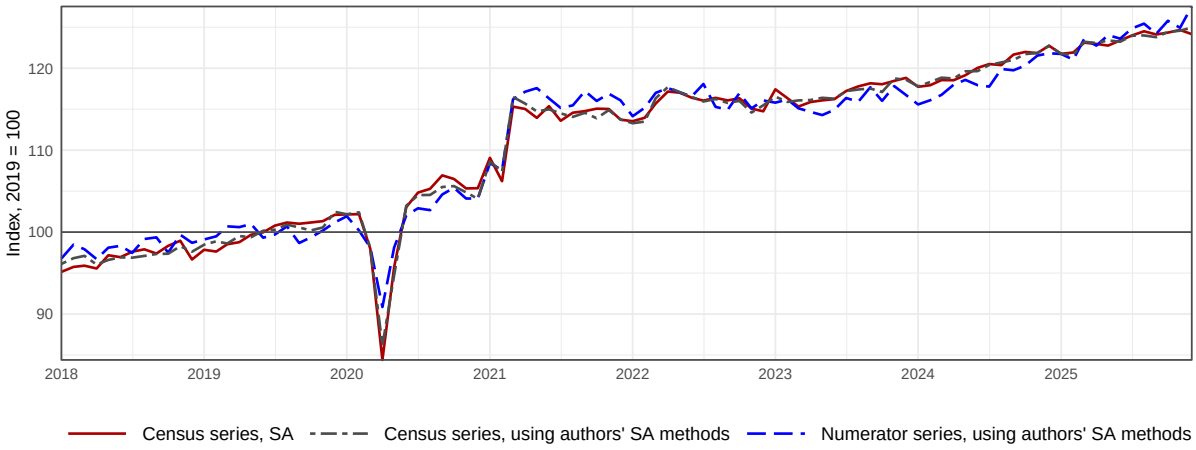
events such as employment transitions during quarterly check-ins (approximately every 3 months). When resurveyed, panelists indicate whether they have moved to a different income bracket. The annual update frequency with event-triggered adjustments ensures that measurement error from income changes remains within acceptable bounds for our 24-month analysis window.

B Proof of Concept

To validate that the Numerator household transaction data reliably captures the spending and price dynamics faced by U.S. consumers, we construct an aggregate retail sales spending measure and monthly price index spanning 2018 to 2025, and compare them with the officially published statistics. What follows in this section borrows from our earlier analyses in Hacıoğlu Hoke et al. (2024) and Hacıoğlu Hoke et al. (2025) where the reader can refer to for the details.

Figure B.1 plots three lines. The solid red line indicates the Census Bureau's published seasonally-adjusted total retail sales excluding motor vehicles and parts. The blue dashed line is the retail spending measure we construct from the Numerator data, which we seasonally adjust using the Census Bureau's X13-ARIMA-SEATS package. The gray dash-dotted line is the non-seasonally adjusted Census series that we then seasonally adjust using the same X13-ARIMA-SEATS methodology we use for Numerator data. The purpose of the gray line is to show that our seasonal adjustment methodology aligns closely with the Census methodology, and therefore, the differences between the Numerator seasonally-adjusted series and the official Census seasonally-adjusted series is not due to differences in seasonal adjustment. The correlation between the Numerator measure and the official seasonally-adjusted retail sales measure is 0.993. In summary, this analysis allows us to verify that the bottom-up construction of the Numerator data, directly from household purchases, closely matches the top-down construction of the Census retail sales series, captured from surveys of retail and food service establishments.

FIGURE B.1: Retail sales, total excluding motor vehicles and parts (seasonally adjusted) constructed using Census Bureau estimates and Numerator panel data

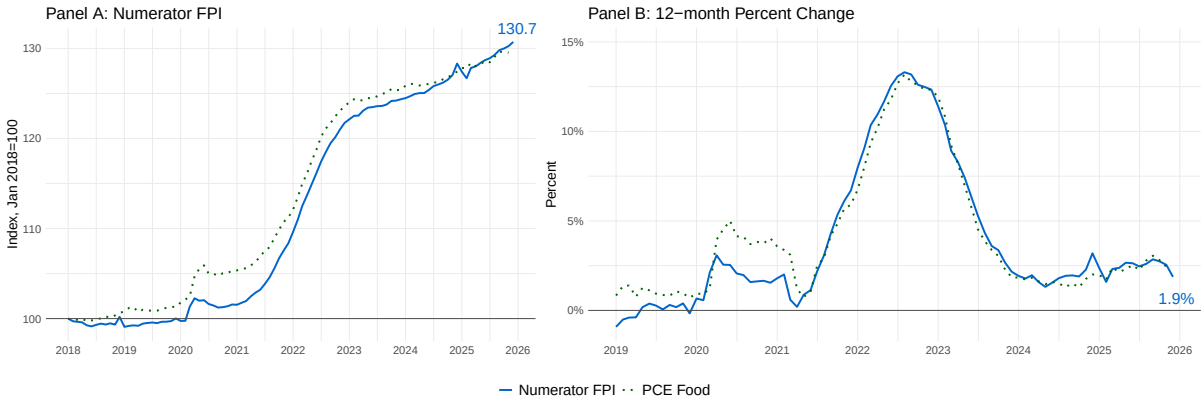


Note: The red solid line is the Census Bureau's seasonally-adjusted retail sales series excluding motor vehicles and parts. The blue dashed line is the retail spending measure we construct from the Numerator data, which we seasonally adjust. The gray dash-dotted line is the non-seasonally adjusted Census series that we then seasonally adjust. The data are monthly from January 2018 through December 2025. Authors' seasonal adjustment method uses X13-ARIMA-SEATS. All three lines are indexed to 100 in 2019.

Source: Census Bureau and Numerator, and authors' own calculations.

Figure B.2 compares the Numerator Fisher Price Index with the Bureau of Economic Analysis's (BEA) PCE deflator for food over 2018-2025, constructed as in Eq. (3). Panel A shows both measures moving in close alignment: stable through 2019, rising sharply from 2021 amid broad inflationary pressures (Shapiro, 2024; Braun et al., 2024), and reaching approximately 130 by mid-2025 which is a cumulative increase of roughly 30% since the base period.

FIGURE B.2: Numerator Fisher Price Index versus the PCE deflator for food



Note: Left panel: Numerator price index for January 2018 through December 2025; BEA PCE price index for food for January 2018 through November 2025. Fisher Price Index constructed using Numerator data in solid blue line, BEA's PCE for food in dotted green line; January 2018=100. The PCE data is seasonally adjusted by the BEA and the Fisher Price Index is seasonally adjusted using X13-ARIMA-SEATS. Right panel: Data for January 2019 through November 2025; the year-over-year percent change in the Fisher Price Index is constructed using Numerator data and shown as the solid blue line, the year-over-year percent change for the PCE Price Index for food is shown as the dotted green line.
Source: Numerator FPI calculated using Numerator Panel Data and based on authors' calculations. PCE Deflator for Food is from the Federal Reserve Bank of St. Louis FRED, series DFXARG3M086SBEA.

Panel B plots year-over-year changes, confirming the strong co-movement. Both series peak near 13% in 2021-2022 before decelerating, and both register a renewed pickup in food price inflation during 2025 relative to 2024. Reassuringly, the correlation coefficients reported in Table B.1 indicate that although PCE food inflation is the most correlated with the Numerator FPI, other measures of inflation show high correlation as well.

TABLE B.1: Correlation between inflation measures and Numerator FPI

PCE Food & Bev	**PCE Goods ex Auto**	**Core PCE**	**CPI**	**CPI Food**
0.96	0.81	0.85	0.85	0.85

Note: Correlation of 12-month percent change of Numerator FPI and the 12-month percent changes of reported inflation measures. Underlying monthly data capture January 2019 to November 2025.
Source: Numerator Panel Data and Federal Reserve Bank of St. Louis FRED, authors' calculations. PCE Deflator for Food is from the Federal Reserve Bank of St. Louis FRED: DFXARG3M086SBEA. Core PCE is from FRED: PCEPILFE. CPI is from FRED: CUSR0000SAC. CPI Food is from FRED: CPIUFDSL. The PCE goods deflator that excludes motor vehicles is based on author's calculations.

C Validation of Tariff Exposure Measure

When the origin of a product is unknown, the tariff exposure for HS code h is the import-share-weighted average of country-specific tariff rates: $\text{TariffExposure}_h = \sum_C \text{ImportShare}_h^C \times \tau_h^C$, as in Equation 1. where the import shares act as probability weights over possible origins. To assess the validatity of this approach, for a subset of items in our data, we can use Label Insight, a dataset of consumer packaged goods sold in the US that includes detailed product information such as country of origin linked to Universal Product Codes (UPCs).

The matching process between Numerator and Label Insight produces approximately 27,000 unique products, predominantly grocery items (over 75 percent), with Health & Beauty, Pet, and Household products comprising an additional 20 percent. Despite the concentration across a few sectors, we use country of origin information to construct a direct tariff exposure measure. For these products, the true tariff exposure is simply the tariff rate applied to the product's actual origin country, $\tau_h^{C_{\text{actual}}}$. This exercises helps assess whether our main results are robust to eliminating the import-share weighting assumption and helps to validate that the tariff exposure measure we construct is a reasonable proxy for the true origin composition of consumer purchases.

For each HS4 code h, we compute the actual tariff exposure as the spending-weighted average of origin-specific tariff rates across all origin-known imported products within h:

$$\text{ActualExposure}_h = \sum_C \omega_h^C \times \tau_h^C, \qquad \omega_h^C = \frac{\sum_{j \in (h,C)} r_j}{\sum_{j \in h} r_j} \tag{C.1}$$

where r_j is total 2024 revenue for product j, ω_h^C is the spending share of country C within HS code h among origin-known imported products, and τ_h^C is the average post-period tariff rate applied to country C for HS code h.

Figure C.1 plots actual against proxy tariff exposure for the 101 HS4 codes with origin-known imported products. The Pearson correlation is 0.63 and the Spearman rank correlation is 0.66, indicating a strong positive association. The mean proxy exposure (13.0 percentage points) closely matches the mean actual exposure (13.5 percentage points), with a mean difference of only 0.5 percentage points, suggesting the proxy is approximately unbiased. To the extent that measurement error in the proxy attenuates

coefficients, the baseline estimates reported in Sections 4 are conservative.

FIGURE C.1: Validation: Actual vs. Proxy Tariff Exposure

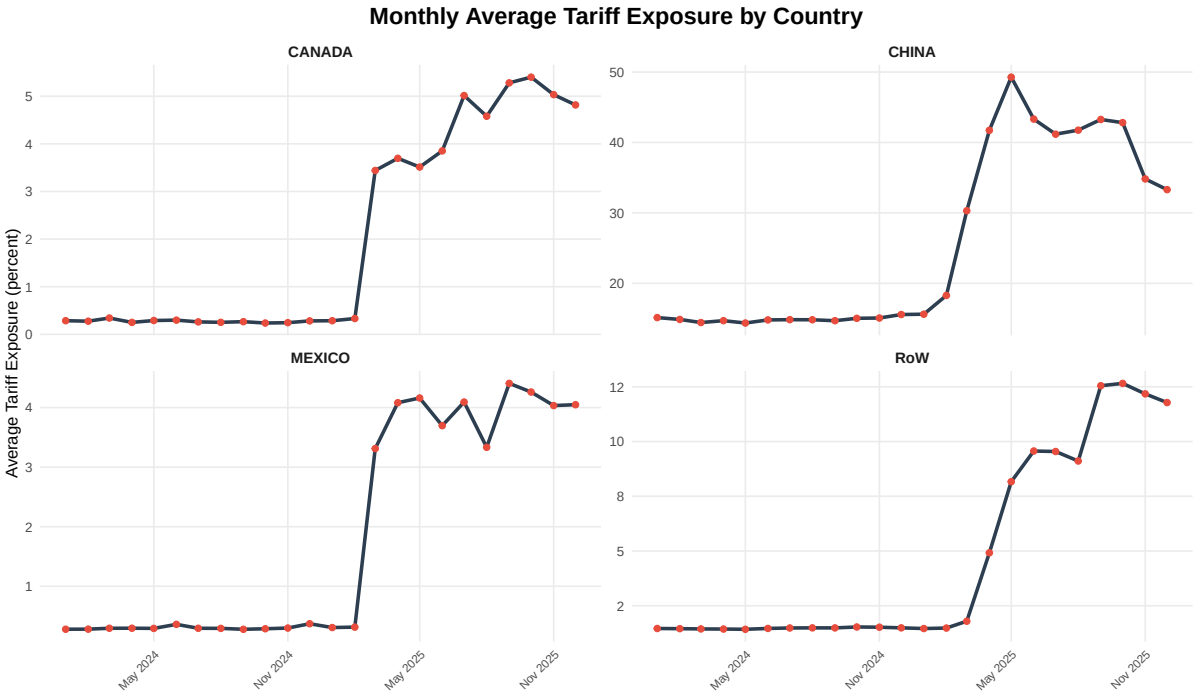


Notes: Each point represents one HS4 code ($N = 101$). The x-axis is the proxy tariff exposure, computed as the import-share-weighted average of country-specific tariff rates using 2024 USITC trade data (Equation 1). The y-axis is the actual tariff exposure, computed from products with verified country of origin using spending-weighted origin shares (Equation C.1). The dashed line is the 45-degree line; the solid line is the OLS fit. Pearson correlation: 0.63; Spearman rank correlation: 0.66.

D Tariff Exposure Measure by Sector, Country, Durability and Essentiality

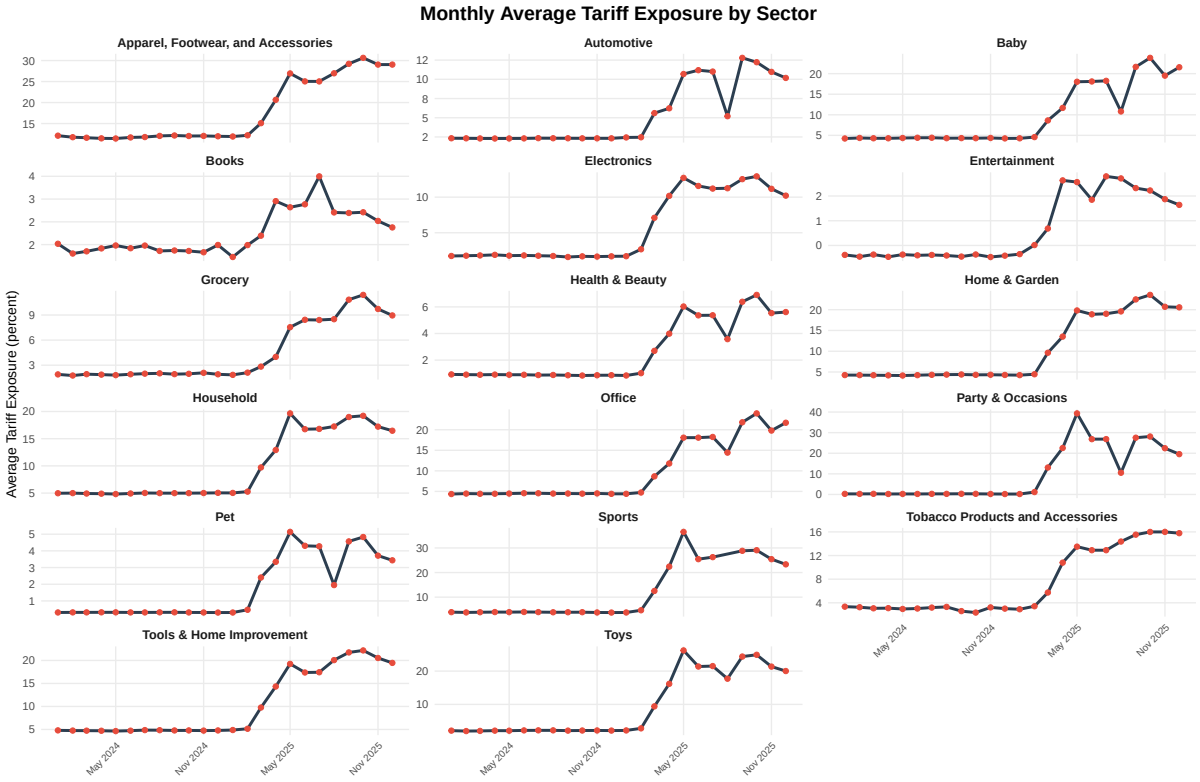
Figure D.1 shows the different tariffs exposures for each country from January 2024 to December 2025. Figure D.2 shows the different tariffs exposures each sector. Figures D.3 and D.4 present the tariff exposure by durability and essentiality as defined in Section 4.

FIGURE D.1: Average Tariff Exposure by Country



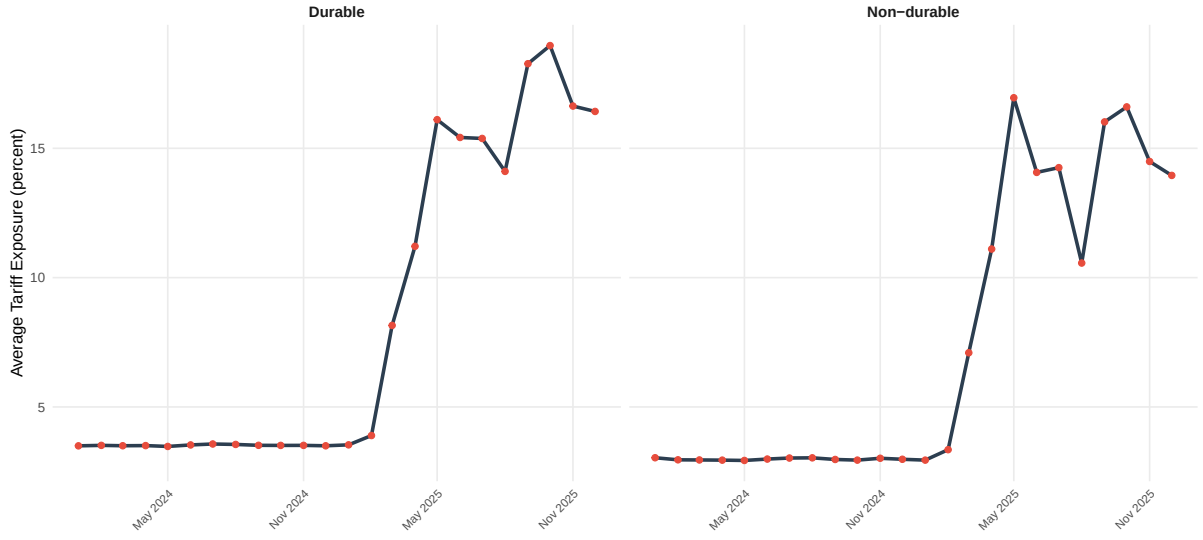
Note: This figure shows the monthly average tariff exposure over the sample period by country. For each year-month, we calculate the mean tariff exposure across all observations. Tariff exposure is measured in percent.

FIGURE D.2: Average Tariff Exposure by Sector



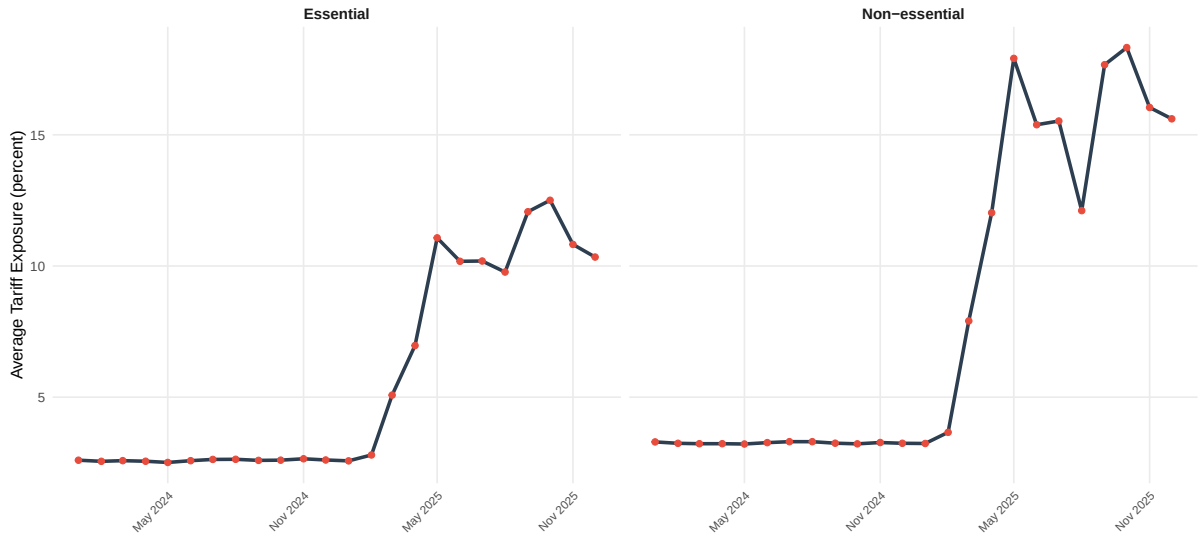
Note: This figure shows the monthly average tariff exposure over the sample period by sector. For each year-month, we calculate the mean tariff exposure across all observations. Tariff exposure is measured in percent.

FIGURE D.3: Average Tariff Exposure by Durability



Note: This figure shows the monthly average tariff exposure over the sample period by durability. Durables: Automotive, Electronics, Tools & Home Improvement, Home & Garden, Office. Non-durables: Grocery, Health & Beauty, Household, Baby, Pet, Tobacco Products and Accessories, Apparel/Footwear/Accessories, Sports, Toys, Books, Entertainment, Party & Occasions. For each year-month, we calculate the mean tariff exposure across all observations. Tariff exposure is measured in percent.

FIGURE D.4: Average Tariff Exposure by Essentiality



Note: This figure shows the monthly average tariff exposure over the sample period by essentiality. Essential: Grocery, Household, Health & Beauty. Non-essential: everything else (Automotive, Electronics, Tools & Home Improvement, Home & Garden, Office, Baby, Pet, Tobacco, Apparel/Footwear/Accessories, Sports, Toys, Books, Entertainment, Party & Occasions). For each year-month, we calculate the mean tariff exposure across all observations. Tariff exposure is measured in percent.

E Event Study Analysis

Section 4 shows the results of the empirical specification laid out in Section 3. To ensure the validity of the difference-in-differences specification in Equation (4), we estimate the dynamic effects of tariff exposure on prices, spending and quantity using an event study framework. For each outcome Y_{it}, we estimate:

$$\ln(Y_{it}) = \sum_{\substack{k=-K \\ k\neq -1}}^{T} \beta_k \left(\text{TariffExposure}_i \times \mathbf{1}[t = k]\right) + \delta_{i,m(t)} + \gamma_t + \varepsilon_{it}, \tag{E.1}$$

where i indexes the panel unit (sector × department × major category × category × HS code), t indexes the year-month, and Y_{it} is one of three outcomes: real spending, quantity, or a Fisher Price Index. The term TariffExposure_i denotes the tariff exposure of product i (the trade-weighted average tariff rate across source countries), $\mathbf{1}[t = k]$ indicates relative month k with respect to the onset of tariffs in February 2025, $\delta_{i,m(t)}$ denotes panel-unit-

by-calendar-month fixed effects where $m(t) \in \{1, \ldots, 12\}$ maps each year-month to its calendar month, and γ_t is a year-month fixed effect. The omitted category is January 2025 ($k = -1$), the month immediately preceding the first tariff actions. Standard errors are clustered at the HS code level.

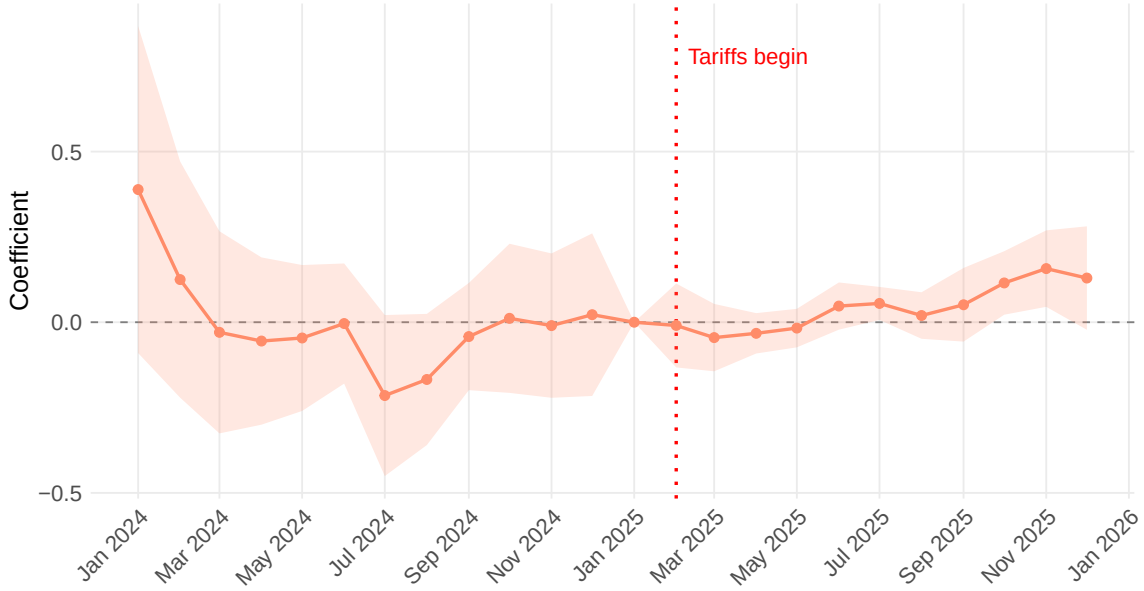
The coefficients β_k trace out the differential path of each outcome for products with higher tariff exposure relative to those with lower exposure, before and after the tariff onset. Pre-period coefficients serve as a test of the parallel trends assumption: if products with different tariff exposures were on similar trajectories prior to the policy, these coefficients should be close to zero.

For the price outcome (the Fisher Price Index), we augment the specification with a unit-specific linear time trend estimated from the pre-tariff period only. This follows the approach in Cavallo et al. (2025), designed to absorb pre-existing price trends that could confound the post-tariff estimates. Specifically, each panel unit's time trend is identified from pre-February 2025 variation.

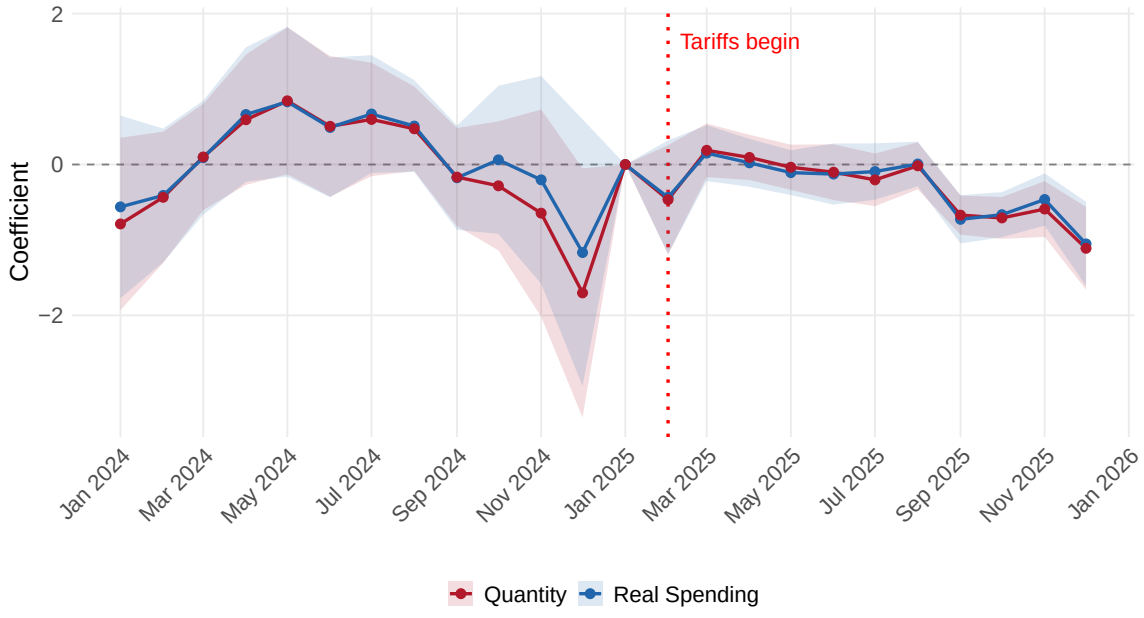
Figure E.1 presents the event study estimates. Panel (A) displays the spending and quantity responses. Pre-period coefficients for both outcomes are statistically indistinguishable from zero and exhibit no discernible trend, supporting the parallel trends assumption. Following the tariff onset, spending and quantity decline modestly, though the effects are not individually significant at conventional levels for most post-period months.

FIGURE E.1: Dynamic Effects of Tariff Exposure

(A) Prices (Fisher Price Index)



(B) Spending and Quantity



Notes: This figure plots event study coefficients $\hat{\beta}_k$ from Equation (E.1). The coefficients are normalized to Jan 2025=0. Shaded bands denote 95% confidence intervals based on standard errors clustered at the HS code level. The vertical dotted line marks February 2025, the first month of tariff implementation. Panel (A) reports the price response using the Fisher Price Index; this specification absorbs unit-specific linear time trends identified from the pre-tariff period, following Cavallo et al. (2025). Panel (B) reports results for real spending and quantity.

Panel (B) shows the price response using the detrended specification. After absorbing unit-specific pre-trends, the post-period coefficients are close to zero for the first several months following the tariff, consistent with limited immediate pass-through to consumer prices. Point estimates turn modestly positive at longer horizons (8–9 months post-tariff), suggesting a delayed and partial price response. Overall, the price evidence points to incomplete pass-through of tariffs to retail prices over the sample period.

F Household Characteristics and Robustness

Our main specifications estimate tariff pass-through at the product level, aggregating household-level transaction data to the HS4 code × month level. A natural concern is whether unobserved heterogeneity in household characteristics such as income, household size, age, or geographic location drives the estimated spending and quantity responses. If, for example, larger households differentially exit tariff-exposed product categories after February 2025, the product-level estimates could reflect compositional shifts rather than causal tariff effects. This appendix presents two complementary exercises to address this concern.

An important caveat applies to interpreting the magnitudes of coefficients reported in this appendix relative to the main text. The household-level specifications aggregate across all products purchased by a household, effectively averaging treatment intensity across heterogeneous product categories with different tariff exposures and consumption elasticities. The product-level specifications in the main text, by contrast, estimate responses within narrowly defined HS4 categories. These differences in aggregation levels, combined with different fixed-effects structures, mean that coefficient magnitudes are not directly comparable across specifications. However, the directional patterns (sign and statistical significance of tariff effects, heterogeneity across household types) provide valuable robustness checks on the main findings. The stability of tariff effects across progressively saturated specifications with household demographic controls, regional fixed effects, and alternative clustering schemes confirms that the baseline results are not driven by compositional changes in household characteristics or confounding regional shocks.

F.1 Household-Level Heterogeneity

We first aggregate each household's transactions to the household × month level and estimate:

$$\ln(Y_{it}) = \alpha_i + \gamma_t + \beta\,(\tau_i \times \text{Post}_t) + \varepsilon_{it}, \tag{F.1}$$

where i indexes households and t indexes months. The key regressor, τ_i, is household i's expenditure-weighted average tariff exposure, computed using only calendar year 2024 spending shares to avoid simultaneity between post-tariff expenditure adjustments and the exposure measure. This follows the standard shift-share (Bartik) approach in which the shares are predetermined.

Table F.1 reports spending responses across four specifications. Column (1) presents the baseline: a 1 percentage point increase in tariff exposure reduces household spending by approximately 1.6%. Column (2) interacts tariff exposure with household size, revealing that single-person households cut spending most aggressively (−1.8%), followed by small households of 2–3 members (−1.5%) and large households of 4 or more (−1.7%). Column (3) interacts with age, showing that younger households (ages 21–34) reduce spending by roughly 1.9%, while older households (ages 55+) reduce spending by 1.3–1.4%. Column (4) adds three-digit postal code × month fixed effects to absorb regional shocks; the tariff coefficient moves only slightly to −1.8%, confirming that geographic heterogeneity in local economic conditions does not drive the results.

Table F.2 reports split-sample estimates by household size. The monotonic gradient—Singles (−2.0%), Small (−1.6%), Large (−1.2%)—suggests that single-person households have more elastic consumption baskets, consistent with fewer committed expenditure obligations.

Table F.3 presents the corresponding quantity responses. Quantities increase for tariff-exposed households, with the effect strongest for large households (+1.8%) and insignificant for singles (+0.35, $p > 0.1$). Combined with the negative spending results, this pattern is consistent with quality downgrading: households substitute toward cheaper varieties within product categories, purchasing more units at lower unit prices. Larger families, facing tighter per-capita budget constraints, engage in this substitution most aggressively.

TABLE F.1: Household Heterogeneity: Spending Response to Tariff Exposure

	(1)	(2)	(3)	(4)
Tariff Exp. × Post	−1.6***			−1.8***
	(0.11)			(0.11)
Tariff Exp. × Post × Single		−1.8***		
		(0.13)		
Tariff Exp. × Post × Small (2-3)		−1.5***		
		(0.12)		
Tariff Exp. × Post × Large (4+)		−1.7***		
		(0.12)		
Tariff Exp. × Post × Age 18-20			−4.4	
			(3.7)	
Tariff Exp. × Post × Age 21-24			−1.9***	
			(0.45)	
Tariff Exp. × Post × Age 25-34			−1.9***	
			(0.14)	
Tariff Exp. × Post × Age 35-44			−1.7***	
			(0.12)	
Tariff Exp. × Post × Age 45-54			−1.6***	
			(0.12)	
Tariff Exp. × Post × Age 55-64			−1.3***	
			(0.12)	
Tariff Exp. × Post × Age 65+			−1.4***	
			(0.12)	
Household FE	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes
Region × Year-month FE				Yes
Observations	3,034,669	2,975,535	3,034,669	3,034,669
R^2	0.645	0.645	0.645	0.649
Adjusted R^2	0.630	0.630	0.630	0.631

Notes: The dependent variable is log real household-level spending in month t. Tariff Exp. is household i's expenditure-weighted average tariff exposure computed using 2024 spending shares. Standard errors clustered at the household level in parentheses. Coefficients are scaled by 100 to represent percentage point changes in spending for a 1 percentage point increase in tariff exposure. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table F.4 reports the full income × household size interaction. All nine cells are negative and statistically significant, ranging from −1.2% to −2.1%. High-income single-person households exhibit the largest spending reduction (−2.1%), likely reflecting greater

TABLE F.2: Spending Response by Household Size

	Single	Small (2-3)	Large (4+)
Tariff Exp. × Post	−2.0***	−1.6***	−1.2***
	(0.26)	(0.15)	(0.24)
Household FE	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes
Observations	590,157	1,699,429	685,949
R^2	0.623	0.617	0.624
Adjusted R^2	0.606	0.600	0.608

Notes: The sample is split by household size. The dependent variable is log real household-level spending in month t. Tariff Exp. is household i's expenditure-weighted average tariff exposure computed using 2024 spending shares. Standard errors clustered at the household level in parentheses. Coefficients are scaled by 100. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

TABLE F.3: Quantity Response by Household Size

	Single	Small (2-3)	Large (4+)
Tariff Exp. × Post	0.35	1.3***	1.8***
	(0.23)	(0.14)	(0.24)
Household FE	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes
Observations	590,157	1,699,429	685,949
R^2	0.618	0.610	0.623
Adjusted R^2	0.602	0.593	0.607

Notes: The sample is split by household size. The dependent variable is log total quantity purchased at the household-month level. Tariff Exp. is household i's expenditure-weighted average tariff exposure computed using 2024 spending shares. Standard errors clustered at the household level in parentheses. Coefficients are scaled by 100. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

discretionary exposure to tariff-affected durable goods that can be easily deferred.

TABLE F.4: Spending Response by Income and Household Size

	Single	Small (2-3)	Large (4+)
Low Income	−1.6***	−1.2***	−1.4***
	(0.16)	(0.15)	(0.21)
Middle Income	−1.7***	−1.2***	−1.2***
	(0.14)	(0.12)	(0.14)
High Income	−2.1***	−1.8***	−2.0***
	(0.23)	(0.13)	(0.13)
Household FE		Yes	
Year-month FE		Yes	
Observations		2,937,473	
R^2		0.644	
Adjusted R^2		0.629	

Notes: Each cell reports the coefficient on Tariff Exp. × Post from a separate regression estimated on the indicated income × household size subsample. The dependent variable is log real household-level spending in month t. Tariff Exp. is household i's expenditure-weighted average tariff exposure computed using 2024 spending shares. Standard errors clustered at the household level in parentheses. Coefficients are scaled by 100. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

F.2 Household-Level DiD with Demographic Controls

We next estimate a disaggregated specification at the household × product × month level using the full transaction-level dataset:

$$\ln(Y_{iht}) = \alpha_i + \delta_h + \gamma_t + \beta\,(\tau_h \times \text{Post}_t) + \Gamma'\,(\mathbf{X}_i \times \text{Post}_t) + \varepsilon_{iht}, \tag{F.2}$$

where i indexes households, h indexes products (HS4 codes), and t indexes months. The vector $\mathbf{X}_i$ includes income group, household size group, and age bucket. Unlike the household-level aggregation in the previous subsection, tariff exposure here varies at the product level rather than the household level, so the pre-period weighting concern does not arise. The demographic × Post controls test whether differential post-tariff trends across household types explain away the tariff coefficient.

Table F.5 presents results for spending across 267 million observations. The tariff

coefficient is −0.05 (i.e., −0.05% per percentage point of tariff exposure) and is unchanged across all three specifications: baseline with household, product, and time fixed effects (Column 1); with demographic × Post controls (Column 2); and with postal code × month fixed effects (Column 3). The demographic controls reveal that higher-income households reduce spending more post-tariff (Middle: −0.19%; High: −0.30%), while small households of 2–3 members increase spending modestly (+0.22%). Age interactions are uniformly insignificant.

TABLE F.5: Household-Product-Level Spending Response

	(1) Baseline	(2) + Demographics	(3) + Region FE
Tariff Exp. × Post	−0.05***	−0.05***	−0.05***
	(0.002)	(0.002)	(0.002)
Middle Income × Post		−0.19***	−0.19**
		(0.07)	(0.07)
High Income × Post		−0.30***	−0.30***
		(0.08)	(0.09)
HH Size 2-3 × Post		0.22***	0.22***
		(0.07)	(0.07)
HH Size 4+ × Post		0.07	0.10
		(0.09)	(0.09)
Household FE	Yes	Yes	Yes
Product (HS4) FE	Yes	Yes	Yes
Year-month FE	Yes	Yes	
Region × Year-month FE			Yes
Observations	277,440,002	267,603,963	267,603,963
R^2	0.413	0.413	0.413
Adjusted R^2	0.412	0.413	0.413

Notes: The dependent variable is log real spending at the household × HS4 × month level. Tariff Exp. is the tariff exposure for HS4 code h. Standard errors clustered at the household level in parentheses. Coefficients are scaled by 100. Age × Post controls included in (2) and (3) but not reported (all insignificant). $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table F.6 reports quantity responses. The tariff coefficient is −0.007 and stable across specifications. Among the demographic controls, only large households (4+) show a significant additional quantity reduction (−0.12%, $p < 0.05$).

In unreported results, the tariff spending coefficient remains significant under user-level clustering (SE = 0.002), HS code clustering (SE = 0.02), and two-way clustering

TABLE F.6: Household-Product-Level Quantity Response

	(1) Baseline	(2) + Demographics	(3) + Region FE
Tariff Exp. × Post	−0.007***	−0.007***	−0.006***
	(0.0009)	(0.0009)	(0.0009)
Middle Income × Post		−0.06	−0.05
		(0.04)	(0.04)
High Income × Post		−0.07	−0.05
		(0.05)	(0.05)
HH Size 2-3 × Post		−0.05	−0.04
		(0.04)	(0.04)
HH Size 4+ × Post		−0.12**	−0.10*
		(0.06)	(0.06)
Household FE	Yes	Yes	Yes
Product (HS4) FE	Yes	Yes	Yes
Year-month FE	Yes	Yes	
Region × Year-month FE			Yes
Observations	277,440,002	267,603,963	267,603,963
R^2	0.166	0.166	0.166
Adjusted R^2	0.166	0.165	0.165

Notes: The dependent variable is log total quantity purchased at the household × HS4 × month level. Tariff Exp. is the tariff exposure for HS4 code h. Standard errors clustered at the household level in parentheses. Coefficients are scaled by 100. Age × Post controls included in (2) and (3) but not reported (all insignificant). $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

by user and HS code (SE = 0.02). For quantities, the coefficient retains its sign and magnitude under all clustering schemes, though statistical significance weakens under HS-level and two-way clustering, consistent with the treatment (tariff exposure) varying at the product level, which inflates standard errors when clustering at that level.

In summary, these exercises reveal three findings. First, the main tariff coefficients are robust to controlling for household demographics and regional shocks; compositional changes across household types do not drive the product-level results. Second, single-person and younger households exhibit the largest spending reductions, while larger households adjust primarily on the quality margin by substituting toward cheaper alternatives. Third, higher-income households reduce spending more in absolute terms, likely reflecting greater discretionary exposure to tariff-affected categories. The stability of the tariff coefficient across progressively saturated specifications, from a simple two-

way fixed effects baseline to models with demographic × Post controls and region × time fixed effects, supports a causal interpretation of the main estimates.

G Stockpiling and Anticipatory Purchasing

A natural concern is that households may have anticipated the tariffs and engaged in stockpiling behavior, purchasing larger quantities of high-exposure goods in the months leading up to tariff implementation. Such anticipatory purchasing could confound our main results by shifting demand forward in time and creating differential pre-trends between high- and low-exposure categories.

To test for anticipatory behavior, we restrict our sample to the pre-tariff period (before February 2025) and estimate the following specification:

$$\ln(Y_{it}) = \gamma_t + \delta_{i,m(t)} + \beta\,(\text{EventualTariffExposure}_i \times \text{Anticipation}_t) + \varepsilon_{it} \tag{G.1}$$

where $\text{EventualTariffExposure}_i$ measures the average tariff exposure that category i will face after February 2025, and Anticipation_t is an indicator variable equal to one for the months November 2024 through January 2025, the period during which tariff announcements became increasingly credible, and zero for earlier months in 2024. As before, γ_t denotes year-month fixed effects and $\delta_{i,m(t)}$ denotes panel-unit-by-calendar-month fixed effects. The coefficient β captures whether categories with higher eventual tariff exposure experienced differential changes in quantities or spending during the anticipation window relative to earlier months, holding constant common time trends and unit-specific seasonality.

Table G.1 presents the results. We find no evidence of anticipatory purchasing behavior. The interaction coefficient for quantity is −0.17 (SE = 0.28), and for spending it is −0.04 (SE = 0.29). Both estimates are small in magnitude, statistically insignificant. These null results indicate that households did not significantly increase their purchases of high-exposure goods in advance of the tariffs, which validates our identification assumption that differential pre-trends are not driving our main results.

TABLE G.1: Stockpiling Test: Anticipatory Purchasing

	Dependent Variable: $\ln(Y_{it})$	
	Quantity	Spending
	(1)	(2)
Eventual Tariff Exp. × Anticipation	−0.17	−0.04
	(0.28)	(0.29)
Year-month FE (γ_t)	Yes	Yes
Panel unit FE (δ_i)	Yes	Yes
Panel unit × month-of-year FE ($\delta_{i,m(t)}$)	Yes	Yes
Observations	57,605	57,605
R^2	0.972	0.958

Notes: This table reports coefficients from equation (G.1), which tests for anticipatory purchasing behavior in the pre-tariff period (before February 2025). The anticipation window covers November 2024 through January 2025. Eventual Tariff Exposure measures the average tariff exposure that each category faces after tariff implementation. Coefficients are scaled by 100 to represent percentage point changes. Standard errors (in parentheses) are clustered at the HS code level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

H Sectoral Level Analysis

This section provides additional sectoral heterogeneity results for durability analysis.

Table H.1 reports the estimates of the main specification separately by durability (durables versus nondurables). Price pass-through is small in magnitude and concentrated among durable goods. China tariff exposure raises durable prices but has no detectable effect on non-durable prices. Although tariff rates on nondurables are modestly lower, Figure D.3 shows that tariff exposure remains similar enough that this cannot fully account for the large difference in price effects. This suggests retailers might be absorbing tariff costs on nondurables through margin compression or supplier renegotiation, while passing them through on durables. Despite this muted price response, both durable and non-durable goods experience significant declines in spending and quantity from China tariff exposure, with durables responding more than non-durables. This observation is consistent with the greater postponability of durable purchases such that consumers can delay replacing electronics or automotive parts in ways they cannot for groceries or household supplies.

The Canada and Mexico coefficients provide evidence of trade diversion: they are

large and positive for durable spending and quantity, consistent with retailers and consumers substituting toward USMCA partners as goods purchased from China become more expensive. RoW coefficient, meanwhile, is statistically insignificant across all outcomes, confirming that the aggregate effects are driven primarily by China-specific tariff shocks.

TABLE H.1: Results by Durability

	Durable			Non-durable		
	Price	Spending	Quantity	Price	Spending	Quantity
Total	0.07***	-0.36**	-0.39***	0.04	-0.31***	-0.21***
	(0.02)	(0.14)	(0.13)	(0.04)	(0.10)	(0.07)
China	0.07***	-0.45***	-0.48***	0.00	-0.42***	-0.32***
	(0.02)	(0.15)	(0.16)	(0.03)	(0.13)	(0.10)
Canada	0.14	4.65***	4.40***	0.02	1.12	0.75
	(0.38)	(1.44)	(1.33)	(0.38)	(1.04)	(0.91)
Mexico	-0.32	3.22**	2.83**	-0.06**	0.28	0.26
	(0.28)	(1.25)	(1.21)	(0.02)	(0.22)	(0.20)
Rest of World	0.14	-0.08	-0.10	0.14	-0.22	-0.10
	(0.09)	(0.42)	(0.40)	(0.10)	(0.23)	(0.18)
Average Adjusted R^2	0.62	0.91	0.95	0.62	0.96	0.97
Observations		33,866			72,490	
Panel unit FE		Yes			Yes	
Year-month FE		Yes			Yes	
Panel unit × month		Yes			Yes	

Notes: Each cell reports the coefficient β from Equation (4) for each group and outcome variable. Coefficients represent the percentage change in the outcome variable associated with a 1 percentage point increase in tariff exposure. Standard errors clustered at the HS4 code level in parentheses. All specifications include year-month and product × calendar-month fixed effects. Adjusted R^2 averaged across tariff source specifications within each outcome. Durables: Automotive, Electronics, Tools & Home Improvement, Home & Garden, Office. Non-durables: Grocery, Health & Beauty, Household, Baby, Pet, Tobacco Products and Accessories, Apparel/Footwear/Accessories, Sports, Toys, Books, Entertainment, Party & Occasions. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table H.2 presents results by durability and income group. Tariff pass-through into prices is concentrated among durable goods for high-income households, where the price coefficient is roughly three times larger than for middle-income households'. Non-durable goods show the opposite pattern, with significant price increases only for low-income households. Spending and quantity reductions for durables are large and significant across all income groups, but the magnitudes increase with income. High-income households cut durable spending and quantities by roughly 0.45-0.48 percentage points per unit of

tariff exposure, compared to around 0.36-0.38 for low-income households.

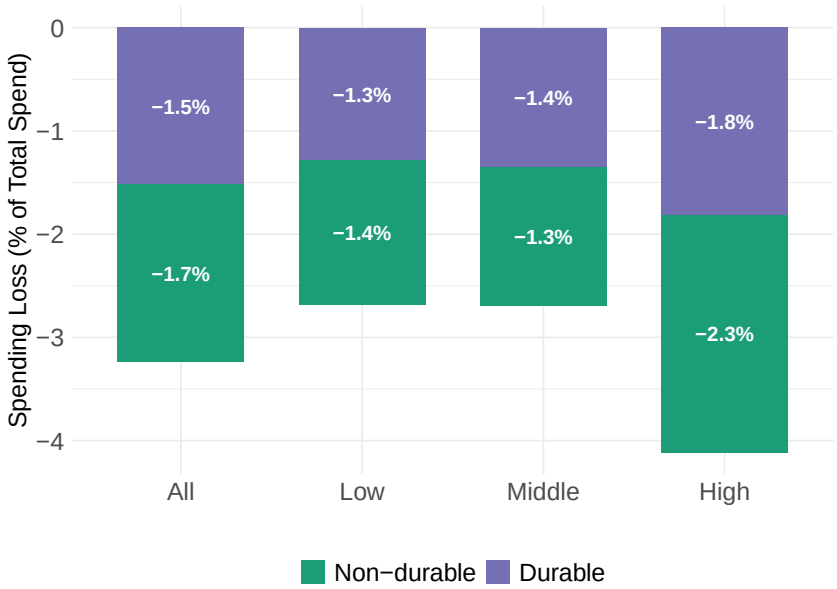
TABLE H.2: Results by Durability and Income Group

	Low Income			Middle Income			High Income		
	Price	Spending	Quantity	Price	Spending	Quantity	Price	Spending	Quantity
Durable	0.04	-0.36**	-0.38***	0.06**	-0.36***	-0.42***	0.19**	-0.44***	-0.48***
	(0.05)	(0.15)	(0.14)	(0.03)	(0.13)	(0.12)	(0.07)	(0.14)	(0.14)
Non-durable	0.10***	-0.18**	-0.11	0.04	-0.18**	-0.10	0.02	-0.28**	-0.21**
	(0.03)	(0.09)	(0.08)	(0.05)	(0.09)	(0.08)	(0.04)	(0.11)	(0.08)
Observations		32,060			33,359			32,823	
Panel unit FE		Yes			Yes			Yes	
Year-month FE		Yes			Yes			Yes	
Panel unit × month		Yes			Yes			Yes	

Notes: Each cell reports the coefficient on Tariff Exposure (Total) × Post from a separate regression estimated on the indicated durability × income group subsample. Coefficients represent the percentage change in the outcome variable associated with a 1 percentage point increase in tariff exposure. Standard errors clustered at the HS4 code level in parentheses. All specifications include year-month and product × calendar-month fixed effects. Income groups: Low (<$40k), Middle ($40k-$125k), High (>$125k). Durables: Automotive, Electronics, Tools & Home Improvement, Home & Garden, Office. Non-durables: Grocery, Health & Beauty, Household, Baby, Pet, Tobacco, Apparel/Footwear/Accessories, Sports, Toys, Books, Entertainment, Party & Occasions. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Figure H.1 decomposes spending losses into durable and nondurable goods. The pattern is relatively balanced: durables and nondurables contribute roughly equally to total spending reductions across all income groups, with the exception of high-income households where the difference between the two is more pronounced. This near-symmetry arises despite differences in both tariff exposure and behavioral responses. Durables face modestly higher average tariff exposure (14 percentage points versus 12.6 for nondurables) and, as shown in Table H.1, exhibit larger quantity elasticities (-0.39 versus -0.21 per percentage point of tariff exposure). Comparing the essentiality decomposition (Figure 3 in the main text) with the durability decomposition reveals a contrast: along the essentials-nonessentials margin, both tariff exposure and demand elasticities reinforce each other, producing a sharp asymmetry in spending losses. Along the durability margin, the gap in tariff exposure is narrower and the difference in elasticities does not translate into unequal aggregate spending losses.

FIGURE H.1: Decomposition of Average Monthly Net Spending Change by Durability



Notes: The figure decomposes the mean monthly net spending effect into durables (Automotive, Electronics, Tools & Home Improvement, Home & Garden, Office) and non-durables (Grocery, Health & Beauty, Household, Baby, Pet, Tobacco Products and Accessories, Apparel/Footwear/Accessories, Sports, Toys, Books, Entertainment, Party & Occasions). Sector shares are estimated from separate regressions for each income group × durability cell and applied to the headline totals from Table 8. Percent values in each bar indicate total mean percent monthly net spending effect for the respective income group.

I Geographic Heterogeneity

A natural question is whether geographic factors such as proximity to international borders or the urban-rural divide shape household responses to tariffs. U.S. households near the Mexican or Canadian border may have better access to cross-border shopping or to retailers carrying a wider range of imported substitutes, potentially attenuating the tariff burden, or they could be more exposed to tariffs without substitution opportunities. Similarly, urban and rural households face different retail environments, with metro areas offering greater product variety and price competition.

We classify households along two geographic dimensions using their 5-digit zip codes. First, using a ZIP-to-county crosswalk from U.S. Department of Housing and Urban Development (HUD) and county-level Federal Information Processing Standards (FIPS) codes, we identify households in border counties which are the 33 U.S. counties on or near

the Mexico border and approximately 60 counties on the Canada border with practical cross-border access (i.e., containing or adjacent to a staffed land or bridge crossing) as well as the broader set of households in border states.[12] Second, we use the US Department of Agriculture (USDA)'s 2023 Rural-Urban Continuum Codes (RUCC) to classify counties as metro (RUCC 1–3), nonmetro urban (RUCC 4–6), or rural (RUCC 7–9).[13]

Table I.1 reports the estimates for expenditure share reallocation, interacted with geographic indicators, mirroring the specification in Equation (4). Column (1) shows that interior households shift expenditure shares away from tariff-exposed categories, while border county households exhibit a small positive but statistically insignificant coefficient, suggesting no reallocation away from tariff-exposed goods. This is consistent with border households having access to cross-border substitution channels that partially obviate the need for domestic category switching. The border state specification in Column (2) yields small and insignificant coefficients for both groups, indicating that the distinction between border and interior areas is not sharp at the state level. Column (3) shows that metro and nonmetro urban households exhibit significant expenditure share reallocation, while rural households show a smaller and insignificant response.

Next, to compute welfare losses that reflect differential spending responses across geographies, we estimate separate spending regressions for each geographic group. Table I.2 reports the results. For interior households, we estimate the spending elasticity with respect to USMCA tariff exposure (the sum of Canada and Mexico tariffs) to ensure comparability with border households, who are evaluated against their adjacent country's tariff. For Mexico and Canada border counties, we estimate elasticities using the respective country-specific tariff exposure. Across the urban-rural dimension, metro households exhibit the largest elasticity, followed by nonmetro urban and rural, although the magnitudes are broadly similar.

Table I.3 reports consumption losses using geography-specific coefficients and the relevant tariff exposure measures. To ensure comparability across the border dimension,

[12]Mexico border states: California, Arizona, New Mexico, and Texas. Canada border states: Washington, Idaho, Montana, North Dakota, Minnesota, Michigan, New York, Vermont, New Hampshire, and Maine. We exclude Alaska boroughs, Great Lakes shoreline counties without bridge or tunnel crossings, and Lake Erie counties in Ohio and Pennsylvania, as these lack practical cross-border retail access.

[13]Zip-County data are downloaded from https://www.huduser.gov/apps/public/uspscrosswalk/home and Rural-Urban Continuum Codes are downloaded from https://www.ers.usda.gov/data-products/rural-urban-continuum-codes.

TABLE I.1: Geographic Heterogeneity in Cross-Category Substitution

	Border County (1)	Border State (2)	Urban/Rural (3)
Tariff × Post × Interior County	−0.12		
	(0.08)		
Tariff × Post × Border County	0.08		
	(0.11)		
Tariff × Post × Interior State		0.01	
		(0.08)	
Tariff × Post × Border State		−0.08	
		(0.09)	
Tariff × Post × Metro			−0.19**
			(0.08)
Tariff × Post × Nonmetro Urban			−0.18**
			(0.09)
Tariff × Post × Rural			−0.12
			(0.08)
HS × Geography FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
Panel × Calendar Month FE	Yes	Yes	Yes
Observations	33,799	33,799	11,360
R^2	0.53	0.52	0.97

Notes: Each column reports estimates from a specification interacting tariff exposure × Post with geographic indicators. The dependent variable is the log expenditure share of HS code h in geographic group g's total spending. Column (1) distinguishes border counties (adjacent to the Mexican or Canadian border with practical cross-border access) from interior counties. Column (2) distinguishes border states from interior states. Column (3) classifies counties as metro (RUCC 1–3), nonmetro urban (RUCC 4–6), or rural (RUCC 7–9) using the USDA's 2023 Rural-Urban Continuum Codes. All specifications include HS-by-geography, year-month, and panel-unit-by-calendar-month fixed effects. Standard errors clustered at the HS code level are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

all three groups in Panel A are evaluated against USMCA-related tariff exposure only: Mexico border households face Mexico tariffs, Canada border households face Canada tariffs, and interior households face the combined Canada-plus-Mexico tariff.

Restricting attention to USMCA-related tariffs reveals a more nuanced pattern than a simple border advantage. Canada border households bear the largest USMCA burden at \$6.90/month (0.51% of spending), followed by interior households at \$5.52/month (0.40%), with Mexico border households facing the smallest losses at \$5.93/month (0.39%). The ordering reflects the asymmetry in tariff levels between the two neighbors: Canadian

TABLE I.2: Geography-Specific Spending Elasticities

	Border Status		Urban/Rural		
	Interior (1)	Border (2)	Metro (3)	Nonmetro (4)	Rural (5)
Tariff × Post	−0.30***	−0.22**	−0.32***	−0.27***	−0.24**
	(0.05)	(0.10)	(0.05)	(0.07)	(0.09)
Panel × Calendar Month FE	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes
Observations	108,556	96,378	108,343	101,152	97,195
Adjusted R^2	0.95	0.88	0.95	0.91	0.88

Notes: Each column reports estimates from Equation (4) estimated separately for each geographic group. For border status (Columns 1–2), interior households are evaluated against total tariff exposure and border households against their adjacent country's tariff exposure. For urban/rural (Columns 3–5), all groups are evaluated against total tariff exposure. All specifications include panel-unit-by-calendar-month and year-month fixed effects. Standard errors clustered at the sector level are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

TABLE I.3: Consumption Losses by Geographic Classification

	N HHs	Mean ($/month)	Median ($/month)	Mean ($/year)	Loss (% Spend)
Panel A: Border Type (USMCA tariffs only)					
Interior	121,026	5.52	3.63	66.18	0.40
Canada Border	2,658	6.90	4.57	80.37	0.51
Mexico Border	2,764	5.93	3.56	71.19	0.39
Panel B: Urban/Rural (total tariff exposure)					
Metro	107,994	54.10	35.45	649.25	3.88
Nonmetro Urban	12,227	41.69	28.36	500.29	3.39
Rural	6,151	35.68	24.58	428.16	2.93

Notes: Monthly consumption lossed computed using Equation (5). Panel A uses geography-specific spending coefficients with USMCA tariff exposure: Mexico tariff for Mexico border counties, Canada tariff for Canada border counties, and the sum of Canada and Mexico tariffs for interior. Panel B uses geography-specific spending coefficients with total tariff exposure.

tariff exposure is substantially higher than Mexican exposure across most HS codes, due to the broader scope of tariffs applied to Canadian imports. Interior households, who face the sum of both countries' tariffs, nevertheless lose less than Canada border households in proportional terms because the USMCA-specific elasticity is estimated on a more diluted

tariff measure that combines two heterogeneous country exposures.[14]

Panel B reports losses under total tariff exposure, which captures the full tariff schedule including China and rest-of-world tariffs. These are an order of magnitude larger than the USMCA-specific losses, underscoring that the majority of the tariff burden falls on goods sourced from outside North America. Metro households bear the largest proportional burden (3.88%) compared to nonmetro urban (3.39%) and rural (2.93%), reflecting the higher spending elasticity estimated for metro areas.

The two panels together highlight an important compositional point: Canada and Mexico tariffs account for roughly one-fifth of the total tariff burden on household consumption, with the remainder driven by tariffs on Chinese and other imports. Geographic proximity to a border matters for the USMCA component, but it is the non-USMCA tariffs, which are geographically uniform, that dominate the overall welfare cost.

[14]The interior spending coefficient is estimated using the sum of Canada and Mexico tariff exposure as the treatment variable. Because Canadian and Mexican tariffs apply to different product mixes and at different rates, the combined measure pools heterogeneous variation, which may attenuate the estimated elasticity relative to the country-specific estimates used for border households. This is a feature of the identification strategy designed to ensure comparability across groups, but it implies that the interior welfare estimate should be interpreted as a lower bound on USMCA-specific losses for interior households.