Tariffs Tax the Poor More: Evidence from Household Consumption During the US-China Trade War *

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August 28, 2025

Abstract

Using disaggregated US household expenditure data, we study the distributional consequences of the US-China trade war. We estimate a highly flexible demand system to compute household-specific price indexes. The increases in US tariffs on Chinese products between 2018 and 2019 led to an average price index increase of 1.09%, with a disproportionately larger impact on low-income households. Specifically, we document a 0.9 percentage point smaller increase in the household price index for the top 20% income households compared to the bottom 20%. The difference stems from wealthier households' greater expenditure adjustments and smaller reductions in product variety.

Keywords: US-China Trade War, Tariffs, Income Inequality, Distributional Effects of Tariffs, Household Consumption.
JEL Codes: F14, D31, F13.

*We thank Christoph Albert, Banu Demir, Pablo Fajgelbaum, Dorothee Hillrichs, David Hummels, David Jinkins, Gianluca Orefice, Anson Soderbery, Kensuke Suzuki, Feicheng Wang, Chong Xiang and seminar participants at ETSG, SETC, CUFE, ECUST, Clark University, Peking University, the Kiel-Gottingen-CEPR conference, University of Southampton, Purdue University, CESIfo Area Conference 2025, ITSG, and University of Würzburg for comments and suggestions. We also thank Liang Bai for sharing with us the concordance from Nielsen product modules to HS six-digit commodities. Hong Ma thanks the financial support of the Social Science Foundation of China (Grant No.23&ZD046) and the Natural Science Foundation of China (Grant No. 72425004). Mingzhi Xu thanks financial support from the Natural Science Foundation of China (Grant No. 72322007). Researchers' own analyses calculated based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at the University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researchers and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein. Contact authors: Hong Ma (corresponding author), School of Economics and Management, Tsinghua University, Beijing, 100084, China, email: mahong@sem.tsinghua.edu.cn, tele: (+86) 10 62794388; Luca Macedoni, University of Milan, Italy, email: luca.macedoni@unimi.it; Jingxin Ning, University of International Business and Economics, China, email: ningjingxin@uibe.edu.cn; Mingzhi Xu, INSE at Peking University, China, email: mingzhixu@nsd.pku.edu.cn.

1 Introduction

The beginning of 2025 marked an unprecedented escalation in the trade war: President Trump extended tariffs beyond China to encompass a wide range of imports from many other countries, temporarily raising the average effective tariff rate from 2.3% to an estimated 30% — the highest level in more than a century.[1] The impact on China has been especially severe, with most Chinese goods initially facing prohibitive tariffs as high as 145%.[2] Although subsequent negotiations led to a partial rollback, the episode reignited fears of a full-scale trade conflict between the world's two largest economies and raised widespread concerns over global supply chain disruptions and inflationary pressures.

How have these tariff changes affected the price index faced by US households? While a growing literature has examined the aggregate trade and welfare consequences of the US–China trade war (Amiti et al., 2019, 2020; Fajgelbaum et al., 2020; Ma et al., 2021; Caliendo and Parro, 2023; Flaaen and Pierce, 2024), much less is known about its distributional effects across households. These heterogeneous impacts depend critically on the sectoral composition of household consumption and on how different households adjust their spending in response to relative price changes.

To address this gap, we quantify the distributional consequences of the US–China trade war using disaggregated household-level expenditure data from 2016 to 2019. Our baseline approach extends the framework of Redding and Weinstein (2020) to estimate household-specific price indexes and to decompose the effects of tariffs into distinct adjustment channels, including expenditure switching and changes in the variety of goods consumed. We complement this structural analysis with reduced-form evidence on how tariffs affect these adjustment channels, and we assess the robustness of our findings using the welfare-relevant price index proposed by Baqaee and Burstein (2023).

Our baseline evaluation of the distributional effects of tariffs employs a highly flexible, nested Constant Elasticity of Substitution (CES) demand system, in which demand shifters for products vary across households and over time. This approach allows our model to account for different expenditure shares for the same items across consumers and different changes in expenditure shares in response to the same price changes. Moreover, the demand shifters in our model can generate zero demand for certain products, enabling the consumption set to vary endogenously across households and over time.[3]

[1] See https://www.tradewartracker.com/. As of August 2025, the average tariff rate is 18.2%.

[2] The US and China engaged in a tit-for-tat escalation of tariffs, which led to US duties on Chinese goods reaching as high as 245%. Subsequent negotiations successfully rolled back some of these measures, reducing the average tariff on Chinese imports to approximately 53%.

[3] This approach can generate the outcomes of non-homothetic utility functions while preserving tractability under homothetic utility. Hottman and Monarch (2020) describe these preferences as effectively non-homothetic. Previous

We use detailed NielsenIQ consumer purchase data, which report prices and quantities at the barcode-household level. These barcodes are categorized into more than a thousand distinct product modules, such as oral hygiene products and batteries. With these data, we estimate the elasticities of substitution within and across product modules, as well as the household-specific demand shifters for barcodes and product modules. With the estimated parameters, we compute the exact price indexes at both the product module-household level and the aggregate household level.

To assess the impact of tariff hikes on household price indexes, we match NielsenIQ product modules to Harmonized System (HS) six-digit codes using the concordance developed by Bai and Stumpner (2019). Roughly 50% of the HS codes targeted by tariffs correspond to goods commonly sold in retail markets. We construct a household-specific measure of tariff exposure by weighting module-level tariffs using each household's initial expenditure shares. Notably, exposure to tariffs is similar across the income distribution. Our results indicate that the US-China trade war imposed substantial costs on American consumers: our baseline estimates suggest that the 2018-2019 tariffs on Chinese imports increased the household-specific price index by 1.09%.

The household price index is influenced by three primary channels: (1) *the price channel*, capturing changes in average price levels; (2) *the expenditure share channel*, reflecting households' ability to reallocate spending across goods; and finally (3) *the variety channel*, accounting for changes in the set of consumed products. All three channels contribute to the aggregate effects of the trade war. The increase in living costs for households is primarily driven by the price channel and the variety channel: higher import tariffs led to higher average prices and reduced product variety. However, these effects are partially offset by the expenditure share channel, as households adjust their consumption spending across products to minimize the burden of higher prices.

Our main finding is that increases in tariffs disproportionately raise the price index of poorer households compared to richer ones: the impact on household-specific price indexes declines monotonically with income. For households in the top income quintile, the increase in the price index is 0.9 percentage points lower than for those in the bottom quintile. This heterogeneous effect is primarily driven by differences in the expenditure share and variety channels: higher-income households exhibit greater flexibility in reallocating spending and experience smaller reductions in variety. In contrast, faced with identical price increases, lower-income households are more likely to drop specific barcodes or product modules from their consumption basket and alter their spending on remaining items to a lesser extent.

work highlights the importance of non-homotheticity for understanding household responses to globalization (Neary, 2004; Fajgelbaum et al., 2011; Feenstra and Romalis, 2014; Simonovska, 2015; Fajgelbaum and Khandelwal, 2016; Bertoletti et al., 2018; Hottman and Monarch, 2020; Macedoni, 2022), and other external shocks such as large exchange rate devaluations (Cravino and Levchenko, 2017). For a recent quantification of non-homothetic preferences, see Comin et al. (2021). Our approach allows for a general, data-driven relationship between income and preferences that is not restricted to a particular functional form.

We validate the main mechanisms underlying our decomposition with reduced-form evidence on two key channels: expenditure switching and variety loss. In response to tariff shocks, low-income households demonstrate less flexibility in reallocating spending toward lower-priced alternatives and experience a sharper decline in product variety. Higher-income households, by contrast, are more responsive in shifting purchases to cheaper barcodes and better able to preserve product diversity — partly by relying more heavily on retail outlets that offer bulk discounts and a wider assortment of goods.

Our analysis is based on NielsenIQ Homescan data, which provide detailed information on household purchases from grocery and mass merchandise retailers. While the dataset focuses on a specific segment of consumer spending, it captures a broad set of frequently purchased items that are highly relevant for assessing the distributional effects of tariffs. In our sample, the average import penetration from China is approximately 6.5%, a meaningful exposure level given the composition of retail purchases and the fact that Chinese goods account for about 21% of total US imports. Although the data may not fully capture some durable goods categories, such as household appliances, it nonetheless covers the types of products that make up a substantial share of spending for the average US consumer.

To complement the retail coverage of the Nielsen data and better align with the actual structure of the tariff war, we extend the analysis to include input tariffs. A large share of duties targeted intermediate goods (e.g., steel and aluminum), which can drive up production costs for final goods. To link these input tariffs to household consumption, we construct an upstream-exposure measure that maps input tariffs into effective cost shocks for each module. Our findings indicate that the indirect effects of the US tariff war amount to approximately one-third of the direct effects. Moreover, these indirect effects disproportionately increase the price indexes faced by poorer households.

Related Literature. Our study offers new insight into how the US-China trade war has impacted consumers unevenly. Although it is evident that these tariff increases have led to a rise in prices in the US (Amiti et al., 2019, 2020; Fajgelbaum et al., 2020) and China (Ma et al., 2021; Feng et al., 2023), the distribution of these economic burdens among consumers remains underexplored. The existing literature on the distributional effects of international trade has mainly concentrated on the heterogeneous effects of international trade on households, primarily through changes in their incomes (Goldberg and Pavcnik, 2003; Zhu and Trefler, 2005; Hanson, 2007; Verhoogen, 2008; Topalova, 2010; Han et al., 2012; Autor et al., 2013a; Pierce and Schott, 2016; Autor et al., 2021; Borusyak and Jaravel, 2021). Our paper, however, aligns with a different line of research that investigates the distributional consequences of trade through heterogeneity in consumption (Porto, 2006; McCalman, 2018; Russ et al., 2017; Bai and Stumpner, 2019; Hottman and Monarch, 2020; Borusyak and Jaravel, 2021; Hillrichs and Vannoorenberghe, 2022; Acosta and Cox, 2024;

Fajgelbaum and Khandelwal, 2024).

The distributional consequences of international trade through the consumption channel remain a subject of active debate. Early work by Porto (2006) documents a pro-poor effect of Mercosur in Argentina, showing that trade liberalization reduced the cost of living more for lower-income households. Extending this line of inquiry, Fajgelbaum and Khandelwal (2016) develop a theoretical and empirical framework suggesting that trade openness disproportionately benefits the poor, given their higher expenditure shares on tradable goods. In the US context, several studies underscore the regressive nature of trade barriers. Russ et al. (2017) show that lower-income households allocate a larger fraction of their after-tax income to tariff-inclusive goods, effectively rendering tariffs a form of regressive taxation. This insight is reinforced by Acosta and Cox (2024), who find that lower-priced variants of goods tend to face higher tariff rates, exacerbating the burden on poorer consumers. Fajgelbaum and Khandelwal (2024) provide further evidence of consumption-side inequality by analyzing the *de minimis* exemption, which allows duty-free imports under $800 per shipment. They find that this policy disproportionately benefits low-income households, and its repeal would result in a regressive shift in the tax burden. However, a separate strand of the literature contests the pro-poor effect of trade liberalization. Bai and Stumpner (2019) report that Chinese imports similarly affect the price index across different income levels. Hottman and Monarch (2020) discover that, between 1998 and 2014, poorer households faced higher import price inflation than wealthier ones. Borusyak and Jaravel (2021) identify minimal variations in import exposure across income brackets, and thus the distributional impacts of trade appear to be limited. Lastly, Hillrichs and Vannoorenberghe (2022) augment the model by Fajgelbaum and Khandelwal (2016) with a home bias, and find greatly reduced pro-poor gains from trade.[4]

While existing research focuses primarily on the effects of reduced trade costs, our study uniquely examines the distributional consequences of increased tariffs. Our findings offer a reconciliation between two divergent viewpoints. We observe that higher tariffs disproportionately hurt poorer consumers, suggesting that if the effects are symmetric, lower tariffs disproportionally benefit the poorer, similarly to the findings of Fajgelbaum and Khandelwal (2016). However, unlike Fajgelbaum and Khandelwal (2016) but in agreement with Borusyak and Jaravel (2021), we find that this outcome is not due to a higher import share among poorer consumers. Instead, it is because poorer households change their expenditures by less and are more likely to remove varieties from their consumption bundles.

Another distinction from the aforementioned studies is our methodological approach. To deduce the distributional effects of trade, the canonical method relies on sufficient statistics (i.e., the expenditure share on imports), while our approach is based on reduced-form impacts of tariffs on

[4]Relatedly, Farrokhi et al. (2022) validate standard price indices from the literature, such as ours, using household food Engel curves. They show that these indices track household consumption better than the official CPI.

price indexes. In this respect, our methodology resembles more closely that of Bai and Stumpner (2019) and Hottman and Monarch (2020).

A study closely related to ours is Waugh (2019), which investigates the effects of Chinese retaliatory tariffs on the consumption patterns of new cars in various US counties. The differential impact on consumption in Waugh (2019) stems from varying labor market exposures to tariff changes. In contrast, our paper delves into the influence of different consumption baskets and diverse household demand responses. Our paper complements the findings of Cavallo et al. (2021), who focus on the broader economic effects, such as tariff pass-through to import and retail prices and the response of US exporters to foreign retaliatory tariffs. While both Cavallo et al. (2021) and our work find that US consumers largely bear the cost of tariffs, our paper provides a more granular analysis of household-level impacts, highlighting uneven distributional effects and offering critical insights for policymakers to consider the regressive nature of tariffs in future trade policies.[5] Our paper also complements Jaravel and Sager (2024), who find that trade between the US and China led to lower prices, especially for poorer households. While Jaravel and Sager (2024) focus only on price levels, we examine the role of expenditure switching and variety changes.[6]

Finally, our paper relates to the work of Auer et al. (2024), who examine the distributional effects of exchange rate appreciation across different income groups in Switzerland. The main difference is that the approach by Auer et al. (2024) uses sufficient statistics to measure the unequal impacts of price changes, whereas we provide reduced-form evidence of the effects of rising import prices. This allows us to distinctly analyze the variations in both the number of varieties consumed (which is lower for richer households) and changes in expenditures across product modules (which is higher for richer households).

The remainder of the paper is organized as follows. Section 2 describes the data sources. Section 3 presents the structural framework, which we estimate in Section 4. Section 5 discusses our empirical findings and Section 6 concludes.

2 Data Description

This section describes the main data sources and how we construct the key variables used in the empirical analysis. Our variable of interest is the household's exposure to increasing import tariffs, and its construction uses US household consumption data and trade and import tariff information.

[5] Consistent with Cavallo et al. (2021), we find a positive but modest pass-through of tariffs to barcode-level prices within product modules. However, using a coarse proxy for product origin, we estimate a higher pass-through for goods imported from China.

[6] Direct evidence of expenditure switching in the literature is limited, with Bems and Di Giovanni (2016) being one of the earliest contributions. Their study demonstrates that shifts in income can drive expenditure switching. In contrast, we show that tariff-induced expenditure switching varies with income levels.

2.1 Consumer Panel Database

We use the NielsenIQ Consumer Panel (also known as the Home Scanner database), made available through the Kilts Center for Marketing at the University of Chicago Booth School of Business. The dataset contains approximately 263 million barcode-level transactions from 91,535 households across 2,803 U.S. counties, spanning 2016 to 2019. For each purchase, we observe prices and quantities at weekly frequency, along with store identifiers.[7] The data capture household expenditures on consumer packaged goods purchased through retail outlets, including categories such as food and beverages (e.g., cheese, eggs, beer); health and beauty products (e.g., oral care, baby products, skincare); household supplies (e.g., cleaners, laundry detergent); and general merchandise (e.g., batteries, cookware, office supplies). As noted by Borusyak and Jaravel (2021), this panel covers roughly 30–35% of total household expenditure on tangible goods typically found in national accounts—such as food, household products, and other everyday consumer goods.

A product is defined by a unique barcode, a 12-digit Universal Product Code (UPC). UPCs are categorized into more than a thousand product modules, such as oral hygiene products and batteries. We follow Bai and Stumpner (2019) and aggregate these product modules into 232 product categories and further into seven broad product groups, which we use in the descriptive tables and figures of this section.

While the raw data are available at the shopping trip level, we aggregate consumer purchases to the household-barcode level on an annual basis and across all stores. This approach minimizes potential data sparsity and aligns with our objective of examining the effects of tariffs on prices regardless of the location in which a product is purchased. Our empirical regression is based on a balanced household panel consisting of households appearing in 2016-2019. The final dataset contains 39,403 households in 2,467 counties that cover the entire mainland United States (i.e., 48 states and the District of Columbia) between 2016 and 2019.

In addition to detailed budget shares for households, the Consumer Panel Database also contains information on household characteristics such as race, age, education, marital status, income level, and presence of children. In particular, household incomes are reported as 16 different discrete income ranges, from under $5,000 per year to above $100,000 per year. As the proportion of households in each income group varies greatly, we categorize households into five distinct income groups (i.e., lowest income, lower-middle income, middle income, upper-middle income, and highest income) based on the quintiles of household per capita income in 2016 to study heterogeneous responses across income groups.[8]

[7]Households scan each item they purchase using handheld devices provided by NielsenIQ. For further details on the data, see Hottman et al. (2016), Faber and Fally (2022), and Feenstra et al. (2022).

[8]We aggregate the provided income ranges in quintiles in order to compare income groups of similar size. In fact, in 2016, only 0.54% of the household total income was in the range of $5,000-$7,999, while 21.61% of the household

In Online Appendix B1, we present descriptive statistics on expenditure shares across product modules and broad categories, comparing households across different income levels. The highest-income households allocate a smaller share of their expenditures to food and miscellaneous items compared to the lowest-income households, with a difference of 5.2 percentage points. Conversely, high-income households spend a larger proportion on drinks and household, office, and school supplies, with differences of 1.7 and 1.5 percentage points, respectively. Differences also emerge within specific product modules. For example, in the drinks category, the lowest-income group allocates relatively more to soft drinks, beer, and malt liquor, while the highest-income group spends more on domestic dry wine and scotch. Wealthier households tend to allocate a higher share to animal food, cellular phones, and both anti-smoking and tobacco-smoking products. Meanwhile, lower-income households spend more on disposable diapers, dairy and milk products, ready-to-eat cereals, and frozen poultry and pizza. Finally, low-income households display more concentrated expenditure shares across a narrower set of product modules than wealthier households.

While the Nielsen data primarily cover grocery and other fast-moving consumer goods, they capture a substantial share of household spending on tariff-affected items. To assess representativeness, we benchmark our sample against several reference points from the 2016 Consumer Expenditure Survey, prior to the imposition of new tariffs.[9] Tariff-affected goods in our sample account for 5.3% of total household income, 6.8% of total consumption, 20.3% of tradable-sector spending, and 54.7% of grocery expenditure. These figures indicate that while our data do not capture all spending categories—most notably, durable goods—they provide strong coverage of the sectors where tariff exposure is most concentrated, making them well-suited for analyzing the direct impact of trade policy on day-to-day consumption. Although our analysis focuses on consumer goods, it is important to note that capital and intermediate goods represented 18.9% and 39.6% of U.S. imports from China in 2016. These categories are not directly observed in the household data, but our extended analysis incorporates input tariffs and finds that their welfare effects are relatively limited compared to those borne by consumers.

2.2 US Trade and Import Tariff Data

The MFN import tariffs imposed by the United States during 2016 and 2019 are from the World Integrated Trade Solution (WITS) database.[10] The additional trade war tariffs are collected

total income was in the range of $70,000-$99,999. The per capita income is computed by dividing the midpoint of the self-reported income interval by the household size.

[9] Online Appendix B1 outlines the expenditure categories, maps them to Nielsen product modules, and reports the resulting coverage ratios.

[10] In our sample, approximately 8% of the US MFN tariff data is missing, which account for only 1.81% of the expenditure share in the consumption data. Applying the method proposed by Teti (2020), we fill approximately 1 percentage point of the missing data. The remaining 7 percentage points is missing due to non-ad valorem tariffs. We

from the US International Trade Commission (USITC) and we aggregate them into annual average rates. Specifically, we scale tariffs in proportion to their duration within a 12-month interval. For example, a 20% tariff implemented for six months in a year would be assigned a value of 10% (=20% $\times$ 6/12). Online Appendix A provides information on the seven waves of tariffs imposed by the US on Chinese products.

There is no direct link between the product classifications used in tariffs and in the consumer panel data: tariffs are reported at the Harmonized System (HS) level, while consumer data classifies UPCs into different product modules. We use the classification concordance between product modules and HS six-digit codes developed by Bai and Stumpner (2019) to trace the average exposure to tariffs for each product module.[11] In our sample, 1,279 six-digit HS products were matched, and the products subject to additional tariffs covered 47.3% of the products subject to additional tariffs imposed by the US on China. As there is no more disaggregated concordance between barcodes and HS codes, in our analysis, tariffs vary only across product modules and not across barcodes within a product module. This inherent data limitation implies that we can precisely trace the effects of trade war tariffs across different product modules but not across different barcodes within the same product module.[12]

Online Appendix B2 provides summary statistics regarding the distribution of tariffs imposed by the US on China across various product modules. The data reveal that most product modules were affected by these tariffs, with only 77 modules exempted from additional charges during the trade conflict. The tariff impact varies significantly across modules, largely depending on the tariff wave that primarily affected each category. Modules facing the highest additional tariffs include 'water softeners & conditioners,' 'salt water softening,' 'ice cream and yogurt makers,' 'water conditioner filters and units,' and 'water filtration storage containers,' each subject to an additional

did not use the ad valorem equivalent (AVE) tariffs because these rates are excessively high for certain products (e.g., the AVE tariff for cigarettes is 3000%) and exhibit significant fluctuations from year to year. Teti (2020) also considers the potentially missing AVEs to be a relatively minor issue.

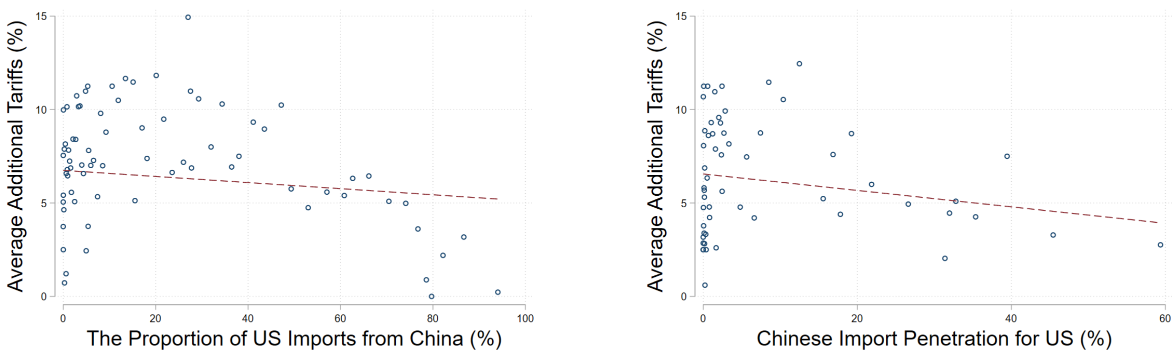
[11] Bai and Stumpner (2019) construct a concordance between NielsenIQ product modules and HS six-digit codes using the U.S. Census Bureau's Schedule B search tool and the Canadian Importers Database, aiming to maximize the number of merged categories. A category is defined as a unique grouping that links one or more NielsenIQ product modules with one or more HS6 codes, based on their descriptions in the NielsenIQ and COMTRADE systems. Each product module and HS6 code is assigned to exactly one category, ensuring mutual exclusivity and full coverage of all relevant modules and codes. The final concordance contains 324 distinct categories, spanning 1,147 NielsenIQ product modules and 878 HS6 codes. Among these, 125 are one-to-one matches (a single product module paired with a single HS6 code). Another 51 categories reflect one-to-many matches, where one NielsenIQ module maps to multiple HS6 codes, and 87 categories represent many-to-one matches, where multiple modules correspond to a single HS6 code. The remaining 61 categories involve many-to-many matches, which occur when product definitions differ between the NielsenIQ and COMTRADE classifications. For example, "tea" is split into several modules in NielsenIQ and simultaneously spans multiple HS6 codes in trade data.

[12] In a robustness exercise, we attempt to identify the likely origin of products using the GS1 barcode prefix, which—while not a definitive indicator of manufacturing origin—can signal a higher probability of association with a particular country. Specifically, we use this approach to flag barcodes commonly linked to China.

18.75% tariff (refer to Online Appendix Table B2.1).

Figure 1 plots the additional US tariff imposed across product modules against both the import share and import penetration rate from China.[13] Among these modules, the average share of US imports from China is 17.6%, while the average import penetration rate is 6.5%. Notably, many product modules, such as toasters, baby accessories, and bathroom scales, exhibit high import penetration rates and substantial import shares from China. The figure further suggests that the tariff-induced price effects could potentially have been greater if modules with high import shares from China had been subject to the highest tariffs. Instead, these products generally face low to medium additional tariffs.

Figure 1: US Additional Tariffs on China and Import Metrics



(a) Import Share from China

(b) Import Penetration from China

Notes: The vertical axis in both figures represents the average additional tariff imposed during 2018-2019. In (a), the horizontal axis illustrates the import share from China in 2016, defined as the share of imports from China in total US imports. In (b), the horizontal axis represents the import penetration rate from China in 2016, defined as the share of imports from China in total expenditure, calculated as domestic output plus imports minus exports. Blue circles represent the means of 100 evenly-sized bins. The red line is a linear fit.

2.3 Household Exposure to Trade War Tariffs

Our key explanatory variable is a measure of exposure to US import tariffs for household h in year t, which we denote as TAR_{ht} and is constructed by combining the consumer panel and import tariff data. We measure each household's exposure to tariffs by summing module-level tariffs, weighted by each household's expenditure share on each module before the trade war. TAR_{ht} is computed according to the following equation:

$$TAR_{ht} = \sum_{m \in \Omega^M_{ht_0}} S_{hmt_0} \tau^{US,CHN}_{mt} \tag{1}$$

[13] Online Appendix B2 details the computation of these measures.

where S_{hmt_0} denotes household h's expenditure share on module m before the trade war in $t_0 = 2016$ and $\Omega^M_{ht_0}$ denotes the set of modules purchased by household h in $t_0 = 2016$. By construction, $\sum_{m\in\Omega^M_{ht_0}} S_{hmt_0} = 1$ for any household. The variable $\tau^{US,CHN}_{mt}$ is the tariff rate imposed by the US on Chinese goods in module m, including MFN tariff rates and additional tariffs during the 2018-2019 trade war. The intuition behind this measure is to exploit the exogenous changes in tariff rates imposed by the US, while maintaining a stable composition of consumption baskets for each household over time.

Since we match tariffs at the product module level, it remains unclear whether the observed price effects, measured by our tariff exposure, stem from higher prices of UPCs originating from China or from price increases by Chinese competitors in response to the tariffs. The tariff impacts that we quantify encompass both effects. Additionally, in our baseline regression, we abstract from the indirect effects of the trade war caused by higher tariffs on intermediate inputs, which could contribute to increased prices of final goods. We explore this channel in a subsequent extension presented below.

Figure 2 illustrates the correlation between the change in household tariff exposure (i.e., before and after the US-China trade war) and per capita household income. Notably, the upward-sloping lines in Figure 2 suggests that richer households experienced higher tariff shocks, while poorer households faced lower tariff shocks. Yet, the difference between income groups is minimal, ranging from 5.0% for the lowest-income group to almost 5.3% for the second highest-income group. As we demonstrate below, the results of our reduced-form regressions suggest that richer households experience a smaller increase in the price index. Therefore, relying solely on the tariff exposure measure as a sufficient statistic would yield misleading conclusions.

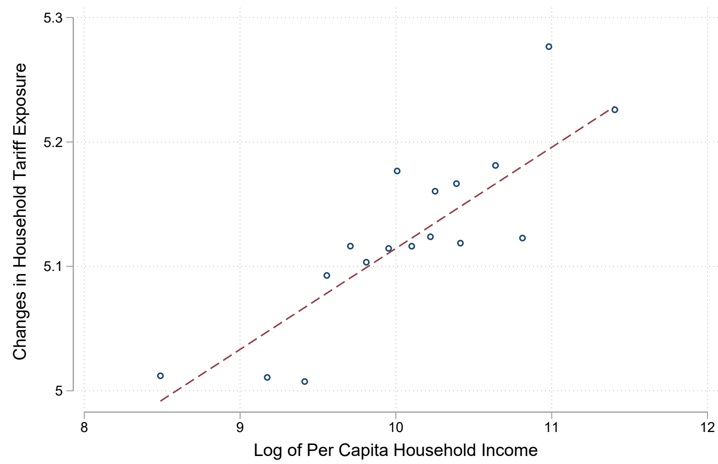
3 Quantification Framework

This section extends the framework of Redding and Weinstein (2020) to account for heterogeneous consumers, developing a structural model to quantify the effects of tariffs on household price indexes across income levels and to decompose these effects into distinct channels of adjustment.

3.1 Model Environment

Households enjoy the consumption of a discrete number of varieties of differentiated goods. We denote each household with the subscript h and varieties with v, equivalent to a UPC in the empirical application. Each UPC belongs to a single module, denoted by m. For example, a UPC is "Colgate Total Toothpaste" and the corresponding product module is "Oral Hygiene Products". Households have a nested preference structure with two layers. The first layer is a CES aggregation

Figure 2: Changes in Tariff Exposure and Household Income



Notes: The figure describes the correlation between changes in household tariff exposure (i.e., 2016-2017 average and 2018-2019 average) and per capita household income in 2016. Each observation is a household. Blue circles represent the means of 18 evenly-sized bins. The red line is a linear fit.

over product modules $m \in \Omega^M_{ht}$, such that the utility of household h at time t, denoted with U_{ht}, is given by the following equation:

$$U_{ht} = \Big[\sum_{m \in \Omega^M_{ht}} \Phi_{hmt}^{\frac{\sigma-1}{\sigma}} Q_{hmt}^{\frac{\sigma-1}{\sigma}} \Big]^{\frac{\sigma}{\sigma-1}} \tag{2}$$

where Q_{hmt} is the consumption index of module m for household h at time t; $\Phi_{hmt} \geq 0$ is household h's taste parameter for module m; $\sigma > 0$ denotes the elasticity of substitution across modules, and Ω^M_{ht} is the set of product modules. If $\Phi_{hmt} = 0$, the household does not purchase any varieties of module m. The consumption index Q_{hmt} of module m for household h at time t is the second layer of the preference, and it is a CES aggregation over UPCs:

$$Q_{hmt} = \Big[\sum_{v \in \Omega_{hmt}} \varphi_{hvt}^{\frac{\sigma^m-1}{\sigma^m}} q_{hvt}^{\frac{\sigma^m-1}{\sigma^m}} \Big]^{\frac{\sigma^m}{\sigma^m-1}} \tag{3}$$

where q_{hvt} is the consumption of product v in module m for household h at time t; φ_{hvt} captures the demand shifter of household h for UPC v; σ^m is the elasticity of substitutions across varieties within the product module m; Ω_{hmt} is the set of varieties in module m at time t. While in a standard CES framework, households purchase all varieties, in our model, if $\varphi_{hvt} = 0$, UPC v is not purchased by household h. Given the demand system, we derive the household-specific price index in the following equation:

$$P_{ht} = \Big[\sum_{m \in \Omega^M_{ht}} (P_{hmt}/\Phi_{hmt})^{1-\sigma} \Big]^{1/(1-\sigma)}, \quad P_{hmt} = \Big[\sum_{v \in \Omega_{hmt}} (p_{vt}/\varphi_{hvt})^{1-\sigma^m} \Big]^{1/(1-\sigma^m)} \tag{4}$$

where P_{hmt} is the household module-specific price index. The utility-maximizing expenditures of household h on module m and variety v are expressed in equation (5):

$$Y_{hmt} = \frac{\Phi^{\sigma-1}_{hmt} P^{1-\sigma}_{hmt}}{\sum_{n \in \Omega^M_{ht}} \Phi^{\sigma-1}_{hnt} P^{1-\sigma}_{hnt}} Y_{ht}, \quad Y_{hvt} = \frac{\varphi^{\sigma^m-1}_{hvt} p^{1-\sigma^m}_{vt}}{\sum_{v' \in \Omega_{hmt}} \varphi^{\sigma^m-1}_{hv't} p^{1-\sigma^m}_{v't}} Y_{hmt} \tag{5}$$

where Y_{ht} denotes the total household income, and Y_{hmt} and Y_{hvt} are the expenditures on module m and UPC v, respectively. As implied by the demand system, heterogeneity across households in demand shifters for modules and UPCs generates heterogeneity in product expenditure shares across consumers of different incomes, conditional on the same prices.

The market demand for product v in module m at time t (i.e., $q_{vt} = \sum_h q_{hvt}$) can be written in equation (6):

$$q_{vt} = \sum_h \Big(\frac{\varphi^{\sigma^m-1}_{hvt} p^{-\sigma^m}_{vt}}{P^{1-\sigma^m}_{hmt}} \Big) Y_{hmt} = \sum_h \Big(\frac{\varphi^{\sigma^m-1}_{hvt} Y_{hmt}}{P^{1-\sigma^m}_{hmt}} \Big) p^{-\sigma^m}_{vt} \tag{6}$$

Following the framework established by Feenstra (1994) and Broda and Weinstein (2006, 2010), we assume a general and tractable upward-sloping supply curve with constant elasticity, represented as:

$$p_{vt} = exp(\delta_{vt}) q^{\omega^m}_{vt} \tag{7}$$

where $\omega^m \geq 0$ is the inverse supply elasticity in sector m, δ_{vt} capture unobservable variety-specific supply shocks.

The above quantitative framework extends the models of Bai and Stumpner (2019) and Hottman and Monarch (2020) by introducing heterogeneity in consumer taste across households over the same product in a similar way to Feenstra et al. (2022). In particular, the CES framework in Bai and Stumpner (2019) cannot capture heterogeneity in expenditure shares over an identical product across households. Hence, that framework cannot fully capture the variance in how individuals with different income levels respond to price changes. With a more general setting, Hottman and Monarch (2020) construct household-specific import price indexes within a two-tier CES framework, where they allow the household-specific taste shifters to vary across sectors but not across products within a sector. Our approach extends this framework by introducing heterogeneity in demand shifters at a more granular level.[14]

Our approach nests the non-homothetic CES preferences of Comin et al. (2021). In their model, product demand shifters can be decomposed into an exogenous component and a non-homothetic component that depends on both household utility and a product-specific income elasticity. Our methodology differs from Comin et al. (2021) in that it does not prescribe a specific functional relationship between income and demand shifters. This flexibility allows for arbitrary relationships between these variables and accommodates cases in which demand shifters may be zero. Additionally, our model simplifies the identification of product-specific demand shifters within a nested preference framework by treating them as demand residuals. As we show below, the fact that demand shifters depend on income (or respond to tariff changes) does not bias our estimation of demand.

3.2 Household-specific Consumer Price Indexes

Following Redding and Weinstein (2020), we express the exact household price index as a function of four components: (i) the average UPC price, (ii) the average UPC expenditure share within its product module, (iii) the module's expenditure share in total spending, and (iv) a variety-adjustment term capturing the entry and exit of UPCs.

We derive this decomposition by inverting the demand function Y_{hvt} in (5) to solve for the household–module-specific price index:

$$P_{hmt} = s_{hvt}^{1/(\sigma^m-1)} \left(\frac{p_{vt}}{\varphi_{hvt}} \right) \tag{8}$$

where $s_{hvt} = Y_{hvt}/Y_{hmt}$ is the expenditure on UPC v as a share of total expenditure in module m for household h in year t. Taking the unweighted geometric mean across all N_{hmt} varieties in Ω_{hmt}, we obtain the following expression for the household-module specific price index:

$$P_{hmt} = \left[\prod_{v \in \Omega_{hmt}} s_{hvt}^{\frac{1}{N_{hmt}(\sigma^m-1)}} \right] \left[\prod_{v \in \Omega_{hmt}} (p_{vt})^{\frac{1}{N_{hmt}}} \right] \tag{9}$$

To derive the expression in the second bracket, we normalize the geometric mean of the demand shifters across UPCs to one, i.e., $\widetilde{\varphi_{mt}} = \prod_{v \in \Omega_{hmt}} (\varphi_{hvt})^{\frac{1}{N_{hmt}}} = \widetilde{\varphi} = 1$, following Hottman and Monarch (2020).[15] Thus, the changes in the household-module-specific price index are driven by changes in

[14]In a robustness exercise, we quantify the welfare costs of the tariffs using the model by Hottman and Monarch (2020). Without assuming heterogeneity in demand shifters across households within a product module, we overestimate the increase in the price index due to the tariffs (1.6% relative to our baseline result of 1.09%) for all households and, in particular, for richer households.

[15]We use a tilde above a variable to denote a geometric mean across UPCs.

the prices of UPCs and changes in expenditure shares.

Next, we invert equation (5) to obtain P_{ht} as a function of the expenditure share S_{hmt} on module m for household h:

$$P_{ht} = S_{hmt}^{1/(\sigma-1)} \left(\frac{P_{hmt}}{\Phi_{hmt}} \right) \tag{10}$$

where $S_{hmt} = Y_{hmt}/Y_{ht}$ is the expenditure on module m as a share of total expenditure for household h in year t.

To capture the effect of the entry and exit of product modules in the households' consumption bundles, we compute the share of expenditures on product modules that are continuously purchased by households. This expenditure share is informative of the welfare gains from variety as purchases of new product modules lead to a smaller expenditure share on continuously purchased products (Feenstra, 1994). Let $\bar{\Omega}_h^M$ denote the set of common product modules that appear in the consumption basket of household h continuously from 2016 to 2019, defined as: $\bar{\Omega}_h^M = \Omega_{ht}^M \cap \Omega_{ht'}^M$, $\forall t, t' = 2016, ..., 2019$.[16] Let λ_{ht} denote the spending on the set of common modules $\bar{\Omega}_h^M$ in year t by household h, relative to her total spending at time t, which can be expressed by the following equation:

$$\lambda_{ht} \equiv \frac{\sum_{m \in \bar{\Omega}_h^M} \sum_{v \in \Omega_{hmt}} p_{vt} q_{hvt}}{\sum_{m \in \Omega_{ht}^M} \sum_{v \in \Omega_{hmt}} p_{vt} q_{hvt}} = 1 - \frac{\sum_{m \in \Omega_{ht}^M \setminus \bar{\Omega}_h^M} \sum_{v \in \Omega_{hmt}} p_{vt} q_{hvt}}{\sum_{m \in \Omega_{ht}^M} \sum_{v \in \Omega_{mt}} p_{vt} q_{hvt}} \tag{11}$$

where λ_{ht} also equals one minus household h's expenditure share on modules consumed only at time t.

The expenditure share on common products λ_{ht} can be written as $S_{hmt}/S_{hmt}(\bar{\Omega}_h^M)$, where $S_{hmt}(\bar{\Omega}_h^M) \equiv \frac{\sum_{v \in \Omega_{hmt}} p_{vt} q_{hvt}}{\sum_{g \in \bar{\Omega}_h^M} \sum_{v \in \Omega_{hgt}} p_{vt} q_{hvt}}$ for $\forall m \in \bar{\Omega}_h^M$. We can replace the share S_{hmt} in equation (10) by using $S_{hmt} = S_{hmt}(\bar{\Omega}_h^M)\lambda_{ht}$, as shown in following equation:

$$P_{ht} = S_{hmt}(\bar{\Omega}_h^M)^{1/(\sigma-1)} \left(\frac{P_{hmt}}{\Phi_{hmt}} \right) \lambda_{ht}^{1/(\sigma-1)} \tag{12}$$

We derive the exact price index by substituting equation (9) into equation (12), and taking the unweighted geometric mean over the modules in the common set $\bar{\Omega}_h^M$. We follow the normalization assumption of Hottman and Monarch (2020), that is, $\widetilde{\Phi}_t = \prod_{m \in \bar{\Omega}_h^M} (\Phi_{hmt})^{\frac{1}{M_h}} = \widetilde{\Phi} = 1$, where $M_h = \|\bar{\Omega}_h^M\|$ denotes the number of common modules consumed by the household h. The exact

[16] We define the set of common products at the product module level, i.e., as modules continuously purchased by a household, rather than at the UPC level. This choice is motivated by the sparsity of continuously consumed UPCs: in approximately 82.46% of household-module observations, no single UPC is purchased in all periods, meaning the set of common UPCs is empty. Given the high level of disaggregation in our product modules, our analysis focuses on the entry and exit of modules. We later examine how tariffs affect the number of UPCs consumed.

price index is equal to:

$$P_{ht} = \left[\prod_{m \in \bar{\Omega}_h^M} \prod_{v \in \Omega_{hmt}} (p_{vt})^{\frac{1}{M_h N_{hmt}}} \right] S_{ht}(\bar{\Omega}_h^M) \Lambda_{ht}(\bar{\Omega}_h^M) \tag{13}$$

where the expenditure share term $S_{ht}(\bar{\Omega}_h^M)$ and the variety adjustment term $\Lambda_{ht}(\bar{\Omega}_h^M)$ are defined as:

$$S_{ht}(\bar{\Omega}_h^M) \equiv \left[\prod_{m \in \bar{\Omega}_h^M} S_{hmt}(\bar{\Omega}_h^M)^{\frac{1}{M_h(\sigma-1)}} \right] \left[\prod_{m \in \bar{\Omega}_h^M} \prod_{v \in \Omega_{hmt}} s_{hvt}^{\frac{1}{M_h N_{hmt}(\sigma^m - 1)}} \right] \tag{14}$$

$$\Lambda_{ht}(\bar{\Omega}_h^M) \equiv \left[\prod_{m \in \bar{\Omega}_h^M} \lambda_{ht}^{\frac{1}{M_h(\sigma-1})} \right] = \lambda_{ht}^{\frac{1}{\sigma-1}} \tag{15}$$

The decomposition of the exact price index has an intuitive interpretation. We refer to the first term on the right-hand side of equation (13) as the *price channel*, as it represents the geometric mean of prices across varieties within the common module set. This corresponds to the Jevons price index established by Jevons (1865), which is widely used in official statistics for measuring inflation at the lowest level of aggregation. In the special case where UPCs are perfect substitutes, the exact price index simplifies to the Jevons index, since the exponents on the second and third terms of equation (13) converge to zero.

The second term $S_{ht}(\bar{\Omega}_h^M)$, which we refer to as the *expenditure share channel*, depends on the geometric mean of expenditure shares for varieties and modules. This term was first introduced by Redding and Weinstein (2020). We interpret this term as an adjustment in the price index driven by differences in tastes for specific products, but subject to normalizations $\widetilde{\varphi_{mt}} = \widetilde{\varphi} = 1$ for UPCs and $\widetilde{\Phi}_t = \widetilde{\Phi} = 1$ for modules in the common set $\bar{\Omega}_h^M$. The term $S_{ht}(\bar{\Omega}_h^M)$ can be further decomposed into two components as shown in equation (14): the geometric mean of expenditures shares across common product modules and the geometric mean of expenditure shares across varieties within a module. The first component captures the extent of heterogeneity in expenditure share among common modules, and the second component captures the degree of heterogeneity in expenditure shares across barcodes within modules.

The expenditure share channel is influenced by the dispersion of expenditure shares across modules and UPCs. As expenditure shares become more concentrated, the term increases. Hence, a higher concentration of expenditures on fewer modules or UPCs increases the price index, and a more even distribution of expenditures reduces the price index. The underlying intuition for this share term is that when faced with varieties of a differentiated good, consumers inherently benefit from a spread in taste-adjusted prices. This spread among varieties is valuable because it affords them the flexibility to maximize their utility by selecting varieties with lower taste-adjusted prices over those with higher taste-adjusted prices.[17]

The last term of equation (13) represents the *variety channnel* as it captures how the availability of varieties affects the exact price index and accounts for the effect resulting from the entry and exit of product modules, a canonical term first introduced in the literature by Feenstra (1994). In the case that new varieties are more attractive than disappearing ones for household h, her share of expenditures on modules only available at time t increases, which reduces $\Lambda_{ht}(\bar{\Omega}_h^M)$ and thus lowers the consumer price index.

4 Calibration of Model Parameters

To apply our method to compute the exact price index for households and investigate the distributional impact of tariff changes, we need to calibrate the key model parameters, which include the elasticities of substitution across modules and UPCs and the consumer demand shifters over product modules and UPCs. The estimation proceeds in two stages: first, we estimate the second-layer utility parameters; second, we estimate the first-layer parameters. To address the issue of endogeneity in estimating demand parameters, we closely follow the method of Feenstra (1994) in estimating parameters in the first stage and that of Hottman and Monarch (2020) in the second stage. The estimation is based on the data from the NielsenIQ's Consumer Panel Database.

4.1 Estimating Parameters of the Second Layer

For each module m, we estimate four key parameters: (i) the elasticity of substitution, σ^m; (ii) the inverse supply elasticity, ω^m; (iii) the UPC-specific demand shifters, φ_{vt}; and (iv) the UPC-specific supply shifters, δ_{vt}. Following Feenstra (1994), we exploit identification from heteroskedasticity to recover the first two parameters—a strategy that has become standard in the literature (Broda and Weinstein, 2006; Soderbery, 2015; Hausmann and Xu, 2019; Feenstra et al., 2020; Hottman and Monarch, 2020).

Double-Differenced Demand. We begin by taking logs of equation (6) and then applying a double difference—first over time t, and second across another UPC k within the same module m. This transformation isolates the demand relationship linking changes in expenditures to changes

[17]Concerns may arise regarding how to evaluate the welfare effects of tariffs if they are linked to preference changes caused by shifting demand shifters. In this context, the price index serves as a valid welfare measure because it incorporates adjustments in consumer preferences. Specifically, the price index captures changes in the cost of achieving a given level of utility, reflecting both changes in prices and demand shifters induced by the tariff.

in prices, while sweeping out unobserved factors common to all UPCs in the module:

$$\Delta^{k,t} \ln(p_{vt} q_{vt}) = (1 - \sigma^m)\Delta^{k,t} \ln p_{vt} + \nu_{vt} \tag{16}$$

where $\Delta^{k,t} x_{vt} \equiv (x_{vt} - x_{vt-1}) - (x_{kt} - x_{kt-1})$ denotes the double difference operation and ν_{vt} is the unobserved error term, defined by the following equation $\nu_{vt} \equiv \Delta^t \ln \sum_h \left(\frac{\varphi_{hvt}^{\sigma^m - 1} Y_{hmt}}{P_{hmt}^{1-\sigma^m}} \right) - \Delta^t \ln \sum_h \left(\frac{\varphi_{hkt}^{\sigma^m - 1} Y_{hmt}}{P_{hmt}^{1-\sigma^m}} \right)$, and $\Delta^t x_t \equiv x_t - x_{t-1}$ denotes the single difference across time. The term ν_{vt} captures the unobserved double-differenced idiosyncratic demand shocks.

Double-Differenced Supply. Taking logs of equation (7) and adding $\omega^m \ln p_{vt}$ to both sides, we then double-difference the equation with respect to time and to another product k. This yields the following equation for the supply relationship between product expenditures and prices:

$$\Delta^{k,t} \ln p_{vt} = \frac{\omega^m}{\omega^m + 1} \Delta^{k,t} \ln(p_{vt} q_{vt}) + \kappa_{vt} \tag{17}$$

where $\kappa_{vt} \equiv 1/(1 + \omega^m)[\Delta^t \delta_{vt} - \Delta^t \delta_{kt}]$ measures the unobserved double-differenced idiosyncratic supply shocks.

Moment Conditions. As in Feenstra (1994), we obtain a set of moment conditions holding for each UPC based on an orthogonality condition between the unobserved double-differenced idiosyncratic shocks to demand (ν_{vt}) and to supply (κ_{vt}):

$$G_v(\beta_m) = \mathbb{E}_T[\nu_{vt}(\beta_m)\ \kappa_{vt}(\beta_m)] = 0 \tag{18}$$

where $\mathbb{E}_T$ denotes the expectation over time and $\beta_m = (\sigma^m, \omega^m)$. The identification assumption that the expectation of the double-differenced demand shocks and supply shocks equal to zero defines a rectangular hyperbola in the (σ_m, ω_m) space for each UPC within a given product module m (Leamer, 1981). As a result, this rectangular hyperbola effectively delineates bounds on the demand and supply elasticities for each unique UPC within the product module, even in the absence of instruments for demand and supply. Additionally, when the variances of double-differenced demand and supply shocks are heteroskedastic across UPCs, the rectangular hyperbolas differ for each pair of UPCs within the product module. Thus, the intersection of these hyperbolas enables us to separately identify the demand and supply elasticities for that specific product module (Feenstra, 1994). The double-difference operation is critical in our analysis, as it differences out the UPC and module-time fixed effects, thereby addressing most standard endogeneity concerns.[18]

For each module m, we estimate $\hat{\beta}_m$ by minimizing the following objective function:

$$\hat{\beta}_m = \arg\min_{\beta_m} \{G(\beta_m)' W G(\beta_m)\} \tag{19}$$

where $G(\beta_m)$ is a vector of the UPC-specific moments G_v defined in (18) and W is a positive definite weighting matrix. We follow Broda and Weinstein (2006) and Hottman and Monarch (2020)'s choice of weighting matrix that gives larger weights to varieties appearing in the data for longer periods and being sold with larger quantities, which are expected to have less measurement error in their unit value.[19]

With the estimated σ^m and ω^m for module m, we recover the variety-specific demand shifters. Recall that we normalize the geometric average of demand shifters in each module to be one for all periods ($\widetilde{\varphi_{mt}} = \widetilde{\varphi} = 1$). With this parametrization, the demand shifter for each UPC v can be recovered by differencing Y_{hvt} in (5) relative to its geometric mean:

$$\ln \varphi_{hvt} = \frac{1}{\sigma^m - 1}\Big[\ln p_{vt} q_{hvt} - \ln \widetilde{pq_{hmt}} + (\sigma^m - 1)(\ln p_{vt} - \ln \widetilde{p_{mt}})\Big] \tag{20}$$

where $\widetilde{pq_{hmt}}$ and $\widetilde{p_{mt}}$ denote the geometric mean of $p_{kt} q_{hkt}$ and p_{kt} across all UPCs $k \in \Omega_{hmt}$ at time t. Finally, we can directly compute δ_{vt} using equation (7).

4.2 Estimating Parameters of the First Layer

In the second stage, we estimate the elasticity of substitution across product modules σ. We take logs of equation (5) and take the double difference over time and relative to a product module n to obtain:

$$\Delta^{n,t} \ln Y_{hmt} = (1 - \sigma)\Delta^{n,t} \ln P_{hmt} + \nu_{hmt} \tag{21}$$

where $\nu_{hmt} = (\sigma - 1)\Delta^{n,t} \ln \Phi_{hmt}$. Given the estimated parameters from the first stage, we can compute the household-module-specific price index using equation (8). Then, we estimate the above equation by pooling the double-differenced variables across households h, modules m, and time t. After the double difference, any time-invariant heterogeneity across modules does not affect the estimation.

[18] By differencing across UPCs within the module, we eliminate common module-level shocks that could affect both demand residuals and supply residuals. Similarly, differencing over time within UPCs eliminates time-invariant heterogeneity between varieties (e.g. different production technologies).

[19] Specifically, we weight products according to $T_v^{3/2}(\frac{1}{q_{vt}} + \frac{1}{q_{vt-1}})^{-1/2}$, where T_v denotes the number of periods that UPC v is present in the sample, and q_{vt} is the quantity of UPC v purchased by all households.

Instrumental Variable. A regression of $\Delta^{n,t} \ln Y_{hmt}$ on $\Delta^{n,t} \ln P_{hmt}$ is subject to endogeneity bias, as the price index is affected by v_{hmt}, the error term of (21), which includes household-module-specific demand shifters. To address this bias, we employ an instrumental variable (IV) approach as in Hottman et al. (2016) and Hottman and Monarch (2020), who decompose the module-level price index into four components and use the component unaffected by demand shifters as the instrumental variable. Specifically, the change in the log of the module price index can be linearly decomposed into four terms:

$$\Delta^{n,t} \ln P_{hmt} = \Delta^{n,t} \left(\frac{1}{N_{hmt}} \sum_{v \in \Omega_{hmt}} \ln p_{vt} \right) - \left(\frac{1}{N_{hmt}} \sum_{v \in \Omega_{hmt}} \ln \varphi_{hvt} \right)$$
$$- \Delta^{n,t} \frac{1}{\sigma^m - 1} \ln N_{hmt} - \Delta^{n,t} \frac{1}{\sigma^m - 1} \ln \left(\frac{1}{N_{hmt}} \sum_{v \in \Omega_{hmt}} \frac{(p_{vt}/\varphi_{hvt})^{1-\sigma^m}}{\widetilde{(p/\varphi)}_{hmt}^{\,1-\sigma^m}} \right)$$

where N_{hmt} is the number of UPCs consumed by household h in module m at time t.[20] The change in the sector-level demand shifter is likely correlated with the first and third terms on the right-hand side of this equation. For instance, positive sector demand shocks could lead to increasing average prices and entry of new varieties. In contrast, the last term measures the change in dispersion in demand shifter-adjusted prices across UPCs within a module. The validity of the IV requires that the changes in dispersion in quality-adjusted prices within a module m are uncorrelated with the changes in the module-level demand shifter, as argued in Hottman et al. (2016) and Hottman and Monarch (2020). Hence, we use this term as an instrument for the change in the price index. The instrument Z_{hmt} is defined as:

$$Z_{hmt} = -\Delta^{k,t} \frac{1}{\sigma^m - 1} \ln \left(\frac{1}{N_{hmt}} \sum_{v \in \Omega_{hmt}} \frac{(p_{vt}/\varphi_{hvt})^{1-\sigma^m}}{\widetilde{(p/\varphi)}_{hmt}^{\,1-\sigma^m}} \right) \tag{22}$$

The parameter σ can be obtained by estimating (21) using two-stage least squares with Z_{hmt} as IV to $\Delta^{n,t} \ln P_{hmt}$. The first-stage F statistics exceeds the recommended threshold of 10 from Stock et al. (2002), suggesting that the relevance condition is satisfied.

Given the estimated σ, we can recover the household-specific demand shifters for each module. Similarly to how we estimate φ_{hvt}, we obtain them from (5) by normalizing $\widetilde{\Phi}_t = \widetilde{\Phi} = 1$ for modules in the common set $\bar{\Omega}_h^M$:

$$\ln \Phi_{hmt} = \frac{1}{\sigma - 1} \left[\ln Y_{hmt} - \ln \widetilde{Y_{ht}} + (\sigma - 1)(\ln P_{hmt} - \ln \widetilde{P_{ht}}) \right] \tag{23}$$

where the demand shifter Φ_{hmt} depends on household h's expenditure on product module m and the

[20]For the detailed derivation process for this decomposition, please refer to Online Appendix C.

aggregate household module-level price index, relative to the household's geometric mean across the common product modules consumed in all periods by the household.

Discussion on Demand Shifters and Identification. Our treatment of demand shifters serves as a flexible shorthand that allows our framework to capture any changes in demand, conditional on prices and the demand elasticity. In this setup, policy interventions such as tariff changes may indeed influence these demand shifters. This raises potential concerns about our identification strategy. However, our approach does not rely on the assumption that demand shocks are entirely independent of policy changes. Instead, the key identifying assumption is that the *double-differenced* idiosyncratic demand shocks remain orthogonal to the *double-differenced* idiosyncratic supply shocks. In other words, even if tariffs systematically affect consumer preferences—say, by shifting demand toward cheaper goods in a way that depends on household's income—identification is not compromised unless these shifts also induce correlated changes in the idiosyncratic component of supply, which is driven primarily by firm- or UPC-level productivity or cost shocks.

There are strong reasons to believe this orthogonality assumption holds. First, US tariffs are typically imposed at the HS-code or product-category level and apply uniformly across firms and varieties, regardless of their individual cost structures. Consequently, any supply-side responses to tariffs are likely to be broad and systematic, rather than idiosyncratic at the UPC level. Our use of double-differencing across both time and UPCs further isolates high-frequency, variety-specific shocks and effectively filters out low-frequency policy-driven changes.

Second, potential channels through which tariffs might affect supply—such as disruptions to input sourcing or heightened regulatory uncertainty—are unlikely to vary meaningfully across UPCs within a product category. Such effects are better captured by time-varying fixed effects or firm-level shocks, and are unlikely to generate the sort of narrowly-targeted distortions that would violate the orthogonality assumption.

4.3 Calibration Results

Panel (A) of Table 1 shows the distribution of the GMM estimates for the elasticity of substitution among varieties within a product module (σ_m).[21] The estimated elasticity ranges from 3.06 at the 10th percentile to 7.96 at the 90th percentile, with a median of 5, aligning with trade elasticities reported by Broda and Weinstein (2006).[22] Additionally, Panel (A) reports the inverse

[21] In the robustness exercises (Tables E3.5-E3.7), we allow for the possibility that rich and poor households have distinct elasticities of substitution.

[22] We also present the elasticity of substitution within each product module and display them in Online Appendix Figure B3.1. Broda and Weinstein (2006) estimate σ^m at the HS ten-digit code level for US imports from 1990-2001. For comparison, we map HS ten-digit level code with NielsenIQ product modules using the concordance between HS six-digit and product modules provided by Bai and Stumpner (2019). As shown in Figure B3.1, our estimates are

supply elasticity (ω_m), which spans from 0.13 at the 10th percentile to 0.99 at the 90th percentile, with a median of 0.30.

Panel (B) of Table 1 presents the elasticity of substitution across product modules, with OLS results in column (2) and IV estimates in column (3). The estimated elasticity of substitution across product modules using the instrumental variable approach is about 2.86, consistent with that in Hottman and Monarch (2020), who use the BLS Consumer Expenditure Survey and trade data for the United States.

Table 1: Summary of Estimated Parameters

Panel A: Estimates for σ^m and ω^m											
Percentiles	1%	5%	10%	25%	50%	75%	90%	95%	99%	Mean	Observations
σ^m	1.70	2.49	3.06	3.89	5.00	6.29	7.96	9.86	21.21	5.72	953
ω^m	0.04	0.09	0.13	0.19	0.30	0.47	0.99	2.03	8.88	0.71	953

Panel B: Estimates for σ			
	OLS	IV	IV 95% C.I.
σ	1.66	2.86	2.838-2.872

Notes: The parameter σ^m denotes the elasticity of substitution among UPCs within a product module m; ω^m is the inverse supply elasticity; σ is the elasticity of substitution across product modules. The 95% confidence intervals for σ are computed using heteroscedasticity-robust standard errors.

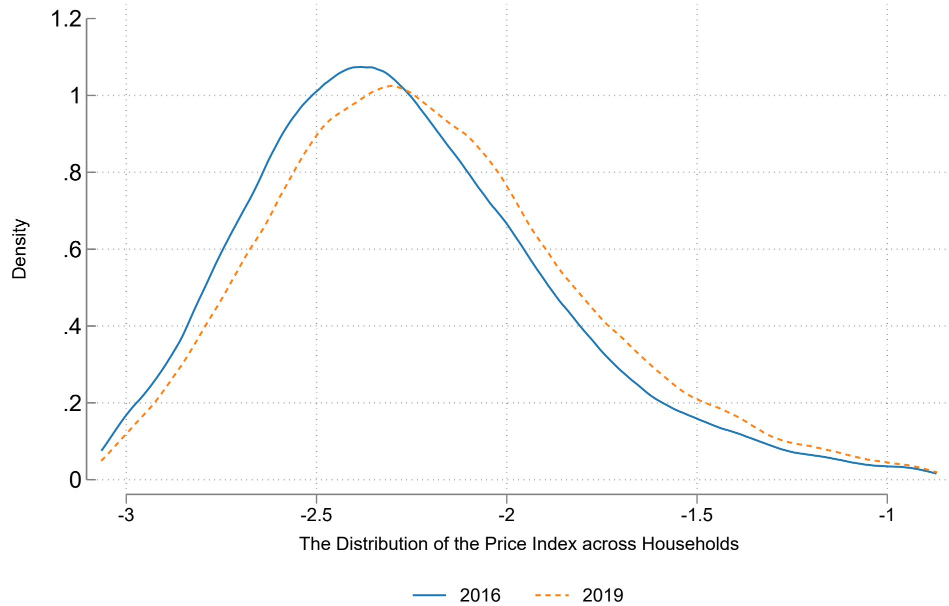
With these parameters, we can compute the change in the consumer price index according to (13) as implied by the model. We winsorize the price indexes by dropping those below the 1st percentile and above the 99th percentile to mitigate the impact of extreme values. Figure 3 provides the distribution of the log of household price index before and after the US-China trade war. In 2016, the average log of household price index was -2.27. However, by 2019, the average log of household price index increases to -2.20, indicating a substantial increase of approximately 7% in the exact price index.

5 Empirical Results

We proceed to investigate the distributional consequences of tariffs on Chinese imports and discuss potential mechanisms. First, we find that tariff hikes led to a notable increase in the household price index, with higher-income households experiencing a relatively lower impact. Second, we find that this difference in effects is attributed to the greater ability of richer households to adjust spending patterns and to reduce the number of purchased varieties by less.

strongly positively correlated with those by Broda and Weinstein (2006) with the 10th percentile value of sigma being 2.29, the median being 6.05, and the 90th percentile being 21.37.

Figure 3: Change of Household Price Index



Notes: This figure displays the distribution across households of the log of price index before and after the US-China trade conflict.

5.1 Baseline Results

Our baseline regression investigates the impact of tariff shocks on the household-specific exact price index, which captures the expenditure required to attain a fixed level of utility.[23] We estimate the following regression specification:

$$\ln P_{ht} = \mu_h + \mu_{ct} + \mu \ln(1 + TAR_{ht}) + \epsilon_{ht}, \tag{24}$$

where $\ln P_{ht}$ is the price index of household h at time t from equation (13). In all regressions, we control for time-invariant household-specific characteristics with household fixed effects μ_h, and county-specific time trend with county-year fixed effects.

Panel (A) of Table 2 presents the baseline results. Column (1) shows that greater tariff exposure is associated with a statistically significant increase in the household price index. The point estimate implies that, on average, a 10% rise in import tariffs raises the household price index by 2.32%. To gauge the economic magnitude of the U.S.–China trade war, we perform a simple

[23]While our focus is on the effects of tariffs on the price index, others have studied their effects on income (Flaaen and Pierce, 2024). The combination of both is required to assess welfare. Moreover, our analysis centers on the price index for goods in the Nielsen data. Hence, if poorer households spend a larger share of their total expenditures on groceries, the larger increase we document in their grocery price index would translate into a disproportionately higher rise in their overall cost of living compared to richer households.

back-of-the-envelope calculation: increasing tariff exposure, $\ln(1+TAR_{ht})$, from its pre–trade war average of 4.8% to its trade war average of 9.5% implies a $1.09\% = (9.5\% - 4.8\%) \times 0.232$ increase in the average household price index.[24]

Table 2: Tariff Shock and Household Price Index

	$\ln P_{ht} = \ln \widetilde{p_{ht}} + \ln S_{ht} + \ln \Lambda_{ht}$				$\ln S_{ht} = \ln \widetilde{s^m_{ht}} + \ln \widetilde{s^v_{ht}}$	
Dep var.	(1) $\ln P_{ht}$	(2) $\ln \widetilde{p_{ht}}$	(3) $\ln S_{ht}$	(4) $\ln \Lambda_{ht}$	(5) $\ln \widetilde{s^m_{ht}}$	(6) $\ln \widetilde{s^v_{ht}}$
Panel (A): Tariff Shock and Household Price Index						
$\ln(1+TAR_{ht})$	0.232***	0.097***	-0.107**	0.242***	-0.131***	0.024
	(0.062)	(0.034)	(0.043)	(0.034)	(0.040)	(0.023)
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	152,359	152,359	152,359	152,359	152,359	152,359
R^2	0.951	0.963	0.974	0.865	0.978	0.692
Panel (B): Heterogeneous Effects Across Households						
$\ln(1+TAR_{ht})$	0.346***	0.107***	-0.017	0.256***	-0.117***	0.100***
	(0.067)	(0.037)	(0.046)	(0.037)	(0.041)	(0.025)
$\ln(1+TAR_{ht}) \times Second\ Income_{t_0}$	-0.023	0.006	-0.031*	0.003	-0.010	-0.021*
	(0.031)	(0.018)	(0.018)	(0.015)	(0.014)	(0.012)
$\ln(1+TAR_{ht}) \times Third\ Income_{t_0}$	-0.081***	-0.003	-0.075***	-0.002	-0.028*	-0.048***
	(0.029)	(0.017)	(0.018)	(0.015)	(0.014)	(0.012)
$\ln(1+TAR_{ht}) \times Fourth\ Income_{t_0}$	-0.127***	-0.015	-0.094***	-0.018	-0.003	-0.091***
	(0.031)	(0.018)	(0.019)	(0.016)	(0.015)	(0.012)
$\ln(1+TAR_{ht}) \times Highest\ Income_{t_0}$	-0.192***	-0.021	-0.141***	-0.030*	-0.016	-0.125***
	(0.031)	(0.018)	(0.019)	(0.016)	(0.016)	(0.012)
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	152,359	152,359	152,359	152,359	152,359	152,359
R^2	0.951	0.963	0.974	0.865	0.978	0.693

Notes: Observations are at the household-year level from 2016 to 2019. The dependent variable in column (1) is the household price index ($\ln P_{ht}$) as shown in equation (13), which can be decomposed into three components: price term ($\ln \widetilde{p_{ht}}$), share term ($\ln S_{ht}$), and variety adjustment term ($\ln \Lambda_{ht}$). Specifically, columns (2)-(4) use price term, share term, and variety adjustment term as dependent variables respectively. The share term can be decompose into two components: the expenditure share adjustment across product modules ($\ln \widetilde{s^m_{ht}}$), corresponding to the dependent variable in column (5); and the expenditure share adjustment within product modules ($\ln \widetilde{s^v_{ht}}$), corresponding to the dependent variable in column (6). In panel B, households are divided into five groups based on their income quantile, with the lowest income group serving as the reference group. All columns include household fixed effects and county-year fixed effects. Robust standard errors clustered at household level are in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

To identify the channels driving these results, we separately regress each component of the index on tariff exposure. The three components capture the main mechanisms through which tariffs influence the price index: changes in average prices, shifts in expenditure shares, and adjustments

[24]Summary statistics for the key variables are reported in Online Appendix Tables B3.1 and B3.2.

in product variety. Columns (2)–(4) of Table 2 report the estimates. A 10% increase in import tariffs is associated with a 0.97% rise in average product prices. Prior studies find that U.S. tariffs are almost fully passed through to the prices of affected imports, implying a one-for-one increase in import prices following a tariff hike (Amiti et al., 2020; Fajgelbaum et al., 2020). In contrast, our estimate is an order of magnitude smaller. This muted response reflects the limited share of Chinese goods in overall retail sales and aligns with the low pass-through rates of tariffs into prices to final consumers documented by Cavallo et al. (2021).

In contrast, a 10% increase in tariffs leads to a 1.07% decrease in the share term, suggesting that households respond to the additional tariffs by reallocating their expenditure shares across product modules and UPCs. We split the share term into expenditure reallocation across product modules and that across UPCs with a module according to equation (14). Columns (5) and (6) indicate that this reallocation of expenditure shares is primarily driven by shifts between different modules.

The additional tariffs also decrease product varieties, as shown in column (4) – a 10% increase in import tariffs comes with a 2.42% increase in $\Lambda_{ht}(\bar{\Omega}_h^M)$ suggesting the significant impact of the entry and exit of products on households' price index.[25] The product modules most likely to be dropped belong to the electrical appliances category (e.g., various types of lamps) and the household, office, and school supplies category, including items such as inkjet and toner cartridges, different types of pencils, and kitchen utensils and gadgets. On average, the dropped product modules tend to have higher average prices and lower consumption shares compared to those that remain in the common set. A detailed comparison of average prices and consumption shares across continuously purchased modules and dropped modules is provided in Online Appendix Table B1.2.

To shed light on the distributional consequences of tariff shocks on the price index of US households of different income groups, we divide households into five groups based on per capita income and introduce interaction terms between tariff exposure and dummy variables for income groups. We use the lowest-income group of households as the reference group. The estimated impact of tariffs on the exact price index across consumers with different income levels is reported in column (1) of panel (B) of Table 2.

Compared with households in the lowest income group, additional tariffs have a smaller effect on higher-income households, as indicated by the negative and statistically significant interaction terms for the third, fourth, and highest income quintiles. Moreover, the magnitude of these coefficients increases with income, implying a monotonic decline in tariff impacts as income rises. A simple back-of-the-envelope calculation suggests that the increase in the price index for households in the highest income quintile is about 0.9 percentage points lower than for those in the lowest quintile (calculated as $(9.5\% - 4.8\%) \times 0.192$).

[25] We also find that tariffs had no impact on the introduction or discontinuation rates of UPCs within the full dataset, thus alleviating concerns about sample selection bias.

Income, however, is only an imperfect proxy for a household's budget constraint, which also depends on accumulated wealth. Without direct wealth measures, misclassification can occur—for example, low-income but asset-rich households may be labeled "poor," biasing welfare estimates downward. To address this, Online Appendix E2 examines tariff impacts by demographic characteristics correlated with wealth and long-run consumption capacity. The patterns reinforce our main message: households with highly educated heads face smaller price increases, consistent with higher lifetime earnings and asset holdings; younger households face larger increases, reflecting less time to build wealth buffers; white households see smaller rises than nonwhite households, consistent with well-documented racial wealth gaps; single households face smaller increases than married ones; and households with children experience the largest effects, consistent with higher spending needs and thinner financial cushions.[26]

5.2 Price Index Decomposition across Income Groups

In this section, we explore the effects of tariffs on the three elements in which we can decompose the price index following Redding and Weinstein (2020): a price channel, an expenditure share channel, and a variety channel, as discussed in Section 3.2. We find that heterogeneity in the tariff response is mainly related to the difference in the expenditure share and variety channels.

Price Channel. As shown in column (2) at panel (B) of Table 2, rising tariffs significantly increase the average price for a barcode. However, the pattern does not show a meaningful difference in the impact across households with different income levels, and thus, the increase in average prices does not seem to play a role in generating heterogeneity among households in different income groups.

Expenditure Share Channel. In column (3) of panel (B) of Table 2, we find that the share term of the price index tends to decrease more for richer households. This result implies that expenditure reallocation helps mitigate the increase in the price index, and rich households can better take advantage of such an adjustment margin. As richer households readjust their expenditures, their budget shares across products become less concentrated and, as a result, the price index declines.

We further investigate the factors driving the expenditure share channel, which can be due to changes in expenditures across product modules or across UPCs within a module. To distinguish between these two scenarios, we split the expenditure share into two parts as shown in equation (14). As presented in columns (5) and (6) of panel (B), the primary driving force for reallocation of expenditure shares is product switching across UPCs within the same product modules rather than

[26] Detailed results are reported in Tables E2.1–E2.5, showing that low-education, younger, Black/African American, married, and child-rearing households experience more pronounced price increases.

switching between modules. A simple back-of-the-envelope calculation reveals that the mechanism of product switching within the product module accounts for 73.4% (= 0.141/0.192) of the smaller increase in the price index for the highest income group compared to the lowest income group.

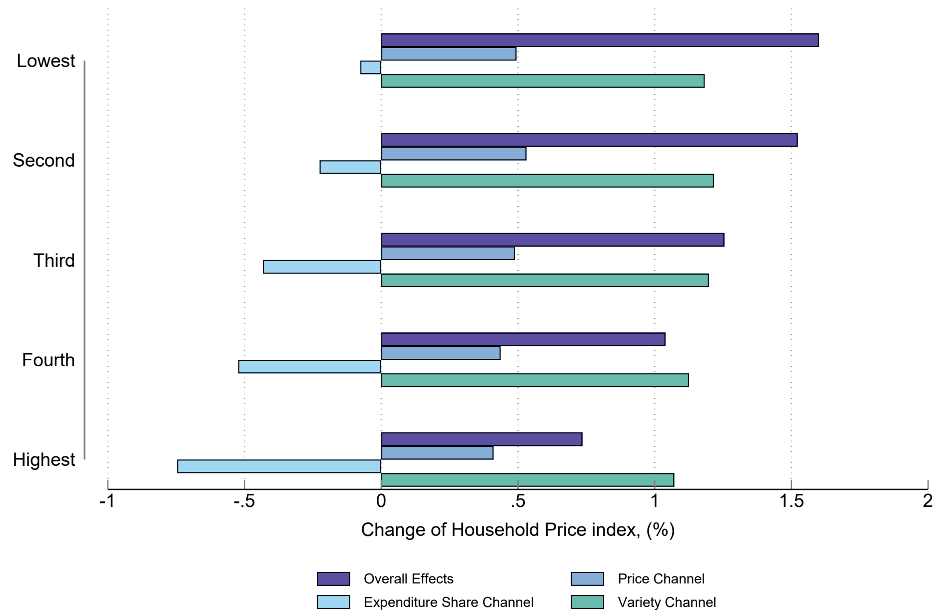
For an example of this mechanism, consider the following purchases of lighting products by high- and low-income households before and after a tariff increase. Before the tariff, low-income households primarily opted for cost-effective lighting products, such as the "Cyber Tech Lighting" brand model "S-W 43W," priced at $3.96. After the tariff, the price of this model rose modestly to $4.12, yet these households continued to purchase the same product. In contrast, high-income households displayed greater flexibility in their purchasing behavior following the tariff. Initially, they often chose the "FEIT ELECTRIC" brand model "S-W 11.5W" at an average price of $12.51. After the tariff, they shifted to other models within the same brand, such as "FEIT ELECTRIC ENHANCE" options like "T-L 8.8W" ($11.14) and "T-L 17.5W" ($11.50).

Variety Channel. The variety adjustment term (i.e., $\Lambda_{ht}(\bar{\Omega}_h^M)$) takes into account the entry and exit of product modules, which can also contribute to the relatively lower increase in the price index for high-income households (Feenstra, 1994). An increase in the expenditure share on products appearing in both periods raises the price index of the household. As reported in column (4) in panel (B), compared to the group with the lowest income, additional tariffs lead to a smaller increase in the variety adjustment term, indicating richer consumers face a smaller reduction in product diversity. Overall, the variety adjustment accounts for 15.6% (= 0.030/0.192) of the relatively smaller rise in the price index for the highest-income group compared to the lowest-income group.

In summary, the US tariffs have a more pronounced impact on the price index for lower-income households, while the effects are relatively milder for top earners. Figure 4 shows the estimated impact of the increase in US import tariffs during 2018-2019 on the overall household price index across various income groups.[27] Moreover, we decompose the change in the index into the contribution of the three mechanisms we discussed above. While richer households exhibit slightly greater exposure to additional tariffs (Figure 2), the results indicate that tariff increases led to an increase in the price index and households with higher income experienced a relatively lower impact. This discrepancy is attributed to wealthier households' greater ability to adjust their spending patterns and to reduce product diversity to a lesser extent.

[27]Specifically, we calculate the average increase in US tariffs on China's exports before and after the US-China trade conflict for each income quintile (Table B3.1) and multiply the tariff changes by the corresponding tariff pass-through rate (Table 2, panel B) to estimate the impact for each income group.

Figure 4: Impact on Household Price Index



Notes: This figure illustrates the estimated effects on household price index due to the increase of US import tariffs on China during 2018-2019, along with the results of a mechanism decomposition.

5.3 Validating the Decomposition: Reduced-Form Evidence

We next provide reduced-form evidence that corroborates the three channels identified in our decomposition. The goal is to show that the observed patterns—and the differential expenditure responses of high- and low-income households to tariff shocks—are not artifacts of the decomposition procedure or the assumptions embedded in the price index. Instead, the decomposition delivers a welfare-consistent measure that accurately reflects changes in household spending behavior.

Price Channel. To further validate our results, we aggregate the data to the barcode level and estimate tariff pass-through to average barcode prices. A limitation of the data is that we cannot observe the origin of each barcode. We therefore regress average barcode prices on module-specific tariff rates. Columns (1) and (2) of Table E1.1 show that import tariffs significantly raise barcode-level prices, with an estimated pass-through rate of approximately 0.12. This magnitude aligns closely with our baseline household-level estimates (see column (2) of Table 2) and is in line with the results of Cavallo et al. (2021). In column (3), we address the lack of origin information by focusing on a subset of products whose GS1 barcode prefixes are commonly associated with China.[28] There is an important caveat, which is that this approach is likely underestimating the

[28]While GS1 prefixes do not definitively indicate country of origin, they suggest a higher likelihood of association with China. Using this method, we identify around 1,500 barcodes, representing roughly 0.03 percent of total house-

share of products coming from China. For this China-linked subset, the estimated pass-through rate is substantially higher, at approximately 1.5, suggesting a much stronger price response to tariffs for directly affected imports.

Expenditure Share Channel. Our findings suggest that low-income households exhibit significantly less flexibility in adjusting their expenditure in response to tariff shocks. In particular, faced with tariff hikes, higher-income households are more likely to switch from higher-priced barcodes to lower-prices ones within the same module. Online Appendix Table E1.2 explores substitution from higher- to lower-priced UPCs within a module.[29] Consistent with the previous section, the results show that higher-income households are more likely to reallocate their spending toward these lower-priced barcodes when faced with tariff shocks.

Next, we investigate potential drivers of the observed heterogeneity in expenditure switching. A plausible explanation lies in differential access to retail channels across income groups. Table 3 documents clear disparities in shopping behavior: first, lower-income households experienced a larger decline in shopping frequency following the tariff shock; second, lower-income households allocate a larger share of their expenditures to dollar stores, while higher-income households rely more heavily on warehouse clubs, hypermarkets, and online platforms. These latter channels typically offer a broader array of product varieties and more favorable unit prices—especially for bulk purchases or generic substitutes—thus enabling greater flexibility in responding to price increases. In contrast, limited access to these outlets may constrain the consumption choices of poorer households, making it harder for them to substitute toward cheaper or untaxed alternatives.

Online Appendix Table E1.3 further sheds light on how households adjust shopping behavior in response to tariff shocks. Column (1) shows that tariffs reduce shopping frequency among poorer households, suggesting that rising prices may force them to consolidate purchases or ration consumption. Columns (2) to (5) examine shifts across retail channels. In response to tariffs, households reallocate spending toward warehouse clubs, hypermarkets, and online platforms—channels that offer lower prices and more variety. However, this shift is largely driven by high-income households, who have greater access to these outlets and the flexibility to buy in bulk. In contrast, low-income households remain reliant on dollar stores, where substitution options are limited and prices are less responsive.

Variety Channel. In Table 4, we investigate whether the increase in tariffs leads households to consume fewer product modules, and the outcome variable is the number of product modules per household. Column (1) suggests that households consume fewer product modules in response to

hold consumption. Notably, the number of these barcodes declined sharply after tariff shocks, falling from an annual average of 866 during 2016–2017 to 391 during 2018–2019.

[29] We define low-price barcodes as those with average 2016–2017 prices below the median in each module.

Table 3: Summary Statistics of Shopping Behavior by Income Group, 2016–2019

	2016-2017		2018-2019	
	Low Income	High Income	Low Income	High Income
Shopping Frequency	187.06	189.54	175.72	183.48
	(122.88)	(123.45)	(119.88)	(122.24)
Expenditure Share (%)				
Dollar store	2.37	1.29	2.48	1.35
	(4.98)	(3.24)	(5.47)	(3.45)
Warehouse Club/ Hypermarket	8.63	11.03	8.81	11.35
	(14.02)	(15.03)	(14.40)	(15.48)
Online Shopping	2.48	3.27	2.81	3.71
	(6.49)	(7.48)	(7.51)	(8.28)
Others	86.52	84.42	85.91	85.59
	(15.18)	(16.25)	(15.99)	(16.88)

Notes: This table reports summary statistics on shopping behavior for low-income and high-income households, both before and after tariff shocks. It includes annual household spending, shopping frequency, and the expenditure shares across different retail channels. For each variable, the table presents the mean values with standard deviations in parentheses.

tariff increases. On average, a 1% increase in import tariffs reduces the number of product modules by 2.5%. To provide some insights into which characteristics might be associated with the new and disappearing products, we categorize non-common product modules into "high-tariff products" and "low-tariff products" according to whether the additional tariff rate is above the top 25 percentile of the distribution of tariffs. As shown in columns (2) and (3) of Table 4, households tend to consume fewer products in modules exposed to high tariff shock, while there is no obvious decrease in module number among those with low-tariff exposure. We add interaction terms between tariff exposure and household income groups in columns (4)-(6) of Table 4, and all interaction terms exhibit a statistically significant positive coefficient, suggesting that higher-income households experienced comparatively less variety loss compared to lower-income households.

Next, we use the number of UPCs of a module consumed by a household as the dependent variable in column (1) of Table 5, and the Herfindahl-Hirschman Index (HHI) that captures the within-module concentration of expenditure as the outcome variable in column (2).[30] Therefore, the HHI is related to the expenditure share channel discussed above. Our results indicate that tariff shocks lead households to concentrate their purchases on fewer UPCs within a given module—suggesting a reduction in product variety. However, this contraction in variety is not uniform across income groups. As shown in columns (3) and (4), higher-income households experience a smaller decline in the number of UPCs consumed and a less pronounced increase in expenditure concentration. To ensure consistency with our exact price index decomposition, we replicate the analysis using only modules in the common set across households (i.e., $m \in \bar{\Omega}_h^M$). The results, shown in columns

[30] $HHI_{hmt} = \sum_{v \in \Omega_{hmt}} (esh_{hvt})^2$, where esh_{hvt} is the expenditure share on UPC v within the module m consumed by household h. A higher HHI indicates a higher concentration of consumption within a module and vice versa.

Table 4: Mechanism: variety loss

Dep var.:Log module number	(1) Total number in Ω_{hmt} $\ln N_{ht}$	(2) High tariff products in $\Omega_{hmt} \setminus \bar{\Omega}_h^M$ $\ln N_{ht,high\ tariff}$	(3) Low tariff products in $\Omega_{hmt} \setminus \bar{\Omega}_h^M$ $\ln N_{ht,low\ tariff}$	(4) Total number in Ω_{hmt} $\ln N_{ht}$	(5) High tariff products in $\Omega_{hmt} \setminus \bar{\Omega}_h^M$ $\ln N_{ht,high\ tariff}$	(6) Low tariff products in $\Omega_{hmt} \setminus \bar{\Omega}_h^M$ $\ln N_{ht,low\ tariff}$
$\ln(1+TAR_{ht})$	-0.245***	-1.401***	-0.064	-0.406***	-1.792***	-0.382***
	(0.079)	(0.172)	(0.130)	(0.086)	(0.186)	(0.141)
$\ln(1+TAR_{ht}) \times Second\ Income_{t_0}$				0.021	0.152*	0.047
				(0.039)	(0.088)	(0.067)
$\ln(1+TAR_{ht}) \times Third\ Income_{t_0}$				0.111***	0.287***	0.203***
				(0.037)	(0.085)	(0.064)
$\ln(1+TAR_{ht}) \times Fourth\ Income_{t_0}$				0.188***	0.431***	0.370***
				(0.039)	(0.089)	(0.068)
$\ln(1+TAR_{ht}) \times Highest\ Income_{t_0}$				0.268***	0.607***	0.544***
				(0.039)	(0.089)	(0.067)
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	152,359	152,333	152,359	152,359	152,333	152,359
R^2	0.907	0.685	0.711	0.907	0.685	0.711

Notes: Observations are at the household-year level from 2016 to 2019. The dependent variables in column (1) and (4) represent the logarithm of the number of modules consumed by household h. Further, by categorizing the product modules outside the common set into "high tariff modules" and "low tariff modules", column (2) and (5) correspond to the number of high tariff modules, while column (3) and (6) correspond to the number of low tariff modules. Households are divided into five groups based on their income quantile, with the lowest income group serving as the reference group. All columns include household fixed effects and county-year fixed effects. Robust standard errors clustered at household level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

(5) through (8), confirm the earlier findings: tariff shocks reduce the number of UPCs and raise expenditure concentration, but these effects are notably weaker among high-income households.

Discussion of Theoretical Implications. Online Appendix D presents a purposefully simple model to provide a microfoundation of the two main mechanisms identified in our empirical analysis, which describe how consumers with varying income levels react to increased tariffs. The focus is to explain why wealthier consumers typically face a smaller reduction in the variety of goods they purchase and demonstrate a greater tendency to shift their spending. In contrast to the empirical analysis model, where any changes in consumption patterns can be rationalized with an appropriate change in demand shifters, in the theory part, we rely on a generalized Constant Elasticity of Substitution (CES), also known as the Pollak preference structure (Arkolakis et al., 2019; Jung et al., 2019), to better understand the consumer's decision making process. For the expenditure share channel, we show that although richer consumers exhibit less sensitivity to price fluctuations, they predominantly opt for the pricier products, which inherently have a more elastic demand. Hence, this higher demand elasticity implies that richer households are more likely to mitigate the impact of tariffs through changes in expenditures. For the variety channel, we show that richer households, with higher reservation prices, are less affected by tariff-induced price increases, as these remain within their affordability range, resulting in minimal loss of product variety. In contrast, for poorer households with lower reservation prices, these tariff increases often exceed their spending capacity, leading to a more significant reduction in available product choices.

5.4 Robustness Analysis

We conduct a series of robustness exercises to assess the validity of our identification strategy and the stability of our baseline estimates. These exercises address potential concerns about alternative transmission channels, model specification, and measurement choices, ensuring that our findings are not driven by idiosyncratic assumptions or data limitations.

Accounting for Input-Output Linkages. Our baseline exposure measure assumes that an increase in tariffs on a given product module raises its price, although we remain agnostic about the degree of pass-through. However, the price of a product module may also increase indirectly if tariffs increase the cost of inputs used in its production.

To capture these indirect effects of US import tariffs through input-output linkages (Acemoglu et al., 2016), we construct an upstream exposure measure for each module m using the BEA input-output table for the US economy in 2012. We then reconstruct the household tariff shock as specified in Equation (1). The upstream tariff shock for industry i is calculated as $\tau_{it}^{U} = \sum_{j=1}^{N} \omega_{ij}\tau_{jt}$, where ω_{ij} represents the cost share of input j in the production of i. As a robustness check, we

Table 5: Product Switching Within Module

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All sample				Common module set			
Dep var.:	Log UPC number	HHI_{hmt}	Log UPC number	HHI_{hmt}	Log UPC number	HHI_{hmt}	Log UPC number	HHI_{hmt}
$\ln(1+TAR_{ht})$	-0.136***	0.057***	-0.316***	0.121***	-0.167***	0.066***	-0.394***	0.138***
	(0.051)	(0.020)	(0.055)	(0.022)	(0.063)	(0.023)	(0.068)	(0.025)
$\ln(1+TAR_{ht}) \times Second\ Income_{t_0}$			0.055**	-0.019*			0.074**	-0.023*
			(0.028)	(0.011)			(0.034)	(0.012)
$\ln(1+TAR_{ht}) \times Third\ Income_{t_0}$			0.116***	-0.043***			0.149***	-0.049***
			(0.026)	(0.010)			(0.032)	(0.011)
$\ln(1+TAR_{ht}) \times Forth\ Income_{t_0}$			0.204***	-0.068***			0.267***	-0.081***
			(0.028)	(0.011)			(0.034)	(0.012)
$\ln(1+TAR_{ht}) \times Highest\ Income_{t_0}$			0.302***	-0.107***			0.371***	-0.119***
			(0.027)	(0.011)			(0.034)	(0.012)
Household-Module FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26,120,982	26,120,982	26,120,982	26,120,982	13,681,112	13,681,112	13,681,112	13,681,112
R^2	0.724	0.635	0.724	0.635	0.705	0.594	0.705	0.594

Notes: Observations are at the household-module-year level from 2016 to 2019. The dependent variable $LogUPCnumber$ represents the number of barcode variety consumed by household within module m. The dependent variable HHI_{hmt} is the concentration of household consumption, using the Herfindahl-Hirschman Index (HHI) to measure the concentration within each module product. Households are divided into five groups based on their income quantile, with the lowest income group serving as the reference group. All columns include household-module fixed effects and county-year fixed effects. Robust standard errors clustered at household level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

also construct an alternative measure of upstream exposure that excludes diagonal elements from the input-output matrix. This adjustment removes double counting and reduces the collinearity between direct and indirect channels (Wang et al., 2018).

Appendix Table 6 presents our findings. Columns (2) and (4) incorporate the upstream tariff shock, revealing statistically significant coefficients. These results suggest that tariff shocks on upstream inputs are passed on to consumers through input-output linkages, with the magnitude of the effect being approximately one-third of the direct impact shown in our baseline regression. Furthermore, Columns (3) and (5) highlight the distributional consequences of tariffs on inputs, showing that poorer households bear a disproportionate share of the burden.

Homogeneous UPC Demand Shifters for All Households. In our baseline model, the demand shifters for each UPC are household-specific, as shown in Equation (3). We now consider a model where these demand shifters are not household-specific, aligning with the approaches of Hottman et al. (2016) and Hottman and Monarch (2020). Specifically, we replace ϕ_{hvt} with ϕ_{vt} in equation (3); however, the demand shifters in the outer layer of the utility function continue to be household-specific for each module. Under this revised framework, we derive a new household price index, which we then use as the dependent variable in our analysis.

The results, as presented in Table 7, are qualitatively similar to our baseline regression. However, there is an important quantitative difference between our model and the predictions implied by the model by Hottman and Monarch (2020). In fact, the assumption that demand shifters within a module are the same across all households, and are unaffected by tariffs, causes an overestimation of the tariff's effect on the price index and an underestimation of its pro-rich effects. Using the coefficient from column (1) of Table 7, a simple back-of-the-envelope calculation reveals that the additional tariff imposed by the US on China's exports resulted in a $1.59\% = (9.5\% - 4.8\%) * 0.339$ increase in the average household's price index, significantly higher than our baseline calculation of 1.09%. Regarding the distributional impact (i.e., column (5)), households in the highest 20% income bracket experienced a 0.27 percentage point (calculated as $(9.5\% - 4.8\%) * 0.058$) lower increase in the price index compared to those in the lowest 20% income bracket, notably lower than our baseline calculation of 0.9 percentage points.

This is because failing to account for changes in UPC-specific demand shifters reduces the adjustment in expenditure shares in response to price increases, leading to a higher price index driven by larger average prices. Since all households switch expenditures identically, the variation in tariff impacts across income levels is underestimated. In fact, we showed that richer households are less impacted by tariffs because they can more easily adjust their spending patterns. However, this adjustment is only properly measured by assuming heterogeneity in demand shifters within a product module. As this extension does not allow for it, the difference between rich and poor households in response to tariffs is reduced.

Welfare-Relevant Price Index. A key limitation of the approach by Redding and Weinstein (2020) is the assumption that average demand shifters remain constant over time–an untestable restriction, as it pertains to household utility, which is inherently unobservable. To ensure the robustness of our findings, we adopt the welfare-relevant price index developed by Baqaee and Burstein (2023) who account for taste shocks using Hicksian expenditure shares derived from non-homothetic CES preferences. We show the details of the approach in the Appendix. This approach refines the measurement of welfare by incorporating both income effects and shifts in consumer preferences.

To maintain consistency with our baseline framework, we implement their welfare-relevant deflator in a chained index format and re-estimate the regressions. As shown in Table 8, the results remain broadly consistent with our main specification. A 10% increase in import tariffs raises the household price index by 2.38% on average, with the impact falling disproportionately on low-income households. This result is entirely driven by the variety channel, as the decomposition excludes the expenditure share channel, and the effect is concentrated in the top income quintile.

Validating the Bartik Strategy. Next, we address concerns that could affect the validity of the Bartik identification strategy, given that our household-level tariff shocks are constructed using a shift-share approach. The "shock" component captures module-level tariff increases, while the "share" component reflects each household's initial consumption share. The Bartik strategy can be implemented in two ways: one relies on the exogeneity of the shock for identification (Borusyak et al., 2022), and the other relies on the exogeneity of the share (Goldsmith-Pinkham et al., 2020). In our analysis, the US tariff increases on Chinese imports during the 2018–2019 trade war function as an exogenous shock.[31] The validity of the shift-share design in this context hinges on the assumption that these shocks are indeed exogenous. To further ensure robustness, following Borusyak et al. (2022), we test whether the module-level tariff shocks are balanced across households' initial characteristics, weighted by exposure. The results, presented in Table E3.1, indicate that none of these correlations are statistically significant at conventional levels, supporting the reliability of our identification strategy.

Borusyak et al. (2022) demonstrate that the estimating equation can be reformulated as a module-level regression, yielding an export shock effect of the same magnitude. We present the

[31]First, this trade conflict functions as a quasi-natural experiment, characterized by the abrupt and broad implementation of tariffs across a wide range of industries and products—events that households could neither foresee nor influence. Second, tariff policies are determined at the national level, driven largely by political and strategic factors, rather than by household consumption patterns or preferences, further ensuring their exogeneity relative to individual households.

results of these module-level regressions in column (2) of Table E3.2. As noted by Borusyak et al. (2022) and Adao et al. (2019), households with similar initial expenditure shares may experience correlated shocks, indicating that clustering by household alone may be insufficient. The module-level regressions reported in Table E3.2 address this concern by enabling more accurate statistical inference after collapsing the household dimension.

Furthermore, we confirm that if the household-level regression were maintained as the baseline, the results remain robust under various alternative clustering protocols. These include clustering by county and using a separate partitioning of households based on the similarity of their consumption baskets. Specifically, we employ the k-means algorithm to group households with similar expenditure shares. The corresponding results are shown in columns (3)–(5) of Table E3.2, demonstrating that the baseline findings hold consistently across these alternative clustering approaches.

A final concern is that our results may be confounded by industry-specific shocks or influenced by initial specialization in industries with pre-existing trends.[32] To address the possibility of unobserved shocks disproportionately affecting certain industries (Goldsmith-Pinkham et al., 2020), we adopt the approach of Campante et al. (2023). Specifically, we re-estimate the baseline regressions, systematically excluding one product category at a time and reconstructing the household tariff shock. The maximum and minimum coefficient estimates, along with their standard errors, are presented in Table E3.3. Both extremes remain highly significant, confirming that our baseline findings are robust and not driven by any single industry.

Controlling for China's Retaliatory tariff. During 2018–2019, China significantly escalated retaliatory tariffs on US goods, raising the simple average tariff rate from 9.32% to 22.53%. These tariffs likely impacted US prices through multiple channels. For instance, by reducing US exports to China, they created excess supply in the domestic US market, potentially driving prices downward. Moreover, due to supply chain linkages (Handley et al., 2024), these tariffs likely increased input costs for Chinese firms reliant on US imports, which could, in turn, elevate the prices of Chinese exports to the US. To capture these effects, we incorporated exposure to China's retaliatory tariffs into our analysis, as shown in Table E3.4, revealing a significant negative impact on the household price index. Importantly, controlling for these retaliatory tariffs does not alter our baseline regression results.

Differential Substitution Elasticities Across Household Groups. In our baseline analysis, the elasticities of substitution, both between modules (σ) and within modules (σ^m), are assumed to be the same across household groups. In this robustness exercise, we relax this assumption to allow

[32] For instance, a sudden technological advance in the consumer electronics sector could lead to reduced consumption prices for households with a preference for such products, independent of tariff shocks.

for the possibility that rich and poor households have distinct elasticities of substitution. To this end, we divide the sample into high-income and low-income groups based on whether household per capita income exceeds the median income level. Then, we re-estimate the elasticities applying the algorithm of Section 4 for each group separately and we calculate the corresponding price index. The estimation parameters for wealthy households are summarized in Table E3.5, while the estimation parameters for poor households are summarized in Table E3.6. Within product modules, the elasticities of substitutions are higher for richer households than poorer households, which is in line with the appendix's theoretical model that richer consumers purchase a higher share of high-elasticity goods. Table E3.7 presents the estimation results using the new household price index as the dependent variable. Our baseline results are robust to this specification.

Alternative Substitution Elasticities. Soderbery (2015) highlights a potential upward bias in demand elasticities estimated using the Feenstra (1994) method. As a robustness check, we incorporate Soderbery's alternative elasticity estimates, averaging them at the product module level (σ^m) to serve as the inner-CES elasticities in our price index calculations. The regression results, reported in Table E3.10, closely mirror the qualitative patterns of our baseline findings but yield somewhat larger coefficient estimates. This suggests that, if the baseline elasticities are indeed biased upward, our original results may be conservative and represent a lower bound on the true impact of tariff shocks.

Alternative Measurement of Tariff Shock. The household tariff exposure measure in our baseline analysis is constructed using tariffs levied by the US on imports from China, aligned with the households' consumption structure pre-tariff shock, i.e., $TAR_{ht} = \sum_{m \in \Omega^M_{h_0}} S_{hmt_0} \tau^{US,CHN}_m$. Alternatively, we adjust this term by adding the US import penetration rate from China; that is, $TAR\_IMP_{ht} = \sum_{m \in \Omega^M_{h0}} S_{hmt_0} IMP^{CHN}_{mt-1} \tau^{US,CHN}_m$, where IMP^{CHN}_{mt-1} denotes the US import penetration rate of product module m from China in the initial equilibrium $t-1$. As in the baseline model, we use 2016 as the initial period. Table E3.8 reports results using the new tariff exposure measure, which remains consistent with our baseline results. In this case, the average exposure to tariffs increases from 0.08% before the tariff war to 0.23% after the tariff war. Using the results from the estimation, a simple back-of-the-envelope calculation indicated that the additional tariffs levied by the US on China's goods led to an increase of $0.46\% (= (0.23\% - 0.08\%) * 3.078)$ in the price index for US households. Moreover, this increase in the price index is lower for the highest-income group, compared to the lowest-income group, by 0.71 percentage points $(=(0.23\% - 0.08\%) * 4.755)$, which is consistent to the baseline estimation. In addition, we also incorporate US import share from China when constructing household tariff exposure. The results are shown in Table E3.11, which is align with our baseline results.

Heterogeneous Effects across Counties. The regression analysis incorporates county-year fixed effects to account for county-specific time trends. To explore potential heterogeneity in responses to tariff shocks, we interact tariffs with regional characteristics, including counties with high exposure to China shocks, higher income levels, and larger Gini indices. As reported in Online Appendix Table E3.9, the results reveal no significant heterogeneity, mitigating concerns about the influence of pre-existing county-specific trends on the findings.

Other Robustness Checks. A range of additional robustness checks are available upon request. These include placebo tests, alternative measurement strategies, and alternative empirical specifications such as a first-difference model. We also control for household income directly and restrict the sample to households whose income remained within the same bracket throughout the 2016–2019 period. In addition, we re-estimate the results using an alternative household sample. For measurement robustness, we explore several variations: alternative normalization assumptions in the construction of the price index, alternative definitions of common product modules, different tariff exposure measures (including average log tariffs and China-specific tariffs), and an alternative household income definition. Across all specifications and samples, the core results remain consistent, reinforcing the robustness and reliability of our baseline estimates.

6 Conclusion

During the 2018–2019 US–China trade war, both countries implemented major shifts in trade policy, most notably sharp increases in tariff rates. This paper examines how these tariffs affected household-level consumer price indexes and evaluates the distribution of welfare losses across income groups in the US. While previous research has primarily focused on aggregate product-level data to estimate the overall welfare effects of tariffs, relatively little attention has been paid to heterogeneity in these effects across households.

We study the distributional consequences of the trade war by focusing on how tariff-induced price index increases vary across US households. Given households' ability to substitute across products in response to price changes, an accurate measure of household-level price index is crucial. To this end, we employ a structural model with a flexible utility function that allows for heterogeneous preferences. We estimate household-level utility parameters using detailed disaggregated expenditure data from 2016 to 2019 and construct household-specific ideal price indexes that reflect changes in both prices and consumption patterns.

The additional tariffs imposed on Chinese imports during 2016–2019 led to a substantial increase in household-specific price indexes. On average, these tariffs increased the price index by 1.09%. However, the effects were highly uneven: the increase for households in the top income quintile was 0.9 percentage points lower than that for households in the bottom quintile. This disparity is largely driven by differences in substitution behavior and access to product variety. Higher-income households exhibited greater flexibility in reallocating expenditures and were better able to maintain consumption variety, while lower-income households faced sharper constraints in both dimensions. These findings underscore the importance of accounting for consumer heterogeneity when evaluating the welfare effects of trade policy.

Our findings provide broader insight into how tariff increases affect consumer welfare across the income distribution. In light of the sweeping US tariff escalations in the first half of 2025, these results take on renewed significance. Using tariffs as a political tool imposes tangible costs on US households, with lower-income families bearing a disproportionate share of the burden. The result is a regressive price shock that amplifies inflationary pressures where they are most acutely felt and exacerbates existing socioeconomic disparities.

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Appendix

Accounting for Input-output Linkages. We incorporate upstream tariff shocks in Table 6.

Homogeneous UPC Demand Shifters for All Households. In Table 7, we assume that the UPC-specific demand shifters are not household-specific, as in Hottman et al. (2016) and Hottman and Monarch (2020), while the demand shifters in the outer part of the utility function remain household-specific for each module. Relative to our baseline price index, there are two key differences that we should highlight. First, the price index for module m does not vary across households (as households do not differ in their UPC-specific taste. The module-specific price index equals $P_{mt} = s_{vt}^{1/(\sigma^m-1)}\left(\frac{p_{vt}}{\varphi_{vt}}\right)$, where $s_{vt} = Y_{vt}/Y_{mt} = \frac{p_{vt}\sum_h q_{hvt}}{Y_{mt}}$ is the average expenditure on UPC v as a share of total expenditure in module m in year t. Second, in the baseline exercise, the set of UPCs consumed varies by household, while that is not the case here, where all households have the same UPC-specific demand shifters.

Welfare-Relevant Price Index. Following Baqaee and Burstein (2023), we construct an exact hat-algebra CES price deflator that accounts for both continuing and newly available goods. Specifically, the household-level chained price index is given by:

$$\frac{P_{ht}}{P_{ht-1}} = \frac{P^{Inten}_{ht}}{P^{Inten}_{ht-1}} \left(\frac{\lambda_{ht}}{\lambda_{ht-1}} \right)^{\frac{1}{\sigma-1}}, \qquad \frac{P^{Inten}_{ht}}{P^{Inten}_{ht-1}} = \left(\sum_{m \in \Omega^{cn}_{ht}} S_{hmt} \left(\frac{P_{hmt}}{P_{hmt-1}} \right)^{\sigma-1} \right)^{\frac{1}{\sigma-1}} \tag{25}$$

where $\frac{P^{Inten}_{ht}}{P^{Inten}_{ht-1}}$ captures price changes among continuing goods, and $\frac{\lambda_{ht}}{\lambda_{ht-1}}$ is the adjustment for new varieties following Feenstra (1994). At the household-module level, the price index is defined as:

$$\frac{P_{hmt}}{P_{hmt-1}} = \left(\sum_{v \in \Omega^{cn}_{hmt}} s_{hvt} \left(\frac{p_{hvt}}{p_{hvt-1}} \right)^{\sigma^m-1} \right)^{\frac{1}{\sigma^m-1}} \left(\frac{\lambda_{hmt}}{\lambda_{hmt-1}} \right)^{\frac{1}{\sigma^m-1}} \tag{26}$$

where p_{hvt} is the barcode-level price paid by household h, and $\frac{\lambda_{hmt}}{\lambda_{hmt-1}}$ reflects the introduction of new varieties within the module. To ensure comparability with our baseline specification, we use the chained household-level price index as the dependent variable in the regression.

Table 6: Robustness: Input-Output Linkages

	(1) $\ln P_{ht}$	(2) $\ln P_{ht}$	(3) $\ln P_{ht}$	(4) $\ln P_{ht}$	(5) $\ln P_{ht}$
$\ln(1 + TAR_{ht})$	0.232***	0.231***	0.257***	0.237***	0.261***
	(0.062)	(0.062)	(0.063)	(0.063)	(0.063)
$\ln(1 + TAR^{UP}_{ht})$		0.086*	0.115**	0.087**	0.117***
		(0.044)	(0.045)	(0.042)	(0.043)
$\ln(1 + TAR^{UP}_{ht}) \times Second\ Income_{t_0}$			-0.018		-0.018
			(0.020)		(0.019)
$\ln(1 + TAR^{UP}_{ht}) \times Third\ Income_{t_0}$			-0.058***		-0.059***
			(0.019)		(0.019)
$\ln(1 + TAR^{UP}_{ht}) \times Fourth\ Income_{t_0}$			-0.088***		-0.088***
			(0.020)		(0.020)
$\ln(1 + TAR^{UP}_{ht}) \times Highest\ Income_{t_0}$			-0.139***		-0.139***
			(0.020)		(0.020)
Observations	152,359	152,359	152,359	152,359	152,359
R^2	0.951	0.951	0.951	0.951	0.951

Notes: Observations are at the household-year level from 2016 to 2019. The upstream tariff shock to i is a weighted average of the direct import shocks to its suppliers j, where the weight on industry j equals i's purchases from j divided by i's total inputs, using 2012 BAE input-output table for the US economy. In column (4) and (5), we calculate the upstream shock ignoring the input-output relationship of the industry itself, which means the diagonal elements in the input-output matrix are marked as 0. All columns include household fixed effects and county-year fixed effects. Robust standard errors clustered at household level are in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table 7: Uniform Barcode Demand Shifters Across All Households

	$\ln P_{ht} = ln\widetilde{p_{ht}} + \ln S_{ht} + \ln \Lambda_{ht}$							
Dep var.	(1) $\ln P_{ht}$	(2) $\ln \widetilde{p_{ht}}$	(3) $\ln S_{ht}$	(4) $\ln \Lambda_{ht}$	(5) $\ln P_{ht}$	(6) $\ln \widetilde{p_{ht}}$	(7) $\ln S_{ht}$	(8) $\ln \Lambda_{ht}$
$\ln(1 + TAR_{ht})$	0.339***	0.227***	-0.130***	0.242***	0.377***	0.237***	-0.116***	0.256***
	(0.043)	(0.007)	(0.040)	(0.034)	(0.046)	(0.007)	(0.041)	(0.037)
$\ln(1 + TAR_{ht}) \times Second\ Income_{t_0}$					-0.014	-0.007***	-0.010	0.003
					(0.018)	(0.003)	(0.014)	(0.015)
$\ln(1 + TAR_{ht}) \times Third\ Income_{t_0}$					-0.041**	-0.011***	-0.028*	-0.002
					(0.018)	(0.003)	(0.014)	(0.015)
$\ln(1 + TAR_{ht}) \times Fourth\ Income_{t_0}$					-0.032*	-0.011***	-0.003	-0.018
					(0.019)	(0.003)	(0.015)	(0.016)
$\ln(1 + TAR_{ht}) \times Highest\ Income_{t_0}$					-0.058***	-0.012***	-0.015	-0.030*
					(0.019)	(0.003)	(0.016)	(0.016)
Observations	152,359	152,359	152,359	152,359	152,359	152,359	152,359	152,359
R^2	0.963	0.996	0.978	0.865	0.963	0.996	0.978	0.865

Notes: Observations are at the household-year level from 2016 to 2019. The dependent variable in column (1) and (5) is the household price index ($\ln P_{ht}$) as shown in equation (13), which can be decomposed into three components: price term $\ln \widetilde{p_{ht}}$, corresponding to the dependent variables in columns (2) and (6); share term $\ln S_{ht}$, corresponding to the dependent variables in columns (3) and (7); and variety adjustment term $\ln \Lambda_{ht}$, corresponding to the dependent variables in columns (4) and (8). Households are divided into five groups based on their income quantile, with the lowest income group serving as the reference group. All columns include household fixed effects and county-year fixed effects. Robust standard errors clustered at household level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Welfare-Relevant Price Index (Baqaee and Burstein, 2023)

	$\ln P_{ht} = \ln p_{ht}^{Inten} + \ln \Lambda_{ht}$					
Dep var.	(1) $\ln P_{ht}$	(2) $\ln p_{ht}^{Inten}$	(3) $\ln \Lambda_{ht}$	(4) $\ln P_{ht}$	(5) $\ln p_{ht}^{Inten}$	(6) $\ln \Lambda_{ht}$
$\ln(1 + TAR_{ht})$	0.247***	0.007	0.242***	0.277***	0.021	0.256***
	(0.054)	(0.042)	(0.034)	(0.059)	(0.046)	(0.037)
$\ln(1 + TAR_{ht}) \times Second\ Income_{t_0}$				0.030	0.030	0.003
				(0.027)	(0.021)	(0.015)
$\ln(1 + TAR_{ht}) \times Third\ Income_{t_0}$				0.008	0.010	-0.002
				(0.026)	(0.020)	(0.015)
$\ln(1 + TAR_{ht}) \times Fourth\ Income_{t_0}$				-0.016	0.003	-0.018
				(0.028)	(0.022)	(0.016)
$\ln(1 + TAR_{ht}) \times Highest\ Income_{t_0}$				-0.101***	-0.069***	-0.030*
				(0.028)	(0.022)	(0.016)
Observations	152,329	152,329	152,329	152,329	152,329	152,329
R^2	0.671	0.698	0.581	0.671	0.698	0.581

Notes: Observations are at the household-year from 2016 to 2019. Following Baqaee and Burstein (2023), we construct the chained price index as the dependent variable in columns (1) and (4). This index can be decomposed into two components: the intensive margin, reported in columns (2) and (5), and the extensive margin, reported in columns (3) and (6). Households are grouped into income quintiles, with the lowest income group serving as the reference category. All specifications include household fixed effects and county-by-year fixed effects. Robust standard errors clustered at the household level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Online Appendix for

"Tariffs Tax the Poor More: Evidence from Household Consumption During the US-China Trade War"[2]

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Appendix A: Background of the US-China Trade War

This section summarizes the key events that characterized the US-China trade war between 2018 and 2019. During Donald Trump's presidency (2016-2020), the US government levied new tariffs on a number of products. These tariff changes were implemented in seven waves. The average US tariff on China increased from 2.46% in January 2018 to 16.28% in December 2019. The additional tariffs are worth approximately $331.1 billion and cover 9,863 eight-digit HS products, including high-end manufacturing industries such as machinery, transportation and precision instruments, and middle- and low-end manufacturing industries such as textiles and furniture. In the following, we briefly summarize the timeline and coverage of the seven waves of tariffs imposed by the US government.[3]

Wave 1: In February 2018, the initial wave of additional tariffs was implemented, imposing a 30% duty on solar panels and duties varying between 20%-50% on washing machines. This wave affected imports of approximately $10 billion. Notably, China has refrained from retaliating against this initial round of tariff hikes.

Wave 2: In March 2018, a second wave of tariff increases was implemented, targeting approximately $18 billion worth of aluminum and steel products. The additional import duty for aluminum products was set at 10%, and for steel products it was 25%. In response, China imposed retaliatory tariffs on approximately $3 billion worth of products in April 2018. These included 25% tariffs on items such as pork and recycled aluminum and 15% tariffs on products such as fresh fruit and wine.

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[3]For more detailed information on the US-China trade war, see Ma et al. (2021). Bown and Kolb provide a detailed and up-to-date timeline for the US-China trade war: https://www.piie.com/blogs/trade-investment-policy-watch/trump-trade-war-china-date-guide.

Following these actions, both countries adopted a "tit-for-tat" strategy, mirroring each other's protectionist measures. In the remainder, we do not describe the retaliatory tariffs imposed by China and only present the US protectionist measures, which are the focus of the paper.

Wave 3: In April 2018, the United States Trade Representative (USTR) announced a 2% duty on a list of 1,333 eight-digit HS products, representing about $50 billion in Chinese imports. This list was revised on June 15, 2018, reducing its coverage to about $34 billion, including 818 eight-digit HS products. The tariffs were implemented on July 6, 2018.

Wave 4: On June 15, a new list comprising 284 products identified as beneficiaries of Chinese industrial policies, such as "Made in China 2025," was announced to incur a 25% tariff. This affected approximately $16 billion worth of imports from China and became effective on August 23, 2018.

Wave 5: On July 10, the USTR unveiled a new list targeting $200 billion worth of Chinese imports. The US imposed an additional 10% tariff on products in this list, which took effect in September 2018.

Wave 6: After a period of negotiations, the Trump administration decided to impose an additional 15% tariffs on $200 billion of Chinese products on May 10, 2019.

Wave 7: On August 1, 2019, the US announced tariffs on nearly all remaining imports from China. This announcement was marked by significant uncertainty, with the US initially postponing the tariff increase on some portions of the Wave 7 goods and later releasing two lists on August 13. The first list, effective on September 1, 2019, imposed 15% tariffs on $125 billion worth of imports from China. The second list, originally scheduled to take effect on December 15, was later canceled.

On January 15, 2020, China and the US signed the "Phase One" economic and trade agreement. Subsequently, both countries issued announcements to reduce the previously imposed tariffs. The USTR announced that, starting on February 14, 2020, the US would lower tariffs from 15% to 7.5% on approximately $120 billion worth of imports from China, which are part of the Wave 7 goods list.

The range of products affected by the additional tariffs imposed by the United States is extensive. Wave 1 only targeted solar panels and washing machines; Wave 2 mainly focused on steel and aluminum products. Subsequent waves were initially concentrated on the high-tech industries mentioned by the "Made in China 2025" initiative, such as aerospace, information technology and auto parts, and then gradually expanded to more mid to low-end manufacturing industries, such as textiles, clothing, plastics, and rubber. Our analysis combines the tariff changes of the seven waves with the Most Favored Nation (MFN) tariffs imposed by the US on imports from China. Our focus is on goods sold in retail markets, which comprise almost 50% of the HS six-digit products affected by the tariffs.

Appendix B: Tables & Figures

Appendix B1: Descriptive Results

This section provides more descriptive results on the household expenditure structure. Figure B1.1 plots the relationship between household per capita income and expenditure shares across various product categories. Table B1.1 lists the top 10 products with the largest differences in expenditure shares between low- and high-income households. Table B1.2 provides mean and standard deviation of average prices and consumption shares across continuously purchased modules and dropped modules.

To benchmark the representativeness of our sample, we calculate the share of tariff-affected goods relative to four key reference points derived from the 2016 Consumer Expenditure Survey (CEX): (i) household income, (ii) total household consumption, (iii) consumption of tradable goods, and (iv) grocery or fast-moving consumer goods (FMCG) expenditure.

We begin by noting that in our Nielsen sample, tariff-affected goods account for 59% of total household spending on FMCG products. In 2016, the average annual FMCG spending per household in our sample was $5,279, which amounts to 8.9% of average household income.[4] Multiplying these two figures, we estimate that tariff-affected goods represent 5.3% (= 59% × 8.9%) of average household income. To put this in broader perspective, CEX data indicate that total household consumption accounts for 76.8% of income. Using this ratio, we find that tariff-affected goods in our sample correspond to 6.8% of total household consumption (= 5.3% / 76.8%).

We then narrow the scope to tradable goods.[5] According to the CEX, tradable consumption accounts for 25.9% of household income. This implies that tariff-affected goods in our sample represent roughly 20.3% of tradable consumption (= 5.3% / 25.9%).

Finally, if we restrict the denominator to FMCG categories only, which comprise 9.6% of household income in the CEX, then tariff-affected goods in our sample account for 54.7% of total FMCG spending (= 5.3% / 9.6%).[6] These benchmarks highlight that while our sample does not cover all spending categories, particularly durables, it captures a sizable share of tariff-exposed consumption, especially in everyday goods, and thus provides a strong basis for analyzing household-level responses to trade policy shocks.

[4] We impute income using the midpoint of each income bracket. For the open-ended brackets—less than $5,000 and more than $100,000—we impute income as $5,000 and $100,000, respectively.

[5] Tradable goods include spending on food at home, alcoholic beverages, apparel and related services, vehicle purchases, gasoline and motor oil, other vehicle expenses, personal care products and services, reading, tobacco, housekeeping supplies, household furnishings, and miscellaneous items.

[6] We define FMCG in line with Nielsen's coverage: food at home, alcoholic beverages, personal care, reading materials, tobacco, miscellaneous, and housekeeping supplies.

Table B1.1: Top 10 Products with the Largest Differences in Expenditure Shares Between Low- and High-Income Consumers

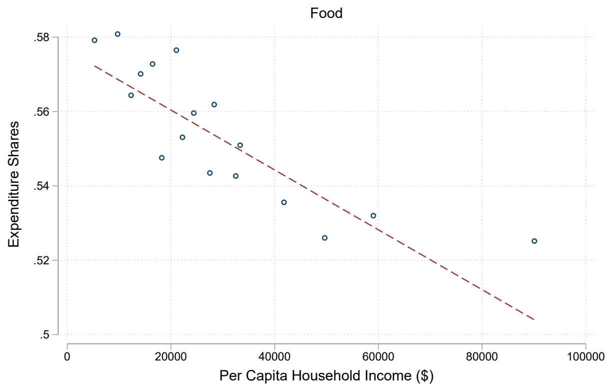
Group Name	Module Name	Expenditure Share (%) Low Income Group	Expenditure Share (%) High Income Group	Difference (p.p.)
Panel (A): Top 10 Products with Higher Expenditure Shares Among Low-Income Consumers Compared to High-Income Consumers				
Drinks	Soft drinks - carbonated	2.24	1.28	-0.96
Household/Office/School Supplies	Disposable diapers	1.55	0.91	-0.65
Drinks	Dairy-milk-refrigerated	2.02	1.49	-0.53
Drinks	Beer	1.72	1.27	-0.45
Food	Cereal - ready to eat	1.66	1.23	-0.44
Drinks	Malt liquor	0.82	0.44	-0.39
Food	Entrees - poultry - 1 food - frozen	1.02	0.70	-0.32
Food	Bakery - bread - fresh	1.49	1.23	-0.27
Food	Fresh meat	1.05	0.80	-0.26
Food	Pizza-frozen	1.10	0.85	-0.25
Panel (B): Top 10 Products with Higher Expenditure Shares Among High-Income Consumers Compared to Low-Income Consumers				
Electrical Appliances	Cellular phone	1.77	3.95	2.17
Health & Beauty	Anti-smoking products	2.57	4.48	1.91
Miscellaneous	Tobacco-smoking	2.70	4.34	1.64
Drinks	Wine-domestic dry table	1.45	2.97	1.52
Electrical Appliances	Cameras	1.79	3.24	1.45
Household/Office/School Supplies	Prepaid gift cards	1.90	3.29	1.38
Food	Cat food - wet type	1.97	3.28	1.31
Drinks	Scotch	1.30	2.51	1.21
Health & Beauty	Nutritional supplements	1.54	2.52	0.98
Food	Dog food - dry type	2.17	3.11	0.95

Table B1.2: The Intensive and Extensive Margin of Module Price and Expenditure Share

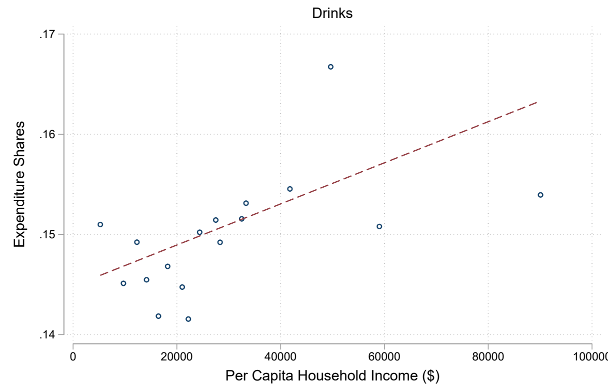
	Intensive Margin $m \in \bar{\Omega}_h^M$		Extensive Margin $m \in \Omega_{hmt} \setminus \bar{\Omega}_h^M$	
	2016	2019	2016	2019
Module Price Index	0.68	0.75	0.94	0.98
	(0.30)	(0.31)	(0.27)	(0.28)
Average Module Price	1.03	1.07	1.05	1.08
	(0.29)	(0.30)	(0.27)	(0.28)
Average Consumption Share	0.97	1.01	0.33	0.37
	(1.01)	(1.30)	(0.22)	(0.31)

Notes: This table presents the mean and standard deviation (in parentheses) of three variables—average module-level price index, average module price (calculated as total expenditures divided by total quantity for each module), and average expenditure share—calculated separately for common modules and non-common modules. For each household, we first calculate the average of these three variables within the two groups of modules: common modules (representing the intensive margin) and non-common modules (representing the extensive margin). Then, we report the mean and standard deviation of these variables across all households.

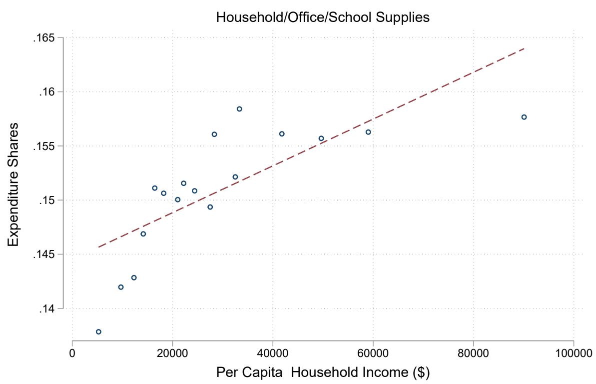
Figure B1.1: Distribution of Consumption Shares by Product Group



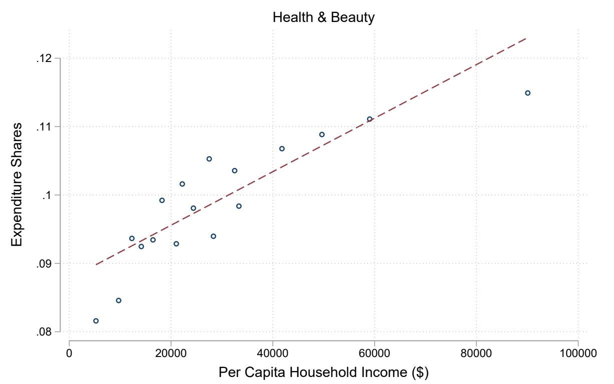
(a) Food



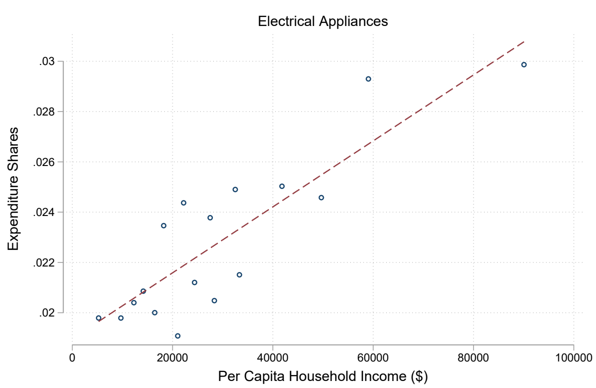
(b) Drinks



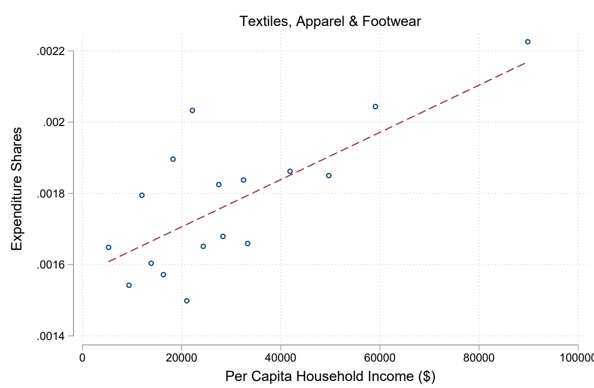
(c) Household/Office/School Supplies



(d) Health & Beauty



(e) Electrical Appliances



(f) Textiles,Apparel & Footwear

Notes: These figures plot the relationship between per capita household income and their expenditure shares across various product categories.

Appendix B2: Descriptive Statistics on Tariffs

This section provides more descriptive statistics on tariffs. Panel (A) of Table B2.1 summarizes the additional trade war tariff rates and the number of modules included in each broad product group. Panel (B) presents the top and bottom ten product modules that experienced the highest and lowest average additional tariffs during 2018-2019, respectively.

Figures 1a and 1b in the main text are constructed using trade flow data at the HS six-digit level, which we map to product modules via a standardized crosswalk. The construction of key variables proceeds as follows:

- **Share of U.S. Imports from China**: Using 2016 trade data, we compute the share of each HS six-digit product imported from China as a fraction of total U.S. imports. These HS-level import shares are then mapped to product modules using a module–HS crosswalk.

- **U.S. Import Penetration from China**: We calculate import penetration as the ratio of U.S. imports from China to total domestic absorption—defined as domestic output plus imports minus exports—at the industry level. Domestic output data, measured at the SIC (1987) level, come from the NBER-CES Manufacturing Industry Database. We first aggregate HS six-digit trade flows to the SIC level using a SIC–HS concordance, compute import penetration from China by SIC industry, and then map these values back to HS six-digit products and finally to modules.

- **Average Additional Tariff (2018–2019)**: We begin with U.S. tariff data at the HS ten-digit level and compute simple averages to aggregate up to the HS six-digit level. These six-digit tariffs are then mapped to modules using the module–HS crosswalk. If multiple HS codes map to the same module, we take the unweighted average of the corresponding tariffs to assign a single module-level tariff.

Appendix B3: Summary Statistics

In this section, we present summary statistics for key variables. Table B3.1 provides the summary statistics for the key variables used in the baseline regressions, detailing their means and standard deviations before and after the US-China trade war. Panel (A) of Table B3.2 summarizes the descriptive statistics for all variables, while Panel B focuses on household characteristics, and Panel C provides details on the characteristic of the product.

Figure B3.1 presents the GMM estimators of the elasticity of substitution among UPCs within the product modules (σ^m). The estimated median elasticity is 5, with food products typically exhibiting lower elasticities, while appliance products tend to have higher elasticities.

Table B2.1: Summary of module-level tariffs

Panel (A): Summary of Additional Tariffs by Product Groups

Group Name	Additional Tariff (2018, %)		Additional Tariff (2019, %)		Number of Modules
	Mean	STD	Mean	STD	
Food	1.02	1.06	11.07	6.39	562
Drinks	0.84	0.86	10.00	5.17	96
Household/Office/School Supplies	2.02	2.05	14.12	7.35	308
Health & Beauty	1.14	1.22	9.38	9.57	145
Electrical Appliances	2.91	2.98	10.89	8.40	67
Textiles, Apparel and Footwear	0.34	0.79	6.29	5.03	19
Miscellaneous	1.58	1.56	11.69	8.00	49

Panel (B): The Top/Bottom Ten Products with the Highest/Lowest Average Additional Tariffs in 2018-2019

Top Ten Product Modules			Bottom Ten Product Modules (Tariff=0)		
Module Name	Group Name	Additional Tariff (%)	Module Name	Group Name	Consumption share in 2016 (%)
Water Softeners & Conditioners	Household/Office/School Supplies	18.75	Nutritional Supplements	Health & Beauty	1.49
Salt-Water Softening	Household/Office/School Supplies	18.75	Cold Remedies - Adult	Health & Beauty	0.57
Ice Cream and Yogurt Maker Appliance	Electrical Appliances	18.75	Pain Remedies - Headache	Health & Beauty	0.37
Water Conditioners Filters and Units	Household/Office/School Supplies	18.75	Antacids	Health & Beauty	0.32
Water Filtration Storage Container	Household/Office/School Supplies	18.75	Adult-Incontinence	Health & Beauty	0.30
Plumbing Accessories	Household/Office/School Supplies	18.20	Vitamins-Remaining	Health & Beauty	0.28
Humidifier and Vaporizer Appliance	Electrical Appliances	17.71	Vitamins-Multiple	Health & Beauty	0.26
Home Canning Supply	Household/Office/School Supplies	17.19	Laxatives	Health & Beauty	0.25
Home Canning Accessories	Household/Office/School Supplies	17.19	Cookware Product	Household/Office/School Supplies	0.20
Power Pressure Washer Appliance	Electrical Appliances	17.01	Protein Supplements	Health & Beauty	0.17

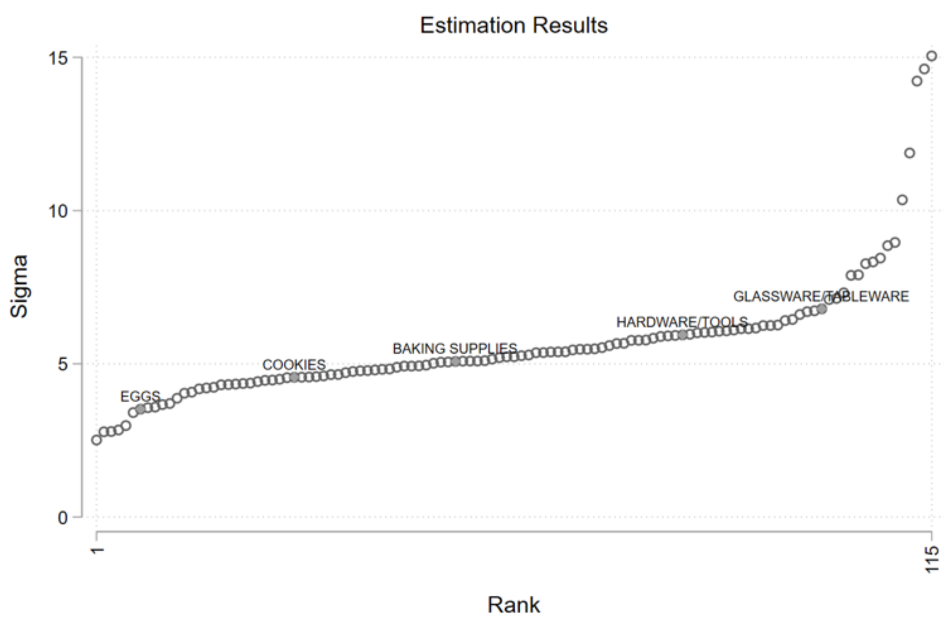
Notes: Panel (A) describes the module-level additional tariff shocks for each broad product group in 2018 and 2019. Panel (B) presents the top and bottom ten products experiencing the highest and lowest average additional tariffs during 2018-2019. Since 77 product modules are unaffected by tariff shocks (additional tariff equaling zero), we report on the bottom ten products with the largest consumption share in 2016.

Table B3.1: Summary Statistics of Key Variables Before and After Trade Shocks

Variable Description	Before (2016-2017) Mean	Before (2016-2017) SD	After (2018-2019) Mean	After (2018-2019) SD
$\ln P_{ht}$: Household price index	-2.258	0.398	-2.217	0.406
$\ln \widetilde{p_{ht}}$: Price term	1.003	0.266	1.026	0.271
$\ln S_{ht}$: Expenditure share term	-3.033	0.328	-3.025	0.331
$\ln \Lambda_{ht}$: Variety adjustment term	-0.228	0.127	-0.218	0.122
$\ln \widetilde{s^m_{ht}}$: Average module expenditure share	-2.715	0.306	-2.723	0.307
$\ln \widetilde{s^v_{ht}}$: Average UPC expenditure share	-0.318	0.064	-0.302	0.063
$\ln(1 + TAR_{ht})$: Tariff exposure	0.048	0.027	0.095	0.046
Tariff exposure by income group:				
Lowest:	0.049	0.031	0.096	0.047
Second:	0.048	0.031	0.095	0.048
Third:	0.048	0.028	0.095	0.046
Fourth:	0.047	0.025	0.095	0.044
Highest:	0.047	0.047	0.095	0.044
$\ln(1 + TAR\_IMP_{ht})$: Tariff exposure (Robustness)	0.001	0.000	0.002	0.002
$\ln(1 + TAR\_Impsh_{ht})$: Tariff exposure (Robustness)	0.003	0.001	0.009	0.006
Observations	76211		76148	

Notes: The table describes the summary statistics of the key variables used in the baseline regressions.

Figure B3.1: Estimated Elasticity of Substitution within Product Module



Notes: The figure presents the GMM estimators of the elasticity of substitution among UPCs within product modules.

Table B3.2: Summary Statistics

Panel A: Summary Statistics for key variables used in the regressions					
Variable Description	Observations	Mean	SD	Min	Max
$\ln P_{ht}$: Household price index	152,359	-2.238	0.402	-3.066	-0.869
$\ln \widetilde{p_{ht}}$: Price term	152,359	1.015	0.268	0.076	2.146
$\ln S_{ht}$: Expenditure share term	152,359	-3.029	0.33	-4.199	-0.344
$\ln \Lambda_{ht}$: Variety adjustment term	152,359	-0.223	0.125	-2.264	-0.012
$\ln \widetilde{s^m_{ht}}$: Average barcode expenditure share	152,359	-2.719	0.307	-3.801	0.000
$\ln \widetilde{s^v_{ht}}$: Average module expenditure share	152,359	-0.31	0.064	-0.897	0.000
$\ln(1 + TAR_{ht})$: Tariff expsoure	152,359	0.071	0.044	0.000	1.052
$\ln(1 + TAR\_IMP_{ht})$:Tariff expsoure (Robust Check)	152,359	0.002	0.001	0.000	0.021
$\ln(1 + TAR\_Impsh_{ht})$:Tariff expsoure (Robust Check)	152,359	0.006	0.005	0.000	0.049
# Variety (module) number					
Log (Total variety number in Ω_{hmt})	152,359	5.212	0.358	1.792	6.335
Log (Variety number in $\Omega_{hmt} \setminus \bar{\Omega}^M_h$)	152,359	4.637	0.341	1.386	5.922
Log (Number of High tariff product in $\Omega_{hmt} \setminus \bar{\Omega}^M_h$)	152,335	2.903	0.463	0.000	4.317
Log (Number of Low tariff product in $\Omega_{hmt} \setminus \bar{\Omega}^M_h$)	152,359	4.434	0.343	1.099	5.759
Household per capita income	152,359	31434.351	19349.262	714.2857	100000
# Household-Module Level					
Log (barcode number)	31,004,629	0.612	0.729	0.000	5.762
HHI_{hmt}	31,004,629	0.71	0.312	0.006	1

Panel B : Household characteristic		
Type	Observations	Share
# Household income		
Under $9999	3,640	2.39
$10,000-$19,999	9,174	6.02
$20,000-$29,999	14,884	9.77
$30,000-$39,999	17,106	11.23
$40,000-$49,999	17,184	11.28
$50,000-$59,999	15,720	10.32
$60,000-$69,999	12,479	8.19
$70,000-$99,999	32,930	21.61
$10,000+	29,242	19.19
# Household size		
Group 1	39,541	25.95
Group 2	67,098	44.04
Group 3	20,635	13.54
Group 4	15,791	10.36
Group 5+	9,294	6.1

Table B3.2: Summary Statistics (continued)

Panel B : Household characteristic		
Type	Observations	Share
# Income Group		
Lowest Income Group (Highest: Bottom 20%)	30,572	20.07
Lower-Middle Income Group (Second: pp 20%-pp40%)	30,505	20.02
Middle Income Group (Third: pp 40%-pp60%)	34,113	22.39
Upper-Middle Income Group (Fourth: pp 60%-pp80%)	27,105	17.79
Highest Income Group (Highest: Top 20%)	30,064	19.73
# Head Education		
Graduated High School and below	27,851	18.28
Some college	42,038	27.59
Graduated collge	52,404	34.4
Post College Grad	30,066	19.73
# Race		
White/Caucasian	119,245	78.27
Black/African American	15,812	10.38
Asian	4,934	3.24
Hispansic	8,872	5.82
Other	3,496	2.29

Panel C: Product characteristic		
Group	Number of UPCs	Log of UPC price
Food	567,541	1.087 (0.807)
Drinks	133,516	1.439 (1.065)
Household/Office/School Supplies	422,731	1.544 (1.052)
Health & Beauty	173,076	1.604 (0.981)
Electrical Appliances	38,323	2.537 (1.267)
Textiles, Apparel and Footwear	8,157	1.381 (0.906)
Miscellaneous	28,365	1.993 (1.086)

Notes: Panel A describes the summary statistics for all variables used in the analysis, while Panel B outlines household characteristics, and Panel C provides details on product characteristics.

Appendix C: Decomposing Changes in Household-Module Price Index

To find a suitable instrument for changes in household-module price index, we use the model's structure to represent changes in module price index in terms of the underlying UPC characteristics within the module. Inverting the demand equation (5), we can get the CES expenditure shares and express relative UPC expenditures in terms of relative UPC prices and relative UPC demand shifters: we calculate

$$s_{hvt} = \frac{\left(\frac{p_{vt}}{\varphi_{hvt}}\right)^{1-\sigma^m}}{P_{hmt}^{1-\sigma^m}}, \quad \frac{s_{hvt}}{\widetilde{s_{hmt}}} = \frac{\left(\frac{p_{vt}}{\varphi_{hvt}}\right)^{1-\sigma^m}}{\left(\frac{\widetilde{p_{mt}}}{\widetilde{\varphi_{mt}}}\right)^{1-\sigma^m}}, \quad v \in \Omega_{hmt} \tag{27}$$

where a tilde above a variable denotes the geometric mean of the variable across UPCs within a module, consumed by household h. Using this expression for relative expenditure shares to substitute for UPC price and demand shifter (φ_{hvt}) in the CES price index (4), we can derive the household-module price index in terms of the geometric mean of UPC prices and relative expenditures:

$$\begin{aligned}
\ln P_{hmt} &= \frac{1}{1-\sigma^m} \ln\left[\sum_{v\in\Omega_{hmt}} \frac{s_{hvt}}{\widetilde{s_{hmt}}} \left(\frac{\widetilde{p_{mt}}}{\widetilde{\varphi_{mt}}}\right)^{1-\sigma^m}\right] \\
&= \ln \widetilde{p_{mt}} + \ln \widetilde{\varphi_{mt}} + \frac{1}{1-\sigma^m} \ln\left[\sum_{v\in\Omega_{hmt}} \frac{s_{hvt}}{\widetilde{s_{hmt}}}\right] \\
&= \ln \widetilde{p_{mt}} + \ln \widetilde{\varphi_{mt}} + \frac{1}{1-\sigma^m} \ln N_{hmt} + \frac{1}{1-\sigma^m} \ln\left[\frac{1}{N_{hmt}} \sum_{v\in\Omega_{hmt}} \frac{s_{hvt}}{\widetilde{s_{hmt}}}\right]
\end{aligned}$$

By substituting the relative expenditure shares using Equation (27) and applying a double-difference with respect to both time and UPC k within Ω_{hmt}, we are able to reformulate the change in the logarithm of the module price index into four terms:

$$\begin{aligned}
\Delta^{n,t} \ln P_{hmt} = \Delta^{n,t} &\left(\frac{1}{N_{hmt}} \sum_{v\in\Omega_{hmt}} \ln p_{vt}\right) - \left(\frac{1}{N_{hmt}} \sum_{v\in\Omega_{hmt}} \ln \varphi_{hvt}\right) \\
&- \Delta^{n,t} \frac{1}{\sigma^m - 1} \ln N_{hmt} - \Delta^{n,t} \frac{1}{\sigma^m - 1} \ln\left(\frac{1}{N_{hmt}} \sum_{v\in\Omega_{hmt}} \frac{(p_{vt}/\varphi_{hvt})^{1-\sigma^m}}{\widetilde{(p/\varphi)}_{hmt}^{\,1-\sigma^m}}\right)
\end{aligned}$$

Appendix D: Microfoundation

In this section, we provide a microfoundation for the two principal mechanisms identified in our empirical analysis, which describe how consumers with varying income levels react to increased tariffs. Our focus is to explain why wealthier consumers typically face a smaller reduction in the variety of goods they purchase and demonstrate a greater tendency to shift their spending toward goods with lower tariffs. In contrast to the empirical analysis model, where any changes in consumption patterns can be rationalized with an appropriate change in demand shifters, in this section, we rely on a generalized Constant Elasticity of Substitution (CES), also known as Pollak preference structure (Arkolakis et al., 2019; Jung et al., 2019), to better understand the consumer's decision-making process.

For a household h and product module m, the preference structure is illustrated by the following equation:

$$U_h = \sum_{m \in \Omega_h} (q_{hm}(\omega) + \bar{q})^{\frac{\sigma-1}{\sigma}} \, d\omega - \sum_{m \in \Omega_h} \bar{q}^{\frac{\sigma}{\sigma-1}} \, d\omega \tag{28}$$

where $\sigma > 1$ and $\bar{q} > 0$ are constants. In this expression, Ω_h represents the set of products consumed by household h. The households differ according to their income levels, denoted by w_h. These preferences nest the CES case for $\bar{q} = 0$. By solving the consumer's problem, we derive the inverse demand function, given by:

$$p_m = \frac{1}{\lambda_h} (q_{hm}(\omega) + \bar{q})^{-\frac{1}{\sigma}} \tag{29}$$

where λ_h stands for the marginal utility of income. This allows us to state the direct demand function as:

$$q_{hm} = \left(\frac{w_h + \bar{q} \left(\sum_{m \in \Omega_h} p_m \right)}{\sum_{m \in \Omega_h} p_m^{1-\sigma}} \right) p_m^{-\sigma} - \bar{q} \tag{30}$$

To streamline the notation, we introduce the concept of the reservation price, p_h^*, defined as the price that reduces the demand to zero. It is formulated as:

$$p_h^* = \left(\frac{w_h + \bar{q} \left(\sum_{m \in \Omega_h} p_m \right)}{\sum_{m \in \Omega_h} p_m^{1-\sigma}} \right)^{1/\sigma} \bar{q}^{-1/\sigma} \tag{31}$$

Consequently, we can express the demand as:

$$q_{hm} = \bar{q} \left(\left(\frac{p_h^*}{p_m} \right)^{\sigma} - 1 \right) \tag{32}$$

The variation in incomes among consumers inherently leads to differing reservation prices and higher income implies a higher reservation price (Simonovska, 2015) holding constant the number of consumed varieties. Formally, if $w_h > w_v$, then $p_h^* > p_v^*$. Furthermore, this difference in reservation prices impacts the variety of goods that different consumers can afford, with wealthier consumers having access to a broader set of goods; thus $\Omega_h \supseteq \Omega_v$ when $w_h > w_v$.

Now, consider a scenario where a subset of goods, denoted as Ω_t, undergoes a price surge due to the implementation of a tariff t. We first consider the variety channel and then turn to the expenditure share channel.

Variety Channel. In our model, a product is eliminated from a consumer's consumption bundle when its price exceeds the consumer's reservation price. Our empirical analysis has shown that lower-income consumers tend to eliminate more product varieties from their consumption bundles compared to higher-income consumers. This suggests that tariffs disproportionately increase the prices of products commonly purchased by lower-income consumers beyond their reservation prices, in contrast to the impact on products purchased by wealthier consumers, which can still increase, but not beyond their reservation prices.

To further understand this, consider a ranking of products based on their increasing prices: $p_1 < p_2 < ... < p_M$. Let p_h^* represent the reservation price for a wealthier household and p_l^* for a less affluent household, implying that $p_1 < p_2 < ... < p_l^* < ... < p_h^*$. Given that lower-income consumers drop more product varieties, a significant portion of the products affected by the tariff had initial prices below p_l^*, the reservation price of poorer consumers, before the tariff was imposed. This scenario is more likely if the varieties subject to the tariff predominantly fall in the bottom or middle of the price distribution, affecting lower-income consumers more severely.

Expenditure Share Channel. To understand the changes in expenditures shares across two different product in response to tariff increase, consider the ratio of quantities demanded for products i and a product j by a specific household h. The equation is expressed as follows:

$$\frac{q_{hm}}{q_{hj}} = \frac{\left(\frac{p_h^*}{p_m}\right)^{\sigma} - 1}{\left(\frac{p_h^*}{p_j}\right)^{\sigma} - 1} \tag{33}$$

Next, we turn our attention towards understanding the elasticity of this relative quantity with respect to the price of product j:

$$\epsilon_{mj} = \frac{d \ln \left(\frac{q_{hm}}{q_{hj}}\right)}{d \ln p_j} = \sigma \frac{(p_h^*)^{\sigma}}{(p_h^*)^{\sigma} - p_j^{\sigma}} \tag{34}$$

A marginal increase of 1% in the price of the product j will augment the relative demand for product m by $\epsilon_{mj}\%$. Notice that as the reservation price approaches infinity, the elasticity converges to σ, which aligns to the standard CES case.

First, let us consider how ϵ_{ij} varies across consumers of different incomes:

$$\frac{\partial \epsilon_{mj}}{\partial (p_h^*)^\sigma} = -\sigma \frac{p_j^\sigma}{((p_h^*)^\sigma - p_j^\sigma)^2} \tag{35}$$

Hence, the elasticity declines with the reservation price. Consequently, richer consumers, characterized by higher reservation prices, exhibit a decreased response to price increases compared to poorer consumers. Intuitively, households in higher income brackets have a relatively inelastic demand for a given product, prompting a more significant reorganization of expenditure distribution among the lower income consumers in response to a tariff increase. This mechanism is not in line with our findings.

To solve this apparent contradiction, let us now consider how ϵ_{ij} varies across different products:

$$\frac{\partial \epsilon_{mj}}{\partial p_j^\sigma} = +\sigma \frac{(p_h^*)^\sigma}{((p_h^*)^\sigma - p_j^\sigma)^2} \tag{36}$$

Hence, the elasticity is higher for more expensive goods: more expensive goods, which tend to be luxuries, are more responsive to price changes. Given that wealthier consumers gravitate towards these pricier varieties, this mechanism aligns well with the empirical findings of the paper. Drawing a comparative analysis of these two last mechanisms, the tariff's effect on expenditure switching is ambiguous. Although affluent consumers exhibit less sensitivity to price fluctuations, they predominantly opt for the pricier products, which inherently have a more elastic demand. The paper's evidence underscores that this latter channel dominates the previous one in governing the dynamics of consumer responses to price changes.

Appendix E: Additional Empirical Results and Checks

Appendix E1: Validating the Decomposition

Table E1.1 presents results from a regression analysis estimating tariff pass-through to average barcode-level prices.

Table E1.1: Tariff Pass-Through to Barcode-Level Prices

Dep var.	(1) $\ln p_{vt}$	(2) $\ln p_{vt}$	(3) $\ln p_{vt}$
$\ln(1 + TAR_{mt})$	0.105***	0.122***	1.526**
	(0.008)	(0.009)	(0.754)
Observations	2,035,037	1,060,096	436
R^2	0.992	0.993	0.959

Notes: This table reports the effects of import tariff shocks on barcode-level prices using data from 2016 to 2019. The dependent variable in all columns is the logarithm of average barcode price. The key independent variable is the module-level tariff rate. Column (1) uses the full sample. Column (2) restricts the analysis to a balanced panel, including only barcodes consistently present from 2016 to 2019. Column (3) further narrows the sample to a subset of barcodes likely associated with imports from China, identified using GS1 prefixes. Estimation is performed using weighted least squares, with weights proportional to household consumption frequency. Barcodes purchased by more households receive greater weights, while those purchased less frequently are given smaller weights. All regressions include barcode and year fixed effects. Robust standard errors clustered at the barcode level are reported in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table E1.2 provides additional evidence on the mechanism by examining the product switching behavior from high-price to low-price barcodes within each product module. Low-price barcodes are identified based on their average prices during the 2016–2017 period.[7] Within each module, barcodes are ranked by their average prices, and those below the median (50th percentile) are classified as low-price barcodes. Table E1.2 uses the consumption share of low-price barcodes within the module as the dependent variable. The results show that higher-income households are more likely to reallocate their spending toward these lower-priced barcodes in response to tariff shocks.

Retail Access and Substitution Constraints

Table E1.3 then quantifies the impact of tariff shocks on various dimensions of household shopping behavior, including total spending, shopping frequency, and expenditure reallocation across retail channels. These results suggest that lower-income households face structural constraints that

[7]Because low-price barcodes are defined using average prices from 2016–2017, newly introduced barcodes in 2018–2019 are excluded due to the absence of historical price information. Consequently, the regression sample in Table E1.2 is slightly smaller than that used in Table 5.

Table E1.2: Mechanism: Expenditure Share Switching (Within Modules)

	(1)	(3)	(2)	(4)
	All sample		Common module set	
Dep var: *Within -module consumption share of low-price barcodes*				
$\ln(1 + TAR_{ht})$	0.027	-0.020	0.032	-0.019
	(0.018)	(0.020)	(0.020)	(0.022)
$\ln(1 + TAR_{ht}) \times Second\ Income_{t_0}$		0.026***		0.029***
		(0.010)		(0.010)
$\ln(1 + TAR_{ht}) \times Third\ Income_{t_0}$		0.038***		0.041***
		(0.009)		(0.010)
$\ln(1 + TAR_{ht}) \times Fourth\ Income_{t_0}$		0.060***		0.065***
		(0.010)		(0.010)
$\ln(1 + TAR_{ht}) \times Highest\ Income_{t_0}$		0.060***		0.065***
		(0.010)		(0.011)
Observations	25,072,193	25,072,193	13,417,489	13,417,489
R^2	0.702	0.702	0.710	0.710

Notes: Observations are at the household-module-year level from 2016 to 2019. The dependent variable is the consumption share of low-price barcodes within each module. Low-price barcodes are defined based on the average price of each barcode in 2016–2017. Within each module, barcodes are ranked by their average price, and those with an average price below the 50th percentile are classified as low-price barcodes. All columns include household-module fixed effects and county-year fixed effects. Robust standard errors clustered at household level are in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

limit their ability to substitute across products and retailers. This limited flexibility likely contributes to the disproportionate burden they bear from tariff-induced price increases, reinforcing the regressive nature of trade protection.

Table E1.3: Effects of Tariff Shocks on Household Shopping Behavior

	(1)	(2)	(3)	(4)	(5)
		Expenditure Share			
	Shopping Frequency	Dollar store	Warehouse Club/ Hypermarket	Online Shopping	Others
Panel (A): Tariff Shock and Household Shopping Behavior					
$\ln(1 + TAR_{ht})$	-0.026	0.005	0.109***	0.040*	-0.154***
	(0.124)	(0.011)	(0.025)	(0.021)	(0.033)
Observations	152,359	152,359	152,359	152,359	152,359
R^2	0.912	0.883	0.923	0.836	0.902
Panel (B): Heterogeneous Effects Across Households					
$\ln(1 + TAR_{ht})$	-0.630***	-0.002	0.099***	0.026	-0.122***
	(0.135)	(0.013)	(0.027)	(0.023)	(0.036)
$\ln(1 + TAR_{ht}) \times Second\ Income_{t_0}$	0.326***	0.011*	0.000	0.012	-0.022
	(0.068)	(0.006)	(0.014)	(0.010)	(0.017)
$\ln(1 + TAR_{ht}) \times Third\ Income_{t_0}$	0.429***	0.009	0.002	0.003	-0.013
	(0.066)	(0.006)	(0.013)	(0.010)	(0.017)
$\ln(1 + TAR_{ht}) \times Fourth\ Income_{t_0}$	0.714***	0.004	0.010	0.021*	-0.035*
	(0.069)	(0.006)	(0.014)	(0.011)	(0.018)
$\ln(1 + TAR_{ht}) \times Highest\ Income_{t_0}$	0.866***	0.006	0.024*	0.020*	-0.050***
	(0.067)	(0.006)	(0.014)	(0.011)	(0.018)
Observations	152,359	152,359	152,359	152,359	152,359
R^2	0.912	0.883	0.923	0.836	0.902

Notes: This table reports the effects of import tariff shocks on household shopping behavior using household-year level data from 2016 to 2019. The dependent variable in column (2) is the logarithm of shopping frequency, measured as the number of shopping trips per year. Columns (3) through (6) report the household expenditure shares across retail channels: Dollar Stores, Warehouse Clubs/Hypermarkets, Online Shopping, and Other Retailers. Panel (A) presents average effects of tariff shocks, while Panel (B) explores heterogeneous effects across income quintiles. All regressions include household fixed effects and county-by-year fixed effects. Robust standard errors clustered at the household level are shown in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

Appendix E2: Heterogeneous Effects

This section examines the heterogeneous effects of tariffs across different household characteristics. Table E2.1 presents the heterogeneous effects by the education level of household heads, categorizing households into high- and low-education groups based on whether the minimum education level of the female and male heads exceeds a high school diploma. The findings indicate that households with highly educated heads experience a less pronounced increase in the price index. Table E2.2 explores the heterogeneous effects based on the age of household heads, revealing that younger households, defined as those with the minimum age of the female and male heads below 45, tend to experience a more pronounced increase in the price index. Table E2.3 investigates the heterogeneous effects by household race, indicating that white households tend to experience a less pronounced increase in the price index. Table E2.4 examines the heterogeneous effects by household marital status, showing that single households experience a less pronounced increase in the price index compared to married households. Finally, we also explore the heterogeneous effects based on whether households have children in Table E2.5. The results demonstrate that households with children tend to experience a more pronounced increase in the price index.

Table E2.1: Heterogeneous Effects by Head Education

	$\ln P_{ht} = ln\widetilde{p_{ht}} + \ln S_{ht} + \ln \Lambda_{ht}$				$\ln S_{ht} = \ln \widetilde{s^m_{ht}} + \ln \widetilde{s^v_{ht}}$	
Dep var.	(1) $\ln P_{ht}$	(2) $\ln \widetilde{p_{ht}}$	(3) $\ln S_{ht}$	(4) $\ln \Lambda_{ht}$	(5) $\ln \widetilde{s^m_{ht}}$	(6) $\ln \widetilde{s^v_{ht}}$
$\ln(1 + TAR_{ht})$	0.269***	0.107***	-0.088**	0.250***	-0.134***	0.046*
	(0.064)	(0.035)	(0.044)	(0.034)	(0.040)	(0.024)
$\ln(1 + TAR_{ht}) \times High\ Education_{t_0}$	-0.054***	-0.015	-0.027**	-0.011	0.005	-0.032***
	(0.020)	(0.011)	(0.012)	(0.010)	(0.010)	(0.008)
Observations	152,359	152,359	152,359	152,359	152,359	152,359
R^2	0.951	0.963	0.974	0.865	0.978	0.692

Notes: Observations are at the household-year level from 2016 to 2019. The dependent variable in column (1) is the household price index ($\ln P_{ht}$) as shown in equation (13), which can be decomposed into three components: price term ($\ln \widetilde{p_{ht}}$), share term ($\ln S_{ht}$), and variety adjustment term ($\ln \Lambda_{ht}$). Specifically, columns (2)-(4) use price term, share term, and variety adjustment term as dependent variables respectively. The share term can be decompose into two components: the expenditure share adjustment across product modules ($\ln \widetilde{s^m_{ht}}$), corresponding to the dependent variable in column (5); and the expenditure share adjustment within product modules ($\ln \widetilde{s^v_{ht}}$), corresponding to the dependent variable in column (6). The independent variable is the interaction between head education level and tariff shocks. We categorize households into high and low education group based on whether the minimum education level of the household head is greater than high school. All columns include household fixed effects and county-year fixed effects. Robust standard errors clustered at household level are in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table E2.2: Heterogeneous Effects by Head Age

	$\ln P_{ht} = ln\widetilde{p_{ht}} + \ln S_{ht} + \ln \Lambda_{ht}$				$\ln S_{ht} = \ln \widetilde{s^m_{ht}} + \ln \widetilde{s^v_{ht}}$	
Dep var.	(1) $\ln P_{ht}$	(2) $\ln \widetilde{p_{ht}}$	(3) $\ln S_{ht}$	(4) $\ln \Lambda_{ht}$	(5) $\ln \widetilde{s^m_{ht}}$	(6) $\ln \widetilde{s^v_{ht}}$
$\ln(1 + TAR_{ht})$	0.497***	0.165***	0.032	0.299***	-0.095**	0.128***
	(0.067)	(0.037)	(0.046)	(0.036)	(0.041)	(0.025)
$\ln(1 + TAR_{ht}) \times I(65 > Age \geq 45)_{t_0}$	-0.308***	-0.074***	-0.157***	-0.076***	-0.043***	-0.114***
	(0.027)	(0.016)	(0.016)	(0.013)	(0.012)	(0.011)
$\ln(1 + TAR_{ht}) \times I(Age \geq 65)_{t_0}$	-0.280***	-0.091***	-0.165***	-0.023	-0.032**	-0.133***
	(0.030)	(0.017)	(0.018)	(0.015)	(0.014)	(0.012)
Observations	152,359	152,359	152,359	152,359	152,359	152,359
R^2	0.951	0.963	0.974	0.865	0.978	0.693

Notes: Observations are at the household-year level from 2016 to 2019. The dependent variable in column (1) is the household price index ($\ln P_{ht}$) as shown in equation (13), which can be decomposed into three components: price term ($\ln \widetilde{p_{ht}}$), share term ($\ln S_{ht}$), and variety adjustment term ($\ln \Lambda_{ht}$). Specifically, columns (2)-(4) use price term, share term, and variety adjustment term as dependent variables respectively. The share term can be decompose into two components: the expenditure share adjustment across product modules ($\ln \widetilde{s^m_{ht}}$), corresponding to the dependent variable in column (5); and the expenditure share adjustment within product modules ($\ln \widetilde{s^v_{ht}}$), corresponding to the dependent variable in column (6). The independent variable is the interaction between head age level and tariff shocks. We categorize households into three groups based on the minimum age of the female and male heads of the household: those where the head is under 45 years old, those aged between 45 to 64 years, and those 65 years or older. We use the group with ages under 45 years as the reference group. All columns include household fixed effects and county-year fixed effects. Robust standard errors clustered at household level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E2.3: Heterogeneous Effects by Household Race

	$\ln P_{ht} = ln\widetilde{p_{ht}} + \ln S_{ht} + \ln \Lambda_{ht}$				$\ln S_{ht} = \ln \widetilde{s^m_{ht}} + \ln \widetilde{s^v_{ht}}$	
Dep var.	(1) $\ln P_{ht}$	(2) $\ln \widetilde{p_{ht}}$	(3) $\ln S_{ht}$	(4) $\ln \Lambda_{ht}$	(5) $\ln \widetilde{s^m_{ht}}$	(6) $\ln \widetilde{s^v_{ht}}$
$\ln(1 + TAR_{ht})$	0.195***	0.081**	-0.120***	0.234***	-0.135***	0.016
	(0.063)	(0.035)	(0.044)	(0.034)	(0.040)	(0.023)
$\ln(1 + TAR_{ht}) \times Race(Black/African\ American)_{t_0}$	0.106***	0.060***	0.022	0.024	0.008	0.014
	(0.034)	(0.020)	(0.020)	(0.018)	(0.016)	(0.014)
$\ln(1 + TAR_{ht}) \times Race(Asian)_{t_0}$	-0.033	0.009	-0.044	0.003	-0.036	-0.008
	(0.060)	(0.036)	(0.034)	(0.031)	(0.027)	(0.021)
$\ln(1 + TAR_{ht}) \times Race(Hispanic)_{t_0}$	0.185***	0.046*	0.113***	0.026	0.053***	0.060***
	(0.044)	(0.026)	(0.025)	(0.021)	(0.019)	(0.017)
$\ln(1 + TAR_{ht}) \times Race(Other)_{t_0}$	0.152**	0.056	0.053	0.042	0.020	0.033
	(0.068)	(0.038)	(0.039)	(0.035)	(0.032)	(0.025)
Observations	152,359	152,359	152,359	152,359	152,359	152,359
R^2	0.951	0.963	0.974	0.865	0.978	0.692

Notes: Observations are at the household-year level from 2016 to 2019. The dependent variable in column (1) is the household price index ($\ln P_{ht}$) as shown in equation (13), which can be decomposed into three components: price term ($\ln \widetilde{p_{ht}}$), share term ($\ln S_{ht}$), and variety adjustment term ($\ln \Lambda_{ht}$). Specifically, columns (2)-(4) use price term, share term, and variety adjustment term as dependent variables respectively. The share term can be decompose into two components: the expenditure share adjustment across product modules ($\ln \widetilde{s_{ht}}$), corresponding to the dependent variable in column (5); and the expenditure share adjustment within product modules ($\ln \widetilde{s_{ht}}$), corresponding to the dependent variable in column (6). The independent variable is the interaction between race group dummy and tariff shocks. We categorize households into five groups based on household race: White/Caucasian, Black/African American, Asian, Hispanic and Other. The White/Caucasian group serves as the control group. All columns include household fixed effects and county-year fixed effects. Robust standard errors clustered at household level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E2.4: Heterogeneous Effects by Household Marital Status

	$\ln P_{ht} = ln\widetilde{p_{ht}} + \ln S_{ht} + \ln \Lambda_{ht}$				$\ln S_{ht} = \ln \widetilde{s^m_{ht}} + \ln \widetilde{s^v_{ht}}$	
Dep var.	(1) $\ln P_{ht}$	(2) $\ln \widetilde{p_{ht}}$	(3) $\ln S_{ht}$	(4) $\ln \Lambda_{ht}$	(5) $\ln \widetilde{s^m_{ht}}$	(6) $\ln \widetilde{s^v_{ht}}$
$\ln(1 + TAR_{ht})$	0.259***	0.097***	-0.095**	0.257***	-0.128***	0.034
	(0.063)	(0.035)	(0.043)	(0.034)	(0.040)	(0.023)
$\ln(1 + TAR_{ht}) \times Marital\ Status(Single)$	-0.113***	0.001	-0.051***	-0.064***	-0.011	-0.040***
	(0.029)	(0.017)	(0.018)	(0.016)	(0.015)	(0.011)
Observations	152,359	152,359	152,359	152,359	152,359	152,359
R^2	0.951	0.963	0.974	0.865	0.978	0.692

Notes: Observations are at the household-year level from 2016 to 2019. The dependent variable in column (1) is the household price index (lnP_{ht}) as shown in equation (13), which can be decomposed into three components: price term ($\ln \widetilde{p_{ht}}$), share term ($\ln S_{ht}$), and variety adjustment term ($\ln \Lambda_{ht}$). Specifically, columns (2)-(4) use price term, share term, and variety adjustment term as dependent variables respectively. The share term can be decompose into two components: the expenditure share adjustment across product modules ($\ln \widetilde{s^m_{ht}}$), corresponding to the dependent variable in column (5); and the expenditure share adjustment within product modules ($\ln \widetilde{s^v_{ht}}$), corresponding to the dependent variable in column (6). The independent variable is the interaction between marital status group and tariff shocks. We categorize households into two groups based on their marital status: single or married. The married group is utilized as the control group. All columns include household fixed effects and county-year fixed effects. Robust standard errors clustered at household level are in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table E2.5: Heterogeneous Effects by Household with/without Children

	$\ln P_{ht} = ln\widetilde{p_{ht}} + \ln S_{ht} + \ln \Lambda_{ht}$				$\ln S_{ht} = \ln \widetilde{s^m_{ht}} + \ln \widetilde{s^v_{ht}}$	
Dep var.	(1) $\ln P_{ht}$	(2) $\ln \widetilde{p_{ht}}$	(3) $\ln S_{ht}$	(4) $\ln \Lambda_{ht}$	(5) $\ln \widetilde{s^m_{ht}}$	(6) $\ln \widetilde{s^v_{ht}}$
$\ln(1 + TAR_{ht})$	0.219***	0.095***	-0.115***	0.239***	-0.131***	0.017
	(0.062)	(0.034)	(0.043)	(0.034)	(0.040)	(0.023)
$\ln(1 + TAR_{ht}) \times Household\ with\ Children$	0.263***	0.048***	0.160***	0.054***	0.011	0.150***
	(0.025)	(0.015)	(0.015)	(0.012)	(0.011)	(0.011)
Observations	152,359	152,359	152,359	152,359	152,359	152,359
R^2	0.951	0.963	0.974	0.865	0.978	0.693

Notes: Observations are at the household-year level from 2016 to 2019. The dependent variable in column (1) is the household price index ($\ln P_{ht}$) as shown in equation (13), which can be decomposed into three components: price term ($\ln \widetilde{p_{hvt}}$), share term ($\ln S_{ht}$), and variety adjustment term ($\ln \Lambda_{ht}$). Specifically, columns (2)-(4) use price term, share term, and variety adjustment term as dependent variables respectively. The share term can be decompose into two components: the expenditure share adjustment across product modules ($\ln \widetilde{s_{hmt}}$), corresponding to the dependent variable in column (5); and the expenditure share adjustment within product modules ($\ln \widetilde{s_{hvt}}$), corresponding to the dependent variable in column (6). The independent variable is the interaction between children group and tariff shocks. We categorize households into two groups based on on the presence of children under the age of 18. Households with no children are utilized as the control group. All columns include household fixed effects and county-year fixed effects. Robust standard errors clustered at household level are in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

Appendix E3: Robustness Checks

Validating the Bartik Strategy

Balanced Tests: We follow Borusyak et al. (2022) to test whether the tariff shocks are balanced with respect to various initial household characteristics. Specifically, we examine a range of household characteristics from 2016, including: the logarithm of household size, whether the head of household is single, whether the head of household is over 45 years old, whether the household has children under 18, the share of coupon value in total expenditure, the share of cash payments in total expenditure, the share of one-dollar store expenditure in total expenditure, the share of online purchases in expenditure, and whether the household has internet access. Table E3.1 presents the results of the balance test. Following the approach recommended by Borusyak et al. (2022), we aggregate household-level regressions to the module level. The lack of statistical significance of the coefficients provides supporting evidence that our empirical setting meets the requirements for treatment balance.

Table E3.1: Robustness: Balance Tests

Balance variable	Coef.	SE
Log household size, 2016	-0.013	(0.018)
The head of household is single, 2016	-0.002	(0.013)
The head of household is over 45 years old, 2016	0.001	(0.011)
Household with children under 18, 2016	0.014	(0.011)
Share of coupon value in total household expenditure, 2016	-0.000	(0.001)
Share of cash payment in total household expenditure, 2016	0.007	(0.008)
Share of one dollar store expenditure in total household expenditure, 2016	0.003	(0.002)
Share of online purchases in household expenditure, 2016	0.000	(0.004)
Household internet connection, 2016	0.011	(0.007)

Notes: This table reports coefficients from regression module-specific weighted averages of beginning-of-period household characteristics on module-level tariff shocks, as recommended by (Borusyak et al., 2022). Robust standard errors clustered at module level are in parentheses. The number of industry-year observations is 3,776. None of the estimates are significant at the 10% level.

Statistical Inference Based on Alternative Specification and Standard Errors: As highlighted by Adao et al. (2019), regression residuals in shift-share empirical specifications can be correlated across households with similar consumption baskets, which can lead to downward bias in standard errors when they are clustered at the household level. Column (2) in Table E3.2 presents the results of module-level regressions, following the approach recommended by Borusyak et al. (2022), which provides consistent standard errors that avoid the issues raised by Adao et al. (2019). Note that, to reformulate the household-level regression into a module-level regression, we approximate the independent variable $\ln(1 + TAR_{ht})$ as TAR_{ht}, which is constructed in the form of a shift-share design. Column (1) in Table E3.2 shows the corresponding household-level regression results using TAR as the independent variable, which produces the same estimated coefficient as in column (2). Columns (3) through (5) confirm that if the household-level regression is maintained as the baseline, the results remain robust under various alternative clustering protocols, including clustering by county and partitioning households based on the similarity of their consumption baskets.

Dropping Category Sections. To assess concerns that our results may be influenced by endogeneity or pre-trend issues that are associated with a particular sector, as raised by Goldsmith-Pinkham et al. (2020), we reconstruct household-level tariff shocks by leaving out the products from one category at a time. Table E3.3 summarizes the range of coefficients obtained from these robustness checks. Panel A reports the minimum and maximum coefficients, while Panel B also includes the second minimum and second maximum coefficients. The results mitigate concern that there may be a particularly pivotal or influential product category.

Table E3.2: Robustness: Statistical Inference Based on Alternative Specification and Standard Errors

Dep var: $\ln P_{ht}$	(1) Approximate independent variable	(2) BHJ shock level Regression	(3) Cluster at county-level	(4) K-mean cluster (100 groups)	(5) K-mean cluster (500 groups)
Tariff shock	0.188***	0.188*	0.232***	0.232**	0.232***
	(0.056)	(0.061)	(0.061)	(0.103)	(0.084)
Observations	152,359	3,776	152,359	152,359	152,359

Notes: This table reports results from inference corrections. Column (1) repeats the baseline regression, but approximates the independent variable $\ln(1 + TAR_{ht}) \approx TAR_{ht}$, ensuring that the independent variable is in the form of shift-share, so that the household-level regression can be reformulated to the shock-level regression in column (2). Column (2) reports the results of module-level regressions that yield tariff shock coefficients equivalent to the household-level specifications, as recommended by Borusyak et al. (2022). In column (3)-(5), coefficients are obtained from the primary household-level estimating equation (24), including household fixed effects and county-year fixed effects. In column (3), robust standard errors are clustered at county-level. In column (4)-(5), k-mean clustering approach is applied to categorize households based on similarity of expenditure share, using 100 clusters and 500 clusters respectively. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

China's Retaliatory Tariffs. Table E3.4 examines the impact of China's retaliatory tariffs on US exports, revealing a significant negative effect on the household price index. This may be attributed to the reduction in US exports to China, which likely resulted in excess supply in the domestic US market, potentially driving prices down. Importantly, accounting for these retaliatory tariffs does not affect the results of our baseline regression.

Differential Substitution Elasticities Across Household Groups. We categorize households into two groups, rich and poor, according to per capita income levels and estimate the substitution

Table E3.3: Robustness: Dropping One Category at A Time

	$\ln P_{ht} = \ln \widetilde{p_{ht}} + \ln S_{ht} + \ln \Lambda_{ht}$				$\ln S_{ht} = \ln \widetilde{s^m_{ht}} + \ln \widetilde{s^v_{ht}}$	
Dep var.	(1) $\ln P_{ht}$	(2) $\ln \widetilde{p_{ht}}$	(3) $\ln S_{ht}$	(4) $\ln \Lambda_{ht}$	(5) $\ln \widetilde{s^m_{ht}}$	(6) $\ln \widetilde{s^v_{ht}}$
Panel A: Range of Estimates (Min - Max)						
Min coefficient	0.160**	0.063*	-0.206***	0.200***	-0.217***	-0.012
	(0.070)	(0.034)	(0.048)	(0.034)	(0.044)	(0.023)
Max coefficient	0.405***	0.139***	-0.050	0.316***	-0.100**	0.050**
	(0.064)	(0.035)	(0.044)	(0.034)	(0.039)	(0.024)
Panel B: Range of Estimates (Second Min - Second Max)						
Second min coefficient	0.168***	0.068*	-0.133***	0.217***	-0.144***	-0.002
	(0.062)	(0.035)	(0.043)	(0.034)	(0.040)	(0.023)
Second max coefficient	0.258***	0.117***	-0.076*	0.264***	-0.108***	0.042*
	(0.062)	(0.034)	(0.043)	(0.034)	(0.040)	(0.023)

Notes: For each column, the regression drops one category at a time and reconstruct household tariff shock. The smallest and largest household tariff shock coefficients are reported with the associated standard errors in panel A, while the second smallest and largest coefficients are reported in panel B. All columns include household fixed effects and county-year fixed effects. All robust standard errors are reported in parentheses and are clustered at household level. * p < 0.1, ** p < 0.05, *** p < 0.01. For other detailed notes, see Table 2.

Table E3.4: Robustness: Controlling for China's Retaliatory Tariff

	$\ln P_{ht} = ln\widetilde{p_{ht}} + \ln S_{ht} + \ln \Lambda_{ht}$							
Dep var.	(1) $\ln P_{ht}$	(2) $\ln \widetilde{p_{ht}}$	(3) $\ln S_{ht}$	(4) $\ln \Lambda_{ht}$	(5) $\ln P_{ht}$	(6) $\ln \widetilde{p_{ht}}$	(7) $\ln S_{ht}$	(8) $\ln \Lambda_{ht}$
$\ln(1 + TAR_{ht})$	0.216***	0.089***	-0.104**	0.231***	0.327***	0.095**	-0.009	0.240***
	(0.062)	(0.034)	(0.043)	(0.034)	(0.067)	(0.037)	(0.045)	(0.036)
$\ln(1 + TAR^{CHN}_{ht})$	-0.165***	-0.084***	0.035	-0.116***	-0.139***	-0.081***	0.055*	-0.112***
	(0.045)	(0.025)	(0.029)	(0.024)	(0.045)	(0.025)	(0.029)	(0.024)
$\ln(1 + TAR_{ht}) \times Second\ Income_{t_0}$					-0.020	0.008	-0.033*	0.005
					(0.031)	(0.018)	(0.018)	(0.015)
$\ln(1 + TAR_{ht}) \times Third\ Income_{t_0}$					-0.075**	-0.000	-0.077***	0.002
					(0.029)	(0.017)	(0.018)	(0.015)
$\ln(1 + TAR_{ht}) \times Fourth\ Income_{t_0}$					-0.119***	-0.010	-0.097***	-0.012
					(0.031)	(0.018)	(0.019)	(0.016)
$\ln(1 + TAR_{ht}) \times Highest\ Income_{t_0}$					-0.182***	-0.015	-0.144***	-0.023
					(0.031)	(0.018)	(0.019)	(0.016)
Observations	152,359	152,359	152,359	152,359	152,359	152,359	152,359	152,359
R^2	0.951	0.963	0.974	0.865	0.951	0.963	0.974	0.865

Notes: The unit of observation is the household-year from 2016 to 2019. The variable TAR^{CHN}_{ht} denotes China's retaliatory tariff exposure at the household level. All regressions include household fixed effects and county-by-year fixed effects. Robust standard errors, clustered at the household level, are reported in parentheses. For additional details, see notes to Table 2. * p < 0.1, ** p < 0.05, *** p < 0.01.

elasticity for each group. The estimation results are presented in Tables E3.5 and E3.6. Using these new estimation results, we construct the household price index and examine the effects of tariffs on the new price index, as shown in Table E3.7. Our baseline results remain robust under this specification.

Alternative Demand Elasticities. We calculate the household price index using alternative demand elasticities from Soderbery (2015), averaging them at the product module level (σ^m) to serve as the inner-CES elasticities in our calculations. The results, shown in Table E3.10, exhibit the same qualitative pattern as our baseline findings: import tariffs raise the household-level price index, with disproportionate effects on low-income households. Importantly, the estimated coefficients are larger than those obtained using our baseline elasticities, suggesting that our main results may be conservative and represent a lower bound on the overall burden of tariff-induced price increases.

Table E3.5: Summary of Estimation Parameters for Rich Households

Panel A: Estimation of σ^m and ω^m											
Percentiles	1%	5%	10%	25%	50%	75%	90%	95%	99%	Mean	Observations
σ^m	1.93	2.66	3.21	4.14	5.12	6.58	8.64	11.98	30.39	6.32	889
ω^m	0.05	0.11	0.15	0.21	0.31	0.48	0.91	1.57	9.31	0.77	889
Panel B: Estimation of σ											
	OLS	IV	IV 95% CI								
σ	1.45	2.74	2.71-2.77								

Table E3.6: Summary of Estimation Parameters for Poor households

Panel A: Estimation of σ^m and ω^m											
Percentiles	1%	5%	10%	25%	50%	75%	90%	95%	99%	Mean	Observations
σ^m	1.70	2.46	2.98	4.02	5.16	6.70	8.91	11.78	30.75	6.29	882
ω^m	0.04	0.11	0.15	0.21	0.30	0.48	0.89	1.69	4.48	0.85	882
Panel B: Estimation of σ											
	OLS	IV	IV 95% CI								
σ	1.65	2.74	2.71-2.76								

Alternative Measurement of Tariff Shock. As a robustness check, we construct an additional measure of tariff exposure. Specifically, we incorporate the US import penetration rate from China, and the results are shown in table E3.8.

Table E3.7: Heterogeneous Substitution Elasticities Across Household Groups

	$\ln P_{ht} = ln\widetilde{p_{ht}} + \ln S_{ht} + \ln \Lambda_{ht}$							
Dep var.	(1) $\ln P_{ht}$	(2) $\ln \widetilde{p_{ht}}$	(3) $\ln S_{ht}$	(4) $\ln \Lambda_{ht}$	(5) $\ln P_{ht}$	(6) $\ln \widetilde{p_{ht}}$	(7) $\ln S_{ht}$	(8) $\ln \Lambda_{ht}$
$\ln(1 + TAR_{ht})$	0.341***	0.226***	-0.121***	0.236***	0.366***	0.242***	-0.126***	0.251***
	(0.043)	(0.007)	(0.040)	(0.034)	(0.046)	(0.007)	(0.041)	(0.036)
$\ln(1 + TAR_{ht}) \times Second\ Income_{t_0}$					-0.011	-0.007***	-0.004	0.000
					(0.018)	(0.003)	(0.014)	(0.015)
$\ln(1 + TAR_{ht}) \times Third\ Income_{t_0}$					-0.028	-0.014***	-0.012	-0.002
					(0.018)	(0.003)	(0.014)	(0.014)
$\ln(1 + TAR_{ht}) \times Fourth\ Income_{t_0}$					-0.017	-0.019***	0.021	-0.018
					(0.019)	(0.003)	(0.015)	(0.016)
$\ln(1 + TAR_{ht}) \times Highest\ Income_{t_0}$					-0.040**	-0.020***	0.011	-0.031*
					(0.019)	(0.003)	(0.016)	(0.016)
Observations	152,060	152,060	152,060	152,060	152,060	152,060	152,060	152,060
R^2	0.963	0.996	0.978	0.864	0.963	0.996	0.978	0.864

Notes: Observations are at the household-year level from 2016 to 2019. The dependent variable in column (1) and (5) is the household price index ($\ln P_{ht}$) as shown in equation (13), which can be decomposed into three components: price term $\ln \widetilde{p_{ht}}$, corresponding to the dependent variables in columns (2) and (6); share term $\ln S_{ht}$, corresponding to the dependent variables in columns (3) and (7); and variety adjustment term $\ln \Lambda_{ht}$, corresponding to the dependent variables in columns (4) and (8). Households are divided into five groups based on their income quantile, with the lowest income group serving as the reference group. All columns include household fixed effects and county-year fixed effects. Robust standard errors clustered at household level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In addition, we also construct an alternative measure of tariff exposure by incorporating the share of US imports from China. That is, $TAR\_Impsh_{ht} = \sum_{m\in\Omega_{h0}^{M}} S_{hmt_0} Impsh_{mt-1}^{CHN} \tau_m^{US,CHN}$, where $Impsh_{mt-1}^{CHN}$ denotes the share of US imports of product module m from China in the initial equilibrium $t-1$. Table E3.11 reports the results using the new tariff exposure measure, which remains consistent with our baseline results. In this case, the average exposure to tariffs increases from 0.3% before the tariff war to 1% after the tariff war. Using the results from the estimation, a simple back-of-the-envelope calculation indicated that the additional tariffs levied by the US on China's goods led to an increase of $1\%(= (1\% - 0.3\%) * 1.422)$ in the price index for US households. This increase is close to our baseline results. Moreover, this increase in the price index is lower for the highest-income group, compared to the lowest-income group, by 0.89 percentage points $(=(1\% - 0.3\%) * 1.276)$, which is consistent with the baseline estimation.

Table E3.9 explores the heterogeneous effects across different regions, focusing on counties with high exposure to China shocks, higher income levels, and larger Gini index. The exposure of US local labor markets to Chinese import shocks is sourced from Autor et al. (2013b) Counties with high income are identified using the Nielsen consumer panel data in 2016, with a value of one assigned to counties where the weighted average household income exceeds the national median. The US Gini index in 2000 is derived from the US Census Historical Income Tables. The results show no significant heterogeneity, which alleviates concerns of potential pre-existing trends specific to different counties.

Table E3.8: Alternative Tariff Exposure incorporate the U.S. import penetration rate

	$\ln P_{ht} = ln\widetilde{p_{ht}} + \ln S_{ht} + \ln \Lambda_{ht}$							
Dep var.	(1) $\ln P_{ht}$	(2) $\ln \widetilde{p_{ht}}$	(3) $\ln S_{ht}$	(4) $\ln \Lambda_{ht}$	(5) $\ln P_{ht}$	(6) $\ln \widetilde{p_{ht}}$	(7) $\ln S_{ht}$	(8) $\ln \Lambda_{ht}$
$\ln(1 + TAR\_IMP_{ht})$	3.078***	0.685*	-2.176***	4.568***	5.640***	0.596	-0.094	5.138***
	(0.722)	(0.396)	(0.429)	(0.397)	(1.055)	(0.577)	(0.617)	(0.574)
$\ln(1 + TAR\_IMP_{ht}) \times Second\ Income_{t_0}$					-0.105	0.436	-0.754	0.213
					(1.015)	(0.577)	(0.591)	(0.535)
$\ln(1 + TAR\_IMP_{ht}) \times Third\ Income_{t_0}$					-1.915**	0.162	-1.907***	-0.169
					(0.956)	(0.541)	(0.560)	(0.493)
$\ln(1 + TAR\_IMP_{ht}) \times Fourth\ Income_{t_0}$					-2.813***	0.039	-2.282***	-0.569
					(1.019)	(0.568)	(0.588)	(0.537)
$\ln(1 + TAR\_IMP_{ht}) \times Highest\ Income_{t_0}$					-4.755***	-0.050	-3.340***	-1.365***
					(0.990)	(0.556)	(0.583)	(0.529)
Observations	152,359	152,359	152,359	152,359	152,359	152,359	152,359	152,359
R^2	0.929	0.947	0.962	0.806	0.929	0.947	0.962	0.806

Notes: Observations are at the household-year level from 2016 to 2019. The dependent variable in column (1) and (5) is the household price index ($\ln P_{ht}$) as shown in equation (13), which can be decomposed into three components: price term $\ln \widetilde{p_{ht}}$, corresponding to the dependent variables in columns (2) and (6); Share term $\ln S_{ht}$, corresponding to the dependent variables in columns (3) and (7); and variety adjustment term $\ln \Lambda_{ht}$, corresponding to the dependent variables in columns (4) and (8). The tariff shock also incorporate the US import penetration rate from China. Households are divided into five groups based on their income quantile, with the lowest income group serving as the reference group. All columns include household fixed effects and county-year fixed effects. Robust standard errors clustered at household level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E3.9: Robustness: Heterogeneous Effects across Counties

	(1)	(2)	(3)	(4)
	$\ln P_{ht}$	$\ln P_{ht}$	$\ln P_{ht}$	$\ln P_{ht}$
$\ln(1 + TAR_{ht})$	0.219**	0.201**	0.239*	0.266***
	(0.089)	(0.083)	(0.133)	(0.102)
× High "China Shock" Exposure (1990-2000)	0.026			
	(0.125)			
× High "China Shock" exposure (2000-2007)		0.071		
		(0.126)		
× Counties with High Income			-0.008	
			(0.151)	
× Counties with High Income Inequality (Gini Index)				-0.054
				(0.129)
Observations	152,359	152,359	152,359	152,359
R^2	0.951	0.951	0.951	0.951

Notes: Observations are at the household-year level from 2016 to 2019. The dependent variable is the household price index $\ln P_{ht}$ as shown in equation (14). Column (1) and column (2) examine the county-level heterogeneity with high or low China Shock exposure. The variable "High China shock exposure" is a dummy variable which equals to 1 if the county is exposed to import shocks from China above the median. We use the exposure of US local labor markets to Chinese import shocks from 1990-2000 and 2000-2007 respectively (Autor et al., 2013b). In column (3), the variable "counties with high income" is a dummy variable, taking a value of one if the weighted average income of households in the county is above the national median in 2016. In column (4), the variable "counties with high income inequality" is also a dummy variable, which equals to one if Gini index in the county exceeds the median level in 2000, based on data from the Census Historical Income Tables. All columns include household fixed effects and county-year fixed effects. Robust standard errors clustered at household level are in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table E3.10: Alternative Demand Elasticity

Dep var.	$\ln P_{ht} = \ln \widetilde{p_{ht}} + \ln S_{ht} + \ln \Lambda_{ht}$				$\ln S_{ht} = \ln \widetilde{s^m_{ht}} + \ln \widetilde{s^v_{ht}}$	
	(1) $\ln P_{ht}$	(2) $\ln \widetilde{p_{ht}}$	(3) $\ln S_{ht}$	(4) $\ln \Lambda_{ht}$	(5) $\ln \widetilde{s^m_{ht}}$	(6) $\ln \widetilde{s^v_{ht}}$
Panel (A): Tariff Shock and Household Price Index						
$\ln(1 + TAR_{ht})$	0.765***	0.094***	0.419***	0.252***	-0.118***	0.538***
	(0.115)	(0.035)	(0.101)	(0.034)	(0.041)	(0.096)
Observations	152,379	152,379	152,379	152,379	152,379	152,379
R^2	0.897	0.964	0.904	0.864	0.978	0.799
Panel (B): Heterogeneous Effects Across Households						
$\ln(1 + TAR_{ht})$	0.984***	0.104***	0.612***	0.268***	-0.106**	0.718***
	(0.123)	(0.038)	(0.108)	(0.037)	(0.042)	(0.102)
$\ln(1 + TAR_{ht}) \times Second\ Income_{t_0}$	-0.002	0.005	-0.009	0.002	-0.008	-0.001
	(0.057)	(0.018)	(0.049)	(0.015)	(0.014)	(0.047)
$\ln(1 + TAR_{ht}) \times Third\ Income_{t_0}$	-0.136**	-0.004	-0.128***	-0.004	-0.028**	-0.100**
	(0.054)	(0.017)	(0.047)	(0.015)	(0.014)	(0.045)
$\ln(1 + TAR_{ht}) \times Fourth\ Income_{t_0}$	-0.267***	-0.014	-0.233***	-0.020	-0.004	-0.228***
	(0.058)	(0.018)	(0.050)	(0.016)	(0.015)	(0.048)
$\ln(1 + TAR_{ht}) \times Highest\ Income_{t_0}$	-0.380***	-0.020	-0.327***	-0.034**	-0.009	-0.317***
	(0.058)	(0.018)	(0.050)	(0.016)	(0.015)	(0.048)
Observations	152,379	152,379	152,379	152,379	152,379	152,379
R^2	0.897	0.964	0.904	0.864	0.978	0.799

Notes: Observations are at the household-year level from 2016 to 2019. As robustness, we utilize the demand elasticities from Soderbery (2015) and averaging them at the module level to serve as the inner-CES demand elasticities (σ^m) used in calculating the aggregated price index. All columns include household fixed effects and county-year fixed effects. Robust standard errors clustered at household level are in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table E3.11: Alternative Tariff Exposure

	$\ln P_{ht} = ln\widetilde{p_{ht}} + \ln S_{ht} + \ln \Lambda_{ht}$							
Dep var.	(1) $\ln P_{ht}$	(2) $\ln \widetilde{p_{ht}}$	(3) $\ln S_{ht}$	(4) $\ln \Lambda_{ht}$	(5) $\ln P_{ht}$	(6) $\ln \widetilde{p_{ht}}$	(7) $\ln S_{ht}$	(8) $\ln \Lambda_{ht}$
$\ln(1 + TAR\_Impsh_{ht})$	1.422***	0.260**	-0.298**	1.460***	2.179***	0.289*	0.244	1.646***
	(0.207)	(0.115)	(0.135)	(0.112)	(0.270)	(0.152)	(0.168)	(0.147)
$\ln(1 + TAR\_Impsh_{ht}) \times Second\ Income_{t_0}$					-0.163	0.063	-0.192	-0.034
					(0.227)	(0.131)	(0.135)	(0.116)
$\ln(1 + TAR\_Impsh_{ht}) \times Third\ Income_{t_0}$					-0.550**	-0.011	-0.474***	-0.065
					(0.216)	(0.124)	(0.131)	(0.111)
$\ln(1 + TAR\_Impsh_{ht}) \times Fourth\ Income_{t_0}$					-0.845***	-0.067	-0.585***	-0.193
					(0.229)	(0.131)	(0.135)	(0.118)
$\ln(1 + TAR\_Impsh_{ht}) \times Highest\ Income_{t_0}$					-1.276***	-0.064	-0.844***	-0.368***
					(0.226)	(0.129)	(0.138)	(0.119)
Observations	152,359	152,359	152,359	152,359	152,359	152,359	152,359	152,359
R^2	0.951	0.963	0.974	0.865	0.951	0.963	0.974	0.865

Notes: Observations are at the household-year level from 2016 to 2019. The dependent variable in column (1) and (5) is the household price index ($\ln P_{ht}$) as shown in equation (13), which can be decomposed into three components: price term $\ln \widetilde{p_{ht}}$, corresponding to the dependent variables in columns (2) and (6); Share term $\ln S_{ht}$, corresponding to the dependent variables in columns (3) and (7); and variety adjustment term $\ln \Lambda_{ht}$, corresponding to the dependent variables in columns (4) and (8). The tariff shock also incorporate the US import share from China. Households are divided into five groups based on their income quantile, with the lowest income group serving as the reference group. All columns include household fixed effects and county-year fixed effects. Robust standard errors clustered at household level are in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.